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Application of Multidimensional Chain classifiers to Eddy Current Images for Defect Characterization

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Abstract: Multidimensional learning problem deals with learning a function that maps a vector of input features to a vector of class labels. Dependency between the classes is not taken into account while constructing independent classifiers for each component class of vector. To counteract this limitation, Chain Classifiers (CC) approach for multidimensional learning is proposed in this study. In this approach, the information of class dependency is passed along a chain. Radial Basis Functions (RBF) and Support Vector Machines (SVM) are used as core for CC. Studies on multidimensional dataset of images obtained from simulated eddy current non-destructive evaluation of a stainless steel plate with sub-surface defects clearly indicate that the performance of the chain classifier is superior to the independent classifiers.

Keywords: Chain classifier, eddy current testing, multidimensional learning, nondestructive evaluation, radial basis function, support vector machines

INTRODUCTION

A number of applications in computer vision require an image to be assigned or annotate or classify with multiple classes simultaneously. For instance, a single natural scene image can be classified into several semantic classes such as beach and sunset. An image from non-destructive detection of crack (defect) in an engineering component can be related to the crack characteristics such as depth, height, length and width. This procedure of extracting multiple characteristics information from an input image is termed as Multidimensional Learning (MDL). In MDL, an input data is mapped to a vector of classes (Shuaib *et al*., 2011; Zaragoza *et al*., 2011). This is in contrast to traditional pattern recognition and machine learning, where only one class can be assigned to an input data from a given set of class space (multiclass). MDL problem is normally addressed either by building independent classifiers for learning class of each dimension or by taking the Cartesian product of classes belonging to all dimensions. The first method ignores the dependency relations between the classes while the second method leaves insufficient data for each new class, with a potential for over fitting.

One approach to overcome the limitations of these methods is to add dependency of classes while building independent classifiers for each dimension. This approach is called Chain Classifier (CC) approach and is being recently used in multilabel learning dataset (Zaragoza *et al*., 2011; Read *et al*., 2009). In this study, we propose chain classifiers with Radial Basis Functions (RBF) and Support Vector Machine (SVM) as core. Figure 1 gives an illustration of the independent classifiers and chain classifiers for obtaining the crack characteristics from an input image. The CC approach has been applied to Eddy Current (EC) Non-Destructive Evaluation (NDE) image of hidden sub-surface defects in a stainless steel plate. The EC images for CC approach are generated using CIVA numerical modelling software and the performance of the approach has been evaluated using metrics namely, mean accuracy and global accuracy.

METHODOLOGY

Multidimensional learning: Let $\boldsymbol{X}$ be the domain of instances and $\boldsymbol{C}$ be the domain of dimensions, given a multidimensional training set $\boldsymbol{D} = \{(\boldsymbol{x}_i, \boldsymbol{c}_i)|1\leq i\leq n\}$, then multidimensional learning attempts to learn a function f (.) that would assign a vector of class label $\boldsymbol{c} \in \boldsymbol{C}$ with d dimension for each unseen m dimensional vector of instance given by $\boldsymbol{x} \in \boldsymbol{X}$, such that:

$$f(\mathbf{x}): \phi_{x_1} \times \phi_{x_2} \times \dots \times \phi_{x_m} \rightarrow \phi_{c_1} \times \phi_{c_2} \times \dots \times \phi_{c_d}$$

where, ϕ_{c_i} denoting the sample space of c_i for all i = 1, 2, …, d with $\left|\phi_{c_i}\right| \geq 2$ and space of their joint configuration as $\phi_{c_1} \times \phi_{c_2} \times \dots \dots \times \phi_{c_d}$ is assumed to be discrete throughout and $\left|\phi_{c_i}\right|$ need not be equal to $\left|\phi_{c_j}\right|$ for any $1 \leq \{i, j\} \leq d$ and $i \neq j$. ϕ_{x_k} denoting the

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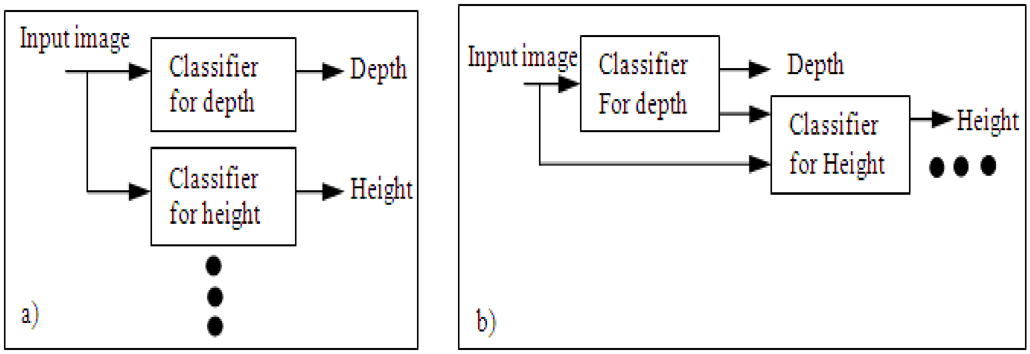

Fig. 1: Multidimensional learning for defect characteristics estimation using a) independent classifiers b) chain classifiers

$$f(\mathbf{x}) \Rightarrow \begin{cases} g_1(\mathbf{x}): \phi_{x_1} \times \phi_{x_2} \times \dots\dots \times \phi_{x_m} \rightarrow \phi_{c_1} \\ g_2(\mathbf{x}, \hat{c}_1): \phi_{x_1} \times \phi_{x_2} \times \dots\dots \times \phi_{x_m} \times \phi_{c_1} \rightarrow \phi_{c_2} \\ \vdots \\ g_m(\mathbf{x}, \hat{c}_1, \dots, \hat{c}_{d-1}): \phi_{x_1} \times \phi_{x_2} \times \dots\dots \times \phi_{x_m} \times \phi_{c_1} \times \dots\dots \times \phi_{c_{d-1}} \rightarrow \phi_{c_d} \end{cases}$$

Fig. 2: Multidimensional learning using chain classifiers

sample space of feature variable x_k for all $k = 1, 2, \dots m$. Generally feature variables x are dimensionally reduced images. Dimensionality reduction can be performed by various techniques (Tan *et al.*, 2006). Performance evaluation metrics for multidimensional learning (Zaragoza *et al.*, 2011) are the following:

- **Mean accuracy:** It takes the average of accuracy predicted for each dimension separately.
- **Global accuracy:** It gives credit only if all classes for an instance are predicted accurately.

Chain classifiers for multidimensional learning: Multidimensional learning problem can be decomposed in a way such that d independent multiclass learning function g (.) can be used to assign a class for each dimension and each increment also includes result of class from previous dimension as shown in Fig. 2. This approach considers the class dependency which is an important characteristic of MDL.

Generation of images and implementation of chain classifier approach: In this study, Radial Basis Function (RBF) and Support Vector Machine (SVM) are used as the core classifiers of the chain classifier (Tan *et al.*, 2006). The studies are carried out using images obtained from eddy current NDE of materials.

Generation of eddy current images: Eddy current technique is widely used NDE technique to detect and size defects in engineering components made of metallic materials. Details about the EC technique can be found elsewhere (Rao, 2007). Accurate

Table 1: Dimension of defects used for generation of images

S. No:	Length (mm)	Width (mm)	Depth (mm)	Height (mm)
1	3	0.50	1	0.5
2	6	0.75	2	1.0
3	9	1.00	3	2.0

characterization of defects with eddy current data requires the use of expert systems and pattern recognition techniques and this is an active area of research (Rao *et al.*, 2012; Shuaib *et al.*, 2012). As experimental generation of EC images is cumbersome, CIVA, benchmarked numerical modeling software has been used to generate images (Reboud *et al.*, 2009). A total of 81 defects at three frequencies (100, 300 and 500 kHz, respectively) are modeled with dimensions of defects shown in Table 1. Figure 3 gives the typical model predicted EC images of a defect in 5 mm thick stainless steel plate at three excited frequencies.

Implementation of chain classifier: The task of MDL is to predict both depth and height of defect from EC images of an unknown defect. The images of defects are dimensionally reduced using PCA. The largest principal component from each frequency along with ratio of principal components at two frequencies is used as input data. Evaluation is carried out using 3-fold cross-validation, with three widths as three test sets comprising of 27 defects in each. Results are interpreted as mean ± std. deviation of 10 independent runs. RBF is developed with 10% of input data as hidden nodes and SVM with polynomial kernel of order 5 is used. CC has been constructed in two ways for two dimensions, by adding the information of depth during classification of height or vice versa.

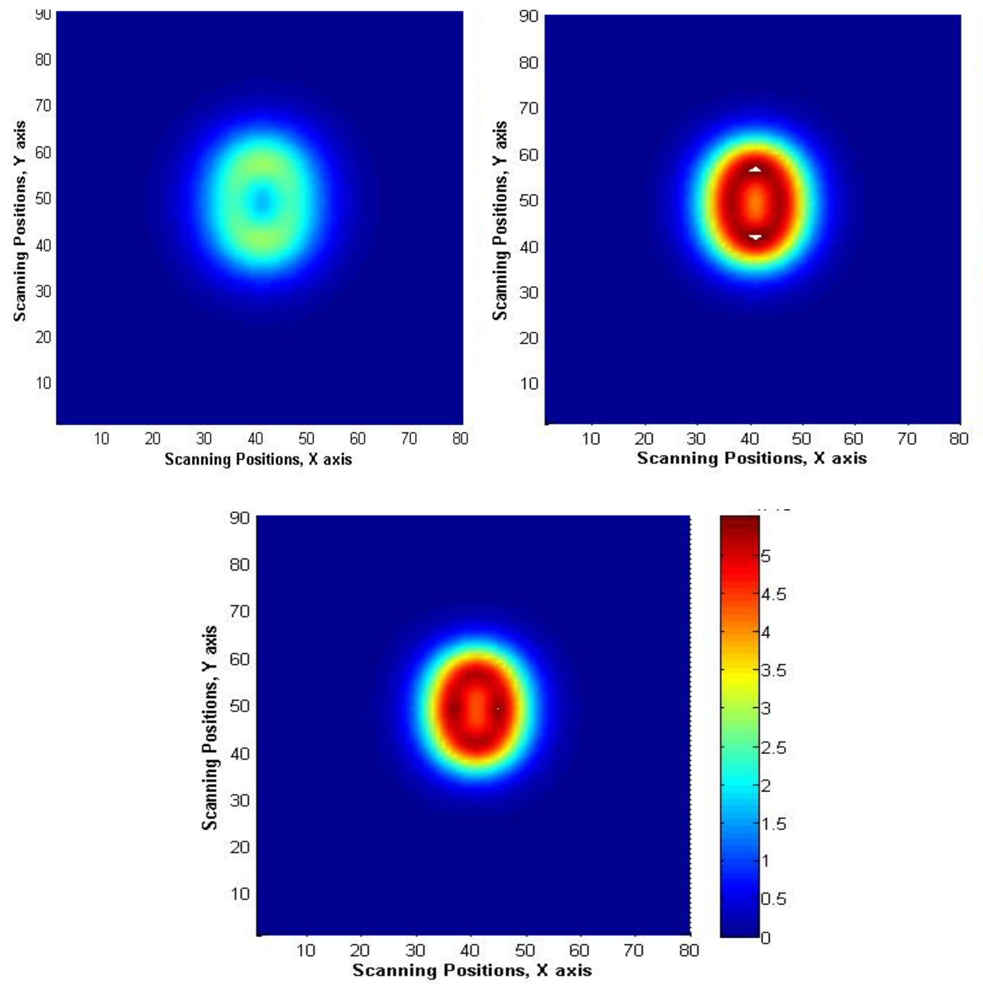

Fig. 3: EC images of a defect (length 3 mm, height 0.5 mm, width 0.5 mm, depth from surface 1 mm) at, (a) 100 kHz, (b) 300 kHz, (c) 500 kHz

Table 2: Performance of chain classifiers and independent classifiers

MDL algorithms	Test-Set 1		Test-Set 2		Test-Set 3	
	Mean accuracy	Global accuracy	Mean accuracy	Global accuracy	Mean accuracy	Global accuracy
Radial Basis Function (RBF)						
Independent	0.83±0.02	0.66±0.04	0.89±0.03	0.78±0.07	0.87±0.03	0.75±0.05
CC (H→D)	0.81±0.04	0.64±0.04	0.88±0.02	0.77±0.05	0.87±0.03	0.75±0.05
CC (D→H)	0.89±0.01	0.78±0.03	0.92±0.03	0.84±0.07	0.93±0.03	0.87±0.06
Support Vector Machine (SVM)						
Independent	0.81±0.00	0.63±0.00	0.79±0.00	0.59±0.00	0.90±0.00	0.81±0.00
CC (H→D)	0.86±0.02	0.72±0.03	0.83±0.01	0.66±0.02	0.90±0.00	0.81±0.00
CC (D→H)	0.87±0.01	0.74±0.02	0.86±0.02	0.83±0.04	0.98±0.00	0.98±0.00

RESULTS AND DISCUSSION

Table 2 shows the result of cross validation on the EC data with RBF and SVM for chain and independent classifier. H→D in Table 2, represents the performance when height is classified independently and results of height is used during the classification of depth and D→H represents the performance of classifier when depth is classified independently and result of depth is used during the classification of height. Results from Table 2 shows that the defect depth and its height can be effectively classified using the chain classifier. It can also be observed that the performance of both the classifiers in CC approach is superior to the independent classifiers. An interesting observation is that the order of dimensions to be used in chain is also an important factor while constructing the chain classifier.

CONCLUSION

Chain Classifiers have been explored for multidimensional dataset of images obtained from simulated eddy current NDE of a stainless steel plate with sub-surface defects. Studies using RBF and SVM as the core classifiers clearly show that defect's depth and its height can be effectively classified using chain classifier as compared to the independent classifiers.

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