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Modified locally linear discriminant embedding for plant leaf recognition

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ABSTRACT

Based on locally linear embedding (LLE) and modified maximizing margin criterion (MMMC), a modified locally linear discriminant embedding (MLLDE) algorithm is proposed for plant leaf recognition in this paper. By MLLDE, the plant leaf images are mapped into a leaf subspace for analysis, which can detect the essential leaf manifold structure. Furthermore, the unwanted variations resulting from changes in period, location, and illumination can be eliminated or reduced. Different from principal component analysis (PCA) and linear discriminant analysis (LDA), which can only deal with flat Euclidean structures of plant leaf space, MLLDE not only inherits the advantages of locally linear embedding (LLE), but makes full use of class information to improve discriminant power by introducing translation and rescaling models. The experimental results on real plant leaf database show that the MLLDE is effective for plant leaf recognition.

1. Introduction

Plant recognition based on leaf images is very important and necessary to agricultural informatization, ecological protection, and automatic plant recognition system. It is well known that the way to validly extract classification features is central to the plant recognition based on leaf images. Currently, the widely used features for plant recognition based on leaf image can be divided into color, shape, and texture features [1–11]. Plant recognition based on leaf color feature is one of the most widely used techniques. The earliest plant recognition studies used color as comparing feature between images [1–3]. A simple color similarity between two images can be measured by comparing their color histograms. More complex color features may involve looking into spatial relationship of multiple colors or looking at the color histograms in automatically segmented regions of the leaf image. Shape is one of the most important characteristics of the plant leaf. Two basic approaches to shape analysis exist: region-based and boundary-based (contour-based) [4]. Region-based systems typically use moment descriptors [5] that include geometrical moments, Zernike moments, and Legendre moments [4]. Boundary-based systems use the contour of the objects and usually give better results for leaf images that are distinguishable by their contours. Curvature scale space methods and deformable templates [6] are some of the common techniques used in contour-based shape recognition. Texture can be described as the spatial patterns formed by the surface characteristics of a leaf that manifests itself as color or grayscale variations in the image. Texture analysis and matching can be done in spatial or frequency domain. Commonly used texture features are gray-level co-occurrence matrices, local binary patterns, Markov random fields, and Gabor wavelets [7–11]. Although they have proven to be effective in some real-world applications; these techniques have not fully considered the following characteristics of plant leaf image data—(1) *Diversity*: Plant leaf images differ from each other in a thousand ways. They vary with period, location, and illumination conditions, and contain a lot of noise and outliers. Fig. 1 shows that the same kind of plant species possesses leaves of different shapes, colors, and textures, which are subjected to different period, location, and illumination conditions. (2) *Holism*: The existing methods only concentrate on feature extraction of every single leaf images while not considering the leaf images as a whole to conduct dimensionality reduction and feature extraction. (3) *Geometry*: They neglect the intrinsic geometrical structures of leaf image subspace. It inevitably increases the difference of the intra-class leaf images and decreases the difference of the inter-class leaf images simultaneously, which will lead to a heavy weakening of their performances on plant recognition. Moreover, most of these methods are computationally expensive, thus limiting their utility in plant leaf image data sets.

Manifold learning plays an important role in many applications such as pattern representation, visualization, and classification. Over the last decade, a large number of nonlinear manifold

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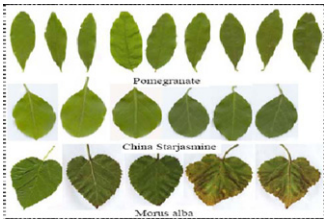

Fig. 1. Plant leaf images of pomegranate, china starjasmine, and morus alba with different seasons, locations, and illuminations.

learning algorithms have been proposed under the assumption that the input dataset lies on or near some low-dimensional manifold embedded in a high-dimensional unorganized Euclidean space. Among the most well known are isometric feature mapping (ISOMAP) [12], locally linear embedding (LLE) [13,14], Laplacian eigenmaps (LE) [15], Hessian-based locally linear embedding (HLLE) [16], maximum variance unfolding (MVU) [17], local tangent space alignment (LTSA) [18], local spline embedding (LSE) [19], and local and global regressive mapping (LGRM) [20]. Each manifold learning algorithm attempts to preserve a different geometrical property of the underlying manifold. Local approaches such as LLE, HLLE, LE, LTSA, and LSE aim to preserve the proximity relationship among the data, while global approaches like ISOMAP aim to preserve the metrics at all scales. These nonlinear methods yield impressive results on some benchmark artificial and real-world data sets due to their nonlinear nature, geometric intuition, and computational feasibility.

In this study, we take an alternative view of manifold learning to develop an efficient algorithm called modified locally linear discriminant embedding approach (MLLDE) for plant leaf recognition. The goal of MLLDE is to map the plant leaf images into a plant leaf subspace for analysis. Different from principal component analysis (PCA) [21] and linear discriminant analysis (LDA) [22], which can only deal with flat Euclidean structures of plant leaf space, MLLDE finds an embedding that not only inherits the advantages of locally linear embedding (LLE) [13,14], which uses local neighborhoods as a representation of the local geometry so as to preserve the local structure, but makes full use of class information to improve discriminant power by introducing translation and rescaling models. In this way, a plant leaf subspace that best detects the essential plant leaf manifold structure can be obtained. Furthermore, the unwanted variations resulting from changes in season, location, and illumination may be eliminated or reduced. It is worthwhile to highlight several aspects of the proposed approach here:

(1) An efficient subspace learning algorithm for plant recognition should be able to discover the nonlinear manifold structure of the leaf image space. Our proposed MLLDE algorithm explicitly considers the intrinsic leaf manifold structure, which is modeled by an adjacency graph.
(2) MLLDE takes local structure and discriminant information into consideration simultaneously and attempts to manage the trade-off between LLE, which is based mainly on preserving local geometry, and MMMC, which emphasizes discriminant power.
(3) MLLDE shares some similar properties to LLE, such as a local neighborhood preserving character. However, their objective functions are totally different. MLLDE computes an explicit linear mapping from the input space to the reduced space; while in LLE, the mapping is implicit and it is not clear how new data samples can be embedded.

The rest of this paper is organized as follows: Section 2 analyzes feasibility of plant leaf recognition based on manifold learning. In Section 3, the MLLDE algorithm is developed. A variety of the experimental results are presented in Section 4. Finally, we provide some concluding remarks in Section 5.

2. Feasibility of plant leaf recognition based on manifold learning

An important advantage of manifold learning [12–20] compared with conventional approaches concerns how the data are treated mathematically. Conventional approaches typically produce a smaller data space from linear combinations of the original data. One common example is PCA, which seeks a low-dimensional linear subspace spanned by the eigenvectors corresponding to the largest eigenvalues of the covariance matrix of all samples. However, for plant leaf images, the assumption of global linearity is a severe constraint since they are sensitive to period, location, and illumination conditions and there is no reason to believe that the leaf image data are linearly separable from each other. Manifold learning approaches recognize this fact and allow the data to be nonlinearly related, which results in the fact that manifold learning approaches can much more accurately capture the proper information relationships among the data, thus allowing for accurate recognition. Fig. 2 shows a simple example that 150 leaf images of two kinds of plants are mapped into two-dimensional subspace by LLE. The size of each image is 32×32 pixels, with 256 gray levels per pixel. Thus, each leaf image is represented by a point in the 1024-dimensional ambient space. The left and right leaf images, respectively, correspond to the points with green and cyan circles in the two-dimensional embedding subspace. As can be seen, the leaf images are divided into two parts. The circles and the asterisks represent leaf images of different classes. It can be clearly seen that the sample points of each class exhibit a sub-manifold distribution. The results demonstrate that LLE successfully derives the discriminative directions while they are not optimal for leaf recognition task. This is because in trying to preserve local structure in the embedding, the LLE implicitly emphasizes the natural clusters in the data. More importantly, LLE is capable of capturing the intrinsic leaf manifold structure to some extent.

3. Method

Although LLE [13,14] is an effective nonlinear dimensionality reduction approach, some limitations are exposed when they are applied to recognition tasks. One is the out-of-sample problem. LLE yields maps that are defined only on the training data points and how to evaluate the maps on novel test data points attracts much attention [23]. To address the drawback, He et al. [24]

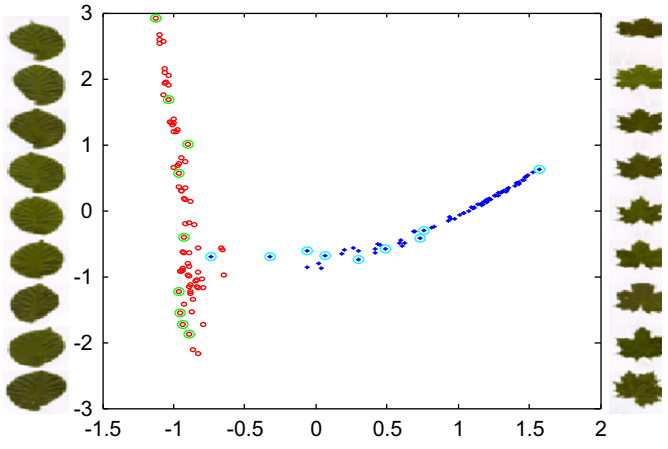

Fig. 2. Two-dimensional embedding of plant leaf images by LLE.

introduced an explicit linear mapping to the original LLE, which made it straightforward for handling new data samples. Another is that the classical LLE neglects the class information, which will inevitably impair their performances on pattern recognition. A typical approach to overcome this limitation is to modify input space distances by taking into account class labels of individual data points, such as supervised LLE [25] using Euclidean distance considering the known class label information, probability-based LLE [26] using a probability-based distance, and weighted locally linear embedding using a cam weighted distance. In this paper, we propose a novel linear subspace learning technique, called modified locally linear discriminant embedding (MLLDE). The neighborhood relationship of each data point is firstly built in our method, which can represent the local geometry of the intrinsic manifold structure. We then compute a transformation matrix, which maps the data points to a subspace. The linear transformation matrix is obtained by optimizing an objective function, which captures the discrepancy of the local geometries in the reduced space and introduces the modified maximizing margin criterion (MMMC) [27,28] simultaneously. Therefore, our method effectively combines the ideas of LLE and MMMC, i.e. it can hold the strong discriminant power of MMMC and at the same time preserve the intrinsic geometry of the data samples.

3.1. Constructing supervised neighborhood graph

Consider a dataset represented by the columns of a matrix $X=[x_1,x_2,\ldots,x_n]\in\mathbb{R}^{D\times n}$. MLLDE commences by constructing a supervised neighborhood graph. In order to build a neighborhood graph aimed at classification task, we hope that the local neighbors of a sample x_i should be composed of samples belonging to the same class only. However, in practice, the neighborhood relationship of each point is destroyed because of many degrees of freedom, heavy noise, and insufficient sampling. In this study, we introduce a distance metric to establish a high-quality neighborhood graph:

$$L(x_i,x_j)=\|x_i-x_j\|+\beta\Pi(1-\delta(x_i,x_j)) \tag{1}$$

where $\Pi=\max_{ij}\|x_i-x_j\|$ is the data diameter in Euclidean distance space, $\beta\in[0,1]$ is a tuning parameter that controls the amount to which class information should be incorporated, and $\delta(,)$ is a character function, if x_i and x_j belong to the same class, $\delta(x_i,x_j)=1$; otherwise $\delta(x_i,x_j)=0$ [31]. According to the distance $L(x_i,x_j)$, we determine the k-nearest neighbors of each data point by KNN or ε-ball algorithm. Here, the class information is employed to form the local neighborhood structure of each point. That is, the nearest neighbors of a given point x_i are chosen only from representatives of the same class as that of x_i by artificially increasing the shift distances between samples belonging to different classes, but leaving them unchanged if samples are from the same class. After the neighborhood relationship of each point is obtained, we need to build an affinity matrix by computing optimal weights, which will relate a given point to its neighbors in some locally optimal way. This phase is identical with that of LLE [13,14]. For completeness, the process of computing the affinity matrix is summarized here, and the details can be found in [13,14]. The basic assumption is that each data sample, along with its k-nearest neighbors (approximately), lies on a locally linear manifold. Hence, each data sample x_i is reconstructed by a linear combination of its k-nearest neighbors. The reconstruction errors are measured by minimizing the objective function.

$$\varepsilon=\sum_i\left\|x_i-\sum_j w_{ij}x_j\right\|_2^2 \tag{2}$$

where the weights w_{ij} represent the linear coefficients for reconstructing the sample x_i from its neighbors (x_j). To compute the weights, we minimize the cost function in Eq. (2), which is subjected to two constraints: a sparseness constraint and an invariance constraint. The sparseness constraint is that each data point x_i is reconstructed only from its neighbors, enforcing $w_{ij}=0$ if x_j does not belong to this set. The invariance constraint is that the rows of the weight matrix sum to one: $\sum_j w_{ij}=1$. The constrained weights w_{ij} satisfy certain optimality properties. They are invariant to rotation, rescaling, and translation. As a consequence of these properties, the supervised neighborhood graph preserves the intrinsic geometric characteristics of each neighborhood.

3.2. Modified maximize margin criterion

It is well known that LLE is completely unsupervised because of not taking the class information of the input data into account, which neglects much useful information for classification and significantly degrades the recognition rate, especially when sufficient data samples are provided. In MLLDE, the properties of the rescaling-invariance and translation-invariance of the reconstructing weights in the original LLE are utilized to improve its classification ability. This can be achieved by constructing different translation and rescaling models for each class. We use the same example as in Fig. 2 to illustrate this point. Fig. 3 shows two-dimensional embedding of plant leaf images after translation, where it can be seen that the discriminability is improved evidently. Moreover, a rescaling coefficient is introduced to the proposed algorithm and the discriminability is also improved, which can be found in Fig. 4. It should be noted that building appropriate translation and rescaling models for each class can improve the recognition accuracy of the classical LLE significantly. However, when applying the proposed algorithm to real-world data, how to explore the optimal translation vectors and rescaling coefficient is still an open problem. In this study, MMMC is adopted to find the optimal translation vectors and rescaling coefficient, which will be explored by transformation.

MMMC [27,28] aims at maximizing the average margin between classes in the projected space. Let S_w and S_b be the within-class scatter matrix and the between-class scatter matrix defined by

$$S_w=\sum_{i=1}^{c}\sum_{j=1}^{n_i}(x_j^i-m_i)(x_j^i-m_i)^T \tag{3}$$

$$S_b=\sum_{i=1}^{c}n_i(m_i-m)(m_i-m)^T \tag{4}$$

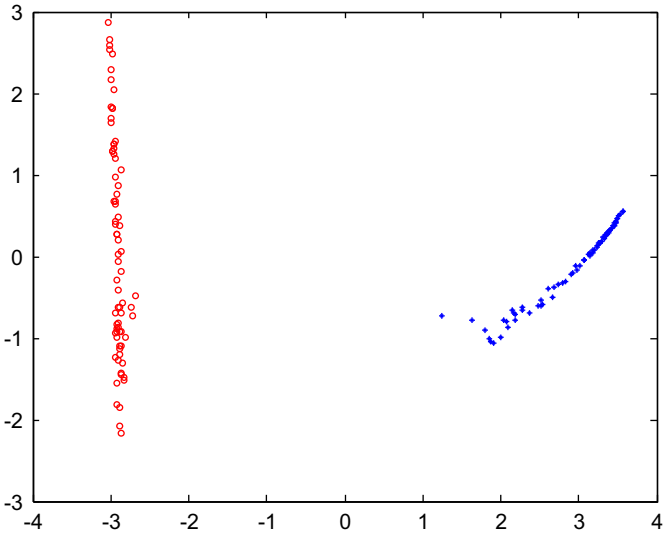

Fig. 3. Two-dimensional embedding of plant leaf images after translation.

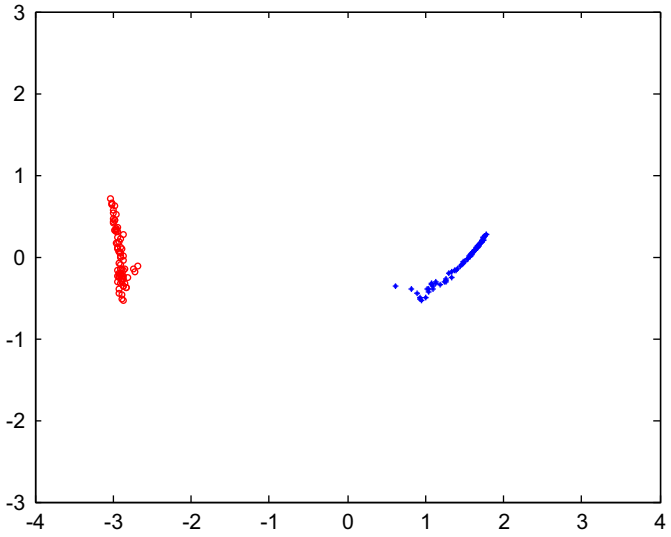

Fig. 4. Two-dimensional embedding of plant leaf images after translation and rescaling.

where c is the number of classes, m is the total sample mean vector, m_i is the average vector of the ith class, n_i is the number of samples in the ith class, and x_j^i is the jth sample in the ith class. The objective function of MMMC under projection matrix V is

$$J(V)=\max tr\{V^T(S_b-\alpha S_w)V\} \tag{5}$$

where α is a positive rescaling parameter. Confining the column vectors in V to be unit vectors, V, that maximizes Eq. (5) can be calculated through the following eigenvalue equation:

$$(S_b-\alpha S_w)v=\lambda v \tag{6}$$

It is reasonable to use MMMC in our study. On one hand, MMMC makes it possible to implicitly model approximately optimal translation and rescaling operators. On the other hand, comparing MMMC with the classical LDA, the former avoids calculating the inverse within-class scatter, i.e. $(S_w)^{-1}S_b$ is substituted by $S_b-\alpha S_w$. This can not only make the computation more efficient but avoid the small sample size (SSS) problem of the within-class scatter.

3.3. Extracting optimal discriminant features

The goal of MLLDE is to produce an explicitly linear mapping from $X=[x_1,x_2,\ldots,x_n]\in\mathbb{R}^{D\times n}$ to $Y=[y_1,y_2,\ldots,y_n]\in\mathbb{R}^{d\times n}$, i.e. $Y=V^TX$. This linear transformation matrix V is solved by holding the strong discriminant power of MMMC and at the same time preserving the intrinsic geometry of the neighbors as LLE. It can be said that this objective optimization consists of two parts: the linearization of the original LLE and MMMC. The linearization of the original LLE can be written as

$$\begin{cases}\min tr(V^TXMX^TV)\\ \text{s.t. } V^TXX^TV=nI\\ Ye=0\end{cases} \tag{7}$$

where $M=(I-W)^T(I-W)$, in which W is the weight matrix solved by Eq. (2).

Then, MLLDE can be described as the following constrained multi-object optimization:

$$\begin{cases}\min tr(V^TXMX^TV)\\ \max tr\{V^T(S_b-\alpha S_w)V\}\\ \text{s.t. } V^TXX^TV=nI\end{cases} \tag{8}$$

The constrained multi-object optimization is conducted to minimize the reconstruction error and maximize the margin between difference classes simultaneously. Note that in MLLDE, the origin-centered constraint $Ye=0$ is neglected because it removes the translational degree of freedom. We formulate this discriminator using the linear manipulation as follows:

$$\begin{cases}\max tr\{V^T((S_b-\alpha S_w)-\gamma XMX^T)V\}\\ \text{s.t. } V^TXX^TV=nI\end{cases} \tag{9}$$

where γ is a scaling factor to balance the two terms $S_b-\alpha S_w$ and XMX^T. It can be solved by Lagrangian multiplier:

$$\frac{\partial}{\partial V}tr\{V^T((S_b-\alpha S_w)-\gamma XMX^T)V-\lambda(V^TXX^TV-nI)\}=0 \tag{10}$$

Thus, we can get

$$((S_b-\alpha S_w)-\gamma XMX^T)v_i=\lambda_i XX^Tv_i,\quad i=1,2,\ldots,d \tag{11}$$

where λ_i is the ith eigenvalue of $((S_b-\alpha S_w)-\gamma XMX^T)$ and XX^T, and v_i is the corresponding eigenvector. Therefore, Eq. (9) is maximized when V is composed of the first d largest eigenvectors of the above eigenvalue decomposition.

According to the above preparation, the procedures of our MLLDE algorithm can be summarized as follows:

Step 1: For each data point x_i, determine its k nearest neighbors based on the distance metric defined by Eq. (1).

Step 2: Compute the reconstruction weights w_{ij} of each point x_i based on Eq. (2) and construct the sparse weight matrix $W=[w_{ij}]_{n\times n}$.

Step 3: Build the matrix $M=(I-W)^T(I-W)$ and then compute the matrix XMX^T.

Step 4: Compute the between-class scatter S_b and within-class scatter S_w, and their weighted difference $S_b-\alpha S_w$, respectively.

Step 5: Solve the d top generalized eigenvalues and the corresponding eigenvectors matrix $V=[v_1,v_2,\ldots,v_d]$ of $((S_b-\alpha S_w)-\gamma XMX^T,XX^T)$, and obtain the d dimensional embedding $Y=V^TX$.

4. Experimental results

In this section, we investigate the performance of our proposed MLLDE method for plant leaf recognition. The system performance is compared with linear discriminant analysis (LDA) [22], locally linear discriminant analysis (LLDA) [29], supervised LLE (SLLE) [30,31], and locally linear discriminant embedding (LLDE) [32] on ICL-PlantLeaf[1] plant leaf database. The ICL-PlantLeaf database was constructed at the Intelligent Computing Laboratory (ICL) of Institute of Intelligent Machines, Chinese Academy of Sciences. It contains more than 20,000 leaf images of 221 plant species. The images were captured at different periods, and have different locations and natural illuminations. In all experiments, preprocessing was performed to crop the original leaf images. The original images were normalized such that all leafstalks were aligned at the same position, then the leaf areas were cropped into the final images for extracting the features. The size of each cropped image is 32×32 pixels with 256 gray levels per pixel. Thus, each image is represented by a 1024-dimension vector in the corresponding image space. No further preprocessing is done. The k-nearest neighborhood parameter in MLLDE, SLLE, and LLDE can be chosen as $k=l-1$, where l denotes the number of training samples per class. The justification for this choice is that each sample should be connected with the remaining $l-1$ samples of the same class provided that within-class samples are well clustered in the observation space. The weight parameter α of MLLDE was set to be 10. The justification for this choice will be

[1] http://www.intelengine.cn/ dataset/index.html.

discussed later. The balance parameter γ of MLLDE was simply set to be 1. Different classifiers have been applied for pattern recognition, including KNN, Support Vector Machine, and Neural Network [33–40]. The 1-nearest-neighbor (1-NN) classifier with Euclidean metric is adopted for its simplicity.

In short, the recognition process of plant leaf images has three steps. First, we calculate the feature subspace from the training set of plant leaf images by the MLLDE algorithm; then the new plant leaf image to be identified is projected into this subspace; finally, the new plant leaf image is identified by the 1-NN classifier.

We employed a subset containing 750 leaf images of 50 classes in our experiments (hence, 15 leaf images for each plant). These plant leaf images were taken at 3 different periods, and have 5 different locations, which determine 5 different natural illuminations. The representative leaf images of 50 plant species are shown in Fig. 5. Fig. 6 shows 15 sample images from dyetree with period, location, and illumination variations.

The first experiment was performed using 10 samples per class plant as training samples and the rest 5 samples were used for test samples. Such a trial was independently performed 10 times, and then the average recognition results were calculated. For the proposed MLLDE algorithm, we determine the tuning parameter β using the global-to-local strategy [41] to make the recognition result optimal. The average recognition rates of MLLDE and the other four methods are given in Table 1. The recognition rates and standard deviations versus the variation of dimensions are, respectively, illustrated in Fig. 7 and Fig. 8. The recognition rates of MLLDE versus the variation of the tuning parameter β are illustrated in Fig. 9.

From Table 1, we can see that MLLDE outperforms all other algorithms. LDA yields the lowest recognition rate. Fig. 7 shows that at the beginning, the recognition rates improve with the increase in dimensions. However, the trend is not maintained for all the dimensions. When they attain their tops for MLLDE, LDA, LLDA, SLLE, and LLDE all recognition rate curves begin to decrease with the increase in the dimensions. Fig. 9 indicates that MLLDE achieves the best performance when $\beta=0.7$, so we choose $\beta=0.7$ for our experiments.

The second experiment is implemented to investigate the effect of the training number on the performance. We randomly selected 2, 4, 6, 8, 10, 12, and 14 training samples from per class and then the rest samples for test ones. We repeated these trails 10 times and computed the average results. The best results obtained in the optimal subspace and their corresponding standard deviations for each method are shown in Table 2. It can be seen that our MLLDE algorithm significantly performs the best

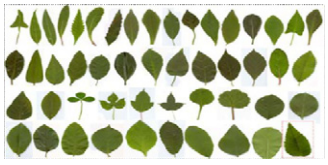

Fig. 5. Representative leaf images of 50 plant species.

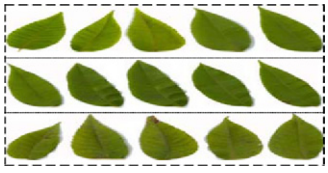

Fig. 6. Sample images from the deytree with 3 different periods and 5 different natural illuminations.

Table 1
Average recognition rates of LDA, LLDA, LLDE, SLLE, and MLLDE.

Method	LDA	LLDA	LLDE	SLLE	MLLDE
Recognition rate	0.8826	0.8901	0.9202	0.8997	0.9363

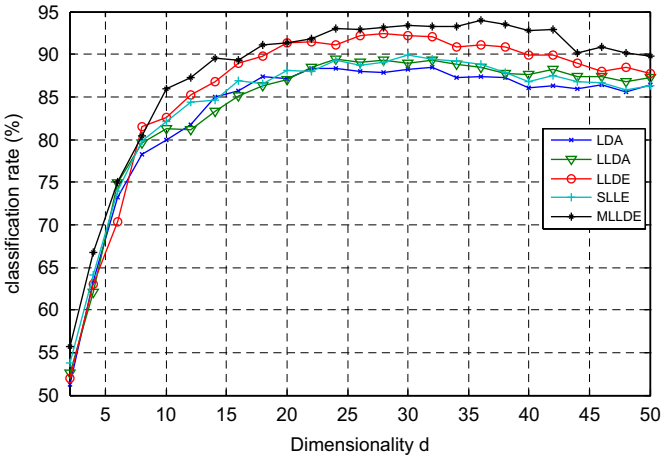

Fig. 7. Recognition rates of LDA, LLDA, LLDE, SLLE, and MLLDE versus the dimensions.

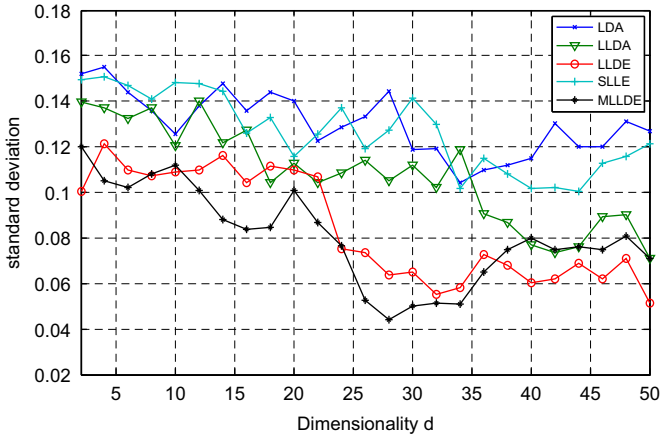

Fig. 8. Standard deviations of LDA, LLDA, LLDE, SLLE, and MLLDE versus the dimensions.

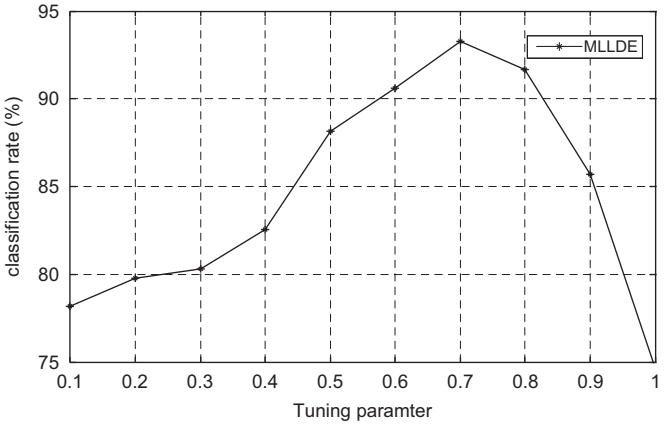

Fig. 9. Classification rate of MLLDE versus the variation in tuning parameter β when the parameters $\alpha=10$ and $k=9$.

Table 2
Average recognition rates and standard deviations of LDA, LLDA, LLDE, SLLE, and MLLDE.

Methods	2 Train	4 Train	6 Train	8 Train	10 Train	12 Train	14 Train
LDA	0.5735 ± 0.081	0.7579 ± 0.093	0.8569 ± 0.096	0.9089 ± 0.092	0.9126 ± 0.098	0.9184 ± 0.094	0.9137 ± 0.097
LLDA	0.5875 ± 0.093	0.7681 ± 0.081	0.8905 ± 0.095	0.9172 ± 0.102	0.9153 ± 0.095	0.9261 ± 0.098	0.9202 ± 0.101
LLDE	0.8237 ± 0.085	0.9083 ± 0.095	0.9126 ± 0.087	0.9224 ± 0.086	0.9264 ± 0.091	0.9239 ± 0.094	0.9267 ± 0.101
SLLE	0.6375 ± 0.084	0.7486 ± 0.079	0.8905 ± 0.086	0.9165 ± 0.121	0.9218 ± 0.097	0.9242 ± 0.103	0.9265 ± 0.096
MLLDE	0.8512 ± 0.095	0.9278 ± 0.079	0.9312 ± 0.091	0.9343 ± 0.085	0.9353 ± 0.087	0.9348 ± 0.089	0.9354 ± 0.086

Table 3
Maximal average recognition rates of MLLDE and the corresponding dimensions by varying the rescaling coefficient α when $k=9$ and $\beta=0.7$.

Rescaling coefficient	0.01	0.1	1	20	100
Accuracy rate (%)	0.9237	0.9308	0.9258	0.9317	0.9274
Dimension	42	42	38	36	31

among all the cases. LDA achieves comparable performance to LLDA with the increase in the number of training samples. SLLE and LLDA performed comparably to each other except for 2 training samples.

The third experiment is executed to test the impact of rescaling coefficient α on the recognition rate. The coefficient α is set to 0.01, 0.1, 1, 20, and 100. The maximal average recognition rates for different coefficient and the corresponding dimensions are stated in Table 3. From Table 3, we can see that the recognition rates are no significant change with variation of the rescaling coefficient α. It demonstrates that our proposed algorithm is insensitive to the rescaling coefficient α on ICL-PlantLeaf database.

5. Conclusion

Plant recognition based on leaf images has so far been an important and difficult task, especially for leaves with complicated background where some overlapping phenomena may exist. Although there are many algorithms for plant leaf recognition, the recognition rates are usually not high because of the complexity of plant leaf. Manifold learning algorithms are promising alternatives to conventional plant leaf recognition methods. In this paper, a supervised feature extraction method, called MLLDE, was presented for leaf recognition. Compared with other four supervised dimension reduction methods, namely, LDA, LLDA, LLDE, and SLLE, the proposed algorithm is feasible and effective for plant leaf recognition.

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