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Automatic Classification Vision Based System for Welds Joints Defects Using Support Vector Machine (SVMs)

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Abstract: The goal of this study is to classify the welds joint defects capture by CCD camera into three categories which are good welds, excess welds and insufficient welds in three weld joint shapes; straight lines, curve and tooth saw. Firstly, we extract the features characteristic from the input images represent in 2D gray values of coocurrence matrix and gray absolute histogram of edge amplitude consists of energy, correlation, homogeneity and contrast. Then zooming input image by 0.5 to calculated the next characteristic feature values. Furthermore, use the Support Vector Machine (SVMs) classifier to classify the welds joint defect according to the feature vector belongs to the same categories as the training data. The experimental result taken from 45 welds joints samples in three welds joint shapes; straight lines, curve and tooth saw where 3 samples as training set and 2 samples as testing set show that the proposal approach able to classify the welds joint defects effective automatically.

Key words: Classify, CCD camera, gray absolute, training data, Support Vector Machine (SVMs)

INTRODUCTION

The advanced technology required in the production process of inspection and quality control automation to solve quality problems of welds has not been completely solved. Due to these shortcomings, research and quality control active inspection is necessary. To control the welding quality, it is used in several non-destructive tests. In the radiographic X-ray method industries to inspect the interior of the welding metal, it is often used.

In previous work on the identification and classification of welding defects, we have observed that this question has been widely studied in various ways. Many researchers have used the X-ray image instead of a CCD camera integrated with an external light source to control the workspace environment to reduce noise (Shah *et al*., 2016a-d). Most researchers used geometric parameters (Wang and Liao, 2002; Liao and Li, 1998; Zapata *et al*., 2010; Kumar*et al*., 2014; Wang *et al*., 2008; Shafeek *et al*., 2004a, b; Sun *et al*., 2005; Tridi *et al*., 2005; Da Silva *et al*., 2001; Lim *et al*., 2007; Swillo and Perzyk, 2013) in the extraction of characteristics (Aoki and Suga, 1999) including size (Wang and Liao, 2002) location (Shafeek *et al*., 2004a, b) shape and attribute (Da Silva *et al*., 2001). Another parameter can be applied to interpret the data such as the value of the gray (Liao, 2003; Vilar *et al*., 2009; Valavanis and Kosmopoulos, 2010; Shafeek *et al*., 2004a, b; Nacereddine *et al*., 2007) and linguistic description (Doring *et al*., 2004; Jelen *et al*., 2008; Kamani *et al*., 2011). The linguistic description is done by a human expert where its need the experience and the ability to observe the linguistic description of the weld defect. The perfect knowledge of the geometry of the weld defect is an important step which is essential to appreciate the quality of the weld.

The other interesting aspect is the ways to classify welding defects (Shah *et al*., 2016a-d). Most previous studies have examined welding categories in terms of weld type, defect form, weld failure and defect information such as width, location and position. There are several methods to inspect the weld fault such as statistical tools (Kumar *et al*., 2014; Da Silva *et al*., 2001; Eichhorn *et al*., 2005; Doring *et al*., 2004; Jelen *et al*., 2008; Kumar *et al*., 2012) neural networks (Wang and Liao, 2002; Liao and Li, 1998; Kumar*et al*., 2014; Tridi *et al*., 2005; Aoki and Suga, 1999; Liao, 2003, 2009; Da Silva *et al*., 2001) fuzzy interference system (Wang and Liao, 2002; Shafeek *et al*., 2004a, b; Liao, 2009) profiles and characteristics of the lines adjusted average gray level (Valavanis and Kosmopoulos, 2010). Statistical approaches implemented in general using classifiers like Bayer, Decision Tree, Support Vector Machine (SVMs) and NEFCLASS.

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MATERIALS AND METHODS

Proposed system: The system consists of a conversion part and processing part is shown in Fig. 1. In conversion part, the input images is capture by a basler camera with 67 frames per second 2 MP resolution. Before sends the input images to processing part, the additional light source need to adjust the quality of images. The processing part consists of frame grabber, monitor and computer. In this part, the frame grabber acquires images and displays the images at the monitor. Then, the images will be analyzed by the proposed algorithms while the result will be displayed on the computer monitor in real-time and store the images for the further actions.

In this proposed system, the type of defects will be categories into three which are good welds, excess welds and insufficient welds with straight lines, curve and tooth saw welds joint shapes (Liao, 2009) according to the value of the extraction of characteristic input traits identified by Support Vector Machine (SVMs) classifier. The categories of weld joints defect are determine by the expert view of the human eye. Figure 2 is shows the categories of the weld joints.

Feature generate and extraction: Feature is a reference value can be obtained from the description object in a digital format. The selection features can be determined in many ways. The features characteristics are important because it can be affect the success of any classification algorithm. Geometric parameters in the extraction of features, including size, location, attribute and shape of weld defects are widely used in features selection. Meanwhile, the gray value and the linguistic description are also considers as parameter to interpret the data. In this research, cooccurrence linked matrix and gray value with absolute gray histogram will be choose where there are 72 features parameter in order to defined the highest likelihood of correcting defects in welds joint images. Detail about features extraction is shown in Fig. 3.

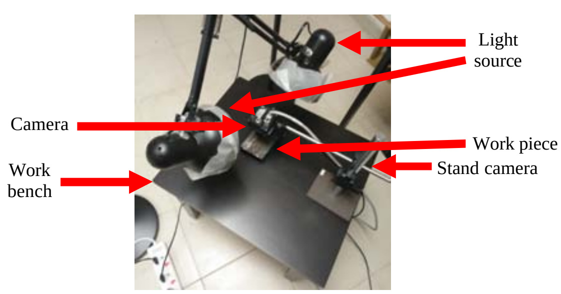

Fig. 1: The welds joint image system setup

Coocurrence matrix: The relationship between the gray value and its neighboring values is called coocurrance matrix. This matrix contains two gray values of the probability that appear side by side determine from regions arriving at what frequency the gray values i and j are located next to each other in a given direction (0, 45, 90, 135°). This number will be stored in the coocurrence matrix at locations (i, j) and (j, i) where the matrix is symmetrical before it need to be scales with the number of entries. Here, the cooccurrence matrix represented into four characteristics: energy, correlation, local homogeneity and contrast. The formula of cooccurence matrix characteristics is shown in Eq. 1-4:

$$\text{Energy} = \sum_{i,\,j=0}^{\text{width}} c_{ij}^2 \tag{1}$$

$$\text{Correlation} = \frac{\sum_{i,\,j=0}^{\text{width}} (i-u_x)(j-u_y)c_{ij}}{s_x s_y} \tag{2}$$

$$\text{Homogeneity} = \sum_{i,\,j=0}^{\text{width}} \frac{1}{1+(i-j)^2} c_{ij} \tag{3}$$

$$\text{Contrast} = \sum_{i,\,j=0}^{\text{width}} (i-j)^2 c_{ij} \tag{4}$$

Where:

Width = Width of coocurrence matrix

c_{ij} = Entry of coocurrence matrix

$$u_x = \sum_{i,\,j=0}^{\text{width}} i \times c_{ij}$$

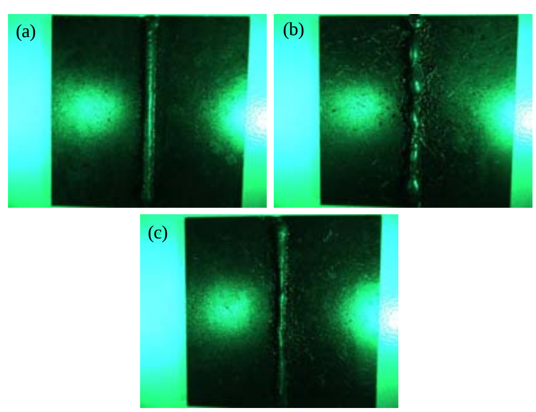

Fig. 2: The different category of the weld joints defects in straight line welds joint shapes: a) Excess weld; b) Insufficient wld and c) Good weld

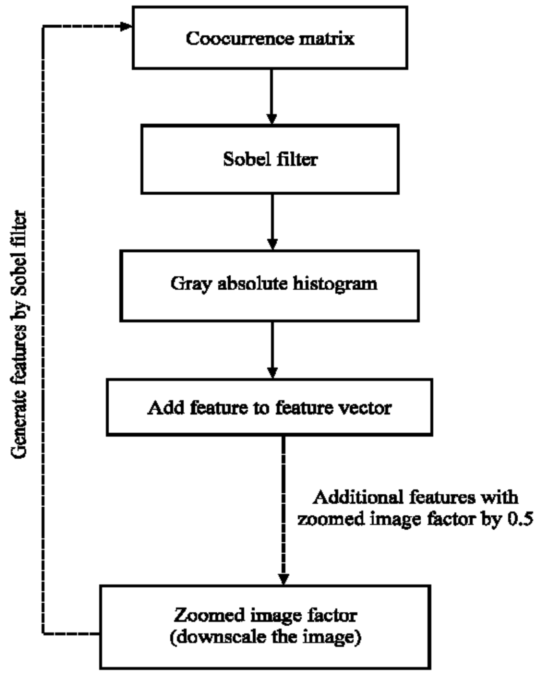

Fig. 3: Block diagram for features extraction

$$u_y = \sum_{i,\,j=0}^{width} j \times c_{ij}$$

$$s_x^2 = \sum_{i,\,j=0}^{width} (i - u_x)^2 \times c_{ij}$$

$$s_y^2 = \sum_{i,\,j=0}^{width} (i - u_y)^2 \times c_{ij}$$

Sobel filter: In this study, the butt welding joint images are filter out using Sobel filter with 3x3 masks instead of median filter (Shah *et al*., 2016a-d; Sulman *et al*., 2013; Sulaiman *et al*., 2014). The filter works by calculate the first derivative of an image uses as an edge detector based on the filtering masks in Eq. 5. This system also uses the absolute filter sum calculate by Eq. 6 where a and b represent results of convolving an image with A and B for a particular pixel:

$$A = \begin{pmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{pmatrix} \text{ and } B = \begin{bmatrix} 1 & 0 & -2 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} \quad (5)$$

$$\frac{(|a| + |b|)}{4} \quad (6)$$

Gray absolute histogram: Absolute gray histogram calculated the distribution the gray value from the images within the image regions. The image region is obtained from Sobel filtering is called the edge amplitude. The result of the absolute histogram contains absolute values of the frequencies with a gray 8 quantization values. In Eq. 7 and 8 shows the frequency value of gray g and a quantization values q in unsigned and signed image types:

$$i = \left[\frac{g+0.5}{q}\right] \text{unsigned image types} \quad (7)$$

$$i = \left[\frac{g-(MIN-0.5)}{q}\right] \text{signed image types} \quad (8)$$

where, MIN denotes the minimal gray value.

Support Vector Machine (SVMs) classifier: The SVMs is an approach to process the features vectors to find the block which one has defects and can handle classes that are not linearly separable. In SVMs no non-linear hyper surface is obtained but the feature space is transformed into a space of higher dimension, so that the features become linearly separable. Because of that the feature vectors can be classified with a linear classifier. In theory SVMs works for classification of general features, image segmentation, OCR and pattern classification.

Figure 4 shows two classes in a 2D feature space are illustrated by black and white squares. In 2D feature space, no line can be found that separates the classes. By adding a third dimension by deforming by feature 1 and Feature 2, the classes can separable by a plane. The suitable masks need to select to transform the feature space into a higher dimension so that the black squares go up and the white ones stay in their place is more challenging.

The separating hyper surfaces in SVMs for two classes are constructed and ensure that the margin between two classes becomes as large as possible. This is because the margin can be defined the closest distance between the separating hyper plane and any training sample. Several possible separating hyper surfaces will be tested and the surface with the largest margin is selected. Therefore in training samples from both classes show in Fig. 5, the closest distance exactly to the hyper surface are called support vectors.

Support Vector Machine (SVMs) training process: The Support Vector Machine (SVMs) was implemented using 72 numbers of the dimension of the patterns with 3 numbers of classes. This classifier was created in one-versus-one mode where the classes are ordered by the value of each sub-classifier. From the test carried out,

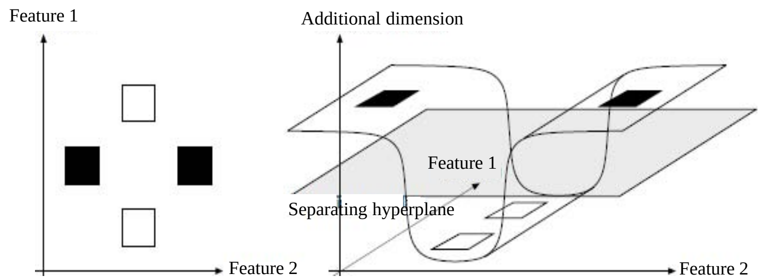

Fig. 4: 2D feature space are illustrated by black and white squares: a) cannot be separated by a straight line and b) can be separated by addition of a further dimension

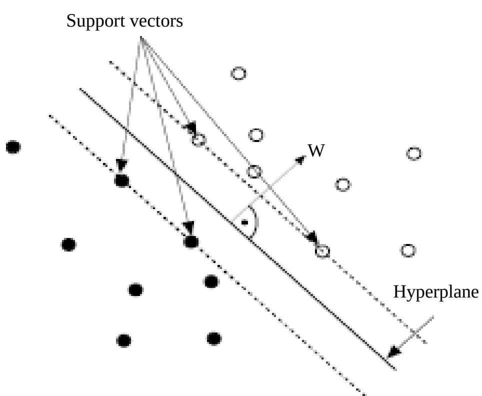

Fig. 5: Samples from both classes to select closest distance exactly to the hyper surface

the best prepossessing to compute a transformation of the feature vectors during the training is normalization. In the training process in order to recognize termination, the gradient of the function that is optimized internally must fall below a threshold where is set in by default value. The default value is 0.001 should be used because this value is the best results in practice. SVMs classifier of a feature vector z is performed according to Eq. 9:

$$f(z) = \text{sign}\left(\sum_{i=1}^{n_{sv}} \alpha_i y_i < x_i, z > + b\right) \quad (9)$$

Where:

- x_i = The support vectors,
- y_i = Encodes their class membership (±1)
- $\propto_I$ = Weight coefficients.
- b = Distance of the hyperplane to the origin
- n_{sv} = Number of support vectors

RESULTS AND DISCUSSION

To verify the proposal system, 45 welds joint sample images consist of 15 sample images for each straight lines, curve and tooth saw joint shapes. Each welds joint shape has 5 sample images for each categories welds joints defect which are good welds, excess welds and insufficient welds. The SVMs classifier computes the best classes of the feature vector and result of classifying them in "class". In SVMs "class" results, all the welds joint defect sample shapes images meet the correct class for each weld joints defects class. The data is taken in 72 features obtained from the matrix occurence and absolute histogram gray value. The matrix occurence consist gray value of corelation, homogeneity, contrast and energy for each weld joint shapes show in Table 1-3.

Table 1: Straight line weld joint shape

Categories classes/homogeneity	Correlation	Energy	Contrast
Good welds			
0.671	0.947	0.053	9.843
0.653	0.972	0.043	5.029
0.694	0.952	0.064	8.824
0.676	0.973	0.053	4.789
0.676	0.949	0.057	9.424
0.661	0.973	0.046	4.836
Excess welds			
0.626	0.924	0.044	13.712
0.605	0.962	0.029	6.522
0.627	0.928	0.044	12.856
0.606	0.961	0.030	6.663
0.641	0.914	0.059	15.551
0.608	0.960	0.034	6.758
Insufficient welds			
0.666	0.938	0.058	11.267
0.647	0.968	0.042	5.523
0.676	0.956	0.045	7.424
0.663	0.972	0.041	4.619
0.691	0.953	0.064	8.468
0.670	0.973	0.051	4.662

The performance of the SVMs classifier has been evaluated in term of recognition rate and execution time. The performance is based on feature vectors in weld joints by using occurrence matrix and gray absolute histogram shown in Table 4. The results shows from 3 weld joint samples for training and 2 welds joints samples for testing, only 1 incorrect class happen in the curve weld joints shapes at insufficient welds classes categories. The others results in classes categories classification for weld joint shapes such as straight lines and tooth saw show that the results are correct in each class categories.

Table 2: Curve weld joint shape

Categories classes/homogeneity	Correlation	Energy	Contrast
Good welds			
0.678	0.944	0.071	10.982
0.658	0.975	0.050	4.693
0.694	0.950	0.078	9.495
0.678	0.976	0.056	4.409
0.730	0.960	0.105	7.432
0.711	0.979	0.077	3.762
Excess welds			
0.672	0.911	0.082	15.926
0.643	0.963	0.051	6.147
0.700	0.941	0.103	11.060
0.672	0.971	0.069	5.082
0.665	0.919	0.083	15.371
0.630	0.962	0.048	6.704
Insufficient welds			
0.721	0.940	0.116	11.089
0.700	0.973	0.083	4.731
0.697	0.932	0.096	12.795
0.666	0.968	0.064	5.761
0.725	0.937	0.122	11.936
0.700	0.972	0.086	4.981

Table 3: Tooth saw weld joint shape

Categories classes/homogeneity	Correlation	Energy	Contrast
Good welds			
0.674	0.945	0.064	9.694
0.651	0.972	0.044	4.781
0.691	0.940	0.089	10.693
0.666	0.971	0.060	4.991
0.679	0.942	0.072	9.964
0.656	0.970	0.050	4.983
Excess welds			
0.644	0.922	0.064	14.074
0.606	0.961	0.038	6.600
0.661	0.927	0.071	12.885
0.631	0.965	0.045	5.876
0.620	0.862	0.064	25.235
0.571	0.940	0.031	9.796
Insufficient welds			
0.665	0.924	0.076	13.252
0.632	0.962	0.049	6.268
0.674	0.925	0.084	12.982
0.649	0.965	0.054	5.710
0.671	0.929	0.079	12.699
0.641	0.965	0.051	5.891

Table 4: Performance using occurrence matrix and gray absolute histogram

Weld joint/classes shapes categories	No. of training sample	No. of testing sample	Results	
			Correct	Incorrect
Straight lines				
Good weld	3	2	2	0
Excess weld	3	2	2	0
Insufficient weld	3	2	2	0
Curve				
Good weld	3	2	2	0
Excess weld	3	2	2	0
Insufficient weld	3	2	2	1
Tooth saw				
Good weld	3	2	2	0
Excess weld	3	2	2	0
Insufficient weld	3	2	2	0
Total	27	18	18	1

Table 5: Comparison of computation time for SVMs in three weld joints shapes

Testing sample	Class categories	Straight lines (m sec^{-1})	Curve (m sec^{-1})	Tooth saw (m sec^{-1})
1	Good Weld	116.2	115.6	115.80
2		116.4	118.6	116.50
1	Excess Weld	118.2	116.9	120.90
2		115.5	117.8	118.68
1	Insufficient Weld	117.3	321.7	319.60
2		117.4	192.7	190.60
Total		701.0	983.3	982.08

In comparison of computation times, straight lines joint shape were shortest in computation time compared to curve and tooth saw weld joints. The average computation time for straight lines joint is <120 m sec^{-1} for each testing sample with the total computation time of 705 m sec^{-1}. Even through in this case the total computation time for curve and tooth saw joint shapes quite same, however the result for class categories show the curve has 1 incorrect class. Table 5 show the comparison of computation time for SVMs in three weld joints shapes classification system.

CONCLUSION

The welds joints defect effectively classify into three categories which are good welds, excess welds and insufficient welds by Support Vector Machine (SVMs) classifier with 2D gray pixels coocurrence matrix and gray absolute histogram of edge amplitude. The total samples in weld joint images is 45 samples where 3 samples as training set and 2 as testing set in three different weld joint shapes. The results show the proposal approach system is able to classify the welds joint defects effective automatically. In further expended, we suggest more defect categories in welds joints not even only good welds, excess welds and insufficient welds. The weld joint shape also need to set more various shapes.

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