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Research paper

Nondestructive testing based weld defect classification using tetrolet transform

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Abstract

The process of visual inspection of weld elements is an important task for providing a safe and reliable outsource in most of the industrial sectors. As most of the industries are still using only the human vision process of manually operation that makes the test results look more subjective. Due to this an image processing algorithm based on the Non-Destructive Testing (NDT) method is introduced to test the welding surface for recognizing the external and internal flaws without disturbing its suitability for service. The proposed system is implemented by using the GD X-ray weld image database. Due to less number of input images, the sub images are extracted and are separated as the normal and the defected images and are used as training and testing set of input images. Then the tetrolet transform is applied for both the testing and training process in order to obtain the maximum coefficients from which the features like energy and entropy features are extracted. Then the testing can be done by using the Support Vector Machines (SVM) classifier for the classification purpose and are validated using the k-fold algorithm. Result shows that the proposed system produces promising results with 100% of classification accuracy

Keywords:*Energy; Entropy; GD X-Ray Weld Images; Non-Destructive Testing; SVM.*

1. Introduction

The information for the automatic control of the welding process is obtained from the weld bead recognition method for post-weld inspection. A method of model based classification system used to automatically segment the bead in the weld surface and the scanner angle of the welding surface is discussed in [1]. The method first uses a combination model of Expectation-Maximization (EM) algorithm and the polynomial model that fits into the profile distance measured by laser sensors. Thus depending on the noise level of the data a small value of threshold is applied to extract the bead shape easily from the welding surfaces.

An image processing method based on the image sequence visual inspection process for the weld defects identification is discussed in [2]. The Convolution Neural Network (CNN) process is used to classify the variations of the weld defects patterns. The CNN method consists of two steps such as; extraction using image convolution without losing the original information by using the Gaussian kernels and the classification of images by using the neural network.

Radiographic based automatic weld defects classification system by using gentle Adaboost algorithm is discussed in [3]. The method extracts the moment-based features by using the segmented radiographic images and is classified by using the gentle Adaboost classifier. The system is trained to classify four classes of each detect patterns such as; lack of penetration, solid inclusion, porosity and cracks.

A framework of automatic weld defect recognition system employed by the pattern recognition and the image processing methods on weld radiographs is discussed in [4]. At first the pre-processing step is done to suppress the undesired distortions and for the enhancement of the image features. Then a set of texture and geometric features are extracted from the segmented image of each object. The extracted features are selected by using the Genetic algorithm and the selected features are classified by using the SVM and Artificial Neural Network (ANN) classifiers in order to recognize the defects.

An automatic classification method for filtering and segmenting of welding defects from the radiographic weld images is discussed in [5]. The classification method is compared to the K-Nearest Neighbor (KNN) and the SVM classifiers. The method is used to recognize some of the linear defects like, incomplete fusion, external undercut and lack of penetrations as classified results.

An approach for extraction of Gray Level Co-occurrence Matrix (GLCM) and the artificial neural network classifier for the detection of multiclass weld flaw are discussed in [6]. The radiographic films are obtained from CCD camera and some of pre-processing steps like RGB to gray conversion, selection of region of interest areas, contrast enhancement and noise reduction methods are used. Then a set of 8, 44 and 64 textures features are extracted by using the GLCM algorithm and are classified by using the neural network based cascade-forward back propagation method.

A weld defect classification and detection method from the radiographic weld image is discussed in [7]. The method helps in detecting and discriminating the discontinuities occurred in the weld images due to the defects or false alarms like gas pores and crack or lack of fusion. A set of 43 descriptors with respect to the geometrical and texture measurements features are extracted from the inputs of each segmented objects. Then the classifier is trained by three fold cross validation scheme with the classifiers like neural network, KNN, and SVM to classify each objects into one of the defect class or the non-defected class.

An artificial neural network classifier based approach for the classification of weld flaws incorporates the extraction of textures features and also for the geometrical feature measurement is discussed in [8]. At first the digital camera is used to digitize the radiographic films and is converted into the gray image from which the region of interest area is selected. The method like noise reduction and contrast enhancement schemes are employed to identify the weld flaws and also the best one of each flaw can be identified by using the segmentation algorithms like region growing, edge base, and watershed methods. From the segmented images a set of GLCM based texture features are extracted. Then the geometrical feature measurement is done to characterize the segmented flaw shapes and is classified by using the training function called Levenberg-Marquardt with cascade-forward back propagation neural network classifier.

Radiographic weld image based welding defect detection system is discussed in [9]. The system method is based on the geometric features for classification and detection of the weld defects. At first, the process of noise reduction is done as the noises in the radiographic images are more. Then the defects are localized by means of minimum intra-class variance and maximum inter-class variance so as to describe the localized objects shape of segmented images for extracting the features. Using these shape descriptors geometric features the artificial neural network classifier will classify the defects.

A method of automatic weld defect detection system to classify the defects in the radiographic images is explained in [10]. Some of the image processing techniques like thresholding, labeling, contrast enhancement and noise reduction are performed at the first stage of the system. In the next stage, a set of geometrical features are extracted between the defect candidates so as to characterize the orientation and the defect shapes. Then in the third stage, the defects are classified with the help of an artificial neural network classifier algorithm.

A method of automatic weld defect classification system based on the algorithms of Principal Component Analysis (PCA) and SVM classifier is discussed in [11]. At first the PCA is used to transform the original defects images by using the PCA algorithm from which the optimal dataset in selected. Finally, the SVM classifier is used for the classification of detects present in the image.

An automatic classification based on the identification and classification of weld defect by using the SVM classifier is discussed in [12]. The systems first extracts the shape based features and are classified by using the multiclass SVM classification type of one-versus-one and one-versus-all approach.

The SVM classifier based automatic weld defect classification system is discussed in [13]. The system first detects the potential defects from the original images by using the grey-level profile analysis operation. Then the potential defect features are extracted from false defects from which three feature vectors are extracted and used for training the SVM classifier. Finally, the SVM classifier is used for classifying the actual defects from the potential defects.

2. Materials and methods

The overall flow of the proposed weld defect classification and identification system is explained in the figure 1. In this system, an automatic weld defects classification system is implemented by means of the GD X-Ray weld images. The implementation of the proposed system consists of some important image processing steps like pre-processing, features extraction and classification stages.

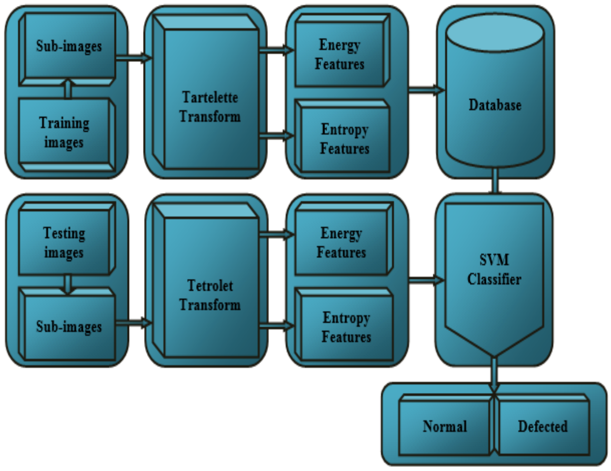

Fig. 1: Block Diagram of the Proposed Weld Image Classification System.

a) Tetrolet transform algorithm

The pre-processing step in our proposed system is carried out by using an adaptive algorithm known as the Tetrolet transform. The underlying concept of this algorithm is simple but enormously effective. The algorithm construction is similar to that of the digital wedgelets [14] in which only the Haar functions on wedge partitions are used. Using this algorithm we divide each image into 4x4 blocks and is determined that in each block a tetromino partition is adapted to the image geometry of each blocks. Using this geometrical shape, a Haar wavelet type called the tetrolet is defined. This filter bank algorithm is used to decompose an image into a suitable size from which a compressed image is obtained by applying a shrinking procedure to the images and the tetrolet coefficients.

The tetrominoes blocks are made by the combination of four equal-sized squares that are connected to each other with at least one square is joined along with an edge. There are five basic tetrominoes shapes are available as shown in figure 2.

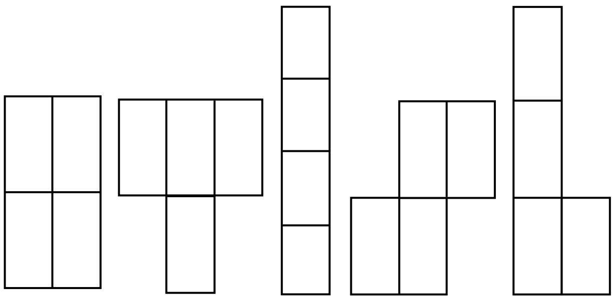

Fig. 2: Basic Five Shapes of Tetrominoes.

The concept of the tetrolet transform can be understood more clearly by elaborating it with suitable notations and terminologies. The algorithm can be used on a 2-dimensional data by first identifying its index sets and its corresponding neighborhood values. For example, let us consider $I = \{(m,n): m,n = 0,\ldots,M-1\}$ be the set of index of an image $I = f(m,n)$ where M = 2J, and the neighborhood $\tilde{n}$ of index (m,n) is either at the vertex or at the boundaries. The equation can be defined as:

$$\tilde{n}(m,n) = \{(m-1,n),(m+1,n),(m,n-1),(m,n+1)\} \quad (1)$$

b) Tetrolet based energy & entropy features

From the tetrolet co-efficient subbands the features like energy and entropy values are obtained which are very useful in any classification system. In general the energy signatures will afford a good indication about the total energy present specifically at any spatial or frequency levels and orientations [15]. It is assumed that in the energy based approaches, different energy distributions are present at various texture patterns of any spatial or frequency domains. Let's assume the energy (E) be an extent of pixel pair repetitions that measures the uniformity of an image respectively. The value of the energy is more when the pixels are similar to one another. The tetrolet based energy feature is defined as:

$$E(I) = \sqrt{\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} M_{i,j}} \quad (2)$$

Where $E(I)$ be the input image, $M_{i,j}$ be the sub-band coefficients at location (i,j) and N be the size of the sub-bands.

Entropy is defined as the statistical measurement of the uncertainty degree and the information content of a message exists in a system [16]. The entropy gives a measurement of information and therefore it is adapted to characterize an image each of which is considered as a specific message. Entropy of an image is stated as a quantity of an image, in which the information amounts of each sub-band are is coded by a compression algorithm. The tetrolet based entropy feature is defined as:

$$Entropy = -\sum_{j-1}^{n} P(x_j) \log_2 P(x_j) \quad (3)$$

Where $P(x_j)$ is the probability distribution, $-\log_2 P(x_j)$ be the information amount of sub-bands.

c) SVM classification

An algorithm of Support Vector Machines (SVMs) classifier based classification of weld defects from the radiographic weld images is discussed in [17]. The SVM classifier can be used as a tool for the recognition and classification process in many machine learning applications. SVM is very useful in binary classification and also as multiclass classification in various applications. It is most popular for its one versus one and the one versus all approach means. The algorithm can be explained as, let $\{x_1, x_2, x_3 ..... x_n\}$ be the training sets of a class X, where $X \subset R^n$. If the mapping function is ϕ then $\phi : X \rightarrow H$ is the feature space. Then the equation can be derived as:

$$\min \left[\frac{1}{2} \|w\|^2 + \frac{1}{vn} \sum_{i=1}^{n} \xi_i - p \right] \quad (4)$$

With subject to $w.\phi(x_i) \geq p - \xi$ let $i = 1,2,\ldots n$ and $\xi_i \geq 0$. Then ξ be the slack variable to penalize misclassification, p be the bias and n be the number of examples.

In our approach the SVM classifier is used as a decision making algorithm that decides the output of our system. In general, the classifier needs two inputs to perform its operation as shown in figure 1. That is the inputs from the training set of features as database and the other inputs from the testing set of features. The classifier is first trained by using the training set of input features to decide the working of the classifier. Then the classifier will classify each of the testing features with respective to its training feature database. As a result the classifier will perform its decision making operation and produces the output whether the given inputs weld image is belonging to its normal or the defective class. The output performance of the system is discussed in the coming section.

3. Results and discussion

The results of the proposed weld defect classification system is obtained by implementing the algorithm with weld image database known as the GD X-ray weld images [18]. The database consists of only 10 weld defects image along with its corresponding ground truth images. But as a classification system is more effective with more number of inputs, we are extracting the sub-images so as to obtain more number of inputs. A size of 256x256 pixel sized images is extracted from the original images with an overlap of 16 pixels in the horizontal direction. That is from a single 256x1024 sized original input weld image; 64-256x256 input images are obtained. Likewise for the whole original weld database image (10 images), 640 sub-images are obtained in total. From that we have randomly selected a set 60 normal and defected images each with respect to its ground truth images. The performance evaluation of the classification method is done by using the k-fold cross-validation algorithm to separate the training and testing data samples. At first, all the images are equally partitioned with k-fold values in the number of images in each folds are equally present. The images in one k-fold are used for testing and the remaining k-1 folds are used for training. Likewise the number of k-folds is increased until all the data samples are used for testing process at least once.

As per the proposed methodology the tetrolet transform is applied and the features like energy and entropy features are extracted and are classified by using the SVM classifier. The performance of the system is evaluated by varying the terms of SVM kernels such as RBF, Linear, Quadratic and Polynomial kernels for all the four coefficient levels of the tetrolet transform. Further the performance evaluation is done in three ways such as accuracy obtained from only the tetrolet based energy features with SVM , then accuracy obtained from only the tetrolet based entropy features with SVM and accuracy obtained from both the tetrolet basedenergy and entropy features with SVM classifier. The performances of these three variations are shown in the following tables.

Table 1: Output Accuracy for Each Tetrolet Level for 4 Different Svm Kernels Using Energy Features

Input kernels	Level 1	Level 2	Level 3	Level 4
RBF	59.1	77.5	91.6	95
Quadratic	54.16	74.16	90.83	90.1
Polynomial	54.16	74.16	90.83	94.16
Linear	51.6	75.8	89.1	90.1

In table I, the evaluation is done between the 4 levels of the tetrolet co-efficient with the different SVM kernels function with respect to the energy features obtained. It is observed that among the four types of the SVM kernels the RBF kernel gives the better accuracy rate than the other kernels. Also when the level of tetrolet co-efficient is increased the accuracy is also increased and when a saturation point is reached the accuracy level is either decreased or remains constant.

Table 2: Output Accuracy for Each Tetrolet Level for 4 Different SVM Kernels Using Entropy Features

Input kernels	Level 1	Level 2	Level 3	Level 4
RBF	93.33	95	100	99.16
Quadratic	93	94.16	98.33	98.33
Polynomial	91.66	91.66	99.16	97.5
Linear	92.5	93	96.6	98.33

In table II, the evaluation is done between the 4 levels of the tetrolet co-efficient with the different SVM kernels function with respect to the entropy features obtained. It is observed that among the four types of the SVM kernels the RBF kernel gives the better accuracy rate than the other kernels. When the level of tetrolet co-efficient is increased the accuracy is also increased and when a saturation point is reached the accuracy level is either decreased or remains constant.

Table 3: Output Accuracy for Each Tetrolet Level for 4 Different SVM Kernels Using Energy and Entropy Features

Input kernels	Level 1	Level 2	Level 3	Level 4
RBF	96.66	99.16	100	100
Quadratic	96	98.33	99.16	98.33
Polynomial	94.1	94.1	99.16	98.33
Linear	94.1	95.33	99.16	99.16

In table III, the evaluation is done between the [4] levels of the tetrolet co-efficient with the different SVM kernels function with respect to the both the energy and the entropy features obtained. It is observed that among the four types of the SVM kernels the RBF kernel gives the better accuracy rate than the other kernels. Also the highest accuracy is obtained at 4^{th} level of the tetrolet co-efficient. The accuracy is increased when the level of tetrolet co-efficient is increased and when a saturation point is reached the accuracy level is either decreased or remains constant. The comparative analysis of the proposed system with other weld defects classification system is shown in table 4.

Table 4: Comparison of Proposed Weld Image Segmentation with Other Methods

Database	Technique used	Accuracy (%)
GD X-rays	PCA based SVM model [11]	90.75
GD X-rays	Shape features and SVM [12]	96.96
GD X-rays	Potential defects based SVM [13]	99.1
GD X-rays	Energy & Entropy based SVM	100

From the table it is clear that our proposed system is compared with other state of art method with different features and classifiers used in it. When compared to the other method, our system provides the better accuracy of 100% of recognition ratio when compared with the other methods used for weld defects.

4. Conclusion

A non destructive testing based weld image classification system to identify the weld defects from X-ray images is discussed and implemented. The objective of the proposed system is to build an automatic weld image classification system based on the tetrolet transform algorithm based energy and entropy features and the SVM classifier. The system is implemented with the help of GD X- ray image database that are publically available for use. As the database contains only minimum number of inputs we have extracted the sub-images and created our own dataset images which are used for the training and the testing process. Further the tetrolet transform is algorithm is applied and four different of co-efficient levels are obtained from which the energy and the entropy features are extracted. Then SVM classifier is applied to classify the extracted features with different SVM kernels for all four co-efficient levels. From the results it is clear that among the four different SVM kernels, the RBF kernels give the better classification accuracy. The highest accuracy obtained by our proposed system is 100% of classification accuracy. Based on the system performance, it is concluded that our proposed system performs better than many other weld image classification systems.

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