

Nonlinear Component Analysis as a Kernel Eigenvalue Problem

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A new method for performing a nonlinear form of principal component analysis is proposed. By the use of integral operator kernel functions, one can efficiently compute principal components in high-dimensional feature spaces, related to input space by some nonlinear map—for instance, the space of all possible five-pixel products in 16×16 images. We give the derivation of the method and present experimental results on polynomial feature extraction for pattern recognition.

1 Introduction ---

Principal component analysis (PCA) is a powerful technique for extracting structure from possibly high-dimensional data sets. It is readily performed by solving an eigenvalue problem or using iterative algorithms that estimate principal components (for reviews of the existing literature, see Jolliffe, 1986, and Diamantaras & Kung, 1996). PCA is an orthogonal transformation of the coordinate system in which we describe our data. The new coordinate values by which we represent the data are called *principal components*. It is often the case that a small number of principal components is sufficient to account for most of the structure in the data. These are sometimes called *factors* or *latent variables* of the data.

We are interested not in principal components in input space but in principal components of variables, or features, which are nonlinearly related to the input variables. Among these are variables obtained by taking arbitrary higher-order correlations between input variables. In the case of image analysis, this amounts to finding principal components in the space of products of input pixels.

To this end, we are computing dot products in feature space by means of kernel functions in input space. Given any algorithm that can be expressed solely in terms of dot products (i.e., without explicit usage of the variables themselves), this kernel method enables us to construct different nonlinear

versions of it (Aizerman, Braverman, & Rozonoer, 1964; Boser, Guyon, & Vapnik, 1992). Although this general fact was known (Burges, private communication), the machine learning community has made little use of it, the exception being support vector machines (Vapnik, 1995). In this article, we give an example of applying this method in the domain of unsupervised learning, to obtain a nonlinear form of PCA.

In the next section, we review the standard PCA algorithm. In order to be able to generalize it to the nonlinear case, we formulate it in a way that uses exclusively dot products. In section 3, we discuss the kernel method for computing dot products in feature spaces. Together, these two sections form the basis for section 4, which presents the proposed kernel-based algorithm for nonlinear PCA. First experimental results on kernel-based feature extraction for pattern recognition are given in section 5. We conclude with a discussion (section 6) and an appendix containing some technical material that is not essential for the main thread of the argument.

2 PCA in Feature Spaces

Given a set of centered observations \mathbf{x}_k , $k = 1, \dots, M$, $\mathbf{x}_k \in \mathbf{R}^N$, $\sum_{k=1}^M \mathbf{x}_k = 0$, PCA diagonalizes the covariance matrix,¹

$$C = \frac{1}{M} \sum_{j=1}^M \mathbf{x}_j \mathbf{x}_j^\top. \quad (2.1)$$

To do this, one has to solve the eigenvalue equation,

$$\lambda \mathbf{v} = C \mathbf{v}, \quad (2.2)$$

for eigenvalues $\lambda \geq 0$ and $\mathbf{v} \in \mathbf{R}^N \setminus \{0\}$. As $C \mathbf{v} = \frac{1}{M} \sum_{j=1}^M (\mathbf{x}_j \cdot \mathbf{v}) \mathbf{x}_j$, all solutions \mathbf{v} with $\lambda \neq 0$ must lie in the span of $\mathbf{x}_1, \dots, \mathbf{x}_M$; hence, equation 2.2 in that case is equivalent to

$$\lambda (\mathbf{x}_k \cdot \mathbf{v}) = (\mathbf{x}_k \cdot C \mathbf{v}) \text{ for all } k = 1, \dots, M. \quad (2.3)$$

In the remainder of this section, we describe the same computation in another dot product space F , which is related to the input space by a possibly nonlinear map,

$$\Phi : \mathbf{R}^N \rightarrow F, \quad \mathbf{x} \mapsto \mathbf{X}. \quad (2.4)$$

¹ More precisely, the covariance matrix is defined as the expectation of $\mathbf{x} \mathbf{x}^\top$; for convenience, we shall use the same term to refer to the estimate in equation 2.1 of the covariance matrix from a finite sample.

Note that F , which we will refer to as the feature space, could have an arbitrarily large, possibly infinite, dimensionality. Here and in the following, uppercase characters are used for elements of F , and lowercase characters denote elements of \mathbf{R}^N .

Again, we assume that we are dealing with centered data, that is $\sum_{k=1}^M \Phi(\mathbf{x}_k) = 0$ (we shall return to this point later). Using the covariance matrix in F ,

$$\bar{C} = \frac{1}{M} \sum_{j=1}^M \Phi(\mathbf{x}_j) \Phi(\mathbf{x}_j)^\top \quad (2.5)$$

(if F is infinite dimensional, we think of $\Phi(\mathbf{x}_j) \Phi(\mathbf{x}_j)^\top$ as the linear operator that maps $\mathbf{X} \in F$ to $\Phi(\mathbf{x}_j)(\Phi(\mathbf{x}_j) \cdot \mathbf{X})$) we now have to find eigenvalues $\lambda \geq 0$ and eigenvectors $\mathbf{V} \in F \setminus \{0\}$ satisfying,

$$\lambda \mathbf{V} = \bar{C} \mathbf{V}. \quad (2.6)$$

Again, all solutions \mathbf{V} with $\lambda \neq 0$ lie in the span of $\Phi(\mathbf{x}_1), \dots, \Phi(\mathbf{x}_M)$. For us, this has two useful consequences. First, we may instead consider the set of equations,

$$\lambda (\Phi(\mathbf{x}_k) \cdot \mathbf{V}) = (\Phi(\mathbf{x}_k) \cdot \bar{C} \mathbf{V}) \text{ for all } k = 1, \dots, M, \quad (2.7)$$

and, second, there exist coefficients α_i ($i = 1, \dots, M$) such that,

$$\mathbf{V} = \sum_{i=1}^M \alpha_i \Phi(\mathbf{x}_i). \quad (2.8)$$

Combining equations 2.7 and 2.8, we get

$$\begin{aligned} \lambda \sum_{i=1}^M \alpha_i (\Phi(\mathbf{x}_k) \cdot \Phi(\mathbf{x}_i)) &= \frac{1}{M} \sum_{i=1}^M \alpha_i (\Phi(\mathbf{x}_k) \cdot \sum_{j=1}^M \Phi(\mathbf{x}_j)) (\Phi(\mathbf{x}_j) \cdot \Phi(\mathbf{x}_i)) \\ &\text{for all } k = 1, \dots, M. \end{aligned} \quad (2.9)$$

Defining an $M \times M$ matrix K by

$$K_{ij} := (\Phi(\mathbf{x}_i) \cdot \Phi(\mathbf{x}_j)), \quad (2.10)$$

this reads

$$M\lambda K\alpha = K^2\alpha, \quad (2.11)$$

where α denotes the column vector with entries $\alpha_1, \dots, \alpha_M$. To find solutions of equation 2.11, we solve the eigenvalue problem,

$$M\lambda\alpha = K\alpha, \quad (2.12)$$

for nonzero eigenvalues. A justification of this procedure is given in appendix A.

Let $\lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_M$ denote the eigenvalues of K (i.e., the solutions $M\lambda$ of equation 2.12), and $\alpha^1, \dots, \alpha^M$ the corresponding complete set of eigenvectors, with λ_p being the first nonzero eigenvalue (assuming $\Phi \neq 0$). We normalize $\alpha^p, \dots, \alpha^M$ by requiring that the corresponding vectors in F be normalized, that is,

$$(\mathbf{V}^k \cdot \mathbf{V}^k) = 1 \text{ for all } k = p, \dots, M. \quad (2.13)$$

By virtue of equations 2.8 and 2.12, this translates into a normalization condition for $\alpha^p, \dots, \alpha^M$:

$$\begin{aligned} 1 &= \sum_{i,j=1}^M \alpha_i^k \alpha_j^k (\Phi(\mathbf{x}_i) \cdot \Phi(\mathbf{x}_j)) = \sum_{i,j=1}^M \alpha_i^k \alpha_j^k K_{ij} \\ &= (\alpha^k \cdot K\alpha^k) = \lambda_k (\alpha^k \cdot \alpha^k). \end{aligned} \quad (2.14)$$

For the purpose of principal component extraction, we need to compute projections onto the eigenvectors \mathbf{V}^k in F ($k = p, \dots, M$). Let \mathbf{x} be a test point, with an image $\Phi(\mathbf{x})$ in F ; then

$$(\mathbf{V}^k \cdot \Phi(\mathbf{x})) = \sum_{i=1}^M \alpha_i^k (\Phi(\mathbf{x}_i) \cdot \Phi(\mathbf{x})) \quad (2.15)$$

may be called its nonlinear principal components corresponding to Φ .

In summary, the following steps were necessary to compute the principal components: (1) compute the matrix K , (2) compute its eigenvectors and normalize them in F , and (3) compute projections of a test point onto the eigenvectors.²

For the sake of simplicity, we have made the assumption that the observations are centered. This is easy to achieve in input space but harder in F , because we cannot explicitly compute the mean of the $\Phi(\mathbf{x}_i)$ in F . There is, however, a way to do it, and this leads to slightly modified equations for kernel-based PCA (see appendix B).

² Note that in our derivation we could have used the known result (e.g., Kirby & Sirovich, 1990) that PCA can be carried out on the dot product matrix $(\mathbf{x}_i \cdot \mathbf{x}_j)_{ij}$ instead of equation 2.1; however, for the sake of clarity and extendability (in appendix B, we shall consider the question how to center the data in F), we gave a detailed derivation.

Before we proceed to the next section, which more closely investigates the role of the map Φ , the following observation is essential: Φ can be an arbitrary nonlinear map into the possibly high-dimensional space F , for example, the space of all d th order monomials in the entries of an input vector. In that case, we need to compute dot products of input vectors mapped by Φ , at a possibly prohibitive computational cost. The solution to this problem, described in the following section, builds on the fact that we exclusively need to compute dot products between mapped patterns (in equations 2.10 and 2.15); we never need the mapped patterns explicitly.

3 Computing Dot Products in Feature Spaces

In order to compute dot products of the form $(\Phi(\mathbf{x}) \cdot \Phi(\mathbf{y}))$, we use kernel representations,

$$k(\mathbf{x}, \mathbf{y}) = (\Phi(\mathbf{x}) \cdot \Phi(\mathbf{y})), \quad (3.1)$$

which allow us to compute the value of the dot product in F without having to carry out the map Φ . This method was used by Boser et al. (1992) to extend the Generalized Portrait hyperplane classifier of Vapnik and Chervonenkis (1974) to nonlinear support vector machines. To this end, they substitute a priori chosen kernel functions k for all occurrences of dot products, obtaining decision functions

$$f(\mathbf{x}) = \text{sgn} \left(\sum_{i=1}^{\ell} v_i k(\mathbf{x}, \mathbf{x}_i) + b \right). \quad (3.2)$$

Aizerman et al. (1964) call F the linearization space, and use it in the context of the potential function classification method to express the dot product between elements of F in terms of elements of the input space. If F is high-dimensional, we would like to be able to find a closed-form expression for k that can be efficiently computed. Aizerman et al. (1964) consider the possibility of choosing k a priori, without being directly concerned with the corresponding mapping Φ into F . A specific choice of k might then correspond to a dot product between patterns mapped with a suitable Φ . A particularly useful example, which is a direct generalization of a result proved by Poggio (1975, lemma 2.1) in the context of polynomial approximation, is

$$\begin{aligned} (\mathbf{x} \cdot \mathbf{y})^d &= \left(\sum_{j=1}^N x_j \cdot y_j \right)^d \\ &= \sum_{j_1, \dots, j_d=1}^N x_{j_1} \cdot \dots \cdot x_{j_d} \cdot y_{j_1} \cdot \dots \cdot y_{j_d} = (C_d(\mathbf{x}) \cdot C_d(\mathbf{y})), \end{aligned} \quad (3.3)$$

where C_d maps \mathbf{x} to the vector $C_d(\mathbf{x})$ whose entries are all possible d th degree ordered products of the entries of \mathbf{x} . For instance (Vapnik, 1995), if $\mathbf{x} = (x_1, x_2)$, then $C_2(\mathbf{x}) = (x_1^2, x_2^2, x_1 x_2, x_2 x_1)$, or, yielding the same value of the dot product,

$$\Phi_2(\mathbf{x}) = (x_1^2, x_2^2, \sqrt{2} x_1 x_2). \quad (3.4)$$

For this example, it is easy to verify that $(\mathbf{x} \cdot \mathbf{y})^2 = (x_1^2, x_2^2, \sqrt{2} x_1 x_2)(y_1^2, y_2^2, \sqrt{2} y_1 y_2)^\top = (\Phi_2(\mathbf{x}) \cdot \Phi_2(\mathbf{y}))$. In general, the function

$$k(\mathbf{x}, \mathbf{y}) = (\mathbf{x} \cdot \mathbf{y})^d \quad (3.5)$$

corresponds to a dot product in the space of d th-order monomials of the input coordinates. If \mathbf{x} represents an image with the entries being pixel values, we can thus easily work in the space spanned by products of any d pixels—provided that we are able to do our work solely in terms of dot products, without any explicit use of a mapped pattern $\Phi_d(\mathbf{x})$. The latter lives in a possibly very high-dimensional space: even though we will identify terms like $x_1 x_2$ and $x_2 x_1$ into one coordinate of F , as in equation 3.4, the dimensionality of F still is $\frac{(N+d-1)!}{d!(N-1)!}$ and thus grows like N^d . For instance, 16×16 pixel input images and a polynomial degree $d = 5$ yield a dimensionality of 10^{10} . Thus, using kernels of the form in equation 3.5 is our only way to take into account higher-order statistics without a combinatorial explosion of time and memory complexity.

The general question that function k does correspond to a dot product in some space F has been discussed by Boser et al. (1992) and Vapnik (1995): Mercer's theorem of functional analysis implies that if k is a continuous kernel of a positive integral operator, there exists a mapping into a space where k acts as a dot product (for details, see appendix C). Besides equation 3.5, radial basis functions,

$$k(\mathbf{x}, \mathbf{y}) = \exp\left(-\frac{\|\mathbf{x} - \mathbf{y}\|^2}{2\sigma^2}\right), \quad (3.6)$$

and sigmoid kernels,

$$k(\mathbf{x}, \mathbf{y}) = \tanh(\kappa(\mathbf{x} \cdot \mathbf{y}) + \Theta), \quad (3.7)$$

have been used in support vector machines. These different kernels allow the construction of polynomial classifiers, radial basis function classifiers, and neural networks with the support vector algorithm, which exhibit very similar accuracy. In addition, they all construct their decision functions from an almost identical subset of a small number of training patterns, the support vectors (Schölkopf, Burges, & Vapnik, 1995).

The application of equation 3.1 to our problem is straightforward. We simply substitute an a priori chosen kernel function $k(\mathbf{x}, \mathbf{y})$ for all occurrences of $(\Phi(\mathbf{x}) \cdot \Phi(\mathbf{y}))$. The choice of k then *implicitly* determines the mapping Φ and the feature space F .

4 Kernel PCA

4.1 The Algorithm. To perform kernel-based PCA (see Figure 1), henceforth referred to as kernel PCA, the following steps have to be carried out. First, we compute the matrix $K_{ij} = (k(\mathbf{x}_i, \mathbf{x}_j))_{ij}$. Next, we solve equation 2.12 by diagonalizing K and normalize the eigenvector expansion coefficients α^n by requiring $\lambda_n(\alpha^n \cdot \alpha^n) = 1$. To extract the principal components (corresponding to the kernel k) of a test point \mathbf{x} , we then compute projections onto the eigenvectors by (cf. equation 2.15 and Figure 2),

$$(\mathbf{V}^n \cdot \Phi(\mathbf{x})) = \sum_{i=1}^M \alpha_i^n k(\mathbf{x}_i, \mathbf{x}). \quad (4.1)$$

If we use a kernel as described in section 3, we know that this procedure exactly corresponds to standard PCA in some high-dimensional feature space, except that we do not need to perform expensive computations in that space. In practice, our algorithm is not equivalent to the form of nonlinear PCA that can be obtained by explicitly mapping into the feature space F . Even though the rank of the matrix K is always limited by the sample size, we may not be able to compute this matrix if the dimensionality is prohibitively high. In that case, using kernels is imperative.

4.2 Properties of (Kernel) PCA. If we use a kernel that satisfies the conditions given in section 3, we know that we are in fact doing a standard PCA in F . Consequently, all mathematical and statistical properties of PCA (see, e.g., Jolliffe, 1986; Diamantaras & Kung, 1996) carry over to kernel-based PCA, with the modifications that they become statements concerning F rather than \mathbf{R}^N . In F , we can thus assert that PCA is the orthogonal basis transformation with the following properties (assuming that the eigenvectors are sorted in descending order of the eigenvalue size): (1) the first q ($q \in \{1, \dots, M\}$) principal components, that is, projections on eigenvectors, carry more variance than any other q orthogonal directions, (2) the mean-squared approximation error in representing the observations by the first q principal components is minimal, (3) the principal components are uncorrelated, and (4) the first q principal components have maximal mutual information with respect to the inputs (this holds under gaussian assumptions, and thus depends on the data and the chosen kernel).

We conclude this section by noting one general property of kernel PCA in input space: for kernels that depend on only dot products or distances

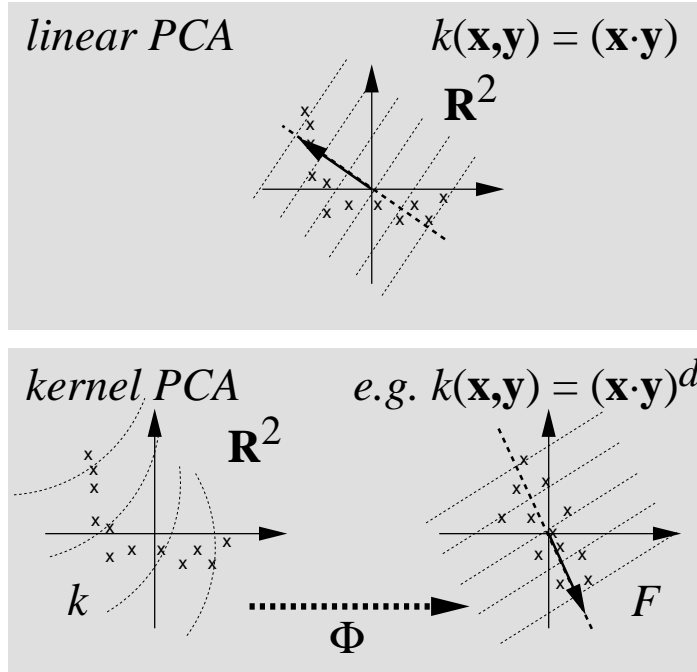


Figure 1: The basic idea of kernel PCA. In some high-dimensional feature space F (bottom right), we are performing linear PCA, just like a PCA in input space (top). Since F is nonlinearly related to input space (via Φ), the contour lines of constant projections onto the principal eigenvector (drawn as an arrow) become nonlinear in input space. Note that we cannot draw a preimage of the eigenvector in input space, because it may not even exist. Crucial to kernel PCA is the fact that there is no need to carry out the map into F . All necessary computations are carried out by the use of a kernel function k in input space (here: \mathbf{R}^2).

in input space (as all the examples that we have given so far do), kernel PCA has the property of unitary invariance, following directly from the fact that both the eigenvalue problem and the feature extraction depend on only kernel values. This ensures that the features extracted do not depend on which orthonormal coordinate system we use for representing our input data.

4.3 Computational Complexity. A fifth-order polynomial kernel on a 256-dimensional input space yields a 10^{10} -dimensional feature space. For two reasons, kernel PCA can deal with this huge dimensionality. First, we do not need to look for eigenvectors in the full space F , but just in the subspace spanned by the images of our observations \mathbf{x}_k in F . Second, we do not

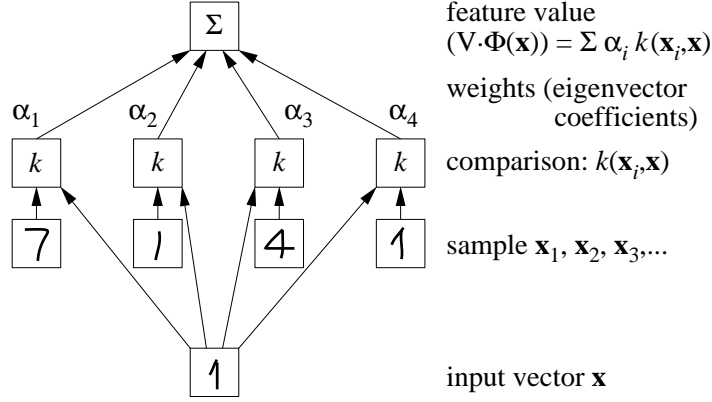


Figure 2: Feature extraction architecture in kernel PCA (cf. equation 4.1). In the first layer, the input vector is compared to the sample via a kernel function, chosen a priori (e.g., polynomial, gaussian, or sigmoid). The outputs are then linearly combined using weights, which are found by solving an eigenvector problem.

need to compute dot products explicitly between vectors in F (which can be impossible in practice, even if the vectors live in a lower-dimensional subspace) because we are using kernel functions. Kernel PCA thus is computationally comparable to a linear PCA on ℓ observations with an $\ell \times \ell$ dot product matrix. If k is easy to compute, as for polynomial kernels, for example, the computational complexity is hardly changed by the fact that we need to evaluate kernel functions rather than just dot products. Furthermore, when we need to use a large number ℓ of observations, we may want to work with an algorithm for computing only the largest eigenvalues, as, for instance, the power method with deflation (for a discussion, see Diamantaras & Kung, 1996). In addition, we can consider using an estimate of the matrix K , computed from a subset of $M < \ell$ examples, while still extracting principal components from all ℓ examples (this approach was chosen in some of our experiments described below).

The situation can be different for principal component extraction. There, we have to evaluate the kernel function M times for each extracted principal component (see equation 4.1), rather than just evaluating one dot product as for a linear PCA. Of course, if the dimensionality of F is 10^{10} , this is still vastly faster than linear principal component extraction in F . Still, in some cases (e.g., if we were to extract principal components as a preprocessing step for classification), we might want to speed things up. This can be done by a technique proposed by Burges (1996) in the context of support vector machines. In the present setting, we approximate each eigenvector $\mathbf{V} = \sum_{i=1}^{\ell} \alpha_i \Phi(\mathbf{x}_i)$ (see equation 2.8) by another vector $\hat{\mathbf{V}} = \sum_{j=1}^m \beta_j \Phi(\mathbf{z}_j)$, where

$m < \ell$ is chosen a priori according to the desired speedup, and $\mathbf{z}_j \in \mathbf{R}^N$, $j = 1, \dots, m$. This is done by minimizing the squared difference $\rho = \|\mathbf{V} - \tilde{\mathbf{V}}\|^2$. The crucial point is that this also can be done without explicitly dealing with the possibly high-dimensional space F . As

$$\rho = \|\mathbf{V}\|^2 + \sum_{i,j=1}^m \beta_i \beta_j k(\mathbf{z}_i, \mathbf{z}_j) - 2 \sum_{i=1}^{\ell} \sum_{j=1}^m \alpha_i \beta_j k(\mathbf{x}_i, \mathbf{z}_j), \quad (4.2)$$

the gradient of ρ with respect to the β_j and the \mathbf{z}_j is readily expressed in terms of the kernel function; thus, ρ can be minimized by gradient descent.

Finally, although kernel principal component extraction is computationally more expensive than its linear counterpart, this additional investment can pay back afterward. In experiments on classification based on the extracted principal components, we found that when we trained on nonlinear features, it was sufficient to use a linear support vector machine to construct the decision boundary. Linear support vector machines, however, are much faster in classification speed than nonlinear ones. This is due to the fact that for $k(\mathbf{x}, \mathbf{y}) = (\mathbf{x} \cdot \mathbf{y})$, the support vector decision function (see equation 3.2) can be expressed with a single weight vector $\mathbf{w} = \sum_{i=1}^{\ell} v_i \mathbf{x}_i$ as $f(\mathbf{x}) = \text{sgn}((\mathbf{x} \cdot \mathbf{w}) + b)$. Thus the final stage of classification can be done extremely fast.

4.4 Interpretability and Variable Selection. In PCA, it is sometimes desirable to be able to select specific axes that span the subspace into which one projects in doing principal component extraction. In this way, it may, for instance, be possible to choose variables that are more accessible to interpretation. In the nonlinear case, there is an additional problem: some directions in F do not have preimages in input space. To make this plausible, note that the linear span of the training examples mapped into feature space can have dimensionality up to M (the number of examples). If this exceeds the dimensionality of input space, it is rather unlikely that each vector of the form in equation 2.8 has a preimage. To get interpretability, we thus need to find directions in input space (i.e., input variables) whose images under Φ span the PCA subspace in F . This can be done with an approach akin to the one already described. We could parameterize our set of desired input variables and run the minimization of equation 4.2 only over those parameters. The parameters can be, for example, group parameters, which determine the amount of translation, say, starting from a set of images.

4.5 Dimensionality Reduction, Feature Extraction, and Reconstruction. Unlike linear PCA, the proposed method allows the extraction of a number of principal components that can exceed the input dimensionality. Suppose that the number of observations M exceeds the input dimensionality N . Linear PCA, even when it is based on the $M \times M$ dot product matrix, can find at

most N nonzero eigenvalues; they are identical to the nonzero eigenvalues of the $N \times N$ covariance matrix. In contrast, kernel PCA can find up to M nonzero eigenvalues—a fact that illustrates that it is impossible to perform kernel PCA directly on an $N \times N$ covariance matrix. Even more features could be extracted by using several kernels.

Being just a basis transformation, standard PCA allows the reconstruction of the original patterns \mathbf{x}_i , $i = 1, \dots, \ell$, from a complete set of extracted principal components $(\mathbf{x}_i \cdot \mathbf{v}_j)$, $j = 1, \dots, \ell$, by expansion in the eigenvector basis. Even from an incomplete set of components, good reconstruction is often possible. In kernel PCA, this is more difficult. We can reconstruct the image of a pattern in F from its nonlinear components; however, if we have only an approximate reconstruction, there is no guarantee that we can find an exact preimage of the reconstruction in input space. In that case, we would have to resort to an approximation method (cf. equation 4.2). Alternatively, we could use a suitable regression method for estimating the reconstruction mapping from the kernel-based principal components to the inputs.

5 Experiments

5.1 Toy Examples. To provide some insight into how PCA in F behaves in input space, we show a set of experiments with an artificial two-dimensional data set, using polynomial kernels (cf. equation 3.5) of degree 1 through 4 (see Figure 3). Linear PCA (on the left) leads to only two nonzero eigenvalues, as the input dimensionality is 2. In contrast, nonlinear PCA allows the extraction of further components. In the figure, note that nonlinear PCA produces contour lines (of constant feature value), which reflect the structure in the data better than in linear PCA. In all cases, the first principal component varies monotonically along the parabola underlying the data. In the nonlinear cases, the second and the third components show behavior that is similar for different polynomial degrees. The third component, which comes with small eigenvalues (rescaled to sum to 1), seems to pick up the variance caused by the noise, as can be nicely seen in the case of degree 2. Dropping this component would thus amount to noise reduction. Further toy examples, using radial basis function kernels (see equation 3.6) and neural network-type sigmoid kernels (see equation 3.7), are shown in Figures 4 and 5.

5.2 Character Recognition. In this experiment, we extracted nonlinear principal components from a handwritten character database, using kernel PCA in the form given in appendix B. We chose the US Postal Service (USPS) database of handwritten digits collected from mail envelopes in Buffalo. This database contains 9298 examples of dimensionality 256; 2007 of them make up the test set. For computational reasons, we decided to use a subset of 3000 training examples for the matrix K . To assess the utility of

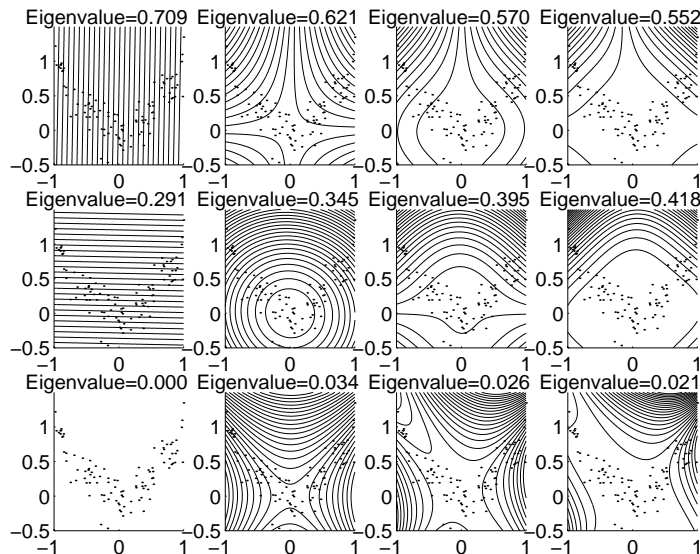


Figure 3: Two-dimensional toy example, with data generated in the following way: x values have uniform distribution in $[-1, 1]$, y values are generated from $y_i = x_i^2 + \xi$, where ξ is normal noise with standard deviation 0.2. From left to right, the polynomial degree in the kernel (see equation 3.5) increases from 1 to 4; from top to bottom, the first three eigenvectors are shown in order of decreasing eigenvalue size. The figures contain lines of constant principal component value (contour lines); in the linear case, these are orthogonal to the eigenvectors. We did not draw the eigenvectors; as in the general case, they live in a higher-dimensional feature space.

the components, we trained a soft margin hyperplane classifier (Vapnik & Chervonenkis, 1974; Cortes & Vapnik, 1995) on the classification task. This is a special case of support vector machines, using the standard dot product as a kernel function. It simply tries to separate the training data by a hyperplane with large margin.

Table 1 illustrates two advantages of using nonlinear kernels. First, performance of a linear classifier trained on nonlinear principal components is better than for the same number of linear components; second, the performance for nonlinear components can be further improved by using more components than is possible in the linear case. The latter is related to the fact that there are many more higher-order features than there are pixels in an image. Regarding the first point, note that extracting a certain number of features in a 10^{10} -dimensional space constitutes a much higher reduction of dimensionality than extracting the same number of features in 256-dimensional input space.

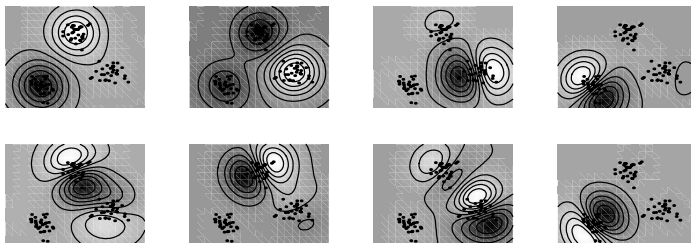


Figure 4: Two-dimensional toy example with three data clusters (gaussians with standard deviation 0.1, depicted region: $[-1, 1] \times [-0.5, 1]$): first eight nonlinear principal components extracted with $k(\mathbf{x}, \mathbf{y}) = \exp(-\frac{\|\mathbf{x}-\mathbf{y}\|^2}{0.1})$. Note that the first two principal components (top left) nicely separate the three clusters. Components 3–5 split up the clusters into halves. Similarly, components 6–8 split them again, in a way orthogonal to the above splits. Thus, the first eight components divide the data into 12 regions. The Matlab code used for generating this figure can be obtained from <http://svm.first.gmd.de>.

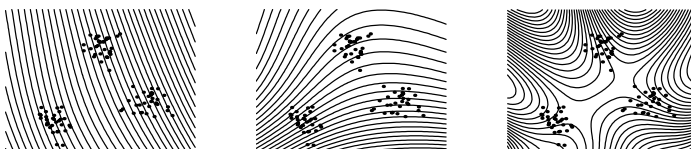


Figure 5: Two-dimensional toy example with three data clusters (gaussians with standard deviation 0.1, depicted region: $[-1, 1] \times [-0.5, 1]$): first three nonlinear principal components extracted with $k(\mathbf{x}, \mathbf{y}) = \tanh(2(\mathbf{x} \cdot \mathbf{y}) + 1)$. The first two principal components (top left) are sufficient to separate the three clusters, and the third component splits the clusters into halves.

For all numbers of features, the optimal degree of kernels to use is around 4, which is compatible with support vector machine results on the same data set (Schölkopf, Burges, & Vapnik, 1995). Moreover, with only one exception, the nonlinear features are superior to their linear counterparts. The resulting error rate for the best of our classifiers (4.0%) is competitive with convolutional five-layer neural networks (5.0% were reported by LeCun et al., 1989) and nonlinear support vector classifiers (4.0%, Schölkopf, Burges, & Vapnik, 1995); it is much better than linear classifiers operating directly on the image data (a linear support vector machine achieves 8.9%; Schölkopf, Burges, & Vapnik, 1995). These encouraging results have been reproduced on an object recognition task (Schölkopf, Smola, & Müller, 1996).

Table 1: Test Error Rates on the USPS Handwritten Digit Database.

Number of components	Test Error Rate for Degree						
	1	2	3	4	5	6	7
32	9.6	8.8	8.1	8.5	9.1	9.3	10.8
64	8.8	7.3	6.8	6.7	6.7	7.2	7.5
128	8.6	5.8	5.9	6.1	5.8	6.0	6.8
256	8.7	5.5	5.3	5.2	5.2	5.4	5.4
512	N.A.	4.9	4.6	4.4	5.1	4.6	4.9
1024	N.A.	4.9	4.3	4.4	4.6	4.8	4.6
2048	N.A.	4.9	4.2	4.1	4.0	4.3	4.4

Note: Linear support vector machines were trained on nonlinear principal components extracted by PCA with kernel (3.5), for degrees 1 through 7. In the case of degree 1, we are doing standard PCA, with the number of nonzero eigenvalues being at most the dimensionality of the space, 256. Clearly, nonlinear principal components afford test error rates that are superior to the linear case (degree 1).

6 Discussion

6.1 Feature Extraction for Classification. This article presented a new technique for nonlinear PCA. To develop this technique, we made use of a kernel method so far used only in supervised learning (Vapnik, 1995). Kernel PCA constitutes a first step toward exploiting this technique for a large class of algorithms.

In experiments comparing the utility of kernel PCA features for pattern recognition using a linear classifier, we found two advantages of nonlinear kernels. First, nonlinear principal components afforded better recognition rates than corresponding numbers of linear principal components; and, second, the performance for nonlinear components can be improved by using more components than is possible in the linear case. We have not yet compared kernel PCA to other techniques for nonlinear feature extraction and dimensionality reduction. We can, however, compare results with other feature extraction methods used in the past by researchers working on the USPS classification problem. Our system of kernel PCA feature extraction plus linear support vector machine, for instance, performed better than LeNet1 (LeCun et al., 1989). Although the latter result was obtained a number of years ago, LeNet1 nevertheless provides an architecture that contains a great deal of prior information about the handwritten character classification problem. It uses shared weights to improve transformation invariance and a hierarchy of feature detectors resembling parts of the human visual system. In addition, our features were extracted without taking into account that we want to do classification. Clearly, in supervised learning, where we are given a set of labeled observations $(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_\ell, y_\ell)$, it

would seem advisable to make use of the labels not only during the training of the final classifier but also in the stage of feature extraction.

Finally, we note that a similar approach can be taken in the case of regression estimation.

6.2 Feature Space and the Curse of Dimensionality. We are doing PCA in 10^{10} -dimensional feature spaces, yet getting results in finite time that are comparable to state-of-the-art techniques. In fact, however, we are not working in the full feature space, but in a comparably small linear subspace of it, whose dimension equals at most the number of observations. The method automatically chooses this subspace and provides a means of taking advantage of the lower dimensionality. An approach that consisted in explicitly mapping into feature space and then performing PCA would have severe difficulties at this point. Even if PCA was done based on an $M \times M$ dot product matrix (M being the sample size), whose diagonalization is tractable, it would still be necessary to evaluate dot products in a 10^{10} -dimensional feature space to compute the entries of the matrix in the first place. Kernel-based methods avoid this problem; they do not explicitly compute all dimensions of F (loosely speaking, all possible features), but work only in a relevant subspace of F .

6.3 Comparison to Other Methods for Nonlinear PCA. Starting from some of the properties characterizing PCA (see above), it is possible to develop a number of possible generalizations of linear PCA to the nonlinear case. Alternatively, one may choose an iterative algorithm that adaptively estimates principal components and make some of its parts nonlinear to extract nonlinear features.

Rather than giving a full review of this field here, we briefly describe five approaches and refer readers to Diamantaras and Kung (1996) for more details.

6.3.1 Hebbian Networks. Initiated by the pioneering work of Oja (1982), a number of unsupervised neural network algorithms computing principal components have been proposed. Compared to the standard approach of diagonalizing the covariance matrix, they have advantages—for instance, when the data are nonstationary. Nonlinear variants of these algorithms are obtained by adding nonlinear activation functions. The algorithms then extract features that the authors have referred to as nonlinear principal components. These approaches, however, do not have the geometrical interpretation of kernel PCA as a standard PCA in a feature space nonlinearly related to input space, and it is thus more difficult to understand what exactly they are extracting.

6.3.2 Autoassociative Multilayer Perceptrons. Consider a linear three-layer perceptron with a hidden layer smaller than the input. If we train

it to reproduce the input values as outputs (i.e., use it in autoassociative mode), then the hidden unit activations form a lower-dimensional representation of the data, closely related to PCA (see, for instance, Diamantaras & Kung, 1996). To generalize to a nonlinear setting, one uses nonlinear activation functions and additional layers.³ While this can be considered a form of nonlinear PCA, the resulting network training consists of solving a hard nonlinear optimization problem, with the possibility of getting trapped in local minima, and thus with a dependence of the outcome on the starting point of the training. Moreover, in neural network implementations, there is often a risk of getting overfitting. Another drawback of neural approaches to nonlinear PCA is that the number of components to be extracted has to be specified in advance. As an aside, note that hyperbolic tangent kernels can be used to extract neural network-type nonlinear features using kernel PCA (see Figure 5). The principal components of a test point \mathbf{x} in that case take the form (see Figure 2) $\sum_i \alpha_i^n \tanh \cdot (\kappa(\mathbf{x}_i, \mathbf{x}) + \Theta)$.

6.3.3 Principal Curves. An approach with a clear geometric interpretation in input space is the method of principal curves (Hastie & Stuetzle, 1989), which iteratively estimates a curve (or surface) capturing the structure of the data. The data are mapped to the closest point on a curve, and the algorithm tries to find a curve with the property that each point on the curve is the average of all data points projecting onto it. It can be shown that the only straight lines satisfying the latter are principal components, so principal curves are indeed a generalization of the latter. To compute principal curves, a nonlinear optimization problem has to be solved. The dimensionality of the surface, and thus the number of features to extract, is specified in advance.

6.3.4 Locally Linear PCA. In cases where a linear PCA fails because the dependences in the data vary nonlinearly with the region in input space, it can be fruitful to use an approach where linear PCA is applied locally (e.g., Bregler & Omohundro, 1994). Possibly kernel PCA could be improved by taking locality into account.

6.3.5 Kernel PCA. Kernel PCA is a nonlinear generalization of PCA in the sense that it is performing PCA in feature spaces of arbitrarily large (possibly infinite) dimensionality, and if we use the kernel $k(\mathbf{x}, \mathbf{y}) = (\mathbf{x} \cdot \mathbf{y})$, we recover standard PCA. Compared to the above approaches, kernel PCA has the main advantage that no nonlinear optimization is involved; it is

³ Simply using nonlinear activation functions in the hidden layer would not suffice. The linear activation functions already lead to the best approximation of the data (given the number of hidden nodes), so for the nonlinearities to have an effect on the components, the architecture needs to be changed to comprise more layers (see, e.g., Diamantaras & Kung, 1996).

essentially linear algebra, as simple as standard PCA. In addition, we need not specify the number of components that we want to extract in advance. Compared to neural approaches, kernel PCA could be disadvantageous if we need to process a very large number of observations, because this results in a large matrix K . Compared to principal curves, kernel PCA is harder to interpret in input space; however, at least for polynomial kernels, it has a very clear interpretation in terms of higher-order features.

7 Conclusion

Compared to other techniques for nonlinear feature extraction, kernel PCA has the advantages that it requires only the solution of an eigenvalue problem, not nonlinear optimization, and by the possibility of using different kernels, it comprises a fairly general class of nonlinearities that can be used. Clearly the last point has yet to be evaluated in practice; however, for the support vector machine, the utility of different kernels has already been established. Different kernels (polynomial, sigmoid, gaussian) led to fine classification performances (Schölkopf, Burges, & Vapnik, 1995). The general question of how to select the ideal kernel for a given task (i.e., the appropriate feature space), however, is an open problem.

The scene has been set for using the kernel method to construct a wide variety of rather general nonlinear variants of classical algorithms. It is beyond our scope here to explore all the possibilities, including many distance-based algorithms, in detail. Some of them are currently being investigated—for instance, nonlinear forms of k -means clustering and kernel-based independent component analysis (Schölkopf, Smola, & Müller, 1996).

Linear PCA is being used in numerous technical and scientific applications, including noise reduction, density estimation, image indexing and retrieval systems, and the analysis of natural image statistics. Kernel PCA can be applied to all domains where traditional PCA has so far been used for feature extraction and where a nonlinear extension would make sense.

Appendix A: The Eigenvalue Problem in the Space of Expansion Coefficients

Being symmetric, K has an orthonormal basis of eigenvectors $(\beta^i)_i$ with corresponding eigenvalues μ_i ; thus, for all i , we have $K\beta^i = \mu_i\beta^i$ ($i = 1, \dots, M$). To understand the relation between equations 2.11 and 2.12, we proceed as follows. First, suppose λ, α satisfy equation 2.11. We may expand α in K 's eigenvector basis as $\alpha = \sum_{i=1}^M a_i\beta^i$. Equation 2.11 then reads $M\lambda \sum_i a_i\mu_i\beta^i = \sum_i a_i\mu_i^2\beta^i$, or, equivalently, for all $i = 1, \dots, M$, $M\lambda a_i\mu_i = a_i\mu_i^2$. This in turn means that for all $i = 1, \dots, M$,

$$M\lambda = \mu_i \text{ or } a_i = 0 \text{ or } \mu_i = 0. \quad (\text{A.1})$$

Note that the above are not exclusive ors. We next assume that λ, α satisfy equation 2.12, to carry out a similar derivation. In that case, we find that equation 2.12 is equivalent to $M\lambda \sum_i a_i \beta^i = \sum_i a_i \mu_i \beta^i$, that is, for all $i = 1, \dots, M$,

$$M\lambda = \mu_i \text{ or } a_i = 0. \quad (\text{A.2})$$

Comparing equations A.1 and A.2, we see that all solutions of the latter satisfy the former. However, they do not give its full set of solutions: given a solution of equation 2.12, we may always add multiples of eigenvectors of K with eigenvalue 0 and still satisfy equation 2.11, with the same eigenvalue. This means that there exist solutions of equation 2.11 that belong to different eigenvalues yet are not orthogonal in the space of the α^k . It does not mean, however, that the eigenvectors of \tilde{C} in F are not orthogonal. Indeed, if α is an eigenvector of K with eigenvalue 0, then the corresponding vector $\sum_i \alpha_i \Phi(\mathbf{x}_i)$ is orthogonal to *all* vectors in the span of the $\Phi(\mathbf{x}_j)$ in F , since $(\Phi(\mathbf{x}_j) \cdot \sum_i \alpha_i \Phi(\mathbf{x}_i)) = (K\alpha)_j = 0$ for all j , which means that $\sum_i \alpha_i \Phi(\mathbf{x}_i) = 0$. Thus, the above difference between the solutions of equations 2.11 and 2.12 is irrelevant, since we are interested in vectors in F rather than vectors in the space of the expansion coefficients of equation 2.8. We thus only need to diagonalize K to find all relevant solutions of equation 2.11.

Appendix B: Centering in High-Dimensional Space

Given any Φ and any set of observations $\mathbf{x}_1, \dots, \mathbf{x}_M$, the points

$$\tilde{\Phi}(\mathbf{x}_i) := \Phi(\mathbf{x}_i) - \frac{1}{M} \sum_{i=1}^M \Phi(\mathbf{x}_i) \quad (\text{B.1})$$

are centered. Thus, the assumptions of section 2 now hold, and we go on to define covariance matrix and $\tilde{K}_{ij} = (\tilde{\Phi}(\mathbf{x}_i) \cdot \tilde{\Phi}(\mathbf{x}_j))$ in F . We arrive at the already familiar eigenvalue problem,

$$\tilde{\lambda} \tilde{\alpha} = \tilde{K} \tilde{\alpha}, \quad (\text{B.2})$$

with $\tilde{\alpha}$ being the expansion coefficients of an eigenvector (in F) in terms of the points in equation B.1, $\tilde{\mathbf{V}} = \sum_{i=1}^M \tilde{\alpha}_i \tilde{\Phi}(\mathbf{x}_i)$. Because we do not have the centered data (see equation B.1), we cannot compute \tilde{K} directly; however, we can express it in terms of its noncentered counterpart K . In the following, we shall use $K_{ij} = (\Phi(\mathbf{x}_i) \cdot \Phi(\mathbf{x}_j))$ and the notations $1_{ij} = 1$ for all i, j , $(1_M)_{ij} := 1/M$, to compute $\tilde{K}_{ij} = (\tilde{\Phi}(\mathbf{x}_i) \cdot \tilde{\Phi}(\mathbf{x}_j))$:

$$\tilde{K}_{ij} = \left(\left(\Phi(\mathbf{x}_i) - \frac{1}{M} \sum_{m=1}^M \Phi(\mathbf{x}_m) \right) \cdot \left(\Phi(\mathbf{x}_j) - \frac{1}{M} \sum_{n=1}^M \Phi(\mathbf{x}_n) \right) \right) \quad (\text{B.3})$$

$$\begin{aligned}
&= K_{ij} - \frac{1}{M} \sum_{m=1}^M 1_{im} K_{mj} - \frac{1}{M} \sum_{n=1}^M K_{in} 1_{nj} + \frac{1}{M^2} \sum_{m,n=1}^M 1_{im} K_{mn} 1_{nj} \\
&= (K - 1_M K - K 1_M + 1_M K 1_M)_{ij}.
\end{aligned}$$

We thus can compute \tilde{K} from K and then solve the eigenvalue problem (see equation B.2). As in equation 2.14, the solutions $\tilde{\alpha}^k$ are normalized by normalizing the corresponding vectors $\tilde{\mathbf{V}}^k$ in F , which translates into $\tilde{\lambda}_k(\tilde{\alpha}^k \cdot \tilde{\alpha}^k) = 1$. For feature extraction, we compute projections of centered Φ -images of test patterns \mathbf{t} onto the eigenvectors of the covariance matrix of the centered points,

$$(\tilde{\mathbf{V}}^k \cdot \tilde{\phi}(\mathbf{t})) = \sum_{i=1}^M \tilde{\alpha}_i^k (\tilde{\Phi}(\mathbf{x}_i) \cdot \tilde{\Phi}(\mathbf{t})). \quad (\text{B.4})$$

Consider a set of test points $\mathbf{t}_1, \dots, \mathbf{t}_L$, and define two $L \times M$ matrices by $K_{ij}^{\text{test}} = (\Phi(\mathbf{t}_i) \cdot \Phi(\mathbf{x}_j))$ and $\tilde{K}_{ij}^{\text{test}} = ((\Phi(\mathbf{t}_i) - \frac{1}{M} \sum_{m=1}^M \Phi(\mathbf{x}_m)) \cdot (\Phi(\mathbf{x}_j) - \frac{1}{M} \sum_{n=1}^M \Phi(\mathbf{x}_n)))$. As in equation B.3, we express \tilde{K}^{test} in terms of K^{test} , and arrive at $\tilde{K}^{\text{test}} = K^{\text{test}} - 1'_M K - K^{\text{test}} 1_M + 1'_M K 1_M$, where $1'_M$ is the $L \times M$ matrix with all entries equal to $1/M$.

Appendix C: Mercer Kernels

Mercer's theorem of functional analysis (e.g., Courant & Hilbert, 1953) gives conditions under which we can construct the mapping Φ from the eigenfunction decomposition of k . If k is the continuous kernel of an integral operator $\mathcal{K} : L^2 \rightarrow L^2$, $(\mathcal{K}f)(\mathbf{y}) = \int k(\mathbf{x}, \mathbf{y}) f(\mathbf{x}) d\mathbf{x}$, which is positive, that is,

$$\int f(\mathbf{x}) k(\mathbf{x}, \mathbf{y}) f(\mathbf{y}) d\mathbf{x} d\mathbf{y} \geq 0 \text{ for all } f \in L^2, \quad (\text{C.1})$$

then k can be expanded into a uniformly convergent series,

$$k(\mathbf{x}, \mathbf{y}) = \sum_{i=1}^{\infty} \lambda_i \phi_i(\mathbf{x}) \phi_i(\mathbf{y}), \quad (\text{C.2})$$

with $\lambda_i \geq 0$. In this case,

$$\Phi : \mathbf{x} \mapsto (\sqrt{\lambda_1} \psi_1(\mathbf{x}), \sqrt{\lambda_2} \psi_2(\mathbf{x}), \dots) \quad (\text{C.3})$$

is a map into F such that k acts as the given dot product, that is, $(\Phi(\mathbf{x}) \cdot \Phi(\mathbf{y})) = k(\mathbf{x}, \mathbf{y})$.

Although formulated originally for the case where the integral operator acts on functions f from $L^2([a, b])$, Mercer's theorem also holds if f is defined on a space of arbitrary dimensionality, provided that it is compact (e.g., Dunford & Schwartz, 1963).

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References

- Aizerman, M., Braverman, E., & Rozonoer, L. (1964). Theoretical foundations of the potential function method in pattern recognition learning. *Automation and Remote Control*, 25, 821–837.
- Boser, B. E., Guyon, I. M., & Vapnik, V. N. (1992). A training algorithm for optimal margin classifiers. In D. Haussler (Ed.), *Proceedings of the 5th Annual ACM Workshop on Computational Learning Theory* (pp. 144–152). Pittsburgh: ACM Press.
- Bregler, C., & Omohundro, M. (1994). Surface learning with applications to lipreading. In J. D. Cowan, G. Tesauro, & J. Alspector (Eds.), *Advances in neural information processing systems 6*. San Mateo, CA: Morgan Kaufmann.
- Burges, C. J. C. (1996). Simplified support vector decision rules. In L. Saitta (Ed.), *Proc. 13th Intl. Conf. on Machine Learning*. San Mateo, CA: Morgan Kaufmann.
- Cortes, C., & Vapnik, V. (1995). Support vector networks. *Machine Learning*, 20, 273–297.
- Courant, R., & Hilbert, D. (1953). *Methods of mathematical physics* (Vol. 1). New York: Interscience.
- Diamantaras, K. I., & Kung, S. Y. (1996). *Principal component neural networks*. New York: Wiley.
- Dunford, N., & Schwartz, J. T. (1963). *Linear operators part II: Spectral theory, self adjoint operators in Hilbert space*. New York: Wiley.
- Hastie, T., & Stuetzle, W. (1989). Principal curves. *JASA*, 84, 502–516.
- Jolliffe, I. T. (1986). *Principal component analysis*. New York: Springer-Verlag.
- Kirby, M., & Sirovich, L. (1990). Application of the Karhunen-Loève procedure for the characterization of human faces. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 12(1), 103–108.
- Le Cun, Y., Boser, B., Denker, J. S., Henderson, D., Howard, R. E., Hubbard, W., & Jackel, L. J. (1989). Backpropagation applied to handwritten zip code recognition. *Neural Computation*, 1, 541–551.
- Oja, E. (1982). A simplified neuron model as a principal component analyzer. *J. Math. Biology*, 15, 267–273.

- Poggio, T. (1975). On optimal nonlinear associative recall. *Biological Cybernetics*, 19, 201–209.
- Schölkopf, B., Burges, C., & Vapnik, V. (1995). Extracting support data for a given task. In U. M. Fayyad & R. Uthurusamy (Eds.), *Proceedings, First Intl. Conference on Knowledge Discovery and Data Mining*. Menlo Park, CA: AAAI Press.
- Schölkopf, B., Smola, A., & Müller, K.-R. (1996). *Nonlinear component analysis as a kernel eigenvalue problem* (Tech. Rep. No. 44). Tübingen: Max-Planck-Institut für biologische Kybernetik.
- Vapnik, V. (1995). *The nature of statistical learning theory*. New York: Springer-Verlag.
- Vapnik, V., & Chervonenkis, A. (1974). *Theory of pattern recognition* [in Russian]. Nauka, Moscow, 1974. (German Translation: W. Wapnik & A. Tscherwonienkis, *Theorie der Zeichener Kennung*, Akademie-Verlag, Berlin).

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12. Kyoungok Kim, Jaewook Lee. 2012. Sequential manifold learning for efficient churn prediction. *Expert Systems with Applications* **39**:18, 13328-13337. [[CrossRef](#)]
13. Chia-Hui Huang. 2012. A reduced support vector machine approach for interval regression analysis. *Information Sciences* **217**, 56-64. [[CrossRef](#)]
14. Jinghua Wang, Jane You, Qin Li, Yong Xu. 2012. Orthogonal discriminant vector for face recognition across pose. *Pattern Recognition* **45**:12, 4069-4079. [[CrossRef](#)]
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16. Jun Liang, Long Chen, Xiaobo Chen. 2012. Discriminant Kernel Learning Using Hybrid Regularization. *Neural Processing Letters* **36**:3, 257-273. [[CrossRef](#)]
17. S. Joe Qin. 2012. Survey on data-driven industrial process monitoring and diagnosis. *Annual Reviews in Control* **36**:2, 220-234. [[CrossRef](#)]
18. Nicolas Duchateau, Mathieu De Craene, Gemma Piella, Alejandro F. Frangi. 2012. Constrained manifold learning for the characterization of pathological deviations from normality. *Medical Image Analysis* **16**:8, 1532-1549. [[CrossRef](#)]
19. S. Barua, A. W. M. Ng, B. J. C. Perera. 2012. Artificial Neural Network-Based Drought Forecasting Using a Nonlinear Aggregated Drought Index. *Journal of Hydrologic Engineering* **17**:12, 1408-1413. [[CrossRef](#)]
20. Lei Zhang, Qixin Cao, Jay Lee. 2012. A novel ant-based clustering algorithm using Renyi entropy. *Applied Soft Computing* . [[CrossRef](#)]
21. Raoof Gholami, Vamegh Rasouli, Andisheh Alimoradi. 2012. Improved RMR Rock Mass Classification Using Artificial Intelligence Algorithms. *Rock Mechanics and Rock Engineering* . [[CrossRef](#)]
22. Jun Li, Dacheng Tao, Xuelong Li. 2012. A probabilistic model for image representation via multiple patterns. *Pattern Recognition* **45**:11, 4044-4053. [[CrossRef](#)]
23. Mingxing Jia, Hengyuan Xu, Xiaofei Liu, Ning Wang. 2012. The optimization of the kind and parameters of kernel function in KPCA for process monitoring. *Computers & Chemical Engineering* **46**, 94-104. [[CrossRef](#)]

24. Jaume Gibert, Ernest Valveny, Horst Bunke. 2012. Feature selection on node statistics based embedding of graphs. *Pattern Recognition Letters* **33**:15, 1980-1990. [[CrossRef](#)]
25. Zhihui Lai, Zhong Jin, Jian Yang, Mingming Sun. 2012. Dynamic transition embedding for image feature extraction and recognition. *Neural Computing and Applications* **21**:8, 1905-1915. [[CrossRef](#)]
26. Hakan Cevikalp, Bill Triggs. 2012. Hyperdisk based large margin classifier. *Pattern Recognition* . [[CrossRef](#)]
27. A. Diaf, B. Boufama, R. Benlamri. 2012. Non-parametric Fisher's Discriminant Analysis with Kernels for Data Classification. *Pattern Recognition Letters* . [[CrossRef](#)]
28. Kalam Narendar Reddy, Vadlamani Ravi. 2012. Differential evolution trained kernel principal component WNN and kernel binary quantile regression: Application to banking. *Knowledge-Based Systems* . [[CrossRef](#)]
29. T. Hitendra Sarma, P. Viswanath, B. Eswara Reddy. 2012. Speeding-up the kernel k-means clustering method: A prototype based hybrid approach. *Pattern Recognition Letters* . [[CrossRef](#)]
30. Leilei Chang, Yu Zhou, Jiang Jiang, Mengjun Li, Xiaohang Zhang. 2012. Structure learning for belief rule base expert system: A comparative study. *Knowledge-Based Systems* . [[CrossRef](#)]
31. Yan Liu, Fu-li Wang, Yu-qing Chang. 2012. Reconstruction in integrating fault spaces for fault identification with kernel independent component analysis. *Chemical Engineering Research and Design* . [[CrossRef](#)]
32. Peter Knee. 2012. Sparse Representations for Radar with MATLAB® Examples. *Synthesis Lectures on Algorithms and Software in Engineering* **4**:1, 1-85. [[CrossRef](#)]
33. Shaban Shataee, Syavash Kalbi, Asghar Fallah, Dieter Pelz. 2012. Forest attribute imputation using machine-learning methods and ASTER data: comparison of k -NN, SVR and random forest regression algorithms. *International Journal of Remote Sensing* **33**:19, 6254-6280. [[CrossRef](#)]
34. References 453-510. [[CrossRef](#)]
35. Wendelin Böhmer, Steffen Grünewälder, Hannes Nickisch, Klaus Obermayer. 2012. Generating feature spaces for linear algorithms with regularized sparse kernel slow feature analysis. *Machine Learning* **89**:1-2, 67-86. [[CrossRef](#)]
36. Jian Tang, Tianyou Chai, Wen Yu, Lijie Zhao. 2012. Feature extraction and selection based on vibration spectrum with application to estimating the load parameters of ball mill in grinding process. *Control Engineering Practice* **20**:10, 991-1004. [[CrossRef](#)]
37. V. Borkar, S.P. Meyn. 2012. Oja's algorithm for graph clustering, Markov spectral decomposition, and risk sensitive control. *Automatica* **48**:10, 2512-2519. [[CrossRef](#)]
38. Valero Laparra, Sandra Jiménez, Gustavo Camps-Valls, Jesús Malo. 2012. Nonlinearities and Adaptation of Color Vision from Sequential Principal Curves Analysis. *Neural Computation* **24**:10, 2751-2788. [[Abstract](#)] [[Full Text](#)] [[PDF](#)] [[PDF Plus](#)]
39. Rebecca B. Horton, Morgan McConico, Currie Landry, Tho Tran, Frank Vogt. 2012. Introducing nonlinear, multivariate 'Predictor Surfaces' for quantitative modeling of chemical systems with higher-order, coupled predictor variables. *Analytica Chimica Acta* **746**, 1-14. [[CrossRef](#)]
40. Shizhun Yang, Ming Lin, Chenping Hou, Changshui Zhang, Yi Wu. 2012. A general framework for transfer sparse subspace learning. *Neural Computing and Applications* **21**:7, 1801-1817. [[CrossRef](#)]
41. Chang Jun Lee, Gibaek Lee, Jong Min Lee. 2012. A fault magnitude based strategy for effective fault classification. *Chemical Engineering Research and Design* . [[CrossRef](#)]
42. Ion Marqués, Manuel Graña. 2012. Fusion of lattice independent and linear features improving face identification. *Neurocomputing* . [[CrossRef](#)]
43. Guoqiang Zhong, Cheng-Lin Liu. 2012. Error-correcting output codes based ensemble feature extraction. *Pattern Recognition* . [[CrossRef](#)]
44. Zhihui Lai, Yajing Li, Minghua Wan, Zhong Jin. 2012. Local sparse representation projections for face recognition. *Neural Computing and Applications* . [[CrossRef](#)]
45. Zafar Ali Khan, Won Sohn. 2012. A hierarchical abnormal human activity recognition system based on R-transform and kernel discriminant analysis for elderly health care. *Computing* . [[CrossRef](#)]
46. Tobias Glasmachers, Jan Koutník, Jürgen Schmidhuber. 2012. Kernel representations for evolving continuous functions. *Evolutionary Intelligence* **5**:3, 171-187. [[CrossRef](#)]
47. Xueqin Liu, Kang Li, Marion McAfee, Jing Deng. 2012. Application of nonlinear PCA for fault detection in polymer extrusion processes. *Neural Computing and Applications* **21**:6, 1141-1148. [[CrossRef](#)]

48. Moshe Salhov, Guy Wolf, Amir Averbuch. 2012. Patch-to-tensor embedding. *Applied and Computational Harmonic Analysis* **33**:2, 182-203. [[CrossRef](#)]
49. Alan Julian Izenman. 2012. Introduction to manifold learning. *Wiley Interdisciplinary Reviews: Computational Statistics* **4**:5, 439-446. [[CrossRef](#)]
50. Prashanth Reddy Marpu, Mattia Pedergnana, Mauro Dalla Mura, Stijn Peeters, Jon Atli Benediktsson, Lorenzo Bruzzone. 2012. Classification of hyperspectral data using extended attribute profiles based on supervised and unsupervised feature extraction techniques. *International Journal of Image and Data Fusion* **3**:3, 269-298. [[CrossRef](#)]
51. Jun-Bao Li. 2012. Gabor filter based optical image recognition using Fractional Power Polynomial model based common discriminant locality preserving projection with kernels. *Optics and Lasers in Engineering* **50**:9, 1281-1286. [[CrossRef](#)]
52. Nopriadi, Yukihiro Yamashita. 2012. A new approach to a maximum a posteriori-based kernel classification method. *Neural Networks* **33**, 247-256. [[CrossRef](#)]
53. Yingwei Zhang, Shuai Li, Zhiyong Hu. 2012. Improved multi-scale kernel principal component analysis and its application for fault detection. *Chemical Engineering Research and Design* **90**:9, 1271-1280. [[CrossRef](#)]
54. K. Jaya Priya, R. S. Rajesh. 2012. Selective local texture features based face recognition with single sample per class. *Journal of the Brazilian Computer Society* **18**:3, 229-235. [[CrossRef](#)]
55. Xiaoran Zhu, Youyun Zhang, Yongsheng Zhu. 2012. Intelligent fault diagnosis of rolling bearing based on kernel neighborhood rough sets and statistical features. *Journal of Mechanical Science and Technology* **26**:9, 2649-2657. [[CrossRef](#)]
56. T. Berka, M. Vajteršić. 2012. Parallel rare term vector replacement: Fast and effective dimensionality reduction for text. *Journal of Parallel and Distributed Computing* . [[CrossRef](#)]
57. Yingwei Zhang, Chuang Wang, Renquan Lu. 2012. Modeling and monitoring of multimode process based on subspace separation. *Chemical Engineering Research and Design* . [[CrossRef](#)]
58. Metin Demiralp, Emre Demiralp. 2012. A contemporary linear representation theory for ordinary differential equations: probabilistic evolutions and related approximants for unidimensional autonomous systems. *Journal of Mathematical Chemistry* . [[CrossRef](#)]
59. Il Memming Park, Sohan Seth, Murali Rao, José C. Príncipe. 2012. Strictly Positive-Definite Spike Train Kernels for Point-Process Divergences. *Neural Computation* **24**:8, 2223-2250. [[Abstract](#)] [[Full Text](#)] [[PDF](#)] [[PDF Plus](#)]
60. Hadi Sadoghi Yazdi, Hamed Modaghegh, Morteza Pakdaman. 2012. Ordinary differential equations solution in kernel space. *Neural Computing and Applications* **21**:S1, 79-85. [[CrossRef](#)]
61. Jun-Bao Li. 2012. Mammographic Image Based Breast Tissue Classification with Kernel Self-optimized Fisher Discriminant for Breast Cancer Diagnosis. *Journal of Medical Systems* **36**:4, 2235-2244. [[CrossRef](#)]
62. Oliver Kramer, Fabian Gieseke. 2012. Evolutionary kernel density regression. *Expert Systems with Applications* **39**:10, 9246-9254. [[CrossRef](#)]
63. Edisanter Lo. 2012. Maximized subspace model for hyperspectral anomaly detection. *Pattern Analysis and Applications* **15**:3, 225-235. [[CrossRef](#)]
64. K. Jaya Priya, R. S. Rajesh. 2012. Score-Level Fusion of Local Spatial, Scale and Directional Features Based Face Recognition Approach for Single Sample Problem. *National Academy Science Letters* **35**:4, 315-322. [[CrossRef](#)]
65. Tingting Mu, Makoto Miwa, Junichi Tsujii, Sophia Ananiadou. 2012. DISCOVERING ROBUST EMBEDDINGS IN (DIS)SIMILARITY SPACE FOR HIGH-DIMENSIONAL LINGUISTIC FEATURES. *Computational Intelligence* no-no. [[CrossRef](#)]
66. Min Zhao, Chongxun Zheng, Chunlin Zhao. 2012. A New Approach for Concealed Information Identification Based on ERP Assessment. *Journal of Medical Systems* **36**:4, 2401-2409. [[CrossRef](#)]
67. Matthias Scholz. 2012. Validation of Nonlinear PCA. *Neural Processing Letters* **36**:1, 21-30. [[CrossRef](#)]
68. Lin Feng, Sheng-lan Liu, Zhen-yu Wu, Bo Jin. 2012. Maximal Similarity Embedding. *Neurocomputing* . [[CrossRef](#)]
69. ZHIHONG ZHANG, EDWIN R. HANCOCK. 2012. KERNEL ENTROPY-BASED UNSUPERVISED SPECTRAL FEATURE SELECTION. *International Journal of Pattern Recognition and Artificial Intelligence* **26**:05, 1260002. [[CrossRef](#)]
70. Horst Bunke, Kaspar Riesen Graph Embedding Using Dissimilarities with Applications in Classification 156-173. [[CrossRef](#)]
71. Xingwei Yang, Xiang Bai, Suzan Köknar-Tezel, Longin Jan Latecki. 2012. Densifying Distance Spaces for Shape and Image Retrieval. *Journal of Mathematical Imaging and Vision* . [[CrossRef](#)]

72. Min Du, Xingshu Chen, Jun Tan. 2012. An efficient method of P2P traffic identification based on wavelet packet decomposition and kernel principal component analysis. *International Journal of Communication Systems* n/a-n/a. [[CrossRef](#)]
73. Yuzhen Xue, Peter J. Ludovice, Martha A. Grover, Lilia V. Nedialkova, Carmeline J. Dsilva, Ioannis G. Kevrekidis. 2012. State reduction in molecular simulations. *Computers & Chemical Engineering* . [[CrossRef](#)]
74. François Fouss, Kevin Francoise, Luh Yen, Alain Pirotte, Marco Saerens. 2012. An experimental investigation of kernels on graphs for collaborative recommendation and semisupervised classification. *Neural Networks* **31**, 53-72. [[CrossRef](#)]
75. Antoni Wibowo, Yoshitsugu Yamamoto. 2012. A note on kernel principal component regression. *Computational Mathematics and Modeling* **23**:3, 350-367. [[CrossRef](#)]
76. Shankar Vembu, Alexander Vergara, Mehmet K. Muezzinoglu, Ramón Huerta. 2012. On time series features and kernels for machine olfaction. *Sensors and Actuators B: Chemical* . [[CrossRef](#)]
77. Mohammad Aghaahmadi, Mohammad Mahdi Dehshibi, Azam Bastanfard, Mahmood Fazlali. 2012. Clustering Persian viseme using phoneme subspace for developing visual speech application. *Multimedia Tools and Applications* . [[CrossRef](#)]
78. Xiaoyong Bian, Tianxu Zhang, Xiaolong Zhang, LuXin Yan, Bo Li. 2012. Clustering-Based Extraction of Near Border Data Samples for Remote Sensing Image Classification. *Cognitive Computation* . [[CrossRef](#)]
79. S. U. Han, S. H. Lee, F. Peña-Mora A Machine-Learning Classification Approach to Automatic Detection of Workers' Actions for Behavior-Based Safety Analysis 65-72. [[CrossRef](#)]
80. Dimitrios Giannakis, Peter Schwander, Abbas Ourmazd. 2012. The symmetries of image formation by scattering I Theoretical framework. *Optics Express* **20**:12, 12799. [[CrossRef](#)]
81. Yahong Han, Zhongwen Xu, Zhigang Ma, Zi Huang. 2012. Image classification with manifold learning for out-of-sample data. *Signal Processing* . [[CrossRef](#)]
82. Ernesto De Vito, Veronica Umanità, Silvia Villa. 2012. An extension of Mercer theorem to matrix-valued measurable kernels. *Applied and Computational Harmonic Analysis* . [[CrossRef](#)]
83. C. Sumana, Ketan Detroja, Ravindra D. Gudi. 2012. Evaluation of nonlinear scaling and transformation for nonlinear process fault detection. *International Journal of Advances in Engineering Sciences and Applied Mathematics* **4**:1-2, 52-66. [[CrossRef](#)]
84. Dapeng Tao, Lingyu Liang, Lianwen Jin, Yan Gao. 2012. Similar handwritten Chinese character recognition by kernel discriminative locality alignment. *Pattern Recognition Letters* . [[CrossRef](#)]
85. SangUk Han, SangHyun Lee, Feniosky Peña-Mora Vision-Based Motion Detection for Safety Behavior Analysis in Construction 1032-1041. [[CrossRef](#)]
86. Kichun Lee, Alexander Gray, Heeyoung Kim. 2012. Dependence maps, a dimensionality reduction with dependence distance for high-dimensional data. *Data Mining and Knowledge Discovery* . [[CrossRef](#)]
87. Alexander Vergara, Shankar Vembu, Tuba Ayhan, Margaret A. Ryan, Margie L. Homer, Ramón Huerta. 2012. Chemical gas sensor drift compensation using classifier ensembles. *Sensors and Actuators B: Chemical* **166-167**, 320-329. [[CrossRef](#)]
88. Yinghua Yang, Yonglu Chen, Xiaobo Chen, Xiaozhi Liu. 2012. Multivariate industrial process monitoring based on the integration method of canonical variate analysis and independent component analysis. *Chemometrics and Intelligent Laboratory Systems* . [[CrossRef](#)]
89. Horst Bunke, Kaspar Riesen. 2012. Towards the unification of structural and statistical pattern recognition. *Pattern Recognition Letters* **33**:7, 811-825. [[CrossRef](#)]
90. Yingwei Zhang, Chi Ma. 2012. Decentralized fault diagnosis using multiblock kernel independent component analysis. *Chemical Engineering Research and Design* **90**:5, 667-676. [[CrossRef](#)]
91. Weilin Huang, Hujun Yin. 2012. On nonlinear dimensionality reduction for face recognition. *Image and Vision Computing* **30**:4-5, 355-366. [[CrossRef](#)]
92. GUANGHUI HE, LINGFENG ZHANG, ZHAOWEI SHANG. 2012. CORRELATION-BASED MULTIDIMENSIONAL SCALING FOR UNSUPERVISED SUBSPACE LEARNING. *International Journal of Wavelets, Multiresolution and Information Processing* **10**:03, 1250030. [[CrossRef](#)]
93. M. Doménech-Moral, F. J. Martínez-Serrano, R. Domínguez-Tenreiro, A. Serna. 2012. Formation of galaxies in #cold dark matter cosmologies - I. The fine structure of disc galaxies. *Monthly Notices of the Royal Astronomical Society* **421**:3, 2510-2530. [[CrossRef](#)]
94. T. C. Pataky, T. Mu, K. Bosch, D. Rosenbaum, J. Y. Goulermas. 2012. Gait recognition: highly unique dynamic plantar pressure patterns among 104 individuals. *Journal of The Royal Society Interface* **9**:69, 790-800. [[CrossRef](#)]

95. Badong Chen, Songlin Zhao, Pingping Zhu, José C. Príncipe. 2012. Mean square convergence analysis for kernel least mean square algorithm. *Signal Processing* . [[CrossRef](#)]
96. Alessandro Rozza, Gabriele Lombardi, Elena Casiraghi, Paola Campadelli. 2012. Novel Fisher discriminant classifiers. *Pattern Recognition* . [[CrossRef](#)]
97. Scott D. McKnight. 2012. Semi-Supervised Classification of Patient Safety Event Reports. *Journal of Patient Safety* 1. [[CrossRef](#)]
98. Peter Mondrup Rasmussen, Trine Julie Abrahamsen, Kristoffer Hougaard Madsen, Lars Kai Hansen. 2012. Nonlinear denoising and analysis of neuroimages with kernel principal component analysis and pre-image estimation. *NeuroImage* **60**:3, 1807-1818. [[CrossRef](#)]
99. Daniel Stahl, Andrew Pickles, Mayada Elsabbagh, Mark H. Johnson, The BASIS Team. 2012. Novel Machine Learning Methods for ERP Analysis: A Validation From Research on Infants at Risk for Autism. *Developmental Neuropsychology* **37**:3, 274-298. [[CrossRef](#)]
100. Na Qi, Zhuoyong Zhang, Yuhong Xiang, Peter de B. Harrington. 2012. Locally linear embedding method for dimensionality reduction of tissue sections of endometrial carcinoma by near infrared spectroscopy. *Analytica Chimica Acta* **724**, 12-19. [[CrossRef](#)]
101. Antoni Wibowo, Mohamad Ishak Desa. 2012. Kernel based regression and genetic algorithms for estimating cutting conditions of surface roughness in end milling machining process. *Expert Systems with Applications* . [[CrossRef](#)]
102. Julian J. Faraway. 2012. Backscoring in Principal Coordinates Analysis. *Journal of Computational and Graphical Statistics* **21**:2, 394-412. [[CrossRef](#)]
103. MingTao Ding, Zi Jin, Zheng Tian, XiFa Duan, Wei Zhao, LiJuan Yang. 2012. Object registration for remote sensing images using robust kernel pattern vectors. *Science China Information Sciences* . [[CrossRef](#)]
104. G. A. Tribello, M. Ceriotti, M. Parrinello. 2012. Using sketch-map coordinates to analyze and bias molecular dynamics simulations. *Proceedings of the National Academy of Sciences* . [[CrossRef](#)]
105. Yongjin Wang, Anastasios Venetsanopoulos Information Fusion for Multimodal Analysis and Recognition **20120443**, 153-171. [[CrossRef](#)]
106. D. Seyed Javan, H. Rajabi Mashhadi, S. Ashkezari Toussi, M. Rouhani. 2012. On-line Voltage and Power Flow Contingencies Ranking Using Enhanced Radial Basis Function Neural Network and Kernel Principal Component Analysis. *Electric Power Components and Systems* **40**:5, 534-555. [[CrossRef](#)]
107. Lorenzo Bruzzone, Claudio Persello, Begüm Demir Active Learning Methods in Classification of Remote Sensing Images 303-324. [[CrossRef](#)]
108. Ingo Steinwart, Clint Scovel. 2012. Mercer's Theorem on General Domains: On the Interaction between Measures, Kernels, and RKHSs. *Constructive Approximation* . [[CrossRef](#)]
109. Zhihui Lai, Cairong Zhao, Minghua Wan. 2012. Fisher Difference Discriminant Analysis: Determining the Effective Discriminant Subspace Dimensions for Face Recognition. *Neural Processing Letters* . [[CrossRef](#)]
110. Jie Gui. 2012. Discriminant sparse neighborhood preserving embedding for face recognition. *Pattern Recognition* . [[CrossRef](#)]
111. Ruiming Liu, Yanhong Lu, Chenglong Gong, Yang Liu. 2012. Infrared point target detection with improved template matching. *Infrared Physics & Technology* . [[CrossRef](#)]
112. Diana Mateus, Christian Wachinger, Selen Atasoy, Loren Schwarz, Nassir Navab Learning Manifolds 374-402. [[CrossRef](#)]
113. Rough-Fuzzy Clustering: Generalized cA-Means Algorithm 47-83. [[CrossRef](#)]
114. Shou-Jen Chang-Chien, Wen-Liang Hung, Miin-Shen Yang. 2012. On mean shift-based clustering for circular data. *Soft Computing* . [[CrossRef](#)]
115. Jun-Bao Li, Wen-He Sun, Yun-Heng Wang, Lin-Lin Tang. 2012. 3D model classification based on nonparametric discriminant analysis with kernels. *Neural Computing and Applications* . [[CrossRef](#)]
116. Behrooz Makki, Mona Noori Hosseini. 2012. Some refinements of the standard autoassociative neural network. *Neural Computing and Applications* . [[CrossRef](#)]
117. M. Serva, F. Petroni, D. Volchenkov, S. Wichmann. 2012. Malagasy dialects and the peopling of Madagascar. *Journal of The Royal Society Interface* **9**:66, 54-67. [[CrossRef](#)]
118. Yingwei Zhang, Shuai Li, Yongdong Teng. 2012. Dynamic processes monitoring using recursive kernel principal component analysis. *Chemical Engineering Science* . [[CrossRef](#)]

119. Till Rumpf, Christoph Römer, Martin Weis, Markus Sökefeld, Roland Gerhards, Lutz Plümer. 2012. Sequential support vector machine classification for small-grain weed species discrimination with special regard to *Cirsium arvense* and *Galium aparine*. *Computers and Electronics in Agriculture* **80**, 89-96. [[CrossRef](#)]
120. Yi Chen, Jun Yin, Jie Zhu, Zhong Jin. 2012. Dimensionality reduction via locally reconstructive patch alignment. *Optical Engineering* **51**:7, 077208. [[CrossRef](#)]
121. Gui-Fu Lu, Zhong Jin, Jian Zou. 2012. Face recognition using discriminant sparsity neighborhood preserving embedding. *Knowledge-Based Systems* **31**, 119. [[CrossRef](#)]
122. Jaume Gibert, Ernest Valveny, Horst Bunke. 2012. Graph embedding in vector spaces by node attribute statistics. *Pattern Recognition* . [[CrossRef](#)]
123. G.-Y. Feng, H.-T. Xiao, Q. Fu. 2012. Local sampling mean discriminant analysis with kernels. *Electronics Letters* **48**:1, 22. [[CrossRef](#)]
124. Zhen Lei, Zhiwei Zhang, Stan Z. Li. 2012. Feature space locality constraint for kernel based nonlinear discriminant analysis. *Pattern Recognition* . [[CrossRef](#)]
125. Arthur Spirling. 2012. U.S. Treaty Making with American Indians: Institutional Change and Relative Power, 1784-1911. *American Journal of Political Science* **56**:1, 84-97. [[CrossRef](#)]
126. Zachary D. Pozun, Katja Hansen, Daniel Sheppard, Matthias Rupp, Klaus-Robert Müller, Graeme Henkelman. 2012. Optimizing transition states via kernel-based machine learning. *The Journal of Chemical Physics* **136**:17, 174101. [[CrossRef](#)]
127. Bibliography 631-685. [[CrossRef](#)]
128. Jiangping Wang, Jieyan Fan, Huanghuang Li, Dapeng Wu. 2012. Kernel-based feature extraction under maximum margin criterion. *Journal of Visual Communication and Image Representation* **23**:1, 53-62. [[CrossRef](#)]
129. Jianping Ma, Jin Jiang. 2012. Detection and Identification of Faults in NPP Instruments Using Kernel Principal Component Analysis. *Journal of Engineering for Gas Turbines and Power* **134**:3, 032901. [[CrossRef](#)]
130. Hao Jing, Yongyi Yang, Robert M. Nishikawa. 2012. Retrieval boosted computer-aided diagnosis of clustered microcalcifications for breast cancer. *Medical Physics* **39**:2, 676. [[CrossRef](#)]
131. Bin Wen, Nicholas Zabaras. 2012. Investigating variability of fatigue indicator parameters of two-phase nickel-based superalloy microstructures. *Computational Materials Science* **51**:1, 455-481. [[CrossRef](#)]
132. Zohreh Ansari, Farshad Almasganj. 2012. Implementing KPCA-based speaker adaptation methods with different optimization algorithms in a Persian ASR system. *Procedia - Social and Behavioral Sciences* **32**, 117-127. [[CrossRef](#)]
133. J.B. Florindo, A.R. Backes, M. de Castro, O.M. Bruno. 2012. A Comparative Study on Multiscale Fractal Dimension Descriptors. *Pattern Recognition Letters* . [[CrossRef](#)]
134. Zhongxi Sun, Changyin Sun, Wankou Yang, Zhenyu Wang. 2012. Feature extraction using kernel Laplacian maximum margin criterion. *Optical Engineering* **51**:6, 067012. [[CrossRef](#)]
135. Xiaoming Zhao, Shiqing Zhang. 2012. Facial expression recognition using local binary patterns and discriminant kernel locally linear embedding. *EURASIP Journal on Advances in Signal Processing* **2012**:1, 20. [[CrossRef](#)]
136. Debashis Sen, Sankar K. Pal. 2012. Improving feature space based image segmentation via density modification. *Information Sciences* . [[CrossRef](#)]
137. S. Li, X. Wang, J. Wang. 2012. Manifold learning-based automatic signal identification in cognitive radio networks. *IET Communications* **6**:8, 955. [[CrossRef](#)]
138. Qingbo He, Ruxu Du, Fanrang Kong. 2012. Phase Space Feature Based on Independent Component Analysis for Machine Health Diagnosis. *Journal of Vibration and Acoustics* **134**:2, 021014. [[CrossRef](#)]
139. Alireza Akhbardeh, Michael A. Jacobs. 2012. Comparative analysis of nonlinear dimensionality reduction techniques for breast MRI segmentation. *Medical Physics* **39**:4, 2275. [[CrossRef](#)]
140. Lijun Cheng, Yongsheng Ding, Kuangrong Hao, Yifan Hu. 2012. An ensemble kernel classifier with immune clonal selection algorithm for automatic discriminant of primary open-angle glaucoma. *Neurocomputing* . [[CrossRef](#)]
141. Deng Xiaogang, Tian Xuemin. 2012. Nonlinear Process Monitoring Using Dynamic Sparse Kernel Classifier. *Procedia Engineering* **29**, 295-300. [[CrossRef](#)]
142. Michael Reutlinger, Gisbert Schneider. 2012. Nonlinear Dimensionality Reduction and Mapping of Compound Libraries for Drug Discovery. *Journal of Molecular Graphics and Modelling* . [[CrossRef](#)]
143. J. SHEEBA RANI. 2012. FACE RECOGNITION USING HYBRID APPROACH. *International Journal of Image and Graphics* **12**:01, 1250005. [[CrossRef](#)]

144. C.-T. Liao, S.-H. Lai. 2012. Robust kernel-based learning for image-related problems. *IET Image Processing* **6**:6, 795. [[CrossRef](#)]
145. Dong Kook Kim, Joon-Hyuk Chang. 2012. Statistical voice activity detection in kernel space. *The Journal of the Acoustical Society of America* **132**:4, EL303. [[CrossRef](#)]
146. J. Jin, K. Xu, N. Xiong, Y. Liu, G. Li. 2012. Multi-index evaluation algorithm based on principal component analysis for node importance in complex networks. *IET Networks* **1**:3, 108. [[CrossRef](#)]
147. Andrew E. Mercer, Michael B. Richman. 2012. Assessing Atmospheric Variability using Kernel Principal Component Analysis. *Procedia Computer Science* **12**, 288-293. [[CrossRef](#)]
148. M. Selvalakshmi Revathy, N. Nirmal Singh. 2012. An Efficient Way of Solving Inverse Problem Using Nonlinear Wiener Filter and its Application to Pattern Recognition. *Procedia Engineering* **38**, 708-717. [[CrossRef](#)]
149. Rosa Chaves, Javier Ramírez, Juan M Górriz, Ignacio A Illán, Manuel Gómez-Río, Cristobal Carnero. 2012. Effective diagnosis of Alzheimer's disease by means of large margin-based methodology. *BMC Medical Informatics and Decision Making* **12**:1, 79. [[CrossRef](#)]
150. Sanjay Saini, Dayang Rohaya Bt Awang Rambli, Suziah Bt Sulaiman, M Nordin B Zakaria, Siti Rohkmah. 2012. Markerless Multi-view Human Motion Tracking Using Manifold Model Learning by Charting. *Procedia Engineering* **41**, 664-670. [[CrossRef](#)]
151. B.P. Rinky, Payal Mondal, K. Manikantan, S. Ramachandran. 2012. DWT based Feature Extraction using Edge Tracked Scale Normalization for Enhanced Face Recognition. *Procedia Technology* **6**, 344-353. [[CrossRef](#)]
152. V. Vidya, Nazia Farheen, K. Manikantan, S. Ramachandran. 2012. Face Recognition using Threshold Based DWT Feature Extraction and Selective Illumination Enhancement Technique. *Procedia Technology* **6**, 334-343. [[CrossRef](#)]
153. C.J. Prabhakar Analysis of Face Space for Recognition using Interval-Valued Subspace Technique 108-127. [[CrossRef](#)]
154. Gui-Fu Lu, Jian Zou. 2011. Feature Extraction Using a Complete Kernel Extension of Supervised Graph Embedding. *Neural Processing Letters* . [[CrossRef](#)]
155. Alan Izenman Spectral Embedding Methods for Manifold Learning 1-36. [[CrossRef](#)]
156. Laurens Maaten, Geoffrey Hinton. 2011. Visualizing non-metric similarities in multiple maps. *Machine Learning* . [[CrossRef](#)]
157. Wei Yang, Kuanquan Wang, Wangmeng Zuo. 2011. Fast neighborhood component analysis. *Neurocomputing* . [[CrossRef](#)]
158. Yingqun Xiao, Lianggui Feng. 2011. A novel linear ridgelet network approach for analog fault diagnosis using wavelet-based fractal analysis and kernel PCA as preprocessors. *Measurement* . [[CrossRef](#)]
159. Ashkan Zarnani, Petr Musilek, Xiaoyu Shi, Xiaodi Ke, Hua He, Russell Greiner. 2011. Learning to predict ice accretion on electric power lines. *Engineering Applications of Artificial Intelligence* . [[CrossRef](#)]
160. B. Raducanu, F. Dornaika. 2011. A supervised non-linear dimensionality reduction approach for manifold learning. *Pattern Recognition* . [[CrossRef](#)]
161. Raoof Gholami, Mansour Ziaii, Faramarz Doulati Ardejani, Shahoo Maleki. 2011. Specification and prediction of nickel mobilization using artificial intelligence methods. *Central European Journal of Geosciences* . [[CrossRef](#)]
162. Takashi Nishikawa, Adilson E. Motter. 2011. Discovering Network Structure Beyond Communities. *Scientific Reports* **1** . [[CrossRef](#)]
163. Yong Xu, Wangmeng Zuo, Zizhu Fan. 2011. Supervised sparse representation method with a heuristic strategy and face recognition experiments. *Neurocomputing* . [[CrossRef](#)]
164. Wenming Zheng, Zhouchen Lin. 2011. A new discriminant subspace analysis approach for multi-class problems. *Pattern Recognition* . [[CrossRef](#)]
165. W.K. Wong. 2011. Discover latent discriminant information for dimensionality reduction: Non-negative Sparseness Preserving Embedding. *Pattern Recognition* . [[CrossRef](#)]
166. G. Quéllec, M.D. Abràmoff, G. Cazuguel, M. Lamard, B. Cochener, C. Roux. 2011. Fouille d'images multi-instance et multi-résolution appliquée au dépistage de la rétinopathie diabétique. *IRBM* . [[CrossRef](#)]
167. R. Gholami, A. Kamkar-Rouhani, F. Doulati Ardejani, Sh. Maleki. 2011. Prediction of toxic metals concentration using artificial intelligence techniques. *Applied Water Science* . [[CrossRef](#)]
168. Minseok Seo, Sejong Oh. 2011. Derivation of an artificial gene to improve classification accuracy upon gene selection. *Computational Biology and Chemistry* . [[CrossRef](#)]
169. Nojun Kwak. 2011. Kernel discriminant analysis for regression problems. *Pattern Recognition* . [[CrossRef](#)]

170. Nan Liu, Han Wang. 2011. Weighted principal component extraction with genetic algorithms. *Applied Soft Computing* . [\[CrossRef\]](#)
171. Xinbo Gao, Xiumei Wang, Xuelong Li, Dacheng Tao. 2011. Transfer latent variable model based on divergence analysis. *Pattern Recognition* **44**:10-11, 2358-2366. [\[CrossRef\]](#)
172. Enrique Romero, Tingting Mu, Paulo J.G. Lisboa. 2011. Cohort-based kernel visualisation with scatter matrices. *Pattern Recognition* . [\[CrossRef\]](#)
173. Matej Žvokelj, Samo Zupan, Ivan Prebil. 2011. Non-linear multivariate and multiscale monitoring and signal denoising strategy using Kernel Principal Component Analysis combined with Ensemble Empirical Mode Decomposition method. *Mechanical Systems and Signal Processing* **25**:7, 2631-2653. [\[CrossRef\]](#)
174. Binbin Pan, Jianhuang Lai, Wen-Sheng Chen. 2011. Nonlinear nonnegative matrix factorization based on Mercer kernel construction. *Pattern Recognition* **44**:10-11, 2800-2810. [\[CrossRef\]](#)
175. Yingqun Xiao, Lianggui Feng. 2011. A novel neural-network approach of analog fault diagnosis based on kernel discriminant analysis and particle swarm optimization. *Applied Soft Computing* . [\[CrossRef\]](#)
176. Imran S. Haque, Vijay S. Pande. 2011. Error Bounds on the SCISSORS Approximation Method. *Journal of Chemical Information and Modeling* 110908075521030. [\[CrossRef\]](#)
177. Horst Bunke, Kaspar Riesen. 2011. Improving vector space embedding of graphs through feature selection algorithms. *Pattern Recognition* **44**:9, 1928-1940. [\[CrossRef\]](#)
178. Jun Yin, Zhonghua Liu, Zhong Jin, Wankou Yang. 2011. Kernel sparse representation based classification. *Neurocomputing* . [\[CrossRef\]](#)
179. Fabian Timm, Erhardt Barth. 2011. Novelty detection for the inspection of light-emitting diodes. *Expert Systems with Applications* . [\[CrossRef\]](#)
180. Jianwu Li, Lu Su, Cheng Cheng. 2011. Finding pre-images via evolution strategies. *Applied Soft Computing* **11**:6, 4183-4194. [\[CrossRef\]](#)
181. Ying Wen, Lianghua He, Pengfei Shi. 2011. Face recognition using difference vector plus KPCA. *Digital Signal Processing* . [\[CrossRef\]](#)
182. Mehran Safayani, Mohammad Taghi Manzuri Shalmani. 2011. Three-dimensional modular discriminant analysis (3MDMA): A new feature extraction approach for face recognition. *Computers & Electrical Engineering* . [\[CrossRef\]](#)
183. Edisanter Lo. 2011. Variable subspace model for hyperspectral anomaly detection. *Pattern Analysis and Applications* . [\[CrossRef\]](#)
184. Charles Bouveyron, Gilles Celeux, Stéphane Girard. 2011. Intrinsic Dimension Estimation by Maximum Likelihood in Isotropic Probabilistic PCA. *Pattern Recognition Letters* . [\[CrossRef\]](#)
185. M. Erdal Özbek, F. Acar Savac#. 2011. Correntropy function for fundamental frequency determination of musical instrument samples. *Expert Systems with Applications* **38**:8, 10025-10030. [\[CrossRef\]](#)
186. Xueqin Liu, Kang Li, Marion McAfee, George W. Irwin. 2011. Improved nonlinear PCA for process monitoring using support vector data description. *Journal of Process Control* . [\[CrossRef\]](#)
187. Flora S. Tsai. 2011. A visualization metric for dimensionality reduction. *Expert Systems with Applications* . [\[CrossRef\]](#)
188. Koichi Fujiwara, Manabu Kano, Shinji Hasebe. 2011. Correlation-based spectral clustering for flexible process monitoring. *Journal of Process Control* . [\[CrossRef\]](#)
189. Trine Julie Abrahamsen, Lars Kai Hansen. 2011. Sparse non-linear denoising: Generalization performance and pattern reproducibility in functional MRI. *Pattern Recognition Letters* . [\[CrossRef\]](#)
190. Jianfeng Shen, Bin Ju, Tao Jiang, Jingjing Ren, Miao Zheng, Chengwei Yao, Lanjuan Li. 2011. Column subset selection for active learning in image classification. *Neurocomputing* . [\[CrossRef\]](#)
191. Ronen Talmon, Israel Cohen, Sharon Gannot. 2011. Transient Noise Reduction Using Nonlocal Diffusion Filters. *IEEE Transactions on Audio, Speech, and Language Processing* **19**:6, 1584-1599. [\[CrossRef\]](#)
192. Hsin-Hsiung Huang, Yi-Ren Yeh. 2011. An iterative algorithm for robust kernel principal component analysis. *Neurocomputing* . [\[CrossRef\]](#)
193. Marcel A.J. van Gerven, Peter Kok, Floris P. de Lange, Tom Heskes. 2011. Dynamic decoding of ongoing perception. *NeuroImage* **57**:3, 950-957. [\[CrossRef\]](#)
194. Hyung Jin Lim, Min Koo Kim, Hoon Sohn, Chan Yik Park. 2011. Impedance based damage detection under varying temperature and loading conditions. *NDT & E International* . [\[CrossRef\]](#)

195. Matthew B. Blaschko, Jacquelyn A. Shelton, Andreas Bartels, Christoph H. Lampert, Arthur Gretton. 2011. Semi-supervised kernel canonical correlation analysis with application to human fMRI. *Pattern Recognition Letters* **32**:11, 1572-1583. [[CrossRef](#)]
196. Ying Wen, Lianghua He. 2011. A classifier for Bangla handwritten numeral recognition. *Expert Systems with Applications* . [[CrossRef](#)]
197. Yoshihiro Yamanishi, Hisashi Kashima Prediction of Compound-protein Interactions with Machine Learning Methods 616-630. [[CrossRef](#)]
198. Wankou Yang, Changyin Sun, Jingyu Yang, Helen S. Du, Karl Ricanek. 2011. Face Recognition Using Kernel UDP. *Neural Processing Letters* . [[CrossRef](#)]
199. C Rutten, V -H Nguyen, J -C Golinval. 2011. Comparison of output-only methods for condition monitoring of industrial systems. *Journal of Physics: Conference Series* **305**, 012101. [[CrossRef](#)]
200. Chi-man Vong, Pak-kin Wong, Weng-fai Ip. 2011. Case-based expert system using wavelet packet transform and kernel-based feature manipulation for engine ignition system diagnosis. *Engineering Applications of Artificial Intelligence* . [[CrossRef](#)]
201. J. Serradilla, J.Q. Shi, A.J. Morris. 2011. Fault detection based on Gaussian process latent variable models. *Chemometrics and Intelligent Laboratory Systems* . [[CrossRef](#)]
202. Gang Zheng, Tian Yu. 2011. Study of Hybrid Strategy for Ambulatory ECG Waveform Clustering. *Journal of Software* **6**:7. . [[CrossRef](#)]
203. Jun Ji, Haiqing Wang, Kun Chen, Yi Liu, Neng Zhang, Junjie Yan. 2011. Recursive weighted kernel regression for semi-supervised soft-sensing modeling of fed-batch processes. *Journal of the Taiwan Institute of Chemical Engineers* . [[CrossRef](#)]
204. Xiaohua Xie, Wei-Shi Zheng, Jianhuang Lai, Pong C Yuen, Ching Y Suen. 2011. Normalization of Face Illumination Based on Large-and Small-Scale Features. *IEEE Transactions on Image Processing* **20**:7, 1807-1821. [[CrossRef](#)]
205. Bibliography 175-191. [[CrossRef](#)]
206. Gisbert Schneider. 2011. From Hits to Leads: Challenges for the Next Phase of Machine Learning in Medicinal Chemistry. *Molecular Informatics* n/a-n/a. [[CrossRef](#)]
207. SangUk Han, SangHyun Lee, Feniosky Peña-Mora Application of Dimension Reduction Techniques for Motion Recognition: Construction Worker Behavior Monitoring 102-109. [[CrossRef](#)]
208. Xiang-tao CHEN, Qian-jin ZHANG. 2011. Gait recognition method based on kernel principal component analysis. *Journal of Computer Applications* **31**:5, 1237-1241. [[CrossRef](#)]
209. Ru-yan ZHANG, Shi-tong WANG, Yao XU. 2011. Maximum a posteriori classification method based on kernel method under t distribution. *Journal of Computer Applications* **31**:4, 1079-1083. [[CrossRef](#)]
210. Jinghua Wang, Qin Li, Jane You, Qijun Zhao. 2011. Fast kernel Fisher discriminant analysis via approximating the kernel principal component analysis. *Neurocomputing* . [[CrossRef](#)]
211. Jong I. Park, Lu Liu, X. Philip Ye, Myong K. Jeong, Young-Seon Jeong. 2011. Improved prediction of biomass composition for switchgrass using reproducing kernel methods with wavelet compressed FT-NIR spectra. *Expert Systems with Applications* . [[CrossRef](#)]
212. Vladimir Tomenko. 2011. Online dimensionality reduction using competitive learning and Radial Basis Function network. *Neural Networks* **24**:5, 501-511. [[CrossRef](#)]
213. Morton J. Canty, Allan A. Nielsen. 2011. Linear and kernel methods for multivariate change detection. *Computers & Geosciences* . [[CrossRef](#)]
214. Zhi-Bo Zhu, Zhi-Huan Song. 2011. A novel fault diagnosis system using pattern classification on kernel FDA subspace. *Expert Systems with Applications* **38**:6, 6895-6905. [[CrossRef](#)]
215. Hai Ma. 2011. Formation drillability prediction based on multi-source information fusion. *Journal of Petroleum Science and Engineering* . [[CrossRef](#)]
216. Binbin Pan, Jianhuang Lai, Pong C. Yuen. 2011. Learning low-rank Mercer kernels with fast-decaying spectrum. *Neurocomputing* . [[CrossRef](#)]
217. Xiang Ma, Nicholas Zabaras. 2011. Kernel principal component analysis for stochastic input model generation. *Journal of Computational Physics* . [[CrossRef](#)]
218. Guanhong Yao, Wei Hua, Binbin Lin, Deng Cai. 2011. Kernel approximately harmonic projection. *Neurocomputing* . [[CrossRef](#)]

219. Asha Viswanath, A. I. J. Forrester, A. J. Keane. 2011. Dimension Reduction for Aerodynamic Design Optimization. *AIAA Journal* **49**:6, 1256-1266. [[CrossRef](#)]
220. Shifei Ding, Hong Zhu, Weikuan Jia, Chunyang Su. 2011. A survey on feature extraction for pattern recognition. *Artificial Intelligence Review* . [[CrossRef](#)]
221. Chang-Dong Wang, Jian-Huang Lai, Jun-Yong Zhu. 2011. Conscience online learning: an efficient approach for robust kernel-based clustering. *Knowledge and Information Systems* . [[CrossRef](#)]
222. Okba Taouali, Elyes Elaissi, Hassani Messaoud. 2011. Design and comparative study of online kernel methods identification of nonlinear system in RKHS space. *Artificial Intelligence Review* . [[CrossRef](#)]
223. Kernel methods 49-75. [[CrossRef](#)]
224. Minghua Wan, Zhihui Lai, Zhong Jin. 2011. Locally Minimizing Embedding and Globally Maximizing Variance: Unsupervised Linear Difference Projection for Dimensionality Reduction. *Neural Processing Letters* . [[CrossRef](#)]
225. Steven Lemm, Benjamin Blankertz, Thorsten Dickhaus, Klaus-Robert Müller. 2011. Introduction to machine learning for brain imaging. *NeuroImage* **56**:2, 387-399. [[CrossRef](#)]
226. Andy Tsai, Joseph Caprioli, Lucy Q. Shen. 2011. Coupled parametric model for estimation of visual field tests based on OCT macular thickness maps, and vice versa, in glaucoma care. *Medical Image Analysis* . [[CrossRef](#)]
227. Asifullah Khan, Abdul Majid, Maqsood Hayat. 2011. CE-PLoc: An ensemble classifier for predicting protein subcellular locations by fusing different modes of Pseudo amino acid composition. *Computational Biology and Chemistry* . [[CrossRef](#)]
228. Estevan P. Seraco, José Gabriel R.C. Gomes. 2011. Computation of the complexity of vector quantizers by affine modeling. *Signal Processing* **91**:5, 1134-1142. [[CrossRef](#)]
229. Dong-Sheng Cao, Yi-Zeng Liang, Qing-Song Xu, Qian-Nan Hu, Liang-Xiao Zhang, Guang-Hui Fu. 2011. Exploring nonlinear relationships in chemical data using kernel-based methods. *Chemometrics and Intelligent Laboratory Systems* **107**:1, 106-115. [[CrossRef](#)]
230. Horst Bunke, Kaspar Riesen. 2011. Recent advances in graph-based pattern recognition with applications in document analysis. *Pattern Recognition* **44**:5, 1057-1067. [[CrossRef](#)]
231. Benjamin Blankertz, Steven Lemm, Matthias Treder, Stefan Haufe, Klaus-Robert Müller. 2011. Single-trial analysis and classification of ERP components — A tutorial. *NeuroImage* **56**:2, 814-825. [[CrossRef](#)]
232. Jianping Li, Liwei Wei, Gang Li, Weixuan Xu. 2011. An evolution strategy-based multiple kernels multi-criteria programming approach: The case of credit decision making. *Decision Support Systems* **51**:2, 292-298. [[CrossRef](#)]
233. Songsong Wu, Mingming Sun, Jingyu Yang. 2011. Stochastic neighbor projection on manifold for feature extraction. *Neurocomputing* . [[CrossRef](#)]
234. Xiaoming Chen, Wanquan Liu, Huining Qiu, Jianhuang Lai. 2011. APSCAN: A parameter free algorithm for clustering. *Pattern Recognition Letters* **32**:7, 973-986. [[CrossRef](#)]
235. C. Sumana, Mani Bhushan, Ch. Venkateswarlu, Ravindra D. Gudi. 2011. Improved nonlinear process monitoring using KPCA with sample vector selection and combined index. *Asia-Pacific Journal of Chemical Engineering* **6**:3, 460-469. [[CrossRef](#)]
236. Claude Cariou, Kacem Chehdi, Steven Le Moan. 2011. BandClust: An Unsupervised Band Reduction Method for Hyperspectral Remote Sensing. *IEEE Geoscience and Remote Sensing Letters* **8**:3, 565-569. [[CrossRef](#)]
237. Minghua Wan, Zhihui Lai, Zhong Jin. 2011. Feature extraction using two-dimensional local graph embedding based on maximum margin criterion. *Applied Mathematics and Computation* . [[CrossRef](#)]
238. XU YONG, DAVID ZHANG, JIAN YANG, JIN ZHONG, JINGYU YANG. 2011. EVALUATE DISSIMILARITY OF SAMPLES IN FEATURE SPACE FOR IMPROVING KPCA. *International Journal of Information Technology & Decision Making* **10**:03, 479-495. [[CrossRef](#)]
239. C. Gómez, J. Buriticá, M. Sánchez-Silva, L. Dueñas-Osorio Vulnerability Assessment of Infrastructure Networks by Using Hierarchical Decomposition Methods 214-221. [[CrossRef](#)]
240. Zhihui Lai, Cairong Zhao, Yi Chen, Zhong Jin. 2011. Maximal local interclass embedding with application to face recognition. *Machine Vision and Applications* . [[CrossRef](#)]
241. Der-Chiang Li, Chiao-Wen Liu, Susan C. Hu. 2011. A fuzzy-based data transformation for feature extraction to increase classification performance with small medical data sets. *Artificial Intelligence in Medicine* . [[CrossRef](#)]
242. Andreas Christmann, Robert Hable. 2011. Consistency of support vector machines using additive kernels for additive models. *Computational Statistics & Data Analysis* . [[CrossRef](#)]

243. Kevin Duh, Katrin Kirchhoff. 2011. Semi-supervised ranking for document retrieval. *Computer Speech & Language* **25**:2, 261-281. [[CrossRef](#)]
244. Xinbo Gao, Xiumei Wang, Dacheng Tao, Xuelong Li. 2011. Supervised Gaussian Process Latent Variable Model for Dimensionality Reduction. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)* **41**:2, 425-434. [[CrossRef](#)]
245. I. Rodriguez-Lujan, C. Santa Cruz, R. Huerta. 2011. On the Equivalence of Kernel Fisher Discriminant Analysis and Kernel Quadratic Programming Feature Selection. *Pattern Recognition Letters* . [[CrossRef](#)]
246. G.J. Postma, P.W.T. Krooshof, L.M.C. Buydens. 2011. Opening the kernel of kernel partial least squares and support vector machines. *Analytica Chimica Acta* . [[CrossRef](#)]
247. Michal Kawulok, Jing Wu, Edwin R. Hancock. 2011. Supervised relevance maps for increasing the distinctiveness of facial images. *Pattern Recognition* **44**:4, 929-939. [[CrossRef](#)]
248. Kun Feng, Zhinong Jiang, Wei He, Bo Ma. 2011. A recognition and novelty detection approach based on Curvelet transform, nonlinear PCA and SVM with application to indicator diagram diagnosis. *Expert Systems with Applications* . [[CrossRef](#)]
249. Claudio A. Perez, Leonardo A. Cament, Luis E. Castillo. 2011. Methodological improvement on local Gabor face recognition based on feature selection and enhanced Borda count. *Pattern Recognition* **44**:4, 951-963. [[CrossRef](#)]
250. Haihong Zhang, Cuntai Guan, Yuanqing Li. 2011. A linear discriminant analysis method based on mutual information maximization. *Pattern Recognition* **44**:4, 877-885. [[CrossRef](#)]
251. YaPing Huang, JiaLi Zhao, YunHui Liu, SiWei Luo, Qi Zou, Mei Tian. 2011. Nonlinear dimensionality reduction using a temporal coherence principle. *Information Sciences* . [[CrossRef](#)]
252. Davide Macagnano, Giuseppe Thadeu Freitas de Abreu. 2011. Gershgorin Analysis of Random Gramian Matrices With Application to MDS Tracking. *IEEE Transactions on Signal Processing* **59**:4, 1785-1800. [[CrossRef](#)]
253. Ahmed Fawzi Otoom, Hatice Gunes, Oscar Perez Concha, Massimo Piccardi. 2011. MLiT: mixtures of Gaussians under linear transformations. *Pattern Analysis and Applications* . [[CrossRef](#)]
254. Shi-Guo CHEN, Dao-Qiang ZHANG. 2011. Experimental Comparisons of Semi-Supervised Dimensional Reduction Methods. *Journal of Software* **22**:1, 28-43. [[CrossRef](#)]
255. Mingfeng Jiang, Lingyan Zhu, Yaming Wang, Ling Xia, Guofa Shou, Feng Liu, Stuart Crozier. 2011. Application of kernel principal component analysis and support vector regression for reconstruction of cardiac transmembrane potentials. *Physics in Medicine and Biology* **56**:6, 1727-1742. [[CrossRef](#)]
256. Jon Sætrom, Henning Omre. 2011. Ensemble Kalman filtering for non-linear likelihood models using kernel-shrinkage regression techniques. *Computational Geosciences* . [[CrossRef](#)]
257. Z. Volkovich, Z. Barzily, G.-W. Weber, D. Toledano-Kitai, R. Avros. 2011. Resampling approach for cluster model selection. *Machine Learning* . [[CrossRef](#)]
258. Enliang Hu, Songcan Chen, Jiankun Yu, Lishan Qiao. 2011. Two-stage nonparametric kernel leaning: From label propagation to kernel propagation. *Neurocomputing* . [[CrossRef](#)]
259. A A Nielsen. 2011. Kernel Maximum Autocorrelation Factor and Minimum Noise Fraction Transformations. *IEEE Transactions on Image Processing* **20**:3, 612-624. [[CrossRef](#)]
260. Hadi Sadoghi Yazdi, Morteza Pakdaman, Hamed Modaghegh. 2011. Unsupervised kernel least mean square algorithm for solving ordinary differential equations. *Neurocomputing* . [[CrossRef](#)]
261. Lei Xu, Yanda Li. 2011. Machine learning and intelligence science: Sino-foreign interchange workshop IScIDE2010 (A). *Frontiers of Electrical and Electronic Engineering in China* **6**:1, 1-5. [[CrossRef](#)]
262. Begüm Demir, Claudio Persello, Lorenzo Bruzzone. 2011. Batch-Mode Active-Learning Methods for the Interactive Classification of Remote Sensing Images. *IEEE Transactions on Geoscience and Remote Sensing* **49**:3, 1014-1031. [[CrossRef](#)]
263. Yin Hujun. 2011. Advances in adaptive nonlinear manifolds and dimensionality reduction. *Frontiers of Electrical and Electronic Engineering in China* **6**:1, 72-85. [[CrossRef](#)]
264. Bei-Wei Lu, Lionel Pandolfo. 2011. Quasi-objective nonlinear principal component analysis. *Neural Networks* **24**:2, 159-170. [[CrossRef](#)]
265. Gyeongyong Heo, Paul Gader. 2011. Robust kernel discriminant analysis using fuzzy memberships. *Pattern Recognition* **44**:3, 716-723. [[CrossRef](#)]

266. Jian Yang. 2011. Kernel feature extraction methods observed from the viewpoint of generating-kernels. *Frontiers of Electrical and Electronic Engineering in China* **6**:1, 43-55. [[CrossRef](#)]
267. Hung-Yuan Chung, Chih-Hsiang Ho, Che-Chang Hsu. 2011. Support vector machines using Bayesian-based approach in the issue of unbalanced classifications. *Expert Systems with Applications* . [[CrossRef](#)]
268. Chunlin Zhao, Chongxun Zheng, Min Zhao, Yaling Tu, Jianping Liu. 2011. Multivariate autoregressive models and kernel learning algorithms for classifying driving mental fatigue based on electroencephalographic. *Expert Systems with Applications* **38**:3, 1859-1865. [[CrossRef](#)]
269. Miao Cheng, Bin Fang, Chi-Man Pun, Yuan Yan Tang. 2011. Kernel-view based discriminant approach for embedded feature extraction in high-dimensional space. *Neurocomputing* . [[CrossRef](#)]
270. Yong Xu, David Zhang. 2011. Accelerating the kernel-method-based feature extraction procedure from the viewpoint of numerical approximation. *Neural Computing and Applications* . [[CrossRef](#)]
271. Du-Ming Tsai, Chung-Chan Lin. 2011. Fuzzy C-means based clustering for linearly and nonlinearly separable data. *Pattern Recognition* . [[CrossRef](#)]
272. Wen-Sheng Chu, Ju-Chin Chen, Jenn-Jier James Lien. 2011. Kernel discriminant transformation for image set-based face recognition. *Pattern Recognition* . [[CrossRef](#)]
273. Guiling Zhang, Yongzhen Ke, Zhichao Li, Mingjie E. 2011. Improvements of Payload-based Intrusion Detection Models by Using Noise Against Fuzzy SVM. *Journal of Networks* **6**:2. . [[CrossRef](#)]
274. Sinno Jialin Pan, Ivor W Tsang, James T Kwok, Qiang Yang. 2011. Domain Adaptation via Transfer Component Analysis. *IEEE Transactions on Neural Networks* **22**:2, 199-210. [[CrossRef](#)]
275. Stefan Gnoth, Rimvydas Simutis, Andreas Lübbert. 2011. Fermentation process supervision and strategies for fail-safe operation: A practical approach. *Engineering in Life Sciences* **11**:1, 94-106. [[CrossRef](#)]
276. Gang Fu, Frank Y. Shih, Haimin Wang. 2011. A kernel-based parametric method for conditional density estimation. *Pattern Recognition* **44**:2, 284-294. [[CrossRef](#)]
277. M B Salah, A Mitiche, I B Ayed. 2011. Multiregion Image Segmentation by Parametric Kernel Graph Cuts. *IEEE Transactions on Image Processing* **20**:2, 545-557. [[CrossRef](#)]
278. Issam Ben Khediri, Mohamed Limam, Claus Weihs. 2011. Variable window adaptive Kernel Principal Component Analysis for nonlinear nonstationary process monitoring. *Computers & Industrial Engineering* . [[CrossRef](#)]
279. Nan Zhang, Su Ruan, Stéphane Lebonvallet, Qingmin Liao, Yuemin Zhu. 2011. Kernel feature selection to fuse multi-spectral MRI images for brain tumor segmentation. *Computer Vision and Image Understanding* **115**:2, 256-269. [[CrossRef](#)]
280. Rui Zhang, Wenjian Wang. 2011. Learning Linear and Nonlinear PCA with Linear Programming. *Neural Processing Letters* . [[CrossRef](#)]
281. Yingwei Zhang, Zhiyong Hu. 2011. On-line batch process monitoring using hierarchical kernel partial least squares. *Chemical Engineering Research and Design* . [[CrossRef](#)]
282. Wei-Yuan Cheng, Chia-Feng Juang. 2011. An incremental support vector machine-trained TS-type fuzzy system for online classification problems. *Fuzzy Sets and Systems* **163**:1, 24-44. [[CrossRef](#)]
283. Xiaofei He, Binbin Lin. 2011. Tangent space learning and generalization. *Frontiers of Electrical and Electronic Engineering in China* . [[CrossRef](#)]
284. M. A. Anusuya, S. K. Katti. 2011. Front end analysis of speech recognition: a review. *International Journal of Speech Technology* . [[CrossRef](#)]
285. Petr Kadlec, Ratko Grbić, Bogdan Gabrys. 2011. Review of adaptation mechanisms for data-driven soft sensors. *Computers & Chemical Engineering* **35**:1, 1-24. [[CrossRef](#)]
286. David Lagorce, Christelle Reynes, Anne-Claude Camproux, Maria A. Miteva, Olivier Sperandio, Bruno O. Villoutreix. In Silico ADME/Tox Predictions 29-124. [[CrossRef](#)]
287. Arta A. Jamshidi, Michael J. Kirby. 2011. Modeling Multivariate Time Series on Manifolds with Skew Radial Basis Functions. *Neural Computation* **23**:1, 97-123. [[Abstract](#)] [[Full Text](#)] [[PDF](#)] [[PDF Plus](#)] [[Supplementary Content](#)]
288. Xuchu Wang, Yanmin Niu. 2011. Improved support vectors for classification through preserving neighborhood geometric structure constraint. *Optical Engineering* **50**:8, 087202. [[CrossRef](#)]
289. Zhen Lei, Shengcai Liao, Matti Pietikainen, Stan Z Li. 2011. Face Recognition by Exploring Information Jointly in Space, Scale and Orientation. *IEEE Transactions on Image Processing* **20**:1, 247-256. [[CrossRef](#)]
290. Xiaohui Wang. 2011. Overlapping block PCA for face recognition. *Energy Procedia* **13**, 3044-3049. [[CrossRef](#)]

291. Yingwei Zhang, Chi Ma. 2011. Fault diagnosis of nonlinear processes using multiscale KPCA and multiscale KPLS. *Chemical Engineering Science* **66**:1, 64-72. [[CrossRef](#)]
292. Takahiro Ogawa, Miki Haseyama. 2011. Adaptive example-based super-resolution using Kernel PCA with a novel classification approach. *EURASIP Journal on Advances in Signal Processing* **2011**:1, 138. [[CrossRef](#)]
293. Tianxi Cai, Giulia Tonini, Xihong Lin. 2011. Kernel Machine Approach to Testing the Significance of Multiple Genetic Markers for Risk Prediction. *Biometrics* no-no. [[CrossRef](#)]
294. Keith Worden, Wieslaw J. Staszewski, James J. Hensman. 2011. Natural computing for mechanical systems research: A tutorial overview. *Mechanical Systems and Signal Processing* **25**:1, 4-111. [[CrossRef](#)]
295. Shih-Wei Chen, Sheng-Huang Lin, Lun-De Liao, Hsin-Yi Lai, Yu-Cheng Pei, Te-Son Kuo, Chin-Teng Lin, Jyh-Yeong Chang, You-Yin Chen, Yu-Chun Lo, Shin-Yuan Chen, Robby Wu, Siny Tsang. 2011. Quantification and recognition of parkinsonian gait from monocular video imaging using kernel-based principal component analysis. *BioMedical Engineering OnLine* **10**:1, 99. [[CrossRef](#)]
296. Andrew E. Mercer, Michael B. Richman, Lance M. Leslie. 2011. Identification of severe weather outbreaks using kernel principal component analysis. *Procedia Computer Science* **6**, 231-236. [[CrossRef](#)]
297. Yu ChuanShuai, Xu Kejia, Zeng Li. 2011. Supervised Classification Based On Labeled Kernel PCA. *Energy Procedia* **13**, 3507-3512. [[CrossRef](#)]
298. Singh Vijendra. 2011. Efficient Clustering for High Dimensional Data: Subspace Based Clustering and Density Based Clustering. *Information Technology Journal* **10**:6, 1092. [[CrossRef](#)]
299. Chen Zhao, Leming Shi, Weida Tong, John D Shaughnessy, André Oberthuer, Lajos Pusztai, Youping Deng, W Fraser Symmans, Tielu Shi. 2011. Maximum predictive power of the microarray-based models for clinical outcomes is limited by correlation between endpoint and gene expression profile. *BMC Genomics* **12**:Suppl 5, S3. [[CrossRef](#)]
300. L.J. Zhao, D.C. Yuan, T.Y. Chai, J. Tang. 2011. KPCA and ELM ensemble modeling of wastewater effluent quality indices. *Procedia Engineering* **15**, 5558-5562. [[CrossRef](#)]
301. Qingsong Gao, Yungang He, Zhongshang Yuan, Jinghua Zhao, Bingbing Zhang, Fuzhong Xue. 2011. Gene- or region-based association study via kernel principal component analysis. *BMC Genetics* **12**:1, 75. [[CrossRef](#)]
302. Guruprasad Ananda, Francesca Chiaromonte, Kateryna D Makova. 2011. A genome-wide view of mutation rate co-variation using multivariate analyses. *Genome Biology* **12**:3, R27. [[CrossRef](#)]
303. M. Wan, G. Yang, Z. Lai, Z. Jin. 2011. Feature extraction based on fuzzy local discriminant embedding with applications to face recognition. *IET Computer Vision* **5**:5, 301. [[CrossRef](#)]
304. George Luta. 2011. On extensions of k-means clustering for automated gating of flow cytometry data. *Cytometry Part A* **79A**:1, 3-5. [[CrossRef](#)]
305. A. Varnavas, M. Petrou. 2011. Comparative study of methods for human performance prediction using electroencephalographic data. *IET Signal Processing* **5**:2, 226. [[CrossRef](#)]
306. Works Cited 303-309. [[CrossRef](#)]
307. Daniel Janssen, Wolfgang I. Schöllhorn, Karl M. Newell, Jörg M. Jäger, Franz Rost, Katrin Vehof. 2010. Diagnosing fatigue in gait patterns by support vector machines and self-organizing maps. *Human Movement Science* . [[CrossRef](#)]
308. L. Journaux, J.-C. Simon, M. F. Destain, F. Cointault, J. Miteran, A. Piron. 2010. Plant leaf roughness analysis by texture classification with generalized Fourier descriptors in a dimensionality reduction context. *Precision Agriculture* . [[CrossRef](#)]
309. Guang-Ho Cha. 2010. Capturing contextual relationship for effective media search. *Multimedia Tools and Applications* . [[CrossRef](#)]
310. Qibin Zhao, Tomasz M. Rutkowski, Liqing Zhang, Andrzej Cichocki. 2010. Generalized optimal spatial filtering using a kernel approach with application to EEG classification. *Cognitive Neurodynamics* **4**:4, 355-358. [[CrossRef](#)]
311. Shaohong Zhang, Hau-San Wong, Zhiwen Yu, Horace H S Ip. 2010. Hybrid Associative Retrieval of Three-Dimensional Models. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)* **40**:6, 1582-1595. [[CrossRef](#)]
312. Grigorios F Tzortzis, C L Likas. 2010. Multiple View Clustering Using a Weighted Combination of Exemplar-Based Mixture Models. *IEEE Transactions on Neural Networks* **21**:12, 1925-1938. [[CrossRef](#)]
313. Chih-Fong Tsai, Yu-Chieh Hsiao. 2010. Combining multiple feature selection methods for stock prediction: Union, intersection, and multi-intersection approaches. *Decision Support Systems* **50**:1, 258-269. [[CrossRef](#)]
314. R. Poranne, C. Gotsman, D. Keren. 2010. 3D Surface Reconstruction Using a Generalized Distance Function. *Computer Graphics Forum* **29**:8, 2479-2491. [[CrossRef](#)]

315. Angel Navia-Vazquez, Manel Martinez-Ramon, Luis Enrique Garcia-Munoz, Christos G. Christodoulou. 2010. Approximate Kernel Orthogonalization for Antenna Array Processing. *IEEE Transactions on Antennas and Propagation* **58**:12, 3942-3950. [[CrossRef](#)]
316. Volker Hähnke, Matthias Rupp, Mireille Krier, Friedrich Rippmann, Gisbert Schneider. 2010. Pharmacophore alignment search tool: Influence of canonical atom labeling on similarity searching. *Journal of Computational Chemistry* **31**:15, 2810-2826. [[CrossRef](#)]
317. K Suzuki, Jun Zhang, Jianwu Xu. 2010. Massive-Training Artificial Neural Network Coupled With Laplacian-Eigenfunction-Based Dimensionality Reduction for Computer-Aided Detection of Polyps in CT Colonography. *IEEE Transactions on Medical Imaging* **29**:11, 1907-1917. [[CrossRef](#)]
318. Hirokazu Yoshino, Chen Dong, Yoshikazu Washizawa, Yukihiro Yamashita. 2010. Kernel Wiener Filter and Its Application to Pattern Recognition. *IEEE Transactions on Neural Networks* **21**:11, 1719-1730. [[CrossRef](#)]
319. Lei Zhang, Qixin Cao. 2010. A novel ant-based clustering algorithm using the kernel method. *Information Sciences* . [[CrossRef](#)]
320. J. Yang, O. Arif, P.A. Vela, J. Teizer, Zhongke Shi. 2010. Tracking multiple workers on construction sites using video cameras. *Advanced Engineering Informatics* **24**:4, 428-434. [[CrossRef](#)]
321. Okba Taouali, Ilyes Elaissi, Hassani Messaoud. 2010. Online identification of nonlinear system using reduced kernel principal component analysis. *Neural Computing and Applications* . [[CrossRef](#)]
322. Basabi Chakraborty Fundamentals of Pattern Analysis: A Brief Overview 39-58. [[CrossRef](#)]
323. Youngmin Cho, Lawrence K. Saul. 2010. Large-Margin Classification in Infinite Neural Networks. *Neural Computation* **22**:10, 2678-2697. [[Abstract](#)] [[Full Text](#)] [[PDF](#)] [[PDF Plus](#)]
324. Hakan Cevikalp, Diane Larlus, Marian Neamtu, Bill Triggs, Frederic Jurie. 2010. Manifold Based Local Classifiers: Linear and Nonlinear Approaches. *Journal of Signal Processing Systems* **61**:1, 61-73. [[CrossRef](#)]
325. Mingtao Ding, Zheng Tian, Zi Jin, Min Xu, Chunxiang Cao. 2010. Registration Using Robust Kernel Principal Component for Object-Based Change Detection. *IEEE Geoscience and Remote Sensing Letters* **7**:4, 761-765. [[CrossRef](#)]
326. Geev Mokryani, Pierluigi Siano, Antonio Piccolo. 2010. Identification of ferroresonance based on S-transform and support vector machine. *Simulation Modelling Practice and Theory* **18**:9, 1412-1424. [[CrossRef](#)]
327. Kai Zhang, James T Kwok. 2010. Clustered Nyström Method for Large Scale Manifold Learning and Dimension Reduction. *IEEE Transactions on Neural Networks* **21**:10, 1576-1587. [[CrossRef](#)]
328. Mohammad Reza Daliri, Vincent Torre. 2010. Shape recognition based on Kernel-edit distance. *Computer Vision and Image Understanding* **114**:10, 1097-1103. [[CrossRef](#)]
329. Jing Chai, Hongwei Liu, Zheng Bao. 2010. Generalized re-weighting local sampling mean discriminant analysis. *Pattern Recognition* **43**:10, 3422-3432. [[CrossRef](#)]
330. Eder Santana, Jose C. Principe, Ewaldo Eder Santana, Raimundo Carlos Silvério Freire, Allan Kardec Barros. 2010. Extraction of Signals With Specific Temporal Structure Using Kernel Methods. *IEEE Transactions on Signal Processing* **58**:10, 5142-5150. [[CrossRef](#)]
331. Hong-Qiao WANG, Fu-Chun SUN, Yan-Ning CAI, Ning CHEN, Lin-Ge DING. 2010. On Multiple Kernel Learning Methods. *Acta Automatica Sinica* **36**:8, 1037-1050. [[CrossRef](#)]
332. Nicola Segata, Enrico Blanzieri. 2010. Operators for transforming kernels into quasi-local kernels that improve SVM accuracy. *Journal of Intelligent Information Systems* . [[CrossRef](#)]
333. H. Zhang, O. Van Kaick, R. Dyer. 2010. Spectral Mesh Processing. *Computer Graphics Forum* **29**:6, 1865-1894. [[CrossRef](#)]
334. Mingm Sun, Jian Yang, Chuancai Liu, Jingyu Yang. 2010. Similarity Preserving Principal Curve: An Optimal 1-D Feature Extractor for Data Representation. *IEEE Transactions on Neural Networks* **21**:9, 1445-1456. [[CrossRef](#)]
335. Sutharshan Rajasegarar, Christopher Leckie, James C. Bezdek, Marimuthu Palaniswami. 2010. Centered Hyperspherical and Hyperellipsoidal One-Class Support Vector Machines for Anomaly Detection in Sensor Networks. *IEEE Transactions on Information Forensics and Security* **5**:3, 518-533. [[CrossRef](#)]
336. Miao Cheng, Bin Fang, Yuan Yan Tang, Taiping Zhang, Jing Wen. 2010. Incremental Embedding and Learning in the Local Discriminant Subspace With Application to Face Recognition. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)* **40**:5, 580-591. [[CrossRef](#)]
337. Shung-Yung Lung. 2010. Improved wavelet feature extraction using kernel analysis for text independent speaker recognition. *Digital Signal Processing* **20**:5, 1400-1407. [[CrossRef](#)]

338. Rui Zhang, Wenjian Wang, Yichen Ma. 2010. Approximations of the standard principal components analysis and kernel PCA. *Expert Systems with Applications* **37**:9, 6531-6537. [[CrossRef](#)]
339. Michiel Debruyne, Tim Verdonck. 2010. Robust kernel principal component analysis and classification. *Advances in Data Analysis and Classification* **4**:2-3, 151-167. [[CrossRef](#)]
340. Faruk O. Alpak, Mark D. Barton, Jef Caers. 2010. A flow-based pattern recognition algorithm for rapid quantification of geologic uncertainty. *Computational Geosciences* **14**:4, 603-621. [[CrossRef](#)]
341. Ann B. Lee. 2010. Spectral Connectivity Analysis. *Journal of the American Statistical Association* **105**:491, 1241-1255. [[CrossRef](#)]
342. Mohammad GhasemiGol, Reza Monsefi, Hadi Sadoghi-Yazdi. 2010. Intrusion Detection by Ellipsoid Boundary. *Journal of Network and Systems Management* **18**:3, 265-282. [[CrossRef](#)]
343. Trine Julie Abrahamsen, Lars Kai Hansen. 2010. Regularized Pre-image Estimation for Kernel PCA De-noising. *Journal of Signal Processing Systems* . [[CrossRef](#)]
344. Xiaoming Wang, Fu-lai Chung, Shitong Wang. 2010. On minimum class locality preserving variance support vector machine. *Pattern Recognition* **43**:8, 2753-2762. [[CrossRef](#)]
345. 2010. Learning Low-Rank Kernel Matrices with Column-Based Methods. *Communications in Statistics - Simulation and Computation* **39**:7, 1485-1498. [[CrossRef](#)]
346. Hujun Yin, Weilin Huang. 2010. Adaptive nonlinear manifolds and their applications to pattern recognition. *Information Sciences* **180**:14, 2649-2662. [[CrossRef](#)]
347. Youngsung Kim, Andrew Beng Jin Teoh, Kar-Ann Toh. 2010. A performance driven methodology for cancelable face templates generation. *Pattern Recognition* **43**:7, 2544-2559. [[CrossRef](#)]
348. Jian Yang, Ning Zhong, Yiyu Yao, Jue Wang. 2010. Record-level peculiarity-based data analysis and classifications. *Knowledge and Information Systems* . [[CrossRef](#)]
349. Luis Rueda, B. John Oommen, Claudio Henríquez. 2010. Multi-class pairwise linear dimensionality reduction using heteroscedastic schemes. *Pattern Recognition* **43**:7, 2456-2465. [[CrossRef](#)]
350. Shankar R. Rao, Allen Y. Yang, S. Shankar Sastry, Yi Ma. 2010. Robust Algebraic Segmentation of Mixed Rigid-Body and Planar Motions from Two Views. *International Journal of Computer Vision* **88**:3, 425-446. [[CrossRef](#)]
351. Zenglin Xu, Irwin King, Michael Rung-Tsong Lyu, Rong Jin. 2010. Discriminative Semi-Supervised Feature Selection Via Manifold Regularization. *IEEE Transactions on Neural Networks* **21**:7, 1033-1047. [[CrossRef](#)]
352. M Herberth, D Koethe, T M K Cheng, N D Krzysztan, S Schoeffmann, P C Guest, H Rahmoune, L W Harris, L Kranaster, F M Leweke, S Bahn. 2010. Impaired glycolytic response in peripheral blood mononuclear cells of first-onset antipsychotic-naïve schizophrenia patients. *Molecular Psychiatry* . [[CrossRef](#)]
353. D. Tolliver, C. Tsourakakis, A. Subramanian, S. Shackney, R. Schwartz. 2010. Robust unmixing of tumor states in array comparative genomic hybridization data. *Bioinformatics* **26**:12, i106-i114. [[CrossRef](#)]
354. Ph. Blanchard, J.R. Dawin, D. Volchenkov. 2010. Markov chains or the game of structure and chance. *The European Physical Journal Special Topics* **184**:1, 1-82. [[CrossRef](#)]
355. Ping Sun, Xin Yao. 2010. Sparse Approximation Through Boosting for Learning Large Scale Kernel Machines. *IEEE Transactions on Neural Networks* **21**:6, 883-894. [[CrossRef](#)]
356. Tinne Tuytelaars, Christoph H. Lampert, Matthew B. Blaschko, Wray Buntine. 2010. Unsupervised Object Discovery: A Comparison. *International Journal of Computer Vision* **88**:2, 284-302. [[CrossRef](#)]
357. Enliang Hu, Xuesong Yin, Yongming Wang, Songcan Chen. 2010. SSPS: A Semi-Supervised Pattern Shift for Classification. *Neural Processing Letters* **31**:3, 243-257. [[CrossRef](#)]
358. Xiaomu Song, Limin Li, Daniil Aksenov, Michael J. Miller, Alice M. Wyrwicz. 2010. Mapping rabbit whisker barrels using discriminant analysis of high field fMRI data. *NeuroImage* **51**:2, 775-782. [[CrossRef](#)]
359. Iulian Ilies. 2010. Projection-Based Partitioning for Large, High-Dimensional Datasets. *Journal of Computational and Graphical Statistics* **19**:2, 474-492. [[CrossRef](#)]
360. Xuehua Li, Hongli Hu, Lan Shu. 2010. Predicting human immunodeficiency virus protease cleavage sites in nonlinear projection space. *Molecular and Cellular Biochemistry* **339**:1-2, 127-133. [[CrossRef](#)]
361. EnLiang Hu, SongCan Chen, XueSong Yin. 2010. Manifold contraction for semi-supervised classification. *Science China Information Sciences* **53**:6, 1170-1187. [[CrossRef](#)]

362. Feng WU, Yan ZHONG, Quan-Yuan WU. 2010. Online Classification Framework for Data Stream Based on Incremental Kernel Principal Component Analysis. *Acta Automatica Sinica* **36**:4, 534-542. [[CrossRef](#)]
363. Ying-Wei ZHANG, S. Joe QIN. 2010. Decentralized Fault Diagnosis of Large-scale Processes Using Multiblock Kernel Principal Component Analysis. *Acta Automatica Sinica* **36**:4, 593-597. [[CrossRef](#)]
364. J MEI. 2010. Fuzzy clustering with weighted medoids for relational data. *Pattern Recognition* **43**:5, 1964-1974. [[CrossRef](#)]
365. Giorgio Gnecco, Marcello Sanguineti. 2010. Error bounds for suboptimal solutions to kernel principal component analysis. *Optimization Letters* **4**:2, 197-210. [[CrossRef](#)]
366. Khalid Chougali, Mohamed Jedra, Nouredine Zahid. 2010. Kernel relevance weighted discriminant analysis for face recognition. *Pattern Analysis and Applications* **13**:2, 213-221. [[CrossRef](#)]
367. Hyun-Woo Cho. 2010. Multivariate calibration for machine health monitoring: kernel partial least squares combined with variable selection. *The International Journal of Advanced Manufacturing Technology* **48**:5-8, 691-699. [[CrossRef](#)]
368. Krzysztof Dobosz, Włodzisław Duch. 2010. Understanding neurodynamical systems via Fuzzy Symbolic Dynamics. *Neural Networks* **23**:4, 487-496. [[CrossRef](#)]
369. OLCAY KURSUN, OLEG V. FAVOROV. 2010. FEATURE SELECTION AND EXTRACTION USING AN UNSUPERVISED BIOLOGICALLY-SUGGESTED APPROXIMATION TO GEBELEIN'S MAXIMAL CORRELATION. *International Journal of Pattern Recognition and Artificial Intelligence* **24**:03, 337-358. [[CrossRef](#)]
370. Matthias Rupp, Gisbert Schneider. 2010. Graph Kernels for Molecular Similarity. *Molecular Informatics* NA-NA. [[CrossRef](#)]
371. Yoshihiro Yamanishi. Supervised Inference of Metabolic Networks from the Integration of Genomic Data and Chemical Information 189-211. [[CrossRef](#)]
372. Paul Honeine, Cédric Richard. 2010. A Closed-form Solution for the Pre-image Problem in Kernel-based Machines. *Journal of Signal Processing Systems* . [[CrossRef](#)]
373. Wei-Shi Zheng, JianHuang Lai, P.C. Yuen. 2010. Penalized Preimage Learning in Kernel Principal Component Analysis. *IEEE Transactions on Neural Networks* **21**:4, 551-570. [[CrossRef](#)]
374. S. Zafeiriou, M. Petrou. 2010. Nonlinear Non-Negative Component Analysis Algorithms. *IEEE Transactions on Image Processing* **19**:4, 1050-1066. [[CrossRef](#)]
375. Yanwei Pang, Lei Wang, Yuan Yuan. 2010. Generalized KPCA by adaptive rules in feature space. *International Journal of Computer Mathematics* **87**:5, 956-968. [[CrossRef](#)]
376. Behrooz Makki, Mona Noori Hosseini, Seyyed Ali Seyyedsalehi, Nasser Sadati. 2010. Unaligned training for voice conversion based on a local nonlinear principal component analysis approach. *Neural Computing and Applications* **19**:3, 437-444. [[CrossRef](#)]
377. Rui Li, Tai-Peng Tian, Stan Sclaroff, Ming-Hsuan Yang. 2010. 3D Human Motion Tracking with a Coordinated Mixture of Factor Analyzers. *International Journal of Computer Vision* **87**:1-2, 170-190. [[CrossRef](#)]
378. Ming-Guang Shi, Jun-Feng Xia, Xue-Ling Li, De-Shuang Huang. 2010. Predicting protein–protein interactions from sequence using correlation coefficient and high-quality interaction dataset. *Amino Acids* **38**:3, 891-899. [[CrossRef](#)]
379. Shiqiao Du, Minoru Sakurai. 2010. Multivariate analysis of properties of amino acid residues in proteins from a viewpoint of functional site prediction. *Chemical Physics Letters* **488**:1-3, 81-85. [[CrossRef](#)]
380. Qinghua Hu, Lei Zhang, Degang Chen, Witold Pedrycz, Daren Yu. 2010. Gaussian kernel based fuzzy rough sets: Model, uncertainty measures and applications. *International Journal of Approximate Reasoning* **51**:4, 453-471. [[CrossRef](#)]
381. Tingting Mu, T.C. Pataky, A.H. Findlow, M.S.H. Aung, J.Y. Goulermas. 2010. Automated Nonlinear Feature Generation and Classification of Foot Pressure Lesions. *IEEE Transactions on Information Technology in Biomedicine* **14**:2, 418-424. [[CrossRef](#)]
382. F.S. Tsai. 2010. Comparative Study of Dimensionality Reduction Techniques for Data Visualization. *Journal of Artificial Intelligence* **3**:3, 119-134. [[CrossRef](#)]
383. Wenming Zheng, Zhouchen Lin, Xiaou Tang. 2010. A Rank-One Update Algorithm for Fast Solving Kernel Foley–Sammon Optimal Discriminant Vectors. *IEEE Transactions on Neural Networks* **21**:3, 393-403. [[CrossRef](#)]
384. CHEONG HEE PARK. 2010. IMPROVED ALGORITHMS FOR UNSUPERVISED DISCRIMINANT PROJECTION. *International Journal of Pattern Recognition and Artificial Intelligence* **24**:02, 193-206. [[CrossRef](#)]
385. Daniel Graves, Witold Pedrycz. 2010. Kernel-based fuzzy clustering and fuzzy clustering: A comparative experimental study. *Fuzzy Sets and Systems* **161**:4, 522-543. [[CrossRef](#)]

386. Run-Da Jia, Zhi-Zhong Mao, Yu-Qing Chang, Shu-Ning Zhang. 2010. Kernel partial robust M-regression as a flexible robust nonlinear modeling technique. *Chemometrics and Intelligent Laboratory Systems* **100**:2, 91-98. [[CrossRef](#)]
387. Taiping Zhang, Bin Fang, Yuan Yan Tang, Zhaowei Shang, Bin Xu. 2010. Generalized Discriminant Analysis: A Matrix Exponential Approach. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)* **40**:1, 186-197. [[CrossRef](#)]
388. Hernn Stamati, Cecilia Clementi, Lydia E. Kavvaki. 2010. Application of nonlinear dimensionality reduction to characterize the conformational landscape of small peptides. *Proteins: Structure, Function, and Bioinformatics* **78**:2, 223-235. [[CrossRef](#)]
389. K. Honda, A. Notsu, H. Ichihashi. 2010. Fuzzy PCA-Guided Robust k -Means Clustering. *IEEE Transactions on Fuzzy Systems* **18**:1, 67-79. [[CrossRef](#)]
390. Dexing Zhong, Jiuqiang Han, Xinman Zhang, Yongli Liu. 2010. Neighborhood discriminant embedding in face recognition. *Optical Engineering* **49**:7, 077203. [[CrossRef](#)]
391. Junbin Gao, Jun Zhang, D. Tien. 2010. Relevance Units Latent Variable Model and Nonlinear Dimensionality Reduction. *IEEE Transactions on Neural Networks* **21**:1, 123-135. [[CrossRef](#)]
392. Dake Zhou, Zhenmin Tang. 2010. Kernel-based improved discriminant analysis and its application to face recognition. *Soft Computing* **14**:2, 103-111. [[CrossRef](#)]
393. Vijay P. Shah, Nicolas H. Younan, Surya S. Durbha, Roger L. King. 2010. Feature Identification via a Combined ICA–Wavelet Method for Image Information Mining. *IEEE Geoscience and Remote Sensing Letters* **7**:1, 18-22. [[CrossRef](#)]
394. E. Kokopoulou, J. Chen, Y. Saad. 2010. Trace optimization and eigenproblems in dimension reduction methods. *Numerical Linear Algebra with Applications* n/a-n/a. [[CrossRef](#)]
395. K.-L. Du. 2010. Clustering: A neural network approach#. *Neural Networks* **23**:1, 89-107. [[CrossRef](#)]
396. Xuchu Wang, Yanmin Niu. 2010. Locality projection discriminant analysis with an application to face recognition. *Optical Engineering* **49**:7, 077201. [[CrossRef](#)]
397. Rui Xu, Donald C. Wunsch. 2010. Clustering Algorithms in Biomedical Research: A Review. *IEEE Reviews in Biomedical Engineering* . [[CrossRef](#)]
398. Montse Pards, Vernica Vilaplana, Cristian Canton-Ferrer Image and Video Processing Tools for HCI 93-118. [[CrossRef](#)]
399. Antnio R.C. Paiva, Il Park, Jos C. Prncipe Inner Products for Representation and Learning in the Spike Train Domain 265-309. [[CrossRef](#)]
400. Paola Costantini, Marielle Linting, Giovanni C. Porzio. 2010. Mining performance data through nonlinear PCA with optimal scaling. *Applied Stochastic Models in Business and Industry* **26**:1, 85-101. [[CrossRef](#)]
401. M. Ben Salah, A. Mitiche, I. Ben Ayed. 2010. Effective Level Set Image Segmentation With a Kernel Induced Data Term. *IEEE Transactions on Image Processing* **19**:1, 220-232. [[CrossRef](#)]
402. M. Sepasi, F. Sassani, R. Nagamune. 2010. Parameter Uncertainty Modeling Using the Multidimensional Principal Curves. *Journal of Dynamic Systems, Measurement, and Control* **132**:5, 054501. [[CrossRef](#)]
403. Masashi Sugiyama, Tsuyoshi Id, Shinichi Nakajima, Jun Sese. 2010. Semi-supervised local Fisher discriminant analysis for dimensionality reduction. *Machine Learning* **78**:1-2, 35-61. [[CrossRef](#)]
404. Ryoza Nagamune, Jongeun Choi. 2010. Parameter Reduction in Estimated Model Sets for Robust Control. *Journal of Dynamic Systems, Measurement, and Control* **132**:2, 021002. [[CrossRef](#)]
405. R. Dianat, S. Kasaei. 2010. Dimension Reduction of Optical Remote Sensing Images via Minimum Change Rate Deviation Method. *IEEE Transactions on Geoscience and Remote Sensing* **48**:1, 198-206. [[CrossRef](#)]
406. Nicola Mastronardi, Eugene E. Tyrtshnikov, Paul Van Dooren. 2010. A Fast Algorithm for Updating and Downsizing the Dominant Kernel Principal Components. *SIAM Journal on Matrix Analysis and Applications* **31**:5, 2376-2399. [[CrossRef](#)]
407. Katarina Domijan, Simon P. Wilson. 2009. Bayesian kernel projections for classification of high dimensional data. *Statistics and Computing* . [[CrossRef](#)]
408. Chang Kook Oh, Hoon Sohn, In-Hwan Bae. 2009. Statistical novelty detection within the Yeongjong suspension bridge under environmental and operational variations. *Smart Materials and Structures* **18**:12, 125022. [[CrossRef](#)]
409. Hanaa E. Sayed, Hossam A. Gabbar, Shigeji Miyazaki. 2009. Improved Evolving Kernel of Fisher’s Discriminant Analysis for Classification Problem. *Journal of Applied Sciences* **9**:12, 2313-2318. [[CrossRef](#)]
410. Stefan Wahl, Konrad Rieck, Pavel Laskov, Peter Domschitz, Klaus-Robert Mller. 2009. Securing IMS against novel threats. *Bell Labs Technical Journal* **14**:1, 243-257. [[CrossRef](#)]
411. Wei-Ya SHI, Yue-Fei GUO, Xiang-Yang XUE. 2009. Efficient Kernel Principal Component Analysis Algorithm for Large-Scale Data Set. *Journal of Software* **20**:8, 2153-2159. [[CrossRef](#)]

412. Su-Yun Huang, Yi-Ren Yeh, Shinto Eguchi. 2009. Robust Kernel Principal Component Analysis. *Neural Computation* **21**:11, 3179-3213. [[Abstract](#)] [[Full Text](#)] [[PDF](#)] [[PDF Plus](#)]
413. Tong Wang, Jie Yang. 2009. Using the nonlinear dimensionality reduction method for the prediction of subcellular localization of Gram-negative bacterial proteins. *Molecular Diversity* **13**:4, 475-481. [[CrossRef](#)]
414. Fei Wang, Xin Wang, Daoqiang Zhang, Changshui Zhang, Tao Li. 2009. marginFace: A novel face recognition method by average neighborhood margin maximization. *Pattern Recognition* **42**:11, 2863-2875. [[CrossRef](#)]
415. M. Humberstone, B. Wood, J. Henkel, J. W. Hines. 2009. Differentiating between expanded and fault conditions using principal component analysis. *Journal of Intelligent Manufacturing* . [[CrossRef](#)]
416. Xiaozheng Zhang, Yongsheng Gao. 2009. Face recognition across pose: A review. *Pattern Recognition* **42**:11, 2876-2896. [[CrossRef](#)]
417. Xuehua Li, Lan Shu, Hongli Hu. 2009. Kernel-based nonlinear dimensionality reduction for electrocardiogram recognition. *Neural Computing and Applications* **18**:8, 1013-1020. [[CrossRef](#)]
418. Claudia Sannelli, Mikio Braun, Klaus-Robert Müller. 2009. Improving BCI performance by task-related trial pruning#. *Neural Networks* **22**:9, 1295-1304. [[CrossRef](#)]
419. Timothy M.D. Ebbels, Rachel Cavill. 2009. Bioinformatic methods in NMR-based metabolic profiling. *Progress in Nuclear Magnetic Resonance Spectroscopy* **55**:4, 361-374. [[CrossRef](#)]
420. Pilsung Kang, Sungzoon Cho. 2009. A hybrid novelty score and its use in keystroke dynamics-based user authentication. *Pattern Recognition* **42**:11, 3115-3127. [[CrossRef](#)]
421. Wang Xing-Zhi, Yan Zheng, Ruan Qian-Tu, Wang Wei. 2009. A kernel-based clustering approach to finding communities in multi-machine power systems. *European Transactions on Electrical Power* **19**:8, 1131-1139. [[CrossRef](#)]
422. O.C. Hamsici, A.M. Martinez. 2009. Rotation Invariant Kernels and Their Application to Shape Analysis. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **31**:11, 1985-1999. [[CrossRef](#)]
423. M.M. López, J. Ramírez, J.M. Górriz, I. Álvarez, D. Salas-Gonzalez, F. Segovia, R. Chaves. 2009. SVM-based CAD system for early detection of the Alzheimer's disease using kernel PCA and LDA. *Neuroscience Letters* **464**:3, 233-238. [[CrossRef](#)]
424. Xiao-zhang LIU, Guo-can FENG. 2009. Multiple kernel discriminant analysis with optimized weight. *Journal of Computer Applications* **29**:9, 2473-2476. [[CrossRef](#)]
425. Jing XU, Xin-min TAO. 2009. One-class intrusion detection system based on KPCA space-similarity. *Journal of Computer Applications* **29**:9, 2459-2463. [[CrossRef](#)]
426. Hiroyuki Yamamoto, Hideki Yamaji, Yuichiro Abe, Kazuo Harada, Danang Waluyo, Eiichiro Fukusaki, Akihiko Kondo, Hiromu Ohno, Hideki Fukuda. 2009. Dimensionality reduction for metabolome data using PCA, PLS, OPLS, and RFDA with differential penalties to latent variables. *Chemometrics and Intelligent Laboratory Systems* **98**:2, 136-142. [[CrossRef](#)]
427. Weifeng Liu, Il (Memming) Park, Yiwen Wang, José C. Principe. 2009. Extended Kernel Recursive Least Squares Algorithm. *IEEE Transactions on Signal Processing* **57**:10, 3801-3814. [[CrossRef](#)]
428. Ji-Dong Shao, Gang Rong. 2009. Nonlinear process monitoring based on maximum variance unfolding projections. *Expert Systems with Applications* **36**:8, 11332-11340. [[CrossRef](#)]
429. Antoni Wibowo. 2009. Robust kernel ridge regression based on M-estimation. *Computational Mathematics and Modeling* **20**:4, 438-446. [[CrossRef](#)]
430. Chenkun Qi, Han-Xiong Li. 2009. Nonlinear dimension reduction based neural modeling for distributed parameter processes. *Chemical Engineering Science* **64**:19, 4164-4170. [[CrossRef](#)]
431. Zenglin Xu, Kaizhu Huang, Jianke Zhu, Irwin King, Michael R. Lyu. 2009. A novel kernel-based maximum a posteriori classification method. *Neural Networks* **22**:7, 977-987. [[CrossRef](#)]
432. Shiming Xiang, Feiping Nie, Changshui Zhang, Chunxia Zhang. 2009. Nonlinear Dimensionality Reduction with Local Spline Embedding. *IEEE Transactions on Knowledge and Data Engineering* **21**:9, 1285-1298. [[CrossRef](#)]
433. Jun-Bao Li, Jeng-Shyang Pan, Zhe-Ming Lu. 2009. Face recognition using Gabor-based complete Kernel Fisher Discriminant analysis with fractional power polynomial models. *Neural Computing and Applications* **18**:6, 613-621. [[CrossRef](#)]
434. C. Dhanjal, S.R. Gunn, J. Shawe-Taylor. 2009. Efficient Sparse Kernel Feature Extraction Based on Partial Least Squares. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **31**:8, 1347-1361. [[CrossRef](#)]
435. Kechang Fu, Liankui Dai, Tiejun Wu, Ming Zhu. 2009. Sensor fault diagnosis of nonlinear processes based on structured kernel principal component analysis. *Journal of Control Theory and Applications* **7**:3, 264-270. [[CrossRef](#)]

436. Dinesh Kumar, Shakti Kumar, C. S. Rai. 2009. Feature selection for face recognition: a memetic algorithmic approach. *Journal of Zhejiang University SCIENCE A* **10**:8, 1140-1152. [[CrossRef](#)]
437. Bing-Peng MA, Shi-Guang SHAN, Xi-Lin CHEN, Wen GAO. 2009. Robust Appearance-Based Method for Head Pose Estimation. *Journal of Software* **20**:6, 1651-1663. [[CrossRef](#)]
438. Yijun Sun, Dapeng Wu. 2009. Feature extraction through local learning. *Statistical Analysis and Data Mining* **2**:1, 34-47. [[CrossRef](#)]
439. B. Buelens, T. Pauly, R. Williams, A. Sale. 2009. Kernel methods for the detection and classification of fish schools in single-beam and multibeam acoustic data. *ICES Journal of Marine Science* **66**:6, 1130-1135. [[CrossRef](#)]
440. Jie Wang, Haiping Lu, K.N. Plataniotis, Juwei Lu. 2009. Gaussian kernel optimization for pattern classification. *Pattern Recognition* **42**:7, 1237-1247. [[CrossRef](#)]
441. Zongbo Xie, Jiuchao Feng. 2009. A sparse projection clustering algorithm. *Journal of Electronics (China)* **26**:4, 549-551. [[CrossRef](#)]
442. Gyeongyong Heo, Paul Gader, Hichem Frigui. 2009. RKF-PCA: Robust kernel fuzzy PCA. *Neural Networks* **22**:5-6, 642-650. [[CrossRef](#)]
443. Takuya Kitamura, Syogo Takeuchi, Shigeo Abe, Kazuhiro Fukui. 2009. Subspace-based support vector machines for pattern classification. *Neural Networks* **22**:5-6, 558-567. [[CrossRef](#)]
444. G.F. Tzortzis, A.C. Likas. 2009. The Global Kernel k -Means Algorithm for Clustering in Feature Space. *IEEE Transactions on Neural Networks* **20**:7, 1181-1194. [[CrossRef](#)]
445. Carl G. Looney. 2009. Fuzzy connectivity clustering with radial basis kernel functions. *Fuzzy Sets and Systems* **160**:13, 1868-1885. [[CrossRef](#)]
446. Rabia Jafri, Hamid R. Arabnia. 2009. A Survey of Face Recognition Techniques. *Journal of Information Processing Systems* **5**:2, 41-68. [[CrossRef](#)]
447. Yi Fang, Jong I. Park, Young-Seon Jeong, Myong K. Jeong, Seung H. Baek, Hyun Woo Cho. 2009. Enhanced predictions of wood properties using hybrid models of PCR and PLS with high-dimensional NIR spectral data. *Annals of Operations Research* . [[CrossRef](#)]
448. Peyman Adibi, Reza Safabakhsh. 2009. Information Maximization in a Linear Manifold Topographic Map. *Neural Processing Letters* **29**:3, 155-178. [[CrossRef](#)]
449. Zhiqiang Ge, Chunjie Yang, Zhihuan Song. 2009. Improved kernel PCA-based monitoring approach for nonlinear processes. *Chemical Engineering Science* **64**:9, 2245-2255. [[CrossRef](#)]
450. K DAS, Z NENADIC. 2009. An efficient discriminant-based solution for small sample size problem. *Pattern Recognition* **42**:5, 857-866. [[CrossRef](#)]
451. Xuehua Li, Lan Shu. 2009. Kernel based nonlinear dimensionality reduction for microarray gene expression data analysis. *Expert Systems with Applications* **36**:4, 7644-7650. [[CrossRef](#)]
452. Chunfeng Wan, Akira Mita. 2009. Pipeline monitoring using acoustic principal component analysis recognition with the Mel scale. *Smart Materials and Structures* **18**:5, 055004. [[CrossRef](#)]
453. Shiming Xiang, Feiping Nie, Yangqiu Song, Changshui Zhang, Chunxia Zhang. 2009. Embedding new data points for manifold learning via coordinate propagation. *Knowledge and Information Systems* **19**:2, 159-184. [[CrossRef](#)]
454. Céline Scheidt, Jef Caers. 2009. Representing Spatial Uncertainty Using Distances and Kernels. *Mathematical Geosciences* **41**:4, 397-419. [[CrossRef](#)]
455. S. Nayak, S. Sarkar, B. Loeding. 2009. Distribution-Based Dimensionality Reduction Applied to Articulated Motion Recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **31**:5, 795-810. [[CrossRef](#)]
456. Y PAN, S GE, A ALMAMUN. 2009. Weighted locally linear embedding for dimension reduction. *Pattern Recognition* **42**:5, 798-811. [[CrossRef](#)]
457. Jia WEI, Hong PENG. 2009. Local and Global Preserving Based Semi-Supervised Dimensionality Reduction Method. *Journal of Software* **19**:11, 2833-2842. [[CrossRef](#)]
458. Mark Jager, Fred A. Hamprecht. 2009. Principal Component Imagery for the Quality Monitoring of Dynamic Laser Welding Processes. *IEEE Transactions on Industrial Electronics* **56**:4, 1307-1313. [[CrossRef](#)]
459. Bor-Chen Kuo, Cheng-Hsuan Li, Jinn-Min Yang. 2009. Kernel Nonparametric Weighted Feature Extraction for Hyperspectral Image Classification. *IEEE Transactions on Geoscience and Remote Sensing* **47**:4, 1139-1155. [[CrossRef](#)]

460. Achmad Widodo, Eric Y. Kim, Jong-Duk Son, Bo-Suk Yang, Andy C.C. Tan, Dong-Sik Gu, Byeong-Keun Choi, Joseph Mathew. 2009. Fault diagnosis of low speed bearing based on relevance vector machine and support vector machine. *Expert Systems with Applications* **36**:3, 7252-7261. [[CrossRef](#)]
461. Ji-Dong Shao, Gang Rong, Jong Min Lee. 2009. Generalized orthogonal locality preserving projections for nonlinear fault detection and diagnosis. *Chemometrics and Intelligent Laboratory Systems* **96**:1, 75-83. [[CrossRef](#)]
462. Y ZHANG. 2009. Enhanced statistical analysis of nonlinear processes using KPCA, KICA and SVM. *Chemical Engineering Science* **64**:5, 801-811. [[CrossRef](#)]
463. Fei Li, Qionghai Dai, Wenli Xu, Guihua Er. 2009. Weighted Subspace Distance and Its Applications to Object Recognition and Retrieval With Image Sets. *IEEE Signal Processing Letters* **16**:3, 227-230. [[CrossRef](#)]
464. Bo Ye, Pingjie Huang, Mengbao Fan, Xiang Gong, Dibo Hou, Guangxin Zhang, Zekui Zhou. 2009. Automatic classification of eddy current signals based on kernel methods. *Nondestructive Testing and Evaluation* **24**:1, 19-37. [[CrossRef](#)]
465. Ruiming Liu. 2009. Eigentargets Versus Kernel Eigentargets: Detection of Infrared Point Targets Using Linear and Nonlinear Subspace Algorithms. *Journal of Infrared, Millimeter, and Terahertz Waves* **30**:3, 278-293. [[CrossRef](#)]
466. Y LIU, S LIN, Y HSUEH, M LEE. 2009. Automatic target defect identification for TFT-LCD array process inspection using kernel FCM-based fuzzy SVDD ensemble. *Expert Systems with Applications* **36**:2, 1978-1998. [[CrossRef](#)]
467. Lisha Chen, Andreas Buja. 2009. Local Multidimensional Scaling for Nonlinear Dimension Reduction, Graph Drawing, and Proximity Analysis. *Journal of the American Statistical Association* **104**:485, 209-219. [[CrossRef](#)]
468. J LI, P CUI. 2009. Improved kernel fisher discriminant analysis for fault diagnosis. *Expert Systems with Applications* **36**:2, 1423-1432. [[CrossRef](#)]
469. Giorgio Gnecco, Marcello Sanguineti. 2009. Accuracy of suboptimal solutions to kernel principal component analysis. *Computational Optimization and Applications* **42**:2, 265-287. [[CrossRef](#)]
470. 2009. Book Reviews. *Journal of the American Statistical Association* **104**:485, 409-426. [[CrossRef](#)]
471. H CHO. 2009. A data mining-based subset selection for enhanced discrimination using iterative elimination of redundancy. *Expert Systems with Applications* **36**:2, 1355-1361. [[CrossRef](#)]
472. Cédric Richard, José Carlos M. Bermudez, Paul Honeine. 2009. Online Prediction of Time Series Data With Kernels. *IEEE Transactions on Signal Processing* **57**:3, 1058-1067. [[CrossRef](#)]
473. António R. C. Paiva, Il Park, José C. Príncipe. 2009. A Reproducing Kernel Hilbert Space Framework for Spike Train Signal Processing. *Neural Computation* **21**:2, 424-449. [[Abstract](#)] [[Full Text](#)] [[PDF](#)] [[PDF Plus](#)]
474. Maurizio Filippone. 2009. Dealing with non-metric dissimilarities in fuzzy central clustering algorithms. *International Journal of Approximate Reasoning* **50**:2, 363-384. [[CrossRef](#)]
475. Y LIU, Y LIU, K CHAN. 2009. Dimensionality reduction for heterogeneous dataset in rushes editing. *Pattern Recognition* **42**:2, 229-242. [[CrossRef](#)]
476. Jianping Fan, D.A. Keim, Yuli Gao, Hangzai Luo, Zongmin Li. 2009. JustClick: Personalized Image Recommendation via Exploratory Search From Large-Scale Flickr Images. *IEEE Transactions on Circuits and Systems for Video Technology* **19**:2, 273-288. [[CrossRef](#)]
477. Chan-Yun Yang, Che-Chang Hsu, Jr-Syu Yang. 2009. Stray Example Sheltering by Loss Regularized SVM and kNN Preprocessor. *Neural Processing Letters* **29**:1, 7-27. [[CrossRef](#)]
478. Kai Zhang, James T. Kwok. 2009. Density-Weighted Nyström Method for Computing Large Kernel Eigensystems. *Neural Computation* **21**:1, 121-146. [[Abstract](#)] [[Full Text](#)] [[PDF](#)] [[PDF Plus](#)]
479. C ZHAO, F WANG, Y ZHANG. 2009. Nonlinear process monitoring based on kernel dissimilarity analysis. *Control Engineering Practice* **17**:1, 221-230. [[CrossRef](#)]
480. Sergios Theodoridis, Konstantinos Koutroumbas Feature Generation I: Data Transformation and Dimensionality Reduction 323-409. [[CrossRef](#)]
481. U SIRIPATRAWAN, R SANGUANDEEKUL, V NARAKAEW. 2009. An alternative freshness index method for modified atmosphere packaged abalone using an artificial neural network. *LWT - Food Science and Technology* **42**:1, 343-349. [[CrossRef](#)]
482. Hyun-Woo Cho. 2009. Enhanced diagnostics using orthogonal de-noising based nonlinear discriminant analysis and its application to multivariate data. *International Journal of Production Research* **47**:3, 801-815. [[CrossRef](#)]
483. I. Kotsia, I. Pitas, S. Zafeiriou, S. Zafeiriou. 2009. Novel Multiclass Classifiers Based on the Minimization of the Within-Class Variance. *IEEE Transactions on Neural Networks* **20**:1, 14-34. [[CrossRef](#)]

484. Sergios Theodoridis, Konstantinos Koutroumbas Clustering Algorithms IV 765-862. [[CrossRef](#)]
485. W. Wu, M.O. Ahmad, S. Samadi. 2009. Discriminant analysis based on modified generalised singular value decomposition and its numerical error analysis. *IET Computer Vision* **3**:3, 159. [[CrossRef](#)]
486. Mathieu Fauvel, Jocelyn Chanussot, Jón Atli Benediktsson. 2009. Kernel Principal Component Analysis for the Classification of Hyperspectral Remote Sensing Data over Urban Areas. *EURASIP Journal on Advances in Signal Processing* **2009**, 1-15. [[CrossRef](#)]
487. H CHO. 2009. Data description and noise filtering based detection with its application and performance comparison. *Expert Systems with Applications* **36**:1, 434-441. [[CrossRef](#)]
488. Xudong Jiang, Bappaditya Mandal, Alex Kot. 2009. Complete discriminant evaluation and feature extraction in kernel space for face recognition. *Machine Vision and Applications* **20**:1, 35-46. [[CrossRef](#)]
489. M. A. Jafarizadeh, R. Sufiani, S. Jafarizadeh. 2009. Recursive calculation of effective resistances in distance-regular networks based on Bose–Mesner algebra and Christoffel–Darboux identity. *Journal of Mathematical Physics* **50**:2, 023302. [[CrossRef](#)]
490. Sergios Theodoridis, Konstantinos Koutroumbas Clustering Algorithms III: Schemes Based on Function Optimization 701-763. [[CrossRef](#)]
491. Carlos H. R. Lima, Upmanu Lall, Tony Jebara, Anthony G. Barnston. 2009. Statistical Prediction of ENSO from Subsurface Sea Temperature Using a Nonlinear Dimensionality Reduction. *Journal of Climate* **22**:17, 4501. [[CrossRef](#)]
492. B LI, C ZHENG, D HUANG. 2008. Locally linear discriminant embedding: An efficient method for face recognition. *Pattern Recognition* **41**:12, 3813-3821. [[CrossRef](#)]
493. S ZHOU, J GAN. 2008. Low-level interpretability and high-level interpretability: a unified view of data-driven interpretable fuzzy system modelling. *Fuzzy Sets and Systems* **159**:23, 3091-3131. [[CrossRef](#)]
494. Magnus O. Ulfarsson, Victor Solo. 2008. Dimension Estimation in Noisy PCA With SURE and Random Matrix Theory. *IEEE Transactions on Signal Processing* **56**:12, 5804-5816. [[CrossRef](#)]
495. Yingwei Zhang, S. Joe Qin. 2008. Improved nonlinear fault detection technique and statistical analysis. *AIChE Journal* **54**:12, 3207-3220. [[CrossRef](#)]
496. Stefanos Zafeiriou, Ioannis Pitas. 2008. Discriminant Graph Structures for Facial Expression Recognition. *IEEE Transactions on Multimedia* **10**:8, 1528-1540. [[CrossRef](#)]
497. Jian-Wu Xu, Ant3nio R. C. Paiva, Il Park (Memming), Jose C. Principe. 2008. A Reproducing Kernel Hilbert Space Framework for Information-Theoretic Learning. *IEEE Transactions on Signal Processing* **56**:12, 5891-5902. [[CrossRef](#)]
498. Fabio Tozeto Ramos, Suresh Kumar, Ben Upcroft, Hugh Durrant-Whyte. 2008. A Natural Feature Representation for Unstructured Environments. *IEEE Transactions on Robotics* **24**:6, 1329-1340. [[CrossRef](#)]
499. Yanwei Pang, Yuan Yuan, Xuelong Li. 2008. Effective Feature Extraction in High-Dimensional Space. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)* **38**:6, 1652-1656. [[CrossRef](#)]
500. N KRAMER, A BOULESTEIX, G TUTZ. 2008. Penalized Partial Least Squares with applications to B-spline transformations and functional data. *Chemometrics and Intelligent Laboratory Systems* **94**:1, 60-69. [[CrossRef](#)]
501. Dit-Yan Yeung, Hong Chang, Guang Dai. 2008. A Scalable Kernel-Based Semisupervised Metric Learning Algorithm with Out-of-Sample Generalization Ability. *Neural Computation* **20**:11, 2839-2861. [[Abstract](#)] [[PDF](#)] [[PDF Plus](#)]
502. F STEINKE, B SCHOLKOPF. 2008. Kernels, regularization and differential equations. *Pattern Recognition* **41**:11, 3271-3286. [[CrossRef](#)]
503. Hong Guo, Qing Zhang, Asoke K. Nandi. 2008. Feature extraction and dimensionality reduction by genetic programming based on the Fisher criterion. *Expert Systems* **25**:5, 444-459. [[CrossRef](#)]
504. B LI, D HUANG, C WANG, K LIU. 2008. Feature extraction using constrained maximum variance mapping. *Pattern Recognition* **41**:11, 3287-3294. [[CrossRef](#)]
505. D. Bacciu, A. Starita. 2008. Competitive Repetition Suppression (CoRe) Clustering: A Biologically Inspired Learning Model With Application to Robust Clustering. *IEEE Transactions on Neural Networks* **19**:11, 1922-1941. [[CrossRef](#)]
506. Xiao-yan ZHOU. 2008. Novel face recognition method based on KPCA plus KDA. *Journal of Computer Applications* **28**:5, 1263-1266. [[CrossRef](#)]
507. Guo-en XIA. 2008. Customer churn prediction on kernel principal component analysis feature abstraction. *Journal of Computer Applications* **28**:1, 149-151. [[CrossRef](#)]
508. Shuiwang Ji, Jieping Ye. 2008. Kernel Uncorrelated and Regularized Discriminant Analysis: A Theoretical and Computational Study. *IEEE Transactions on Knowledge and Data Engineering* **20**:10, 1311-1321. [[CrossRef](#)]

509. A. Sundaresan, R. Chellappa. 2008. Model Driven Segmentation of Articulating Humans in Laplacian Eigenspace. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **30**:10, 1771-1785. [[CrossRef](#)]
510. Yohei Koyama, Tetsuya Kobayashi, Shuji Tomoda, Hiroki Ueda. 2008. Perturbational formulation of principal component analysis in molecular dynamics simulation. *Physical Review E* **78**:4. . [[CrossRef](#)]
511. Jing Li, Xuelong Li, Dacheng Tao. 2008. KPCA for semantic object extraction in images. *Pattern Recognition* **41**:10, 3244-3250. [[CrossRef](#)]
512. Gilles Blanchard, Laurent Zwald. 2008. Finite-Dimensional Projection for Classification and Statistical Learning. *IEEE Transactions on Information Theory* **54**:9, 4169-4182. [[CrossRef](#)]
513. C. Alzate, J. Suykens. 2008. Kernel Component Analysis Using an Epsilon-Insensitive Robust Loss Function. *IEEE Transactions on Neural Networks* **19**:9, 1583-1598. [[CrossRef](#)]
514. Tat-Jun Chin, D. Suter. 2008. Out-of-Sample Extrapolation of Learned Manifolds. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **30**:9, 1547-1556. [[CrossRef](#)]
515. Han-Ming Wu. 2008. Kernel Sliced Inverse Regression with Applications to Classification. *Journal of Computational and Graphical Statistics* **17**:3, 590-610. [[CrossRef](#)]
516. Zhe Chen, Jianting Cao, Yang Cao, Yue Zhang, Fanji Gu, Guoxian Zhu, Zhen Hong, Bin Wang, Andrzej Cichocki. 2008. An empirical EEG analysis in brain death diagnosis for adults. *Cognitive Neurodynamics* **2**:3, 257-271. [[CrossRef](#)]
517. Robert D. Luttrell, Frank Vogt. 2008. Accelerating kernel principal component analysis (KPCA) by utilizing two-dimensional wavelet compression: applications to spectroscopic imaging. *Journal of Chemometrics* **22**:9, 510-521. [[CrossRef](#)]
518. J.A.K. Suykens. 2008. Data Visualization and Dimensionality Reduction Using Kernel Maps With a Reference Point. *IEEE Transactions on Neural Networks* **19**:9, 1501-1517. [[CrossRef](#)]
519. Yi-Hung Liu, Yu-Kai Huang, Ming-Jiu Lee. 2008. Automatic inline defect detection for a thin film transistor-liquid crystal display array process using locally linear embedding and support vector data description. *Measurement Science and Technology* **19**:9, 095501. [[CrossRef](#)]
520. CHONG ZHANG, CHONG-XUN ZHENG, MING-PU ZHAO, XIAO-LIN YU. 2008. ESTIMATION OF MENTAL FATIGUE BASED ON WAVELET PACKET PARAMETERS AND KERNEL LEARNING ALGORITHMS. *International Journal of Wavelets, Multiresolution and Information Processing* **06**:05, 719-737. [[CrossRef](#)]
521. MATÍAS A. BUSTOS, MANUEL A. DUARTE-MERMOUD, NICOLÁS H. BELTRÁN. 2008. NONLINEAR FEATURE EXTRACTION USING FISHER CRITERION. *International Journal of Pattern Recognition and Artificial Intelligence* **22**:06, 1089-1119. [[CrossRef](#)]
522. Chun-jiang PANG. 2008. Face recognition based on fuzzy chaotic neural network. *Journal of Computer Applications* **28**:6, 1549-1551. [[CrossRef](#)]
523. X HE, Y YANG, Y YANG. 2008. Fault diagnosis based on variable-weighted kernel Fisher discriminant analysis. *Chemometrics and Intelligent Laboratory Systems* **93**:1, 27-33. [[CrossRef](#)]
524. Qianjin Guo, Haibin Yu, Jingtao Hu, Aidong Xu. 2008. A method for condition monitoring and fault diagnosis in electromechanical system. *Neural Computing and Applications* **17**:4, 373-384. [[CrossRef](#)]
525. Shahid Ahmed, Er-Ping Li. 2008. Modal Analysis of Microstrip Lines Using Singular Value Decomposition Analysis of FDTD Simulations. *IEEE Transactions on Electromagnetic Compatibility* **50**:3, 687-696. [[CrossRef](#)]
526. S. Dambreville, Y. Rathi, A. Tannenbaum. 2008. A Framework for Image Segmentation Using Shape Models and Kernel Space Shape Priors. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **30**:8, 1385-1399. [[CrossRef](#)]
527. P. Sarma, L. J. Durlofsky, K. Aziz. 2008. Computational Techniques for Closed-loop Reservoir Modeling with Application to a Realistic Reservoir. *Petroleum Science and Technology* **26**:10, 1120-1140. [[CrossRef](#)]
528. A KOLPAS, J MOEHLIS, T FREWEN, I KEVREKIDIS. 2008. Coarse analysis of collective motion with different communication mechanisms. *Mathematical Biosciences* **214**:1-2, 49-57. [[CrossRef](#)]
529. DANIELE VENTURI, XIAOLIANG WAN, GEORGE EM KARNIADAKIS. 2008. Stochastic low-dimensional modelling of a random laminar wake past a circular cylinder. *Journal of Fluid Mechanics* **606**. . [[CrossRef](#)]
530. Yanwei Pang, Yuan Yuan, Xuelong Li. 2008. Gabor-Based Region Covariance Matrices for Face Recognition. *IEEE Transactions on Circuits and Systems for Video Technology* **18**:7, 989-993. [[CrossRef](#)]
531. D. Greene, G. Cagney, N. Krogan, P. Cunningham. 2008. Ensemble non-negative matrix factorization methods for clustering protein-protein interactions. *Bioinformatics* **24**:15, 1722-1728. [[CrossRef](#)]
532. Wenyi ZhaoFace Recognition Techniques . [[CrossRef](#)]

533. Andreas Buja, Deborah F Swayne, Michael L Littman, Nathaniel Dean, Heike Hofmann, Lisha Chen. 2008. Data Visualization With Multidimensional Scaling. *Journal of Computational and Graphical Statistics* **17**:2, 444-472. [[CrossRef](#)]
534. Chong Zhang, ChongXun Zheng, XiaoLin Yu. 2008. Evaluation of mental fatigue based on multippsychophysiological parameters and kernel learning algorithms. *Chinese Science Bulletin* **53**:12, 1835-1847. [[CrossRef](#)]
535. Guiyu Feng, Dewen Hu, Zongtan Zhou. 2008. A Direct Locality Preserving Projections (DLPP) Algorithm for Image Recognition. *Neural Processing Letters* **27**:3, 247-255. [[CrossRef](#)]
536. Y.H. Hung, Y.S. Liao. 2008. Applying PCA and Fixed Size LS-SVM Method for Large Scale Classification Problems. *Information Technology Journal* **7**:6, 890-896. [[CrossRef](#)]
537. H YAMAMOTO, H YAMAJI, E FUKUSAKI, H OHNO, H FUKUDA. 2008. Canonical correlation analysis for multivariate regression and its application to metabolic fingerprinting. *Biochemical Engineering Journal* **40**:2, 199-204. [[CrossRef](#)]
538. Y. Yamanishi, M. Araki, A. Gutteridge, W. Honda, M. Kanehisa. 2008. Prediction of drug-target interaction networks from the integration of chemical and genomic spaces. *Bioinformatics* **24**:13, i232-i240. [[CrossRef](#)]
539. J WANG, K PLATANIOS, J LU, A VENETSANOPOULOS. 2008. Kernel quadratic discriminant analysis for small sample size problem. *Pattern Recognition* **41**:5, 1528-1538. [[CrossRef](#)]
540. Miroslava Cuperlovic-Culf, Nabil Belacel, Adrian Culf. 2008. Integrated analysis of transcriptomics and metabolomics profiles. *Expert Opinion on Medical Diagnostics* **2**:5, 497-509. [[CrossRef](#)]
541. Mu Zhu. 2008. Kernels and Ensembles. *The American Statistician* **62**:2, 97-109. [[CrossRef](#)]
542. Anne-Laure Boulesteix, Athanassios Kondylis, Nicole Krämer. 2008. Comments on: Augmenting the bootstrap to analyze high dimensional genomic data. *TEST* **17**:1, 31-35. [[CrossRef](#)]
543. Erik B. Dam, P. Thomas Fletcher, Stephen M. Pizer. 2008. Automatic shape model building based on principal geodesic analysis bootstrapping. *Medical Image Analysis* **12**:2, 136-151. [[CrossRef](#)]
544. Sang-Woon Kim, B.J. Oommen. 2008. On Using Prototype Reduction Schemes to Optimize Kernel-Based Fisher Discriminant Analysis. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)* **38**:2, 564-570. [[CrossRef](#)]
545. S CHOI, J MORRIS, I LEE. 2008. Nonlinear multiscale modelling for fault detection and identification. *Chemical Engineering Science* **63**:8, 2252-2266. [[CrossRef](#)]
546. Haixian Wang, Sibao Chen, Zilan Hu, Wenming Zheng. 2008. Locality-Preserved Maximum Information Projection. *IEEE Transactions on Neural Networks* **19**:4, 571-585. [[CrossRef](#)]
547. I. Wai-Hung Tsang, A. Kocsor, J.T.-Y. Kwok. 2008. Large-Scale Maximum Margin Discriminant Analysis Using Core Vector Machines. *IEEE Transactions on Neural Networks* **19**:4, 610-624. [[CrossRef](#)]
548. J LI, J PAN, S CHU. 2008. Kernel class-wise locality preserving projection. *Information Sciences* **178**:7, 1825-1835. [[CrossRef](#)]
549. Cheng Yang, Liwei Wang, Jufu Feng. 2008. On Feature Extraction via Kernels. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)* **38**:2, 553-557. [[CrossRef](#)]
550. Gabriel Jarillo, Witold Pedrycz, Marek Reformat. 2008. Aggregation of classifiers based on image transformations in biometric face recognition. *Machine Vision and Applications* **19**:2, 125-140. [[CrossRef](#)]
551. J WU, M TRIVEDI. 2008. A two-stage head pose estimation framework and evaluation. *Pattern Recognition* **41**:3, 1138-1158. [[CrossRef](#)]
552. G QIU, J FANG. 2008. Classification in an informative sample subspace. *Pattern Recognition* **41**:3, 949-960. [[CrossRef](#)]
553. C PARK, H PARK. 2008. A comparison of generalized linear discriminant analysis algorithms. *Pattern Recognition* **41**:3, 1083-1097. [[CrossRef](#)]
554. Zhihua Zhang, Dit-Yan Yeung, James T Kwok, Edward Y Chang. 2008. Sliced Coordinate Analysis for Effective Dimension Reduction and Nonlinear Extensions. *Journal of Computational and Graphical Statistics* **17**:1, 225-242. [[CrossRef](#)]
555. H YIN. 2008. On multidimensional scaling and the embedding of self-organising maps#. *Neural Networks* **21**:2-3, 160-169. [[CrossRef](#)]
556. T ZHANG, X LI, D TAO, J YANG. 2008. Multimodal biometrics using geometry preserving projections. *Pattern Recognition* **41**:3, 805-813. [[CrossRef](#)]
557. Xiaoping Liu, Xia Li, Xun Shi, Shaokun Wu, Tao Liu. 2008. Simulating complex urban development using kernel-based non-linear cellular automata#. *Ecological Modelling* **211**:1-2, 169-181. [[CrossRef](#)]
558. W YINGHUI, N XIAOJUAN, Y CHUNXIA, W QIONGFANG. 2008. A Method of Illumination Compensation for Human Face Image Based On Quotient Image. *Information Sciences* . [[CrossRef](#)]

559. F RATLE, C GAGNE, A TERRETTAZZUFFEREY, M KANEVSKI, P ESSEIVA, O RIBAU. 2008. Advanced clustering methods for mining chemical databases in forensic science#. *Chemometrics and Intelligent Laboratory Systems* **90**:2, 123-131. [[CrossRef](#)]
560. Geert Gins, Ilse Y. Smets, Jan F. Van Impe. 2008. Efficient Tracking of the Dominant Eigenspace of a Normalized Kernel Matrix. *Neural Computation* **20**:2, 523-554. [[Abstract](#)] [[PDF](#)] [[PDF Plus](#)]
561. Robert H. Clewley, John M. Guckenheimer, Francisco J. Valero-Cuevas. 2008. Estimating Effective Degrees of Freedom in Motor Systems. *IEEE Transactions on Biomedical Engineering* **55**:2, 430-442. [[CrossRef](#)]
562. Weifeng Liu, Puskal P. Pokharel, Jose C. Principe. 2008. The Kernel Least-Mean-Square Algorithm. *IEEE Transactions on Signal Processing* **56**:2, 543-554. [[CrossRef](#)]
563. H WONG, B MA, Y SHA, H IP. 2008. 3D head model retrieval in kernel feature space using HSOM. *Pattern Recognition* **41**:2, 468-483. [[CrossRef](#)]
564. Ubonrat Siripatrawan. 2008. Self-organizing algorithm for classification of packaged fresh vegetable potentially contaminated with foodborne pathogens. *Sensors and Actuators B: Chemical* **128**:2, 435-441. [[CrossRef](#)]
565. Manli Zhu, Aleix M. Martinez. 2008. Pruning Noisy Bases in Discriminant Analysis. *IEEE Transactions on Neural Networks* **19**:1, 148-157. [[CrossRef](#)]
566. Tim W. Nattkemper, Andreas Degenhard, Thorsten TwellmannBreast Tumor Classification and Visualization with Machine-learning Approaches 309-323. [[CrossRef](#)]
567. Vitomir S#truc, France Mihelic#, Nikola Paves#ic#. 2008. Face authentication using a hybrid approach. *Journal of Electronic Imaging* **17**:1, 011003. [[CrossRef](#)]
568. Pallav Sarma, Louis J. Durlofsky, Khalid Aziz. 2008. Kernel Principal Component Analysis for Efficient, Differentiable Parameterization of Multipoint Geostatistics. *Mathematical Geosciences* **40**:1, 3-32. [[CrossRef](#)]
569. P. S. Hiremath, C. J. Prabhakar. 2008. Extraction and Recognition of Nonlinear Interval-Type Features Using Symbolic KDA Algorithm with Application to Face Recognition. *Research Letters in Communications* **2008**, 1. [[CrossRef](#)]
570. Weifeng Liu, José C. Príncipe. 2008. Kernel Affine Projection Algorithms. *EURASIP Journal on Advances in Signal Processing* **2008**, 1-13. [[CrossRef](#)]
571. X.-L. Yu, X.-G. Wang. 2008. Kernel uncorrelated neighbourhood discriminative embedding for radar target recognition. *Electronics Letters* **44**:2, 154. [[CrossRef](#)]
572. C SU, C YANG. 2008. Feature selection for the SVM: An application to hypertension diagnosis. *Expert Systems with Applications* **34**:1, 754-763. [[CrossRef](#)]
573. M FILIPPONE, F CAMASTRA, F MASULLI, S ROVETTA. 2008. A survey of kernel and spectral methods for clustering. *Pattern Recognition* **41**:1, 176-190. [[CrossRef](#)]
574. Baochang Zhang, Zongli Wang, Bineng Zhong. 2008. Kernel Learning of Histogram of Local Gabor Phase Patterns for Face Recognition. *EURASIP Journal on Advances in Signal Processing* **2008**, 1-9. [[CrossRef](#)]
575. Yanfeng Gu, Ying Liu, Ye Zhang. 2008. A Selective KPCA Algorithm Based on High-Order Statistics for Anomaly Detection in Hyperspectral Imagery. *IEEE Geoscience and Remote Sensing Letters* **5**:1, 43-47. [[CrossRef](#)]
576. D VOGIATZIS, N TSAPATSOULIS. 2008. Active learning for microarray data. *International Journal of Approximate Reasoning* **47**:1, 85-96. [[CrossRef](#)]
577. Steven Van Vaerenbergh, Javier Vía, Ignacio Santamaría. 2008. Adaptive Kernel Canonical Correlation Analysis Algorithms for Nonparametric Identification of Wiener and Hammerstein Systems. *EURASIP Journal on Advances in Signal Processing* **2008**, 1-14. [[CrossRef](#)]
578. Gwo-Her Lee, Tzuen Wu Hsieh, Jinshih Taur, Chin-Wang Tao. 2008. A posteriori multiresolution-based kernel orthogonal subspace technique for supervised texture segmentation. *Optical Engineering* **47**:7, 077006. [[CrossRef](#)]
579. Rui Xu, Donald C. Wunsch II. 2008. Recent advances in cluster analysis. *International Journal of Intelligent Computing and Cybernetics* **1**:4, 484-508. [[CrossRef](#)]
580. Feng Tang, Ryan Crabb, Hai Tao. 2007. Representing Images Using Nonorthogonal Haar-Like Bases. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **29**:12, 2120-2134. [[CrossRef](#)]
581. HEESUNG KWON, NASSER M. NASRABADI, PATTI GILLESPIE. 2007. NONLINEAR CHEMICAL PLUME DETECTION USING KERNEL-BASED MATCHED SUBSPACE DETECTORS. *International Journal of High Speed Electronics and Systems* **17**:04, 813-826. [[CrossRef](#)]

582. JUN LIU, SONGCAN CHEN, XIAOYANG TAN, DAOQIANG ZHANG. 2007. EFFICIENT PSEUDOINVERSE LINEAR DISCRIMINANT ANALYSIS AND ITS NONLINEAR FORM FOR FACE RECOGNITION. *International Journal of Pattern Recognition and Artificial Intelligence* **21**:08, 1265-1278. [[CrossRef](#)]
583. Ning Sun, Hai-xian Wang, Zhen-hai Ji, Cai-rong Zou, Li Zhao. 2007. An efficient algorithm for Kernel two-dimensional principal component analysis. *Neural Computing and Applications* **17**:1, 59-64. [[CrossRef](#)]
584. Jérôme Louradour, Khalid Daoudi, Francis Bach. 2007. Feature Space Mahalanobis Sequence Kernels: Application to SVM Speaker Verification. *IEEE Transactions on Audio, Speech and Language Processing* **15**:8, 2465-2475. [[CrossRef](#)]
585. Weifeng Liu, Puskal P. Pokharel, Jose C. Principe. 2007. Correntropy: Properties and Applications in Non-Gaussian Signal Processing. *IEEE Transactions on Signal Processing* **55**:11, 5286-5298. [[CrossRef](#)]
586. X JING, Y YAO, D ZHANG, J YANG, M LI. 2007. Face and palmprint pixel level fusion and Kernel DCV-RBF classifier for small sample biometric recognition. *Pattern Recognition* **40**:11, 3209-3224. [[CrossRef](#)]
587. Qisheng Xu, Zhuguo Li. 2007. Recognition of wear mode using multi-variable synthesis approach based on wavelet packet and improved three-line method. *Mechanical Systems and Signal Processing* **21**:8, 3146-3166. [[CrossRef](#)]
588. R PAN, Q YANG, S PAN. 2007. Mining competent case bases for case-based reasoning. *Artificial Intelligence* **171**:16-17, 1039-1068. [[CrossRef](#)]
589. Huaijun Qiu, Edwin R. Hancock. 2007. Clustering and Embedding Using Commute Times. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **29**:11, 1873-1890. [[CrossRef](#)]
590. Cristian Sminchisescu, Atul Kanaujia, Dimitris N. Metaxas. 2007. BM³E : Discriminative Density Propagation for Visual Tracking. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **29**:11, 2030-2044. [[CrossRef](#)]
591. Inderjit S. Dhillon, Yuqiang Guan, Brian Kulis. 2007. Weighted Graph Cuts without Eigenvectors A Multilevel Approach. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **29**:11, 1944-1957. [[CrossRef](#)]
592. Xiaohong Wu, Jianjiang Zhou. 2007. Fuzzy principal component analysis and its Kernel-based model. *Journal of Electronics (China)* **24**:6, 772-775. [[CrossRef](#)]
593. Tobias Kaupp, Bertrand Douillard, Fabio Ramos, Alexei Makarenko, Ben Upcroft. 2007. Shared environment representation for a human-robot team performing information fusion. *Journal of Field Robotics* **24**:11-12, 911-942. [[CrossRef](#)]
594. Hitoshi Suzuki, Yuji Waizumi, Nei Kato, Yoshiaki Nemoto. 2007. Discrimination of similar characters with a nonlinear compound discriminant function. *Systems and Computers in Japan* **38**:11, 36-48. [[CrossRef](#)]
595. Stefanos Zafeiriou, Anastasios Tefas, Ioannis Pitas. 2007. Minimum Class Variance Support Vector Machines. *IEEE Transactions on Image Processing* **16**:10, 2551-2564. [[CrossRef](#)]
596. F WANG, J WANG, C ZHANG, J KWOK. 2007. Face recognition using spectral features. *Pattern Recognition* **40**:10, 2786-2797. [[CrossRef](#)]
597. Sung Won Park, Marios Savvides. 2007. Individual Kernel Tensor-Subspaces for Robust Face Recognition: A Computationally Efficient Tensor Framework Without Requiring Mode Factorization. *IEEE Transactions on Systems, Man and Cybernetics, Part B (Cybernetics)* **37**:5, 1156-1166. [[CrossRef](#)]
598. Q TAO, G WU, J WANG. 2007. Learning linear PCA with convex semi-definite programming#. *Pattern Recognition* **40**:10, 2633-2640. [[CrossRef](#)]
599. Jose Miguel Leiva-Murillo, Antonio Artes-Rodriguez. 2007. Maximization of Mutual Information for Supervised Linear Feature Extraction. *IEEE Transactions on Neural Networks* **18**:5, 1433-1441. [[CrossRef](#)]
600. Rui-ming Liu, Er-qi Liu, Jie Yang, Tian-hao Zhang, Fang-lin Wang. 2007. Infrared small target detection with kernel Fukunaga-Koontz transform. *Measurement Science and Technology* **18**:9, 3025-3035. [[CrossRef](#)]
601. Georgios Goudelis, Stefanos Zafeiriou, Anastasios Tefas, Ioannis Pitas. 2007. Class-Specific Kernel-Discriminant Analysis for Face Verification. *IEEE Transactions on Information Forensics and Security* **2**:3, 570-587. [[CrossRef](#)]
602. Sylvain Lespinats, Michel Verleysen, Alain Giron, Bernard Fertil. 2007. DD-HDS: A Method for Visualization and Exploration of High-Dimensional Data. *IEEE Transactions on Neural Networks* **18**:5, 1265-1279. [[CrossRef](#)]
603. MYUNG-CHEOL ROH, SEONG-WHAN LEE. 2007. PERFORMANCE ANALYSIS OF FACE RECOGNITION ALGORITHMS ON KOREAN FACE DATABASE. *International Journal of Pattern Recognition and Artificial Intelligence* **21**:06, 1017-1033. [[CrossRef](#)]
604. I.P. Androulakis, E. Yang, R.R. Almon. 2007. Analysis of Time-Series Gene Expression Data: Methods, Challenges, and Opportunities. *Annual Review of Biomedical Engineering* **9**:1, 205-228. [[CrossRef](#)]

605. Hau-San Wong, Bo Ma, Zhiwen Yu, Pui Fong Yeung, Horace H. S. Ip. 2007. 3-D Head Model Retrieval Using a Single Face View Query. *IEEE Transactions on Multimedia* **9**:5, 1026-1036. [[CrossRef](#)]
606. Bin Yu. 2007. Embracing Statistical Challenges in the Information Technology Age. *Technometrics* **49**:3, 237-248. [[CrossRef](#)]
607. D. Seghers, D. Loeckx, F. Maes, D. Vandermeulen, P. Suetens. 2007. Minimal Shape and Intensity Cost Path Segmentation. *IEEE Transactions on Medical Imaging* **26**:8, 1115-1129. [[CrossRef](#)]
608. B ZHU, L JIANG, Y LUO, Y TAO. 2007. Gabor feature-based apple quality inspection using kernel principal component analysis. *Journal of Food Engineering* **81**:4, 741-749. [[CrossRef](#)]
609. Jong-Min Lee, S. Joe Qin, In-Beum Lee. 2007. Fault Detection of Non-Linear Processes Using Kernel Independent Component Analysis. *The Canadian Journal of Chemical Engineering* **85**:4, 526-536. [[CrossRef](#)]
610. H.. Cevikalp, M.. Neamtu, A.. Barkana. 2007. The Kernel Common Vector Method: A Novel Nonlinear Subspace Classifier for Pattern Recognition. *IEEE Transactions on Systems, Man and Cybernetics, Part B (Cybernetics)* **37**:4, 937-951. [[CrossRef](#)]
611. H CHO. 2007. Identification of contributing variables using kernel-based discriminant modeling and reconstruction. *Expert Systems with Applications* **33**:2, 274-285. [[CrossRef](#)]
612. Tingting Mu, Asoke K. Nandi, Rangaraj M. Rangayyan. 2007. Classification of breast masses via nonlinear transformation of features based on a kernel matrix. *Medical & Biological Engineering & Computing* **45**:8, 769-780. [[CrossRef](#)]
613. Daniel S. Yeung, Defeng Wang, Wing W. Y. Ng, Eric C. C. Tsang, Xizhao Wang. 2007. Structured large margin machines: sensitive to data distributions. *Machine Learning* **68**:2, 171-200. [[CrossRef](#)]
614. Paul Honeine, Cdric Richard, Patrick Flandrin. 2007. Time-Frequency Learning Machines. *IEEE Transactions on Signal Processing* **55**:7, 3930-3936. [[CrossRef](#)]
615. Hujun Yin. 2007. Nonlinear dimensionality reduction and data visualization: A review. *International Journal of Automation and Computing* **4**:3, 294-303. [[CrossRef](#)]
616. Robert Jenssen, Deniz Erdogmus, Jose C. Principe, Torbjørn Eltoft. 2007. The Laplacian Classifier. *IEEE Transactions on Signal Processing* **55**:7, 3262-3271. [[CrossRef](#)]
617. X YANG, Q SONG, Y WU. 2007. A robust deterministic annealing algorithm for data clustering. *Data & Knowledge Engineering* **62**:1, 84-100. [[CrossRef](#)]
618. Guoqing Wang, Yu-an Sun, Qingzhu Ding, Chunhong Dong, Dexue Fu, Cunhong Li. 2007. Estimation of source spectra profiles and simultaneous determination of polycomponent in mixtures from ultraviolet spectra data using kernel independent component analysis and support vector regression. *Analytica Chimica Acta* **594**:1, 101-106. [[CrossRef](#)]
619. Tat-Jun Chin, David Suter. 2007. Incremental Kernel Principal Component Analysis. *IEEE Transactions on Image Processing* **16**:6, 1662-1674. [[CrossRef](#)]
620. J WU, J WANG, L LIU. 2007. Feature extraction via KPCA for classification of gait patterns. *Human Movement Science* **26**:3, 393-411. [[CrossRef](#)]
621. Yi-Hung Liu, Han-Pang Huang, Chang-Hsin Weng. 2007. Recognition of Electromyographic Signals Using Cascaded Kernel Learning Machine. *IEEE/ASME Transactions on Mechatronics* **12**:3, 253-264. [[CrossRef](#)]
622. Ayan Chakrabarti, A.N. Rajagopalan, Rama Chellappa. 2007. Super-Resolution of Face Images Using Kernel PCA-Based Prior. *IEEE Transactions on Multimedia* **9**:4, 888-892. [[CrossRef](#)]
623. Shang-Ming Zhou, John Q. Gan. 2007. Constructing L2-SVM-Based Fuzzy Classifiers in High-Dimensional Space With Automatic Model Selection and Fuzzy Rule Ranking. *IEEE Transactions on Fuzzy Systems* **15**:3, 398-409. [[CrossRef](#)]
624. A. Asensio Ramos, H. Socas-Navarro, A. Lopez Ariste, M. J. Martinez Gonzalez. 2007. The Intrinsic Dimensionality of Spectropolarimetric Data. *The Astrophysical Journal* **660**:2, 1690-1699. [[CrossRef](#)]
625. Q HE, F KONG, R YAN. 2007. Subspace-based gearbox condition monitoring by kernel principal component analysis. *Mechanical Systems and Signal Processing* **21**:4, 1755-1772. [[CrossRef](#)]
626. S CHEN, Z WANG, Y TIAN. 2007. Matrix-pattern-oriented Ho-Kashyap classifier with regularization learning. *Pattern Recognition* **40**:5, 1533-1543. [[CrossRef](#)]
627. W HSIEH. 2007. Nonlinear principal component analysis of noisy data. *Neural Networks* **20**:4, 434-443. [[CrossRef](#)]
628. Elaine P. M. Sousa, Caetano Traina, Agma J. M. Traina, Leejay Wu, Christos Faloutsos. 2007. A fast and effective method to find correlations among attributes in databases. *Data Mining and Knowledge Discovery* **14**:3, 367-407. [[CrossRef](#)]
629. Joachim Kilian, Dion Whitehead, Jakub Horak, Dierk Wanke, Stefan Weinl, Oliver Batistic, Cecilia D'Angelo, Erich Bornberg-Bauer, Jörg Kudla, Klaus Harter. 2007. The AtGenExpress global stress expression data set: protocols, evaluation and model data analysis of UV-B light, drought and cold stress responses. *The Plant Journal* **50**:2, 347-363. [[CrossRef](#)]

630. Jian Yang, David Zhang, Jing-yu Yang, Ben Niu. 2007. Globally Maximizing, Locally Minimizing: Unsupervised Discriminant Projection with Applications to Face and Palm Biometrics. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **29**:4, 650-664. [[CrossRef](#)]
631. Yijuan Lu, Qi Tian, Feng Liu, Maribel Sanchez, Yufeng Wang. 2007. Interactive Semisupervised Learning for Microarray Analysis. *IEEE/ACM Transactions on Computational Biology and Bioinformatics* **4**:2, 190-203. [[CrossRef](#)]
632. S DURBHA, R KING, N YOUNAN. 2007. Support vector machines regression for retrieval of leaf area index from multiangle imaging spectroradiometer. *Remote Sensing of Environment* **107**:1-2, 348-361. [[CrossRef](#)]
633. Harald Burgsteiner, Mark Kröll, Alexander Leopold, Gerald Steinbauer. 2007. Movement prediction from real-world images using a liquid state machine. *Applied Intelligence* **26**:2, 99-109. [[CrossRef](#)]
634. H CHOI, S CHOI. 2007. Robust kernel Isomap. *Pattern Recognition* **40**:3, 853-862. [[CrossRef](#)]
635. H HOFFMANN. 2007. Kernel PCA for novelty detection. *Pattern Recognition* **40**:3, 863-874. [[CrossRef](#)]
636. Z LIANG, D ZHANG, P SHI. 2007. The theoretical analysis of GLRAM and its applications. *Pattern Recognition* **40**:3, 1032-1041. [[CrossRef](#)]
637. L HOEGAERTS, L DELATHAUWER, I GOETHALS, J SUYKENS, J VANDEWALLE, B DEMOOR. 2007. Efficiently updating and tracking the dominant kernel principal components. *Neural Networks* **20**:2, 220-229. [[CrossRef](#)]
638. Brian Kan-Wing Mak, Roger Wend-Huu Hsiao. 2007. Kernel Eigenspace-Based MLLR Adaptation. *IEEE Transactions on Audio, Speech and Language Processing* **15**:3, 784-795. [[CrossRef](#)]
639. Heesung Kwon, Nasser M. Nasrabadi. 2007. Kernel Spectral Matched Filter for Hyperspectral Imagery. *International Journal of Computer Vision* **71**:2, 127-141. [[CrossRef](#)]
640. H CHO. 2007. Nonlinear feature extraction and classification of multivariate data in kernel feature space. *Expert Systems with Applications* **32**:2, 534-542. [[CrossRef](#)]
641. Ping Zhong, Masao Fukushima. 2007. Second-Order Cone Programming Formulations for Robust Multiclass Classification. *Neural Computation* **19**:1, 258-282. [[Abstract](#)] [[PDF](#)] [[PDF Plus](#)]
642. Hyun-Woo Cho, Myong K. Jeong, Yongjin Kwon. 2007. Support vector data description for calibration monitoring of remotely located microrobotic system. *Journal of Manufacturing Systems* **25**:3, 196-208. [[CrossRef](#)]
643. Yi-Hung Liu, Yen-Ting Chen. 2007. Face Recognition Using Total Margin-Based Adaptive Fuzzy Support Vector Machines. *IEEE Transactions on Neural Networks* **18**:1, 178-192. [[CrossRef](#)]
644. Xiaogang Deng, Xuemin Tian. Multivariate statistical process monitoring using multi-scale kernel principal component analysis 108-113. [[CrossRef](#)]
645. Chuanfeng Lv, Qiangfu Zhao. 2007. PCA: a semi-universal encoder for image compression. *International Journal of Pervasive Computing and Communications* **3**:2, 205-220. [[CrossRef](#)]
646. J.G.R.C. Gomes, A. Petraglia, S.K. Mitra. 2007. Sensitivity analysis of multilayer perceptrons applied to focal-plane image compression. *IET Circuits, Devices & Systems* **1**:1, 79. [[CrossRef](#)]
647. Y WEN, Y LU, P SHI. 2007. Handwritten Bangla numeral recognition system and its application to postal automation. *Pattern Recognition* **40**:1, 99-107. [[CrossRef](#)]
648. Sang Wook Choi, Elaine B. Martin, Julian Morris, In-Beum Lee. Nonlinear multiscale fault detection and identification 120-125. [[CrossRef](#)]
649. G DAI, D YEUNG, Y QIAN. 2007. Face recognition using a kernel fractional-step discriminant analysis algorithm. *Pattern Recognition* **40**:1, 229-243. [[CrossRef](#)]
650. Heesung Kwon, Nasser M. Nasrabadi. 2007. A Comparative Analysis of Kernel Subspace Target Detectors for Hyperspectral Imagery. *EURASIP Journal on Advances in Signal Processing* **2007**, 1-14. [[CrossRef](#)]
651. Xuelian Yu, Xuegang Wang. 2007. Kernel uncorrelated neighborhood discriminative embedding for feature extraction. *Optical Engineering* **46**:12, 120502. [[CrossRef](#)]
652. Takehisa Yairi. 2007. Map Building By Non-linear Dimensionality Reduction of Historical Visibility Data. *Transactions of the Japanese Society for Artificial Intelligence* **22**, 353-363. [[CrossRef](#)]
653. Jonathan Dinerstein, Parris K. Egbert, David Cline. 2006. Enhancing computer graphics through machine learning: a survey. *The Visual Computer* **23**:1, 25-43. [[CrossRef](#)]
654. Shipeng Yu, Kai Yu, V. Tresp, H.-P. Kriegel. 2006. Multi-Output Regularized Feature Projection. *IEEE Transactions on Knowledge and Data Engineering* **18**:12, 1600-1613. [[CrossRef](#)]

655. Peter Rousseeuw, Michiel Debruyne, Sanne Engelen, Mia Hubert. 2006. Robustness and Outlier Detection in Chemometrics. *Critical Reviews in Analytical Chemistry* **36**:3-4, 221-242. [[CrossRef](#)]
656. Phuong H. Nguyen. 2006. Complexity of free energy landscapes of peptides revealed by nonlinear principal component analysis. *Proteins: Structure, Function, and Bioinformatics* **65**:4, 898-913. [[CrossRef](#)]
657. Robert Jenssen, Torbjørn Eltoft, Deniz Erdogmus, Jose C. Principe. 2006. Some Equivalences between Kernel Methods and Information Theoretic Methods. *The Journal of VLSI Signal Processing Systems for Signal, Image, and Video Technology* **45**:1-2, 49-65. [[CrossRef](#)]
658. Martin David Levine, Yingfeng Yu. 2006. Face recognition subject to variations in facial expression, illumination and pose using correlation filters. *Computer Vision and Image Understanding* **104**:1, 1-15. [[CrossRef](#)]
659. Kilian Q. Weinberger, Lawrence K. Saul. 2006. Unsupervised Learning of Image Manifolds by Semidefinite Programming. *International Journal of Computer Vision* **70**:1, 77-90. [[CrossRef](#)]
660. Y F Gu, Y Liu, C Y Wang, Y Zhang. 2006. Curvelet-Based Image Fusion Algorithm for Effective Anomaly Detection in Hyperspectral Imagery. *Journal of Physics: Conference Series* **48**, 324-328. [[CrossRef](#)]
661. J LAUB, V ROTH, J BUHMANN, K MULLER. 2006. On the information and representation of non-Euclidean pairwise data. *Pattern Recognition* **39**:10, 1815-1826. [[CrossRef](#)]
662. L ANGELINI, D MARINAZZO, M PELLICORO, S STRAMAGLIA. 2006. Kernel method for clustering based on optimal target vector. *Physics Letters A* **357**:6, 413-416. [[CrossRef](#)]
663. Chin-Chun Chang. 2006. Deformable shape finding with models based on kernel methods. *IEEE Transactions on Image Processing* **15**:9, 2743-2754. [[CrossRef](#)]
664. Fu-lai Chung, Shitong Wang, Zhaohong Deng, Chen Shu, D. Hu. 2006. Clustering Analysis of Gene Expression Data based on Semi-supervised Visual Clustering Algorithm. *Soft Computing* **10**:11, 981-993. [[CrossRef](#)]
665. Xudong Xie, Kin-Man Lam. 2006. Gabor-based kernel PCA with doubly nonlinear mapping for face recognition with a single face image. *IEEE Transactions on Image Processing* **15**:9, 2481-2492. [[CrossRef](#)]
666. Weihua Li, Tie-lin Shi, Shu-zi Yang. 2006. An approach for mechanical fault classification based on generalized discriminant analysis. *Frontiers of Mechanical Engineering in China* **1**:3, 292-298. [[CrossRef](#)]
667. J WANG, K PLATANOTIS, J LU, A VENETSANOPOULOS. 2006. On solving the face recognition problem with one training sample per subject. *Pattern Recognition* **39**:9, 1746-1762. [[CrossRef](#)]
668. Hiromichi Suetani, Yukito Iba, Kazuyuki Aihara. 2006. Detecting generalized synchronization between chaotic signals: a kernel-based approach. *Journal of Physics A: Mathematical and General* **39**:34, 10723-10742. [[CrossRef](#)]
669. Yoshikazu Washizawa, Yukihiko Yamashita. 2006. Kernel Projection Classifiers with Suppressing Features of Other Classes. *Neural Computation* **18**:8, 1932-1950. [[Abstract](#)] [[PDF](#)] [[PDF Plus](#)]
670. Sung-Moon Cheong, Ki-Bom Kim, Soon-Jwa Hong. 2006. A New Self-Organizing Map based on Kernel Concepts. *The KIPS Transactions: Part B* **13B**:4, 439-448. [[CrossRef](#)]
671. C YOO, I LEE. 2006. Nonlinear multivariate filtering and bioprocess monitoring for supervising nonlinear biological processes. *Process Biochemistry* **41**:8, 1854-1863. [[CrossRef](#)]
672. A MAULUD, D WANG, J ROMAGNOLI. 2006. A multi-scale orthogonal nonlinear strategy for multi-variate statistical process monitoring. *Journal of Process Control* **16**:7, 671-683. [[CrossRef](#)]
673. Man-Jun Kwon, Dong-Hwa Yang, Yong-Sam Kim, Dae-Jong Lee, Myung-Geun Chun. 2006. Multimodal biometrics system using PDA under ubiquitous environments. *Journal of Fuzzy Logic and Intelligent Systems* **16**:4, 430-435. [[CrossRef](#)]
674. J. Verbeek. 2006. Learning nonlinear image manifolds by global alignment of local linear models. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **28**:8, 1236-1250. [[CrossRef](#)]
675. RYO INOKUCHI, SADA AKI MIYAMOTO. 2006. KERNEL METHODS FOR CLUSTERING: COMPETITIVE LEARNING AND c-MEANS. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems* **14**:04, 481-493. [[CrossRef](#)]
676. 2006. Real-time Fault Diagnosis of Induction Motor Using Clustering and Radial Basis Function. *Journal of the Korean Institute of Illuminating and Electrical Installation Engineers* **20**:6, 55-62. [[CrossRef](#)]
677. Chang Kyoo Yoo, In-Beum Lee, Peter A. Vanrolleghem. 2006. On-Line Adaptive and Nonlinear Process Monitoring of a Pilot-Scale Sequencing Batch Reactor. *Environmental Monitoring and Assessment* **119**:1-3, 349-366. [[CrossRef](#)]
678. A M Jade, V K Jayaraman, B D Kulkarni. 2006. Improved time series prediction with a new method for selection of model parameters. *Journal of Physics A: Mathematical and General* **39**:30, L483-L491. [[CrossRef](#)]

679. U OZERTEM, D ERDOGMUS, R JENSSEN. 2006. Spectral feature projections that maximize Shannon mutual information with class labels. *Pattern Recognition* **39**:7, 1241-1252. [[CrossRef](#)]
680. B MOSER. 2006. On the T-transitivity of kernels. *Fuzzy Sets and Systems* **157**:13, 1787-1796. [[CrossRef](#)]
681. Brian Kan-Wing Mak, Roger Wend-Huu Hsiao, Simon Ka-Lung Ho, J.T. Kwok. 2006. Embedded kernel eigenvoice speaker adaptation and its implication to reference speaker weighting. *IEEE Transactions on Audio, Speech and Language Processing* **14**:4, 1267-1280. [[CrossRef](#)]
682. H YIN. 2006. On the equivalence between kernel self-organising maps and self-organising mixture density networks. *Neural Networks* **19**:6-7, 780-784. [[CrossRef](#)]
683. I. Santamaria, P.P. Pokharel, J.C. Principe. 2006. Generalized correlation function: definition, properties, and application to blind equalization. *IEEE Transactions on Signal Processing* **54**:6, 2187-2197. [[CrossRef](#)]
684. Y XU, D ZHANG, Z JIN, M LI, J YANG. 2006. A fast kernel-based nonlinear discriminant analysis for multi-class problems. *Pattern Recognition* **39**:6, 1026-1033. [[CrossRef](#)]
685. S.K. Zhou, R. Chellappa. 2006. From sample similarity to ensemble similarity: probabilistic distance measures in reproducing kernel Hilbert space. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **28**:6, 917-929. [[CrossRef](#)]
686. H WANG, E HANCOCK. 2006. Correspondence matching using kernel principal components analysis and label consistency constraints. *Pattern Recognition* **39**:6, 1012-1025. [[CrossRef](#)]
687. S LEE, H JUNG, B HWANG, S LEE. 2006. Authenticating corrupted photo images based on noise parameter estimation. *Pattern Recognition* **39**:5, 910-920. [[CrossRef](#)]
688. C. Alippi, F. Scotti. 2006. Exploiting Application Locality to Design Low-Complexity, Highly Performing, and Power-Aware Embedded Classifiers. *IEEE Transactions on Neural Networks* **17**:3, 745-754. [[CrossRef](#)]
689. Yonghong Tian, Tiejun Huang, Wen Gao. 2006. Latent linkage semantic kernels for collective classification of link data. *Journal of Intelligent Information Systems* **26**:3, 269-301. [[CrossRef](#)]
690. Xiao-Dong Yu, Lei Wang, Qi Tian, Ping Xue. 2006. A novel multi-resolution video representation scheme based on kernel PCA. *The Visual Computer* **22**:5, 357-370. [[CrossRef](#)]
691. G.P. Stachowiak, P. Podsiadlo, G.W. Stachowiak. 2006. Evaluation of methods for reduction of surface texture features. *Tribology Letters* **22**:2, 151-165. [[CrossRef](#)]
692. J LESKI. 2006. On support vector regression machines with linguistic interpretation of the kernel matrix. *Fuzzy Sets and Systems* **157**:8, 1092-1113. [[CrossRef](#)]
693. G JEMWA, C ALDRICH. 2006. Classification of process dynamics with Monte Carlo singular spectrum analysis. *Computers & Chemical Engineering* **30**:5, 816-831. [[CrossRef](#)]
694. Wenming Zheng . 2006. Class-Incremental Generalized Discriminant Analysis. *Neural Computation* **18**:4, 979-1006. [[Abstract](#)] [[PDF](#)] [[PDF Plus](#)]
695. T.V. Pham, A.W.M. Smeulders. 2006. Sparse representation for coarse and fine object recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **28**:4, 555-567. [[CrossRef](#)]
696. M.H.C. Law, A.K. Jain. 2006. Incremental nonlinear dimensionality reduction by manifold learning. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **28**:3, 377-391. [[CrossRef](#)]
697. Yuko Mizuhara, Akira Hayashi, Nobuo Suematsu. 2006. Embedding of time series data by using dynamic time warping distances. *Systems and Computers in Japan* **37**:3, 1-9. [[CrossRef](#)]
698. L WANG, X WANG, J FENG. 2006. Subspace distance analysis with application to adaptive Bayesian algorithm for face recognition#. *Pattern Recognition* **39**:3, 456-464. [[CrossRef](#)]
699. B USTUN, W MELSEN, L BUYDENS. 2006. Facilitating the application of Support Vector Regression by using a universal Pearson VII function based kernel. *Chemometrics and Intelligent Laboratory Systems* **81**:1, 29-40. [[CrossRef](#)]
700. H. Li, T. Jiang, K. Zhang. 2006. Efficient and Robust Feature Extraction by Maximum Margin Criterion. *IEEE Transactions on Neural Networks* **17**:1, 157-165. [[CrossRef](#)]
701. Luis B. Almeida. 2006. Nonlinear Source Separation. *Synthesis Lectures on Signal Processing* **1**:1, 1-114. [[CrossRef](#)]
702. W. Zheng, X. Zhou, C. Zou, L. Zhao. 2006. Facial Expression Recognition Using Kernel Canonical Correlation Analysis (KCCA). *IEEE Transactions on Neural Networks* **17**:1, 233-238. [[CrossRef](#)]
703. L. M. Galantucci, R. Ferrandes, G. Percoco. 2006. Digital Photogrammetry for Facial Recognition. *Journal of Computing and Information Science in Engineering* **6**:4, 390. [[CrossRef](#)]

704. A. Szymkowiak-Have, M.A. Girolami, J. Larsen. 2006. Clustering via Kernel Decomposition. *IEEE Transactions on Neural Networks* **17**:1, 256-264. [[CrossRef](#)]
705. Ibtissam Constantin, Cdric Richard, Rgis Lengelle, Laurent Soufflet. 2006. Nonlinear Regularized Wiener Filtering With Kernels: Application in Denoising MEG Data Corrupted by ECG. *IEEE Transactions on Signal Processing* **54**:12, 4796-4806. [[CrossRef](#)]
706. Kazunori HOSOTANI, Toyohiko SUZUKI, Yoshitaka OCHIAI. 2006. Reconstruction of the Complex Flow with POD Method (Application to Flows Passing Across Tube Banks Measured by PIV Method). *Transaction of the Visualization Society of Japan* **26**:12, 114-122. [[CrossRef](#)]
707. Defeng Wang, Daniel S. Yeung, Eric C. C. Tsang. 2006. Structured One-Class Classification. *IEEE Transactions on Systems, Man and Cybernetics, Part B (Cybernetics)* **36**:6, 1283-1295. [[CrossRef](#)]
708. Jian-hua Xu, Xue-gong Zhang, Yan-da Li. 2006. Regularized Kernel Forms of Minimum Squared Error Method. *Frontiers of Electrical and Electronic Engineering in China* **1**:1, 1-7. [[CrossRef](#)]
709. Hisashi Kashima, Hiroshi Sakamoto, Teruo Koyanagi. 2006. Design and Analysis of Convolution Kernels for Tree-Structured Data. *Transactions of the Japanese Society for Artificial Intelligence* **21**, 113-121. [[CrossRef](#)]
710. Philippos Mordohai, Gérard Medioni. 2006. Tensor Voting: A Perceptual Organization Approach to Computer Vision and Machine Learning. *Synthesis Lectures on Image, Video, and Multimedia Processing* **2**:1, 1-136. [[CrossRef](#)]
711. J. Lu, K.N. Plataniotis, A.N. Venetsanopoulos, S.Z. Li. 2006. Ensemble-based discriminant learning with boosting for face recognition. *IEEE Transactions on Neural Networks* **17**:1, 166-178. [[CrossRef](#)]
712. Sergios Theodoridis, Konstantinos Koutroumbas Feature Generation I 263-326. [[CrossRef](#)]
713. Sergios Theodoridis, Konstantinos Koutroumbas Clustering Algorithms IV 653-731. [[CrossRef](#)]
714. Qing Song . 2005. A Robust Information Clustering Algorithm. *Neural Computation* **17**:12, 2672-2698. [[Abstract](#)] [[PDF](#)] [[PDF Plus](#)]
715. Heesung Kwon, N.M. Nasrabadi. 2005. Kernel orthogonal subspace projection for hyperspectral signal classification. *IEEE Transactions on Geoscience and Remote Sensing* **43**:12, 2952-2962. [[CrossRef](#)]
716. S. Wu, T.W.S. Chow. 2005. PRSOM: A New Visualization Method by Hybridizing Multidimensional Scaling and Self-Organizing Map. *IEEE Transactions on Neural Networks* **16**:6, 1362-1380. [[CrossRef](#)]
717. S.S. Durbha, R.L. King. 2005. Semantics-enabled framework for knowledge discovery from Earth observation data archives. *IEEE Transactions on Geoscience and Remote Sensing* **43**:11, 2563-2572. [[CrossRef](#)]
718. George Michailidis Principal Components and Extensions . [[CrossRef](#)]
719. L. Y. Han, C. J. Zheng, H. H. Lin, J. Cui, H. Li, H. L. Zhang, Z. Q. Tang, Y. Z. Chen. 2005. Prediction of functional class of novel plant proteins by a statistical learning method. *New Phytologist* **168**:1, 109-121. [[CrossRef](#)]
720. 2005. Automatic model selection for the optimization of SVM kernels. *Pattern Recognition* **38**:10, 1733-1745. [[CrossRef](#)]
721. 2005. Kernel ICA: An alternative formulation and its application to face recognition. *Pattern Recognition* **38**:10, 1784-1787. [[CrossRef](#)]
722. Joseph Medendorp, Robert A. Lodder. 2005. Applications of integrated sensing and processing in spectroscopic imaging and sensing. *Journal of Chemometrics* **19**:10, 533-542. [[CrossRef](#)]
723. Jochen Einbeck, Gerhard Tutz, Ludger Evers. 2005. Local principal curves. *Statistics and Computing* **15**:4, 301-313. [[CrossRef](#)]
724. 2005. SVM decision boundary based discriminative subspace induction. *Pattern Recognition* **38**:10, 1746-1758. [[CrossRef](#)]
725. SATOSHI NIIJIMA, SATORU KUHARA. 2005. MULTICLASS MOLECULAR CANCER CLASSIFICATION BY KERNEL SUBSPACE METHODS WITH EFFECTIVE KERNEL PARAMETER SELECTION. *Journal of Bioinformatics and Computational Biology* **03**:05, 1071-1088. [[CrossRef](#)]
726. Kwa, M.O. Franz, B. Scholkopf. 2005. Iterative kernel principal component analysis for image modeling. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **27**:9, 1351-1366. [[CrossRef](#)]
727. P. Meinicke, S. Klanke, R. Memisevic, H. Ritter. 2005. Principal surfaces from unsupervised kernel regression. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **27**:9, 1379-1391. [[CrossRef](#)]
728. N. Mezghani, A. Mitiche, M. Cheriet. 2005. A new representation of shape and its use for high performance in online Arabic character recognition by an associative memory. *International Journal of Document Analysis and Recognition (IJDAR)* **7**:4, 201-210. [[CrossRef](#)]

729. B. Mak, J.T. Kwok, S. Ho. 2005. Kernel eigenvoice speaker adaptation. *IEEE Transactions on Speech and Audio Processing* **13**:5, 984-992. [[CrossRef](#)]
730. T TAKAHASHI, T KURITA. 2005. A robust classifier combined with an auto-associative network for completing partly occluded images. *Neural Networks* **18**:7, 958-966. [[CrossRef](#)]
731. M. Scholz. 2005. Non-linear PCA: a missing data approach. *Bioinformatics* **21**:20, 3887-3895. [[CrossRef](#)]
732. Wenming Zheng, Cairong Zou, Li Zhao. 2005. An Improved Algorithm for Kernel Principal Component Analysis. *Neural Processing Letters* **22**:1, 49-56. [[CrossRef](#)]
733. Gavin C. Cawley, Nicola L.C. Talbot. 2005. Constructing Bayesian formulations of sparse kernel learning methods. *Neural Networks* **18**:5-6, 674-683. [[CrossRef](#)]
734. Hui Kong, Lei Wang, Eam Khwang Teoh, Xuchun Li, Jian-Gang Wang, Ronda Venkateswarlu. 2005. Generalized 2D principal component analysis for face image representation and recognition#. *Neural Networks* **18**:5-6, 585-594. [[CrossRef](#)]
735. J LEE, J WANG, C ZHANG, Z BIAN. 2005. Visual object recognition using probabilistic kernel subspace similarity. *Pattern Recognition* **38**:7, 997-1008. [[CrossRef](#)]
736. Roland Memisevic, Geoffrey Hinton. 2005. Improving dimensionality reduction with spectral gradient descent. *Neural Networks* **18**:5-6, 702-710. [[CrossRef](#)]
737. Q TIAN, Y WU, J YU, T HUANG. 2005. Self-supervised learning based on discriminative nonlinear features for image classification. *Pattern Recognition* **38**:6, 903-917. [[CrossRef](#)]
738. Hitoshi Sakano, Naoki Mukawa, Taichi Nakamura. 2005. Kernel mutual subspace method and its application for object recognition. *Electronics and Communications in Japan (Part II: Electronics)* **88**:6, 45-53. [[CrossRef](#)]
739. Douglas R. Heisterkamp, Jing Peng. 2005. Kernel Vector Approximation Files for Relevance Feedback Retrieval in Large Image Databases. *Multimedia Tools and Applications* **26**:2, 175-189. [[CrossRef](#)]
740. P. Zhang, J. Peng, C. Domeniconi. 2005. Kernel Pooled Local Subspaces for Classification. *IEEE Transactions on Systems, Man and Cybernetics, Part B (Cybernetics)* **35**:3, 489-502. [[CrossRef](#)]
741. H. Zhang, W. Huang, Z. Huang, B. Zhang. 2005. A Kernel Autoassociator Approach to Pattern Classification. *IEEE Transactions on Systems, Man and Cybernetics, Part B (Cybernetics)* **35**:3, 593-606. [[CrossRef](#)]
742. R. Xu, D. WunschII. 2005. Survey of Clustering Algorithms. *IEEE Transactions on Neural Networks* **16**:3, 645-678. [[CrossRef](#)]
743. Markus Schmid, Timothy S Davison, Stefan R Henz, Utz J Pape, Monika Demar, Martin Vingron, Bernhard Schölkopf, Detlef Weigel, Jan U Lohmann. 2005. A gene expression map of Arabidopsis thaliana development. *Nature Genetics* **37**:5, 501-506. [[CrossRef](#)]
744. HAITAO ZHAO, PONG C. YUEN, JINGYU YANG. 2005. OPTIMAL SUBSPACE ANALYSIS FOR FACE RECOGNITION. *International Journal of Pattern Recognition and Artificial Intelligence* **19**:03, 375-393. [[CrossRef](#)]
745. N. L. M. M. Pochet. 2005. M@CBETH: a microarray classification benchmarking tool. *Bioinformatics* **21**:14, 3185-3186. [[CrossRef](#)]
746. Z.-L. Sun, D.-S. Huang, Y.-M. Cheung, J. Liu, G.-B. Huang. 2005. Using FCMC, FVS, and PCA Techniques for Feature Extraction of Multispectral Images. *IEEE Geoscience and Remote Sensing Letters* **2**:2, 108-112. [[CrossRef](#)]
747. ZHENQIU LIU, DECHANG CHEN, HALIMA BENSMAIL, YING XU. 2005. CLUSTERING GENE EXPRESSION DATA WITH KERNEL PRINCIPAL COMPONENTS. *Journal of Bioinformatics and Computational Biology* **03**:02, 303-316. [[CrossRef](#)]
748. Wang Shitong ., F.L. Chung ., Deng Zhaohong ., L.I.N. Qing ., H.U. Dwen . 2005. New Feature-extraction Criteria and Classification Algorithms for Cancer Gene Expression Datasets. *Biotechnology(Faisalabad)* **4**:3, 163-172. [[CrossRef](#)]
749. H. Xiong, M.N.S. Swamy, M.O. Ahmad. 2005. Optimizing the Kernel in the Empirical Feature Space. *IEEE Transactions on Neural Networks* **16**:2, 460-474. [[CrossRef](#)]
750. Z LIANG, P SHI. 2005. Kernel direct discriminant analysis and its theoretical foundation. *Pattern Recognition* **38**:3, 445-447. [[CrossRef](#)]
751. Jian Yang, A.F. Frangi, Jing-Yu Yang, David Zhang, Zhong Jin. 2005. KPCA plus LDA: a complete kernel Fisher discriminant framework for feature extraction and recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **27**:2, 230-244. [[CrossRef](#)]
752. Z LIANG, P SHI. 2005. Uncorrelated discriminant vectors using a kernel method. *Pattern Recognition* **38**:2, 307-310. [[CrossRef](#)]

753. Daoqiang Zhang, Daoqiang Zhang, Songcan Chen, Keren Tan, Keren Tan. 2005. Improving the Robustness of ?Online Agglomerative Clustering Method? Based on Kernel-Induce Distance Measures. *Neural Processing Letters* **21**:1, 45-51. [[CrossRef](#)]
754. Ying HAO, Jian-guo SUN, Guo-qing YANG, Jie BAI. 2005. The Application of Support Vector Machines to Gas Turbine Performance Diagnosis. *Chinese Journal of Aeronautics* **18**:1, 15-19. [[CrossRef](#)]
755. S CHOI, C LEE, J LEE, J PARK, I LEE. 2005. Fault detection and identification of nonlinear processes based on kernel PCA. *Chemometrics and Intelligent Laboratory Systems* **75**:1, 55-67. [[CrossRef](#)]
756. S KONG. 2005. Recent advances in visual and infrared face recognition?a review. *Computer Vision and Image Understanding* **97**:1, 103-135. [[CrossRef](#)]
757. J CHO, J LEE, S WOOKCHOI, D LEE, I LEE. 2005. Fault identification for process monitoring using kernel principal component analysis. *Chemical Engineering Science* **60**:1, 279-288. [[CrossRef](#)]
758. W. Zheng, L. Zhao, C. Zou. 2005. Foley–Sammon Optimal Discriminant Vectors Using Kernel Approach. *IEEE Transactions on Neural Networks* **16**:1, 1-9. [[CrossRef](#)]
759. Sang-Woon Kim, B.J. Oommen. 2005. On utilizing search methods to select subspace dimensions for kernel-based nonlinear subspace classifiers. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **27**:1, 136-141. [[CrossRef](#)]
760. W ZHAO, R CHELLAPPAA guided tour of face processing 3-53. [[CrossRef](#)]
761. Cheong Hee Park, Haesun Park. 2005. Nonlinear Discriminant Analysis Using Kernel Functions and the Generalized Singular Value Decomposition. *SIAM Journal on Matrix Analysis and Applications* **27**:1, 87-102. [[CrossRef](#)]
762. Rozenn Dahyot, Pierre Charbonnier, Fabrice Heitz. 2004. A Bayesian approach to object detection using probabilistic appearance-based models. *Pattern Analysis and Applications* **7**:3, 317-332. [[CrossRef](#)]
763. S CHOI. 2004. Nonlinear dynamic process monitoring based on dynamic kernel PCA. *Chemical Engineering Science* **59**:24, 5897-5908. [[CrossRef](#)]
764. 2004. Cancer-Subtype Classification Based on Gene Expression Data. *Journal of Control, Automation and Systems Engineering* **10**:12, 1172-1180. [[CrossRef](#)]
765. P. Laskov, C. Schäfer, I. Kotenko, K.-R. Müller. 2004. Intrusion Detection in Unlabeled Data with Quarter-sphere Support Vector Machines. *PIK - Praxis der Informationsverarbeitung und Kommunikation* **27**:4, 228-236. [[CrossRef](#)]
766. SHANG-MING ZHOU, JOHN Q. GAN. 2004. AN UNSUPERVISED KERNEL BASED FUZZY C-MEANS CLUSTERING ALGORITHM WITH KERNEL NORMALISATION. *International Journal of Computational Intelligence and Applications* **04**:04, 355-373. [[CrossRef](#)]
767. J.T.-Y. Kwok, I.W.-H. Tsang. 2004. The Pre-Image Problem in Kernel Methods. *IEEE Transactions on Neural Networks* **15**:6, 1517-1525. [[CrossRef](#)]
768. K KAIEDA. 2004. KPCA-based training of a kernel fuzzy classifier with ellipsoidal regions. *International Journal of Approximate Reasoning* **37**:3, 189-217. [[CrossRef](#)]
769. Mark J. Embrechts, Boleslaw Szymanski, Karsten Sternickel Introduction to Scientific Data Mining: Direct Kernel Methods and Applications 317-362. [[CrossRef](#)]
770. Yoshua Bengio , Olivier Delalleau , Nicolas Le Roux , Jean-François Paiement , Pascal Vincent , Marie Ouimet . 2004. Learning Eigenfunctions Links Spectral Embedding and Kernel PCA. *Neural Computation* **16**:10, 2197-2219. [[Abstract](#)] [[PDF](#)] [[PDF Plus](#)]
771. J YANG. 2004. Essence of kernel Fisher discriminant: KPCA plus LDA. *Pattern Recognition* **37**:10, 2097-2100. [[CrossRef](#)]
772. D. Komura. 2004. Multidimensional support vector machines for visualization of gene expression data. *Bioinformatics* **21**:4, 439-444. [[CrossRef](#)]
773. J LEE. 2004. Fault detection of batch processes using multiway kernel principal component analysis. *Computers & Chemical Engineering* **28**:9, 1837-1847. [[CrossRef](#)]
774. S. Chen, D. Zhang. 2004. Robust Image Segmentation Using FCM With Spatial Constraints Based on New Kernel-Induced Distance Measure. *IEEE Transactions on Systems, Man and Cybernetics, Part B (Cybernetics)* **34**:4, 1907-1916. [[CrossRef](#)]
775. Y. Engel, S. Mannor, R. Meir. 2004. The Kernel Recursive Least-Squares Algorithm. *IEEE Transactions on Signal Processing* **52**:8, 2275-2285. [[CrossRef](#)]
776. P.-J. L?Heureux, J. Carreau, Y. Bengio, O. Delalleau, S. Y. Yue. 2004. Locally Linear Embedding for dimensionality reduction in QSAR. *Journal of Computer-Aided Molecular Design* **18**:7-9, 475-482. [[CrossRef](#)]

777. Wenming Zheng, Li Zhao, Cairong Zou. 2004. A Modified Algorithm for Generalized Discriminant Analysis. *Neural Computation* **16**:6, 1283-1297. [[Abstract](#)] [[PDF](#)] [[PDF Plus](#)]
778. Chengjun Liu. 2004. Gabor-based kernel pca with fractional power polynomial models for face recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **26**:5, 572-581. [[CrossRef](#)]
779. Ying Tan, Jun Wang. 2004. A support vector machine with a hybrid kernel and minimal vapnik-chervonenkis dimension. *IEEE Transactions on Knowledge and Data Engineering* **16**:4, 385-395. [[CrossRef](#)]
780. C Park. 2004. Nonlinear feature extraction based on centroids and kernel functions. *Pattern Recognition* **37**:4, 801-810. [[CrossRef](#)]
781. Sang-Woon Kim, B.John Oommen. 2004. On using prototype reduction schemes to optimize kernel-based nonlinear subspace methods#. *Pattern Recognition* **37**:2, 227-239. [[CrossRef](#)]
782. Changshui Zhang, Jun Wang, Nanyuan Zhao, David Zhang. 2004. Reconstruction and analysis of multi-pose face images based on nonlinear dimensionality reduction. *Pattern Recognition* **37**:2, 325-336. [[CrossRef](#)]
783. KLAUS-ROBERT MÜLLER, RICARDO VIGÁRIO, FRANK MEINECKE, ANDREAS ZIEHE. 2004. BLIND SOURCE SEPARATION TECHNIQUES FOR DECOMPOSING EVENT-RELATED BRAIN SIGNALS. *International Journal of Bifurcation and Chaos* **14**:02, 773-791. [[CrossRef](#)]
784. J Leski. 2004. Fuzzy c-varieties/elliptotypes clustering in reproducing kernel Hilbert space. *Fuzzy Sets and Systems* **141**:2, 259-280. [[CrossRef](#)]
785. Z. Liang, P. Shi. 2004. Efficient algorithm for kernel discriminant analysis. *Electronics Letters* **40**:25, 1579. [[CrossRef](#)]
786. Kai Huang, Robert F. Murphy. 2004. From quantitative microscopy to automated image understanding. *Journal of Biomedical Optics* **9**:5, 893. [[CrossRef](#)]
787. Matej Orešič, Clary B Clish, Eugene J Davidov, Elwin Verheij, Jack Vogels, Louis M Havekes, Eric Neumann, Aram Adourian, Stephen Naylor, Jan van der Greef, Thomas Plasterer. 2004. Phenotype Characterisation Using Integrated Gene Transcript, Protein and Metabolite Profiling. *Applied Bioinformatics* **3**:4, 205-217. [[CrossRef](#)]
788. Jong-Min Lee, ChangKyoo Yoo, Sang Wook Choi, Peter A. Vanrolleghem, In-Beum Lee. 2004. Nonlinear process monitoring using kernel principal component analysis. *Chemical Engineering Science* **59**:1, 223-234. [[CrossRef](#)]
789. H. Choi, S. Choi. 2004. Kernel Isomap. *Electronics Letters* **40**:25, 1612. [[CrossRef](#)]
790. Q. Liu, H. Lu, S. Ma. 2004. Improving Kernel Fisher Discriminant Analysis for Face Recognition. *IEEE Transactions on Circuits and Systems for Video Technology* **14**:1, 42-49. [[CrossRef](#)]
791. Yixin Chen, J.Z. Wang. 2003. Support vector learning for fuzzy rule-based classification systems. *IEEE Transactions on Fuzzy Systems* **11**:6, 716-728. [[CrossRef](#)]
792. V. Roth, J. Laub, M. Kawanabe, J.M. Buhmann. 2003. Optimal cluster preserving embedding of nonmetric proximity data. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **25**:12, 1540-1551. [[CrossRef](#)]
793. F Camastra. 2003. Data dimensionality estimation methods: a survey. *Pattern Recognition* **36**:12, 2945-2954. [[CrossRef](#)]
794. Julian Mintseris, Zhiping Weng. 2003. Atomic contact vectors in protein-protein recognition. *Proteins: Structure, Function, and Genetics* **53**:3, 629-639. [[CrossRef](#)]
795. QingShan Liu, Rui Huang, HanQing Lu, SongDe Ma. 2003. Kernel-based nonlinear discriminant analysis for face recognition. *Journal of Computer Science and Technology* **18**:6, 788-795. [[CrossRef](#)]
796. A Jade. 2003. Feature extraction and denoising using kernel PCA. *Chemical Engineering Science* **58**:19, 4441-4448. [[CrossRef](#)]
797. M. Girolami, Chao He. 2003. Probability density estimation from optimally condensed data samples. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **25**:10, 1253-1264. [[CrossRef](#)]
798. D Cremers. 2003. Shape statistics in kernel space for variational image segmentation. *Pattern Recognition* **36**:9, 1929-1943. [[CrossRef](#)]
799. Shihong Yue, Ping Li, Peiyi Hao. 2003. SVM classification: Its contents and challenges. *Applied Mathematics-A Journal of Chinese Universities* **18**:3, 332-342. [[CrossRef](#)]
800. Qingshan Liu, Hanqing Lu, Songde Ma. 2003. A non-parameter bayesian classifier for face recognition. *Journal of Electronics (China)* **20**:5, 362-370. [[CrossRef](#)]
801. B Thirion. 2003. Dynamical components analysis of fMRI data through kernel PCA. *NeuroImage* **20**:1, 34-49. [[CrossRef](#)]
802. A Leonardis. 2003. Kernel and subspace methods for computer vision. *Pattern Recognition* **36**:9, 1925-1927. [[CrossRef](#)]

803. T Melzer. 2003. Appearance models based on kernel canonical correlation analysis. *Pattern Recognition* **36**:9, 1961-1971. [[CrossRef](#)]
804. Ji-Hoon Cho, Dongkwon Lee, Jin Hyun Park, In-Beum Lee. 2003. New gene selection method for classification of cancer subtypes considering within-class variation. *FEBS Letters* **551**:1-3, 3-7. [[CrossRef](#)]
805. E ParradoHernandez. 2003. Growing support vector classifiers with controlled complexity. *Pattern Recognition* **36**:7, 1479-1488. [[CrossRef](#)]
806. Guilherme de A. Barreto , Aluizio F. R. Araújo , Stefan C. Kremer . 2003. A Taxonomy for Spatiotemporal Connectionist Networks Revisited: The Unsupervised Case. *Neural Computation* **15**:6, 1255-1320. [[Abstract](#)] [[PDF](#)] [[PDF Plus](#)]
807. K. Muller, C.W. Anderson, G.E. Birch. 2003. Linear and nonlinear methods for brain-computer interfaces. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* **11**:2, 165-169. [[CrossRef](#)]
808. 2003. Modified Kernel PCA Applied To Classification Problem. *The KIPS Transactions:PartB* **10B**:3, 243-248. [[CrossRef](#)]
809. S. Mika, G. Ratsch, J. Weston, B. Scholkopf, A. Smola, K. Muller. 2003. Constructing descriptive and discriminative nonlinear features: rayleigh coefficients in kernel feature spaces. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **25**:5, 623-628. [[CrossRef](#)]
810. DAVID M. J. TAX, PIOTR JUSZCZAK. 2003. KERNEL WHITENING FOR ONE-CLASS CLASSIFICATION. *International Journal of Pattern Recognition and Artificial Intelligence* **17**:03, 333-347. [[CrossRef](#)]
811. J.A.K. Suykens, T. Van Gestel, J. Vandewalle, B. De Moor. 2003. A support vector machine formulation to pca analysis and its kernel version. *IEEE Transactions on Neural Networks* **14**:2, 447-450. [[CrossRef](#)]
812. Juwei Lu, K.N. Plataniotis, A.N. Venetsanopoulos. 2003. Face recognition using kernel direct discriminant analysis algorithms. *IEEE Transactions on Neural Networks* **14**:1, 117-126. [[CrossRef](#)]
813. D. Martinez, A. Bray. 2003. Nonlinear blind source separation using kernels. *IEEE Transactions on Neural Networks* **14**:1, 228-235. [[CrossRef](#)]
814. C TWINING, C TAYLOR. 2003. The use of kernel principal component analysis to model data distributions. *Pattern Recognition* **36**:1, 217-227. [[CrossRef](#)]
815. F. Meinecke, A. Ziehe, M. Kawanabe, K.-R. Muller. 2002. A resampling approach to estimate the stability of one-dimensional or multidimensional independent components. *IEEE Transactions on Biomedical Engineering* **49**:12, 1514-1525. [[CrossRef](#)]
816. Jiun-Hung Chen, Chu-Song Chen. 2002. Fuzzy kernel perceptron. *IEEE Transactions on Neural Networks* **13**:6, 1364-1373. [[CrossRef](#)]
817. A Belousov. 2002. A flexible classification approach with optimal generalisation performance: support vector machines. *Chemometrics and Intelligent Laboratory Systems* **64**:1, 15-25. [[CrossRef](#)]
818. H YIN. 2002. Data visualisation and manifold mapping using the ViSOM. *Neural Networks* **15**:8-9, 1005-1016. [[CrossRef](#)]
819. M HARITOPOULOS, H YIN, N ALLINSON. 2002. Image denoising using self-organizing map-based nonlinear independent component analysis. *Neural Networks* **15**:8-9, 1085-1098. [[CrossRef](#)]
820. G. Ratsch, S. Mika, B. Scholkopf, K.-R. Muller. 2002. Constructing boosting algorithms from SVMs: an application to one-class classification. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **24**:9, 1184-1199. [[CrossRef](#)]
821. Kai Yu, Liang Ji. 2002. Karyotyping of comparative genomic hybridization human metaphases using kernel nearest-neighbor algorithm. *Cytometry* **48**:4, 202-208. [[CrossRef](#)]
822. C Corchado. 2002. A comparison of Kernel methods for instantiating case based reasoning systems. *Advanced Engineering Informatics* **16**:3, 165-178. [[CrossRef](#)]
823. B. Moghaddam. 2002. Principal manifolds and probabilistic subspaces for visual recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **24**:6, 780-788. [[CrossRef](#)]
824. T. Van Gestel , J. A. K. Suykens , G. Lanckriet , A. Lambrechts , B. De Moor , J. Vandewalle . 2002. Bayesian Framework for Least-Squares Support Vector Machine Classifiers, Gaussian Processes, and Kernel Fisher Discriminant Analysis. *Neural Computation* **14**:5, 1115-1147. [[Abstract](#)] [[PDF](#)] [[PDF Plus](#)]
825. M. Girolami. 2002. Mercer kernel-based clustering in feature space. *IEEE Transactions on Neural Networks* **13**:3, 780-784. [[CrossRef](#)]
826. Paul Pavlidis, Jason Weston, Jinsong Cai, William Stafford Noble. 2002. Learning Gene Functional Classifications from Multiple Data Types. *Journal of Computational Biology* **9**:2, 401-411. [[CrossRef](#)]
827. Y Wu. 2002. Towards self-exploring discriminating features for visual learning. *Engineering Applications of Artificial Intelligence* **15**:2, 139-150. [[CrossRef](#)]

828. Kwang In Kim, Keechul Jung, Hang Joon Kim. 2002. Face recognition using kernel principal component analysis. *IEEE Signal Processing Letters* **9**:2, 40-42. [[CrossRef](#)]
829. Hujun Yin. 2002. ViSOM - a novel method for multivariate data projection and structure visualization. *IEEE Transactions on Neural Networks* **13**:1, 237-243. [[CrossRef](#)]
830. Eisaku Maeda, Hiroshi Murase. 2002. Kernel-Based Nonlinear Subspace Method for Pattern Recognition. *Systems and Computers in Japan* **33**:1, 38-52. [[CrossRef](#)]
831. S Bermejo. 2001. Oriented principal component analysis for large margin classifiers. *Neural Networks* **14**:10, 1447-1461. [[CrossRef](#)]
832. T. Maddess, Y. Nagai. 2001. Discriminating of isotrigon textures. *Vision Research* **41**:28, 3837-3860. [[CrossRef](#)]
833. A Talukder. 2001. A closed-form neural network for discriminatory feature extraction from high-dimensional data. *Neural Networks* **14**:9, 1201-1218. [[CrossRef](#)]
834. A. Navia-Vazquez, F. Perez-Cruz, A. Artes-Rodriguez, A.R. Figueiras-Vidal. 2001. Weighted least squares training of support vector classifiers leading to compact and adaptive schemes. *IEEE Transactions on Neural Networks* **12**:5, 1047-1059. [[CrossRef](#)]
835. R.C. Williamson, A.J. Smola, B. Scholkopf. 2001. Generalization performance of regularization networks and support vector machines via entropy numbers of compact operators. *IEEE Transactions on Information Theory* **47**:6, 2516-2532. [[CrossRef](#)]
836. T. Van Gestel, J.A.K. Suykens, D.-E. Baestaens, A. Lambrechts, G. Lanckriet, B. Vandaele, B. De Moor, J. Vandewalle. 2001. Financial time series prediction using least squares support vector machines within the evidence framework. *IEEE Transactions on Neural Networks* **12**:4, 809-821. [[CrossRef](#)]
837. Koji Tsuda. 2001. The subspace method in Hilbert space. *Systems and Computers in Japan* **32**:6, 55-61. [[CrossRef](#)]
838. Kristin K. Jerger, Theoden I. Netoff, Joseph T. Francis, Timothy Sauer, Louis Pecora, Steven L. Weinstein, Steven J. Schiff. 2001. Early Seizure Detection. *Journal of Clinical Neurophysiology* **18**:3, 259-268. [[CrossRef](#)]
839. Roman Rosipal, Mark Girolami. 2001. An Expectation-Maximization Approach to Nonlinear Component Analysis. *Neural Computation* **13**:3, 505-510. [[Abstract](#)] [[PDF](#)] [[PDF Plus](#)]
840. K.-R. Muller, S. Mika, G. Ratsch, K. Tsuda, B. Scholkopf. 2001. An introduction to kernel-based learning algorithms. *IEEE Transactions on Neural Networks* **12**:2, 181-201. [[CrossRef](#)]
841. K.I. Kim, S.H. Park, H.J. Kim. 2001. Kernel principal component analysis for texture classification. *IEEE Signal Processing Letters* **8**:2, 39-41. [[CrossRef](#)]
842. A. Ruiz, P.E. Lopez-de-Teruel. 2001. Nonlinear kernel-based statistical pattern analysis. *IEEE Transactions on Neural Networks* **12**:1, 16-32. [[CrossRef](#)]
843. P. L. LAI, C. FYFE. 2000. KERNEL AND NONLINEAR CANONICAL CORRELATION ANALYSIS. *International Journal of Neural Systems* **10**:05, 365-377. [[CrossRef](#)]
844. M. Brown, H.G. Lewis, S.R. Gunn. 2000. Linear spectral mixture models and support vector machines for remote sensing. *IEEE Transactions on Geoscience and Remote Sensing* **38**:5, 2346-2360. [[CrossRef](#)]
845. G. Wubbeler, A. Ziehe, B.-M. Mackert, K.-R. Muller, L. Trahms, C. Curio. 2000. Independent component analysis of noninvasively recorded cortical magnetic DC-fields in humans. *IEEE Transactions on Biomedical Engineering* **47**:5, 594-599. [[CrossRef](#)]
846. R. Lotlikar, R. Kothari. 2000. Bayes-optimality motivated linear and multilayered perceptron-based dimensionality reduction. *IEEE Transactions on Neural Networks* **11**:2, 452-463. [[CrossRef](#)]
847. A.K. Jain, P.W. Duin, Jianchang Mao. 2000. Statistical pattern recognition: a review. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **22**:1, 4-37. [[CrossRef](#)]
848. Azriel Rosenfeld, Harry Wechsler. 2000. Pattern recognition: Historical perspective and future directions. *International Journal of Imaging Systems and Technology* **11**:2, 101-116. [[CrossRef](#)]
849. A. Ziehe, K.-R. Muller, G. Nolte, B.-M. Mackert, G. Curio. 2000. Artifact reduction in magnetoneurography based on time-delayed second-order correlations. *IEEE Transactions on Biomedical Engineering* **47**:1, 75-87. [[CrossRef](#)]
850. K.I. Kim, K. Jung, S.H. Park, H.J. Kim. 2000. Texture classification with kernel principal component analysis. *Electronics Letters* **36**:12, 1021. [[CrossRef](#)]
851. D.J.H. Wilson, G.W. Irwin, G. Lightbody. 1999. RBF principal manifolds for process monitoring. *IEEE Transactions on Neural Networks* **10**:6, 1424-1434. [[CrossRef](#)]

852. B. Scholkopf, S. Mika, C.J.C. Burges, P. Knirsch, K.-R. Muller, G. Ratsch, A.J. Smola. 1999. Input space versus feature space in kernel-based methods. *IEEE Transactions on Neural Networks* **10**:5, 1000-1017. [[CrossRef](#)]
853. Epifanio Bagarinao, K. Pakdaman, Taishin Nomura, Shunsuke Sato. 1999. Reconstructing bifurcation diagrams from noisy time series using nonlinear autoregressive models. *Physical Review E* **60**:1, 1073-1076. [[CrossRef](#)]
854. M.A. Hearst, S.T. Dumais, E. Osman, J. Platt, B. Scholkopf. 1998. Support vector machines. *IEEE Intelligent Systems* **13**:4, 18-28. [[CrossRef](#)]