Nondestructive Testing and Evaluation

ISSN: 1058-9759 (Print) 1477-2671 (Online) Journal homepage: https://www.tandfonline.com/loi/gnte20

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To cite this article: Yuan Chen, Hong-Wei Ma & Guang-Ming Zhang (2014) A support vector machine approach for classification of welding defects from ultrasonic signals, Nondestructive Testing and Evaluation, 29:3, 243-254, DOI: 10.1080/10589759.2014.914210

To link to this article: https://doi.org/10.1080/10589759.2014.914210

Published online: 29 Apr 2014.

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Nondestructive Testing and Evaluation, 2014
Vol. 29, No. 3, 243–254, http://dx.doi.org/10.1080/10589759.2014.914210

A support vector machine approach for classification of welding defects from ultrasonic signals

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(*Received 31 October 2013; accepted 8 April 2014*)

Defect classification is an important issue in ultrasonic non-destructive evaluation. A layered multi-class support vector machine (LMSVM) classification system, which combines multiple SVM classifiers through a layered architecture, is proposed in this paper. The proposed LMSVM classification system is applied to the classification of welding defects from ultrasonic test signals. The measured ultrasonic defect echo signals are first decomposed into wavelet coefficients by the wavelet packet transform. The energy of the wavelet coefficients at different frequency channels are used to construct the feature vectors. The bees algorithm (BA) is then used for feature selection and SVM parameter optimisation for the LMSVM classification system. The BA-based feature selection optimises the energy feature vectors. The optimised feature vectors are input to the LMSVM classification system for training and testing. Experimental results of classifying welding defects demonstrate that the proposed technique is highly robust, precise and reliable for ultrasonic defect classification.

Keywords: support vector machine; bees algorithm; wavelet packet transform; defect classification; ultrasonic non-destructive evaluation

1. Introduction

Welding plays an important role in modern industrial production. Ultrasonic inspection has been widely used for non-destructive evaluation (NDE) of welding defects such as crack, stomata, incomplete penetration and slag inclusion. Defect classification is a challenging issue in ultrasonic NDE of welding defects. [1–4]

Feature extraction is a key step for automated defect classification. In ultrasonic NDE, features from the spatial, frequency and time domains such as maximum amplitude of the signal, pulse duration, waveform kurtosis, and rise- and fall-times were widely used for defect classification. [3–5] Wavelet transform is a more powerful feature extraction method, which extracts time–frequency features of the non-stationary ultrasonic signals. [6–8]

Once a set of optimum features have been chosen, a suitable classifier is needed to classify the waveforms. A number of supervised and unsupervised classification algorithms such as *K*-means clustering algorithm, fuzzy *C*-means, Bayes decision rule, fractal analysis [9] and neural networks have been proposed for classifying ultrasonic test signals. Traditionally, neural networks have been extensively used in defect classification. [3–5,10–11]

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In the community of pattern recognition, support vector machine (SVM) has been demonstrated to be superior in comparison with other classification approaches. [12–15] SVM finds global optimum solutions for classification problems with small-size samples, nonlinear and high dimensions, so that SVM has a great potential for defect classification in ultrasonic testing. However, in practical applications, the SVM parameters have a great impact on the classification accuracy.

The bees algorithm (BA) is a recently developed optimisation technique, which can search the optimal or sub-optimal solutions in a large search space. [16] In this paper, a layered multi-class SVM (LMSVM) classification system is proposed for classifying welding defects. Wavelet packet transform (WPT) is used for feature extraction. The SVM parameters and extracted feature vectors are further optimised using the BA in the proposed classification system.

2. Feature extraction

The feature extraction process in the proposed classification system consists of two steps. In the first step, a recorded ultrasonic signal s is decomposed into wavelet coefficients using WPT with Daubechies wavelets. For n levels of decomposition, the WPT produces 2^n different sets of coefficients (or frequency channels), $a_M, d_1, d_2, \ldots, d_M$. These wavelet coefficients contain the same amount of information as the ultrasonic signal s and have the property [17]:

$$\|s\|^2 = \|a_M\|^2 + \sum_{m=1}^{M} \|d_m\|^2, \tag{1}$$

where the approximation signal a_M and the detail signals d_m provide the significant defect information at different frequency channels.

In the second step, we calculate the signal energy E_j of each frequency channel j ($j = 1, 2, \ldots, M+1$) through the Euclidean norm:

$$E_j = \sqrt{\sum_{i=1}^{k} \left|C_{i,j}\right|^2}, \tag{2}$$

where $C_{i,j}$ ($i = 1, 2, \ldots, K$) are the wavelet coefficients in the frequency channel j, and K is the number of coefficients within the channel. Then, the feature vector T is constructed by

$$T = \left[E_1^*, E_2^*, \ldots, E_{M+1}^*\right] = \frac{\left[E_1, E_2, \ldots, E_{M+1}\right]}{\sqrt{\sum_{j=1}^{M+1} \left|E_j\right|^2}}, \tag{3}$$

where $\sqrt{\sum_{j=1}^{M+1} \left|E_j\right|^2}$ is used to normalise the feature vector. The feature vector based on the signal energy of different channels, which carries the time–frequency information of the ultrasonic test signal, has been demonstrated to be very efficient in signal classification. [8,17] An additional advantage of the energy feature vector is that it is robust to noise. [17]

Moreover, the feature vector T is arranged in the order of frequency channels from low to high frequencies, i.e. $a_M, d_1, d_2, \ldots, d_M$, so that the feature vector represents the energy distribution of frequency channels. It was shown that defect information mainly exists in certain frequency channels in [18] for a given defect. As a result, the energy distribution of frequency channels is likely different for different types of defects. In addition, in order to further increase the classification accuracy and robustness in the proposed classification system, BA is used for further selecting the useful information-bearing frequency channels to optimise the feature vector.

3. A LMSVM classification system

3.1. SVM for classification

SVM classifier is a statistical learning theory-based supervised learning algorithm. In the nonlinear case, the input feature vector is mapped to a high-dimensional feature space using a kernel function if the data cannot be classified clearly in the original input space. The basic principle of SVM is summarised as follows [12]: given training vectors, $x_i \in R^d, i = 1, 2, \ldots, l$, in two classes, its corresponding expectation output is $y_i \in \{+1, -1\}$, where l is the number of training samples and d denotes the dimension of input data. Thus, SVM solves the following primal problem:

$$\min_{w,b,\xi} \frac{1}{2}\left(w^T w\right) + C\sum_{i=1}^{l} \xi_i \quad s.t\, y_i\left[w^T\phi(x_i) + b\right] \geq 1 - \xi_i, \quad \xi_i \geq 0, \quad i = 1, 2, \ldots, l, \quad (4)$$

where $\phi(x_i)$ maps x_i into a higher-dimensional space, and $C > 0$ is the upper bound of Lagrange multipliers α_i, called the penalty factor, which controls the trade-off of the margin maximisation and error minimisation; ξ_i is the relax factors and $\sum_i \xi_i$ controls the number of training samples that have been misclassified. The primal problem is difficult to solve when the vector variable w has a high dimensionality. Thus, we often solve the dual problem defined as

$$\min_{\alpha} \frac{1}{2}\alpha^T Q\alpha - e^T\alpha \quad s.t \quad y^T\alpha = 0, \quad 0 \leq \alpha_i \leq C, \quad i = 1, 2, \ldots, l, \quad (5)$$

where e is the vector of all ones, $Q_{ij} = y_i y_j K(x_i, y_j)$ is a $l \times l$ positive semi-definite matrix and $K(x_i, x_j) = \phi(x_i)^{\mathrm{T}}\phi(x_j)$ is the kernel function.

Once the dual problem is solved, the optimal w can be obtained using the primal–dual relationship as

$$w = \sum_{i=1}^{l} y_i \alpha_i \phi(x_i). \quad (6)$$

The decision function of the classifier is then decided as

$$f(x) = \operatorname{sgn}\left(w^{\mathrm{T}}\phi(x) + b\right) = \operatorname{sgn}\left(\sum_{i=1}^{l} y_i \alpha_i K(x_i, x) + b\right), \quad (7)$$

A number of kernel functions has been developed in the literature such as the polynomial, sigmoid and radial basis function (RBF). The RBF kernel function is defined as follows:

$$K(x, x_i) = \exp\left(\frac{-\|x - x_i\|^2}{2\sigma^2}\right), \quad (8)$$

where $\sigma > 0$ is the width parameter. The RBF has only a parameter to set, and similar overall performance with other kernel functions. Thus, the RBF is used to construct the SVM classifiers in this paper.

Notice that scaling the features in the feature vectors before applying to SVM is very important in order to avoid numerical difficulties during the calculation and features in greater numeric ranges dominating those in smaller numeric ranges. [12] It is recommended linearly scaling each feature to the range $[-1, +1]$ or $[0, 1]$. In this paper, the normalisation in Equation (3) is used to scaling the features to $[0, 1]$.

Moreover, in practical applications, the SVM parameters C and σ have a great impact on the success of the SVM classification. [12] In this paper, BA is used to optimise the SVM parameters, and details are presented in Section 4.

3.2. A layered multi-class classification system

SVM was originally designed for binary classification. However, multi-class classification is a universal problem in practical application, thus how to effectively extend the binary classifier for multi-class classification is still an ongoing research issue. Currently there are two strategies for multi-class SVM. One is by directly considering all data in one optimisation formulation, for example, direct multi-class SVM proposed by Crammer and Singer. [19] This approach needs to solve a larger optimisation problem. Therefore, in general, it is computationally expensive to solve a multi-class problem, and its classification performance is not significantly improved. Hence, this approach is only suitable for a small-scale classification problem. The other strategy is to construct a multi-class classification system by combining multiple binary classifiers together under a given architecture. Several multi-class SVM approaches have been developed, such as 'one-against-all' (OAA), [20] 'one-against-one' (OAO) [21] and 'binary decision tree' (BDT). [13,14] A LMSVM classification system is proposed to handle the multi-class problem in this paper. The architecture of a four-class classification problem by the proposed approach is illustrated in Figure 1.

The basic principle of the approach is described as follows. For a k-class classification problem, $k-1$ SVM binary classifiers are constructed. In the training phase, the SVM1 is trained with the samples in the first class as positive labels, and all other samples as negative labels. The mth SVM is trained with the samples in the mth class as positive labels. In the testing phase, starting from the root/top node of the layered tree, the samples

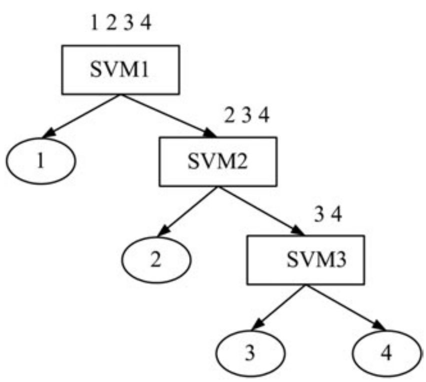

Figure 1. Architecture of a four-class classification problem by the proposed LMSVM classification system.

in the first class are separated from the rest samples through SVM1, and this process is repeated downward the layered tree until all the classes are separated as shown in Figure 1.

The advantages of the proposed approach include decreasing the number of SVM binary classifiers, reducing the number of training samples and increasing the training speed. Comparing with the binary decision tree approach developed in, [14] another big advantage is that the architecture of the proposed approach can be easily expanded to include more classes without the need of re-training the existing SVM classifiers. When a new class is available, we can simply add an extra SVM classifier in the root/top of the architecture in Figure 1 as the new SVM1. The new SVM1 will be trained with the training samples of the new added class to recognise the new defect class. The new SVM1 will class the samples in the new class as positive labels, and all other samples as negative labels. If a sample does not belong to the new class, then it must be one of the existing defect classes. Then, the existing SVMs can be used to class it. Obviously, the existing SVMs do not need to be retrained. Thus, the training speed is greatly improved. This property is very useful for the classification of welding defects from ultrasonic test signals. In practical applications, it is difficult to collect an adequate training database for all classes of defects in the beginning, and training database are normally accumulated and expanded gradually with possible new classes of defects added over a long period of ultrasonic inspection practices during an industrial process.

4. Optimisation of the feature vectors and SVM parameters

The BA [16,22] is a population-based search algorithm to find the optimal solution. The details and pseudo code for the algorithm can be found in. [16]

In this paper, BA is used to optimise the parameters of SVMs and select the useful information-bearing channels from a_M, d_1, d_2, …, d_M for the LMSVM classification system. For a SVM classifier with the RBF kernel function, there are two parameters to be optimised, namely C and σ, and they considerably affect the classification performance of the SVM classifier. The penalty factor C controls the complexity of SVM model and the penalty degree to those samples misclassified. When C is too large or too small, the generalisation capability of SVM is weakened. The width parameter σ has an even greater impact on the classification outcomes than C. A large value for parameter σ results in over-fitting while a small value leads to under-fitting. On the other hand, feature selection affects the classification performance of the SVM classifier. If the number of features is too large or some of the features are insignificant, the dimension of the input space is large or non-clean, degrading the SVM performance. As mentioned in Section 2, for an ultrasonic test signal, defect information may exist in certain frequency channels, and in other words some of the channels may not carry any significant information (i.e. defect information). Removing the insignificant features from the energy feature vector T calculated in Equation (3) can improve the classification speed and accuracy. As described in Section 2, the feature vector has $M + 1$ features, plus two SVM parameters, thus there are total $M + 3$ variables to be optimised by BA. The value of the $M + 1$ feature variables ranges from 0 to 1. If the value of a feature variable is ≤ 0.5, then the feature is not chosen. Conversely, if the value of a feature variable is > 0.5, then the feature is chosen. Table 1 lists the solution representation.

As feature selection and parameter optimisation mainly aim to increase the classification accuracy, the classification accuracy of SVM is taken as the fitness function in BA. The optimisation stopping criterion is set as the iteration number reaches the preset maximum number of iterations. Figure 2 shows the flowchart for BA-based feature

Table 1. Solution representation of the BA optimisation.

Serial number	*1*	*2*	*3*	·	*M + 3*
Solution	C	σ	$\sum_1^*$	·	$\sum_{M+1}^*$

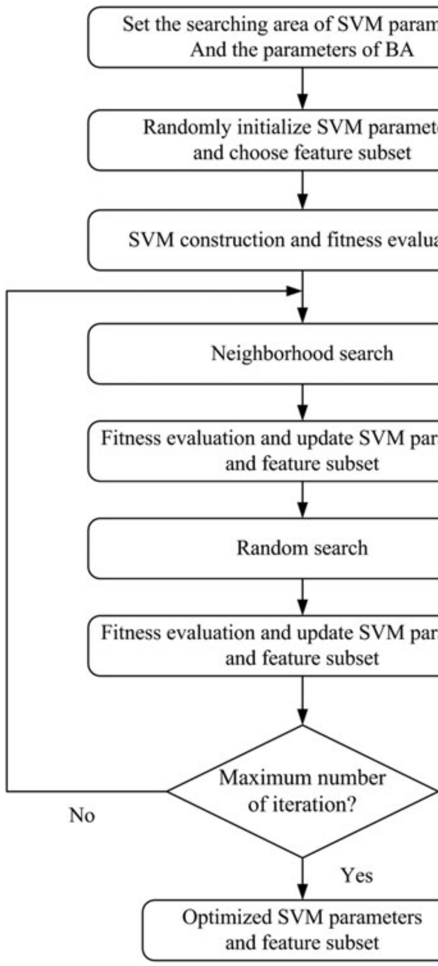

Figure 2. Flowchart of BA-based feature selection and SVM parameter optimisation.

selection and SVM parameter optimisation. The optimisation process is described in detail as follows:

(1) Set the searching area of SVM parameters and the parameters of BA.
(2) Randomly initialise SVM parameters in the allowed parameter space and choose feature subsets in the data-set to form 'scout bees', each tuple (C, σ) and each subset representing a bee.
(3) SVM classifiers are constructed and trained corresponding to the bees formed in step (2) using the given subsets, and the fitness values of the scout bees are evaluated.

(4) Bees are recruited for the m sites discovered by the scout bees for neighbourhood search (more bees are recruited for the best e sites). The fitness values of the selected bees are evaluated, and SVM parameters and feature subsets are updated.
(5) Other scout bees $(n-m)$ are assigned randomly around the search space for random search. The fitness values of the bees are evaluated, and SVM parameters and feature subsets are updated.
(6) Steps 4 and 5 are repeated until the stop criterion is met. Then, the optimised SVM parameters and feature subset are obtained.

5. Experimental results

5.1. Data acquisition and feature extraction in ultrasonic inspection of welding defects

Ten test samples (the test sample material is 45# steel) with four types of welding defects, containing crack, stomata, incomplete penetration and slag inclusion, were fabricated. Cracks are perpendicular to the welding surface. The position and characteristics of welding defects were determined by X-ray negative.

In the experiment, a digital ultrasonic fault detector CTS-4020 was used to acquire ultrasonic signals from the fabricated test samples using a 2.5-MHz angle transducer (the angle is 70°). For each defect on these test samples, signal acquisition was carried out repeatedly by moving the transducer, changing detecting position and direction, and adjusting the gain of digital ultrasonic flaw detector. A total of 240 ultrasonic signals were stored, in which each type of defects contains 60 signals, respectively. Defect echo signals were then obtained by removing the transmission pulse and back-wall echo for each ultrasonic signal. Notice that the maximum amplitude of each defect echo signal varies considerably, depending on the gain of ultrasonic defect detector, defect size, transducer position and detecting direction. In order to eliminate the influences of varying amplitudes on the classification accuracy, the defect echo signals were normalised to [0, 1]. Figure 3 shows the preprocessed ultrasonic test signals for different types of welding defects. Furthermore, if the ultrasonic test signals are quite noisy, an additional preprocessing of denoising these signals may be necessary before feature extraction. This can be done by the wavelet thresholding operation. [23]

For the preprocessed ultrasonic test signals, feature extraction was carried out by WPT using five levels of decomposition with the DB18 wavelet. A feature data-set consisting of 240 feature vectors was then generated. Each feature vector contains 32 features as there are 32 frequency channels at the fifth level for the wavelet packet decomposition. Figure 4 plots the example energy feature distributions of the four types of welding defects. From Figure 4, it is observed that the four energy distributions are obviously different, demonstrating that the energy feature vector is a good choice for classification of welding defects.

5.2. Classification of welding defects using the LMSVM classification system

In this section, the LMSVM classification system proposed in Section 3.2 is applied for classification of welding defects. The feature data-set obtained in Section 5.1 was used as the input of LMSVM classification system, where 160 feature vectors (40 for each type defect) were used to train the LMSVM classification system and the rest 80 feature vectors were used to test its classification performance. Notice that no SVM parameter optimisation and feature selection were carried out here. The performance of the LMSVM is compared with the popular multi-class SVM methods OAA, OAO and BDT, and the test results are shown in Table 2. In addition, additional experiments were carried out on three extra general data-sets: wine, iris and glass from the UCI machine learning databases

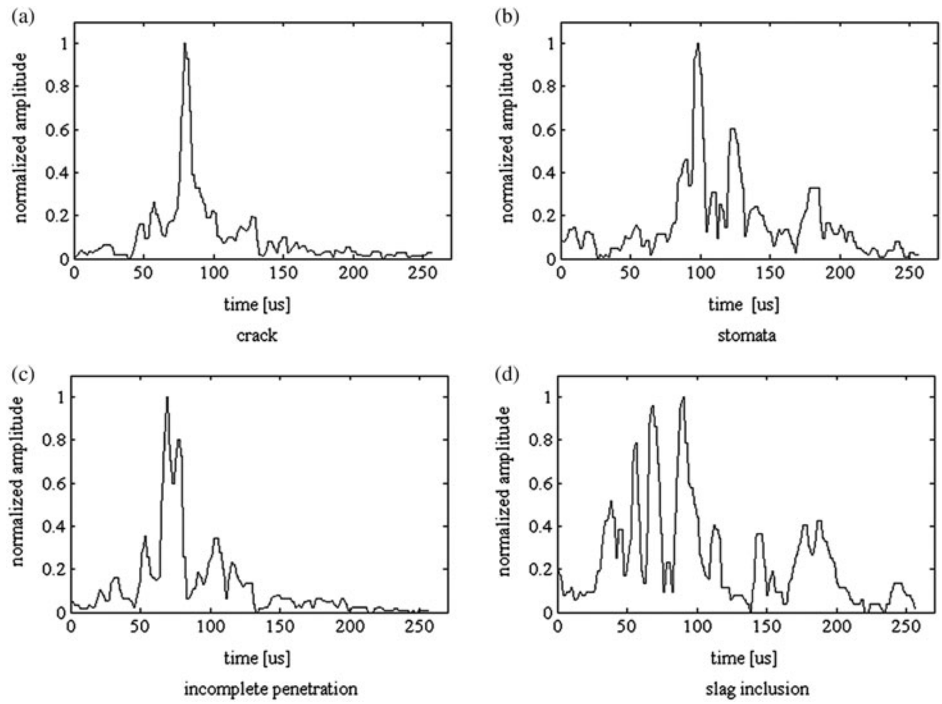

Figure 3. Ultrasonic test signals for four types of welding defects.

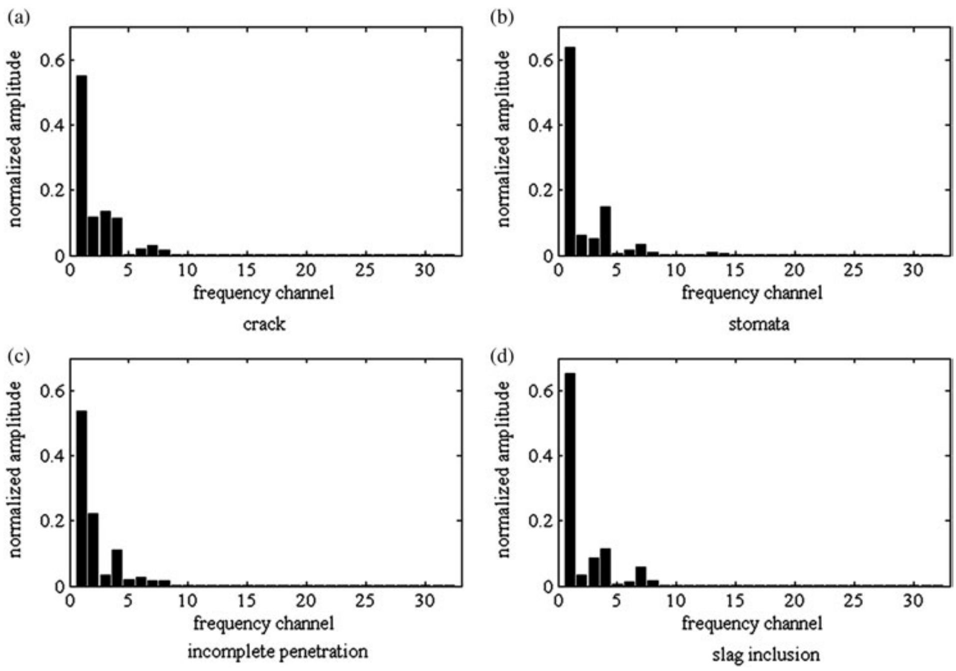

Figure 4. Energy feature distributions of four different types of welding defects.

Table 2. Performance comparison of LMSVM with the OAA, OAO and BDT methods.

Data-sets	*Method*	*Accuracy [%]*	*Training time [s]*	*Testing time [s]*
Wine	OAA	96.6292	0.2453	0.0382
	OAO	97.7528	0.2378	0.0411
	BDT	97.7528	0.2315	0.0403
	LMSVM	98.8764	0.2155	0.0365
Iris	OAA	96	0.2483	0.0370
	OAO	97.3333	0.2316	0.0406
	BDT	96	0.2285	0.0395
	LMSVM	97.3333	0.2093	0.0360
Glass	OAA	66.6667	0.4593	0.0426
	OAO	66.6667	0.4742	0.0493
	BDT	65.7143	0.4358	0.0453
	LMSVM	67.6190	0.3127	0.0395
Welding defects	OAA	93.75	0.5496	0.0418
	OAO	93.75	0.4467	0.0519
	BDT	93.75	0.4321	0.0469
	LMSVM	95	0.4192	0.0413

(ftp://ftp.ics.uci.edu/pub/machine-learning-databases), and the results are also presented in Table 2. The description of all these data-sets is summarised in Table 3.

It can be seen from Table 2 that the LMSVM achieves higher classification accuracy with faster training and testing speed than the OAA, OAO and BDT methods in all the four data-sets.

5.3. *Classification of welding defect using the LMSVM classifier with BA optimisation*

In this section, the LMSVM classification system with BA optimisation (called BA-SVM hereafter) is applied for classification of welding defects. As described in Section 4, SVM parameter optimisation and feature selection were carried out using the BA for the LMSVM classification system. As there are four types of welding defects in our experiment, the LMSVM classification system consists of three SVM classifiers. The searching range of the penalty factor C is from 1 to 100, while the searching range of the parameter σ is from 0.1 to 10. The BA parameters used is shown in Table 4. The optimised C and σ, and the selected features for the LMSVM classification system are presented in Table 5. SVM1 was trained to classify cracks, and SVM2 was trained to classify stomata. SVM3 was trained separate incomplete penetration with slag inclusion.

After the SVM parameter optimisation and feature selection, the BA-SVM classification system was then constructed. Although BA-SVM has the same architecture

Table 3. Description of the used data-sets.

Data-sets	*No. of classes*	*No. of features*	*No. of training samples*	*No. of testing samples*
Wine	3	13	89	89
Iris	3	4	75	75
Glass	6	9	106	105
Welding defects	4	32	160	80

Table 4. BA parameters used for feature selection and SVM parameter optimisation.

Parameter	*Value*
n	30
m	20
e	2
nep	30
nsp	15
ngh_C	1
ngh_σ	0.1
The maximum number of iterations	10

Table 5. Optimised SVM parameters and selected features.

Data-sets	C	σ	*No. of the selected features*
Wine	79.2459	2.7803	2,3,4,5,7,9,10,11,12,13
Iris	52.1711	4.9724	2,3,4
Glass	94.2171	0.2047	1,2,3,5,6
Welding defects	35.5128	0.5291	1,2,3,4,5,7,8,9,10,11,12,13,14,15,16,17, 19,20,22,24,25,26,27,28,30,31,32

Table 6. Classification accuracy by LMSVM with parameter optimisation and feature selection (the accuracy is in %).

Data-sets	*LMSVM*	*LMSVM-PO*	*LMSVM-FS + PO*
Wine	98.8764	98.8764	100
Iris	97.3333	98.6667	98.6667
Glass	65.7143	70.4762	77.1429
Welding defects	95	96.25	97.50

to LMSVM, the BA-SVM classifier used the corresponding optimised SVM parameters, and the input feature vectors for the LMSVM classification system were trimmed according to the significant frequency channels obtained through feature selection. Similar to Section 5.2, we then train the BA-SVM classification system using the training samples. Finally, we test the BA-SVM classification system using the testing samples.

Additional experiments on the general data-sets shown in Table 3 were also carried out. Table 6 shows the classification results by the LMSVM, LMSVM with parameter optimisation (LMSVM-PO) and LMSVM with feature selection plus parameter optimisation (LMSVM-FS+PO).

From Table 6, it can be seen that the LMSVM-PO method yields higher classification accuracy than LMSVM for each data-set except for the wine data-set. The SVM-FS + PO method achieves higher performance than LMSVM for all the data-sets. It is also observed that the BA-SVM with feature selection is better than the BA-SVM without feature selection except for the iris data-set. Moreover, when the number of classes in a data-set is bigger, the BA-SVM classification system is distinctly superior to the LMSVM classification system.

6. Conclusions

We have presented a novel multi-class SVM classification system, termed LMSVM, for classifying welding defects in industrial ultrasonic testing. The LMSVM classification system combines multiple SVM classifiers using a layered architecture. The SVM parameter optimisation and feature selection are carried out using the BA to improve the classification performance. The proposed classification system takes advantage of both the efficient computation of the layered architecture and the high classification accuracy of SVMs. Another big advantage of LMSVM is that its architecture can be easily expanded to include more classes without the need of re-training the existing SVM classifiers.

WPT is applied to extract the features of ultrasonic defect echo signals. The feature vectors are generated on the basis of the energy of different frequency channels. The experimental results for the data-set of welding defects and UCI standard data-sets indicate that the proposed approach is effective and feasible for classification of welding defects, and also for other fields of pattern recognition. The BA optimisation can effectively find the significant frequency channels and the optimal SVM parameters, and consequently further improve the classification accuracy of the LMSVM classification system.

Funding

This work is supported by the National Natural Science Funds [grant number 51074121], the Scientific Research Program Funded by Shaanxi Provincial Education Department of China [grant number 11JK0776] and the Startup Funds for Doctors of Xi’an University of Science and Technology of China [grant number 2010QDJ026].

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