Journal of Physics: Conference Series

PAPER • **OPEN ACCESS**

Welding Defect Identification with Machine Vision System using Machine Learning

To cite this article: R Praveen Kumar *et al* 2020 *J. Phys.: Conf. Ser.* **1716** 012023

Welding Defect Identification with Machine Vision System using Machine Learning

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Abstract. Friction stir welding is a solid-state joining process to join similar or dissimilar metals, which uses the friction developed between the metals to join them. Friction stir welding is an efficient way to join the metals but the welding defects are a little difficult to find through naked eyes. Hence, there is a chance of it being unnoticed even in final inspection in industries. So the welded joints are inspected by machine vision, using camera and an intelligent system. After obtaining the images of the welded joints and processing them using MATLAB, they are differentiated according to the various defects in them, using machine learning technique. For this, the statistical features of the image are extracted and they are classified into different defects using classifiers like Decision Trees, Discriminant Analysis, Support Vector Machine and Nearest Neighbour.

1. Introduction

Aluminum alloys AA5XXX are lighter alloys with good strength and good flexibility, used in rail road applications, ship buildings, aluminum armors etc. They have a good ultimate strength because of the combination of aluminum, magnesium and chromium [1]. Welding plays an important role in joining two sheets of this material. Friction stir welding is used in binding aluminum alloys 5XXX, as the method has greater weld efficiency, with a suitable friction pressure and rotational speed [2]. This technique is very effective to join high-strength aluminum/magnesium alloys and other metallic alloys. Friction Stir Welding (FSW) is a solid state hot shear joining process. In this method, the two plates to be welded are butted together and held in position by clamping and supporting them. FSW is carried out with a special tool which is a short cylindrical pin with a shouldered structure. The FSW tool is brought into the welding zone with a certain depth of penetration as it rotates and it is moved transversely along the joint at a particular speed. The thermomechanical action creates in the end a strong joint between the clamped and butted plates. Mostly this technique is used for the aerospace, aircraft, automotive materials that are hard to weld by conventional fusion welding. Friction Stir is also used to form the metal, which increases the strength of the material. But, fault detection becomes a challenge. Machine vision system can be used to identify and classify the defects in the weldment of Friction Stir Welded joints [3]. The various defects in the Friction Stir Welding are tunnel defects, cracks, surface grooves, void, and flash. The defects that can be classified with machine vision system are, surface grooves, flash, cracks and no defect, i.e, good joint.

Image classification with the help of machine learning has shown very good capability using deep learning techniques [3, 4]. Initially, the image with defects has to be captured and then it has to be pre-processed. After pre-processing, the feature extraction process has to be carried out from the processed image. Then feature classification with the deep learning holds good for classifying defects. It can be done with the classifying algorithms like decision tree algorithm, support vector machines, discriminant analysis and nearest neighbour classifier. On dealing with the pixel value of a classified image, the decision tree algorithm holds good accuracy. Support vector machine and nearest neighbor classifier also hold a very good image classifying accuracies [5]. Till now, several techniques like thermography processing [6], the contour plot of image intensity [7], image reconstruction and blob detection (by MSER) [8,9] have been carried out to detect the failure of the FSW weld.

2. Methodology

While in-process monitoring of FSW is a promising method for detecting and elimination the defective joints, it entails extensive image processing software and hardware. Off-line methods are easier to implement, though with extensive human effort. This paper describes an off-line method for FSW defect detection by applying machine vision and machine learning concepts. The images of defective welded joints are captured using a digital camera and subject to image processing. Then, statistical features are extracted out of the image and are used to identify the weld defects through a machine learning technique. The methodology for defect identification of the Friction Stir Welding joint is as shown in the Fig.1 and is further described.

Figure 1. Methodology of defect identification work

2.1. Image acquisition

Image acquisition is one of the important and primary step in the image processing. The image was captured for fault conditions in the RGB format with 90 samples for each fault condition of the joint, with the help of a camera. Sample images of the different fault conditions namely, crack, flash, grooved and good joint (no defect) are displayed in the figure 2 (a-d). A digital camera (Fujifilm T550) was used for capturing the images of the welded joints by holding them at different orientations and ambient light conditions.

2.2. Image Processing

Image processing is a method of performing certain digital operations on an image, in order to extract some useful information from it. The input is an image and output is the characteristic features associated with that image. Image processing basically includes the following three steps: Importing the image via image acquisition tools, analyzing and manipulating the image, and finally producing an output wherein the result can be an altered image or a report that is based on image analysis.

The obtained image should be first cropped in order to analyze only the welded region (and not the background details). Next, the image available at resolution of 3456x4608 pixels is converted into an image of 640x480 pixels. The new images are seen to still preserve the defect details and it is expected to give computational advantage when working on the image data. The image is further processed to convert from RGB image (color image) format to the greyscale format, having the pixel value from 0 to 255. In MATLAB, the RGB image pixel value at a particular location of a colour image, constituting the red, green and blue components, is converted into a single value in the grey scale. This is carried out by calculating the weighted sum of all the three colour components and the array of pixel values of the image is stored in memory [10, 11].

Thus, greypix = 0.299*redpix + 0.587*greenpix + 0.114bluepix.

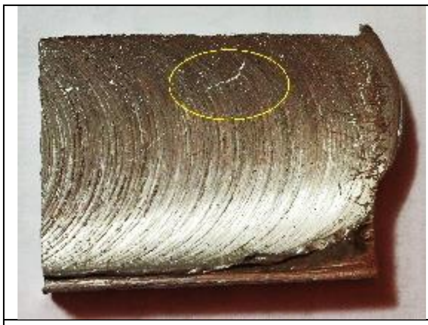	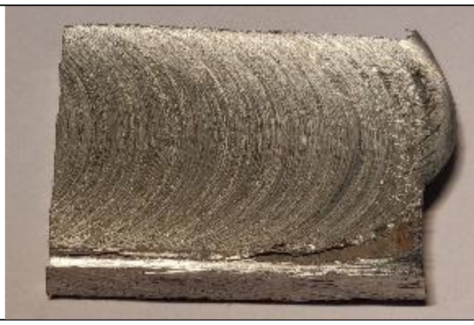
Figure 2(a). Image with crack condition	**Figure 2(b).** Image with good condition
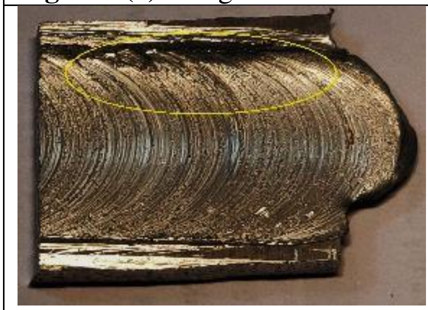	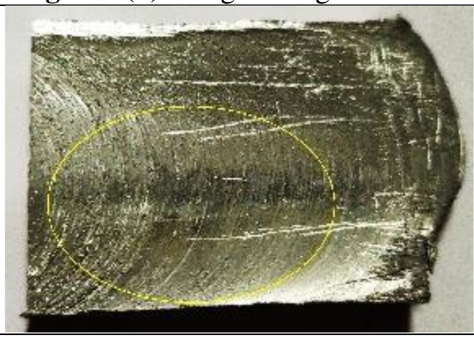
Figure 2(c). Image with flash condition	**Figure 2(d).** Image with groove condition

2.3. Machine Learning Approach

Machine Learning is the way to build an inductive model that learns from a limited amount of data without the help of specialists. The Machine Learning models predict a managed learning factor, with marked knowledge and unattended training, draws inference from details without labelled inputs. For supervised learning, we distinguish between models that predict a numeric variable or a category variable. Model learning means that a model's parameters can be fitted to a particular dataset and updated iteratively through several data passes until a particular predefined function has been minimized.

2.3.1 Feature extraction. Feature extraction is one of the key steps for machine learning approach in which the pixel value data (RGB or grey scale) obtained from the image is used to extract certain statistical features. There are several methods of feature extraction from digital images. For example, the probability histogram value of the image is calculated from its RGB values, which is then divided into several bins and statistical features like standard deviation, skewness, etc. are evaluated for each bin [12]. On the other hand, statistical features may be extracted from the probability distribution of pixel values of an image. But it may be desirable to carry out feature extraction from a region of interest. In this study, for each image of the weld joint, its pixel value array is read and the related statistical features namely, mean, kurtosis, standard deviation, RMS, variance, and skewness are extracted. The features are extracted for several images of all the four fault conditions and they are exported as csv file.

2.3.2 Feature classification. Feature classification helps in classifying the data for different fault conditions. The classification process is performed in two phases - the training and the testing phase. In the training phase, known feature values and their class data are fed into the classifier. It is then tested with feature values whose class is unknown and the classification accuracy is calculated. MATLAB supports different classification algorithms that can be used in this work such as Decision tree algorithm, Discriminant analysis, Nearest Neighbour and Support Vector Machines (SVM). Several authors have carried out comparative assessment of the classifier performance under certain problem domains [13]. The choice of an apt classifier for the weld image classification problem is preceded by an exploratory analysis on the various classifier performances.

2.3.2. (i) Decision tree algorithm

Decision tree is the most powerful tool for classifying and predicting the conditions, with a hierarchical data. A Decision tree has a tree structure, where each internal node represents a test on an attribute, each branch represents an outcome of the test and each leaf node (terminal node) holds a class label. Decision trees can handle high dimensional data with good classifying accuracy without much computation [14, 15].

2.3.2. (ii) Discriminant Analysis

Discriminant analysis is a statistical method to understand the relationship between dependent and independent variables. There are two basic steps in discriminant analysis: the first is to estimate coefficients or weight factors that can be applied to the known characteristics and the second is to use this information and develop decision rules that specify some cut-off value to classify the input data [16, 17].

2.3.2. (iii) Support Vector Machine

Support vector machines are supervised learning models that analyze data for classification. SVM can differentiate the data points into two classes through linear classifiers. Each data point belongs to one of the two classes. It is necessary to choose a hyper plane with maximum margin between two classes for best classification with the help of the supporting vectors used [18, 19].

2.3.2. (iv) Nearest neighbour algorithm

Inspite of many methods of supervised statistical pattern recognition, the Nearest Neighbour rule achieves high performance consistently, without taking initial assumptions involving a training set of both positive and negative cases. A new sample is classified by evaluating the distance to the nearest training case and the sign of that exact point then determines the classification of the sample. The K-NN classifier considers K nearest points and assigns the class to the sample. Larger K values can reduce the effect of noise within the training data [20].

2.4 Confusion matrix. Confusion matrix is used to interpret the results after classification of the different conditions using classification algorithm [21]. It displays the classified results for the different conditions that are rightly classified as that condition and those misclassified as different conditions. In the confusion matrix for weld defect classification, the different defective weld joint samples are indicated as ‘C’ for cracked samples, ‘Gd’ for good samples, ‘F’ for flashed samples and ‘Gr’ for grooved samples.

2.5 Graphical user interface (GUI). GUI is a visual presentation of the communication given to the user for easy interaction with the machine. A common user interface includes Graphical representations like buttons and icons. Communication can be performed by interacting with these icons rather than the usual text-based or command based communication. The GUI actually translates user language which comprises simple one-line commands, single click and double clicks to machine language or assembly language. Machine language is understood by the machine and hence the machine responds to the task initiated, which is translated and communicated to the user via GUI [22].

3. Results and Discussion

The statistical features are obtained from the grayscale images with the help of their pixel value data. The statistical features like mean, standard deviation, kurtosis, skewness, Variance, RMS are extracted for all the training images with MATLAB code and stored as csv file. Then feature classification is one of the key step and used to classify the images based on the statistical features extracted from the image. The csv file obtained from the feature extraction step is imported to MATLAB classifier that firstly learns and relates the feature values to their corresponding images. The extracted features are thus classified using four different algorithms mentioned earlier and their classification results are displayed and compared using confusion matrix as shown below.

3.1 Decision trees.
The decision tree algorithm produces an accuracy of 92.5%. The confusion matrix of this algorithm is shown in the Table1.

Table 1. Confusion matrix using Decision tree algorithm

	C	Gd	F	Gr
C	85	5	0	0
Gd	4	80	4	2
F	0	3	86	1
Gr	1	5	2	82

From the Table 1, it is seen that, the condition of crack (C) is identified as crack 85 times and it is misclassified as good (Gd) for 5 times, the condition of good is classified as good for 80 times and it is misclassified as crack for 4 times, as flash(F) for 4 times and as grove(Gr) for 2 times. The condition of flash is classified as flash 86 times and misclassified as good for 3 times and groove for one time. The condition of groove is classified as groove for 82 times and misclassified as crack for 1 time, as good for 5 times and as flash for 2 times. This classifier is found in good detecting the more obvious ‘crack’ condition but for other conditions, we could see misclassifications and false positives.

3.2 Discriminant analysis.
The discriminant analysis algorithm is used in two degrees, linear discriminant analysis and a quadratic discriminant analysis. Linear discriminant analysis produces an accuracy of 89.2% and the quadratic discriminant analysis produces an accuracy of 95.8%. The confusion matrix using quadratic discriminant analysis is given in the Table 2.

Table 2. Confusion matrix using Quadratic Discriminant Analysis

	C	Gd	F	Gr
C	86	3	1	0
Gd	0	87	2	1
F	0	0	84	6
Gr	0	0	2	88

From Table 2, it is seen that, the condition of crack is identified as crack 86 times and it is misclassified as good for 3 times and as flash for 1 time. The condition of good is classified as good for 87 times and it is misclassified as flash as 2 times and grove for 1 times. The condition of flash is classified as flash 84 times and misclassified as groove for 6 times. The condition of groove is classified as groove for 88 times and misclassified as flash for 2 times. Its confusion matrix is better than the decision tree algorithm with correctly classified rate is high.

3.3 Support vector machines.
The algorithm considered for the support vector machines are Linear SVM, Quadratic SVM, Cubic SVM and Gaussian SVM. The linear SVM produces an accuracy of 86.1%, the quadratic SVM produces an accuracy of 96.1%, the cubic SVM produces an accuracy of 95.8%, and the Gaussian SVM produces an accuracy of 97.2%. The higher classification accuracy of Guassian SVM compared to the linear SVM is notable, though different performance is noted elsewhere [23].

From the Table 3, it is seen that, the condition of crack is identified as crack 87 times and it is misclassified as good for 3 times. The condition of good is classified as good for 90 times and no misclassifications. The condition of flash is classified as flash 88 times and misclassified as good for 2 times. The condition of groove is classified as groove for 85 times and misclassified as good for 5 times. On seeing the confusion matrix of the Gaussian Support Vector Machine, the good condition is classified correctly always but the other defects are misclassified. This is a little risk that the defects can be misclassified into good ones giving a wrong decision.

Table 3. Confusion matrix using Gaussian Support Vector Machine

	C	Gd	F	Gr
C	87	3	0	0
Gd	0	90	0	0
F	0	2	88	0
Gr	0	5	0	85

3.4 Nearest neighbor classifier.

The algorithm considered for nearest neighbor are, simple KNN, Cosine KNN, Cubic KNN and the weighted KNN. The KNN produces an accuracy of 96.1%, the cosine KNN produces an accuracy of 91.4%, the cubic KNN produces an accuracy of 93.3%, and the weighted KNN produces an accuracy of 97.2%

Table 4. Confusion matrix using Nearest Neighbour algorithm

	C	Gd	F	Gr
C	88	2	0	0
Gd	3	84	0	3
F	0	0	90	0
Gr	0	0	2	88

From Table 4, it is seen that, the condition of crack is identified correctly 88 times and it is misclassified as good for 2 times. The condition of good is classified correctly for 84 times and it is misclassified as crack for 3 times and as groove for 3 times. The condition of flash is classified correctly 90 times and no misclassified. The condition of groove is classified correctly 88 times and misclassified as flash for 2 times. On seeing the confusion matrix, weighted KNN is better at classification of defective samples as compared to those of good condition, where more number of misclassification is noted. This is in contrast to the observation in SVM classification result which shows more number of defectives getting classified in to the ‘Gd’ category.

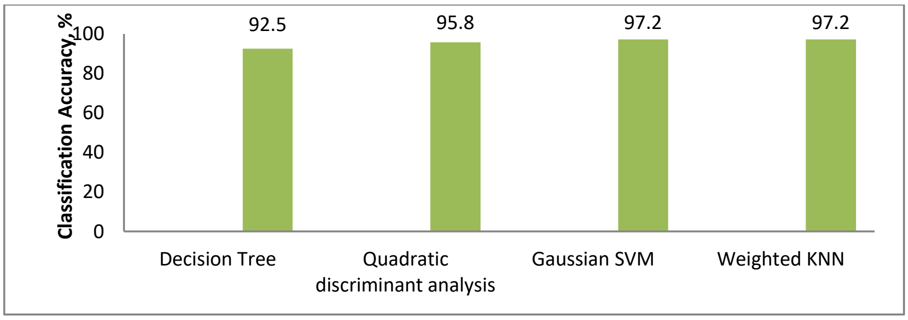

Figure 3. Comparative performance of the four best classifiers used for weld defect identification.

In fig. 3, the performance of the four different classification methods has been compared by looking at the best output produced under each method. It is seen that the Gaussian SVM and weighted KNN methods are better performers than the decision tree and discriminant analysis methods.

3.5 Graphical user interface.

The Graphical User Interface (GUI) is important for the user to interact with the machine. GUI developed consists of two display units, two table units and four push buttons. The display unit 1 is used to show the loaded image and the display unit 2 is used to show the processed images. The table unit 1 is used to display the statistical features of the loaded image and the table unit 2 is used to display the classified result. The four push buttons includes, 'Load image' prompt for loading of the image to be classified, 'Process image' prompt for the conversion of the loaded image to gray scale, 'Stat Features' prompt for obtaining the statistical features of the loaded image and 'Classify' button to classify the weld image into one of the four categories based on statistical features obtained. The GUI developed a shown in the fig. 4.

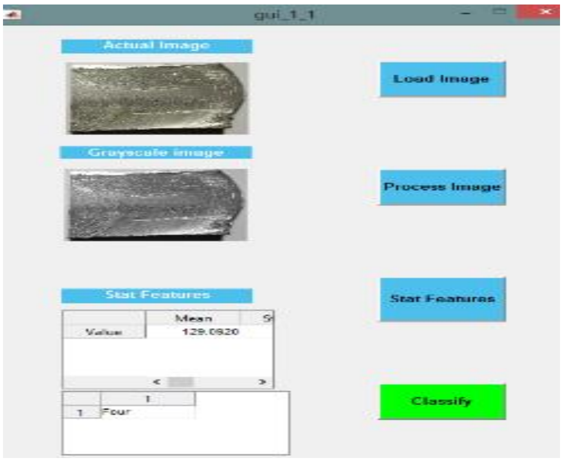

Figure 4. GUI for the intelligent defect classification system.

4. Conclusions

An off-line method for defect inspection of friction stir welded AA5XXX metal joints is proposed, combining the machine vision and machine learning techniques and it is shown to be successful. Several images of the welded joints were captured, processed and machine learning was applied, by which the samples are classified into cracked, grooved, flashed or good ones.

Four different techniques of classification and their variants have been tested in the trial inspection carried out on 90x4 samples. It is observed that decision tree performs satisfactorily with an accuracy of 92.5% and it is accurate at detecting only crack condition but for others, there is a problem of misclassification. The quadratic discriminant analysis classifier performs equally well with an accuracy of 95.8%. The Quadratic SVM performs well giving an accuracy of 96%. But the Gaussian SVM stands better with an accuracy of 97.2%. Then in the case of nearest neighbour classifier it is seen that the weighted KNN performs the best with 97.2% classification accuracy. Overall it can be seen that machine learning algorithms employing higher order functions (quadratic, cubic, etc.) are more accurate.

This weld defect classification method is used with a GUI and it will be a user friendly approach to weld joint inspection. The future scope includes that the defects can be identified with the image segmentation techniques to spot the location and the severity of the defects in the weldment and also identifying the micro pores in the weldment.

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