Feature Extraction through Chaotic Metrics for Weld Flaw Classification

Mohanasundari L, Sivakumar P, Chitra N

Abstract: Most of the Mechanical structures formed by metals are only through the fusion of metals at high temperatures through various welding methods. The strength of the structures depends only on the perfection in welding process failing in which would lead to loss of structural stability. This ultimately results in disasters and attracts huge investment to reconstruct the structures. It is always preferred to check the quality of the weld before the final welded structure is used for its actual application. Though visual inspections could solve problems tentatively valid for low production rates, there are scenarios where visual inspection fails and needs high end methods to analyze the quality of welded joints. Several measurement techniques have evolved and help the user community. The paper aims at proposing a novel feature extraction namely, Kolmogorov-Sinai Entropy which is widely used in chaotic analysis. The classification of weld flaws are done along with the additional metrics such as kurtosis and skewness calculated from the x-ray images took from 'GRIMA' open database.

Keywords: ***Mechanical structures, welding methods, kurtosis and skewness calculated from***

I. INTRODUCTION

Out of all industrial processes existing in world, most significant and ranks high is the process of welding. Any further operations on the welded part in industries or direct usage of such finished product by consumer depend on such welded structures. Welding is done in many ways which needs essentially a high temperature to be produced in the order of melting point of the metals to be joined. Moreover, welding is an art of mechanical process which may be of indoor or outdoor in nature. The concert of welding processes depends on the welding methods, environmental conditions and the accuracy in spotting the area to be welded. A comprehensive survey [23] was made on the various methods of welding. Welding types are classified as follows based on the source of heat.

1. Gas welding
2. Arc welding
3. Resistance welding
4. Thermit welding
5. Solid state welding
6. Electron beam welding and
7. Laser beam welding

Revised Manuscript Received on February 05 2019.

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The core of the survey on earlier works presented in this paper is related to the soft computing methods used in conventional researches.

The source of the test images would be obtained from any type of imaging methods such as ultrasonic imaging, X-ray imaging or a direct positive imaging method. However, the defect identification depends on the efficient classification performed on the test images. This critical survey is intended to provide a wide review on existing defect detection methods and find out the problems and accuracy measures obtained in those papers. The survey has been conducted by focusing the problem only towards the classification issues irrespective of the type of source image used for analysis.

Basic principle behind defect detection is manual inspection. Unfortunately micro sized defects and defects which are beyond the direction vision are not observable and hence it needs intelligent methods to find it. Thanks to image processing, a better way to evaluate the quality of welded joints based on some special features extracted from the test image. Also, such methods lead to automation in testing large data base in smaller time. Most of the welding joints under exposure are tested only with visual inspection but, to achieve accuracy and faith on the results, expert systems are used to ensure the quality of welds.

The basics of imaging techniques rely on transmitting the energy in the form of ultrasonic waves, X-ray or Infrared on the metal joints and acquiring the reflected energy from the metal surface. Literatures [1] and [2] opened the gateway to use pattern recognition methods to classify the echoes from their features. Literature [3] proposed an ultrasonic based pulse echo technique to find the flaws and cracks in the pipes. A classification method to distinguish the features sets of counter bore, counter bore and echoes and waveforms with flaws. After preprocessing stage of FFT (Fast Fourier transform) 33 time domain and 36 frequency domain features from each waveform were used as test sets. A subset of waveform features was selected to distinct waveform classes using k-nearest neighbor algorithm. As a next stage, optimum features were used to train three different classifiers such as Gaussian probability density function classifier, Fisher linear discriminant classifier and F-nearest neighbor classifier. Feature sets were extracted and applied to classifiers could result accuracy in the range of 92-97%. But the same method failed when tested with a different database and could not classify anywhere between 79-88%.

In [4], it is fair to note that neural network had been used to construct a relationship between weld quality parameters and weld pool geometry in TIG (Tungsten Inert Gas) TIG welding. Simulated annealing based optimization is performed to identify the optimal welding parameters which satisfy the required quality metrics. Fuzzy clustering method is used to classify the Aluminium weld quality and to obtain the required. To evaluate the weld quality, the front depth, back height and back width of the weld were considered as shown in Fig.1.

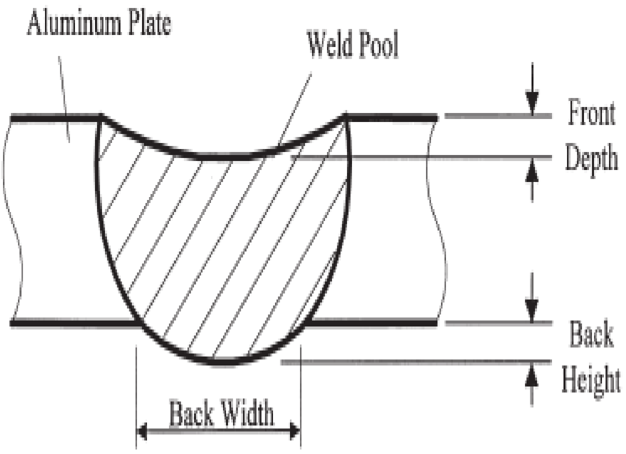

Fig. 1 Aluminium thin plate weld pool geometry

Experimental setup shown in Fig.2 is a welding process done based on TIG useful to weld non- ferrous metals such as Aluminium, Magnesium and Titanium.

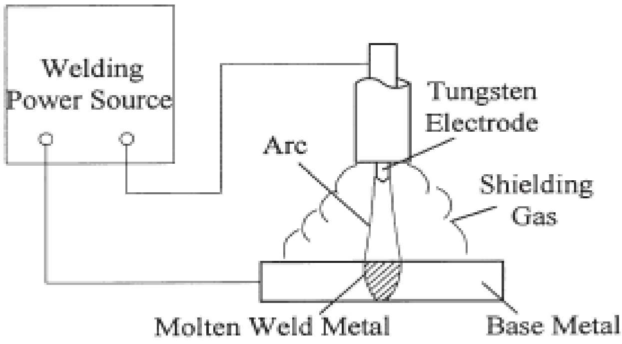

Fig. 2 Tungsten inert gas welding

Cluster centers were extracted in order to obtain a better weld quality by using the optimized values as shown in Table 1

	Cluster center (mm)		
	Front depth	Back height	Back width
Good	0.4258	0.4636	7.9282
Fair	0.6065	0.6697	9.7878
poor	0.9837	1.0214	12.1684

Sylvie Legendre et al in [5] had proposed a weld quality detection method for Aluminium plates based on features obtained through wavelet transforms and further classification by neural networks. The overall aim of this paper is to use ultrasonic signals which lead to an automated system of structure testing. Fig. 3 shows the weld specimen considered in their work.

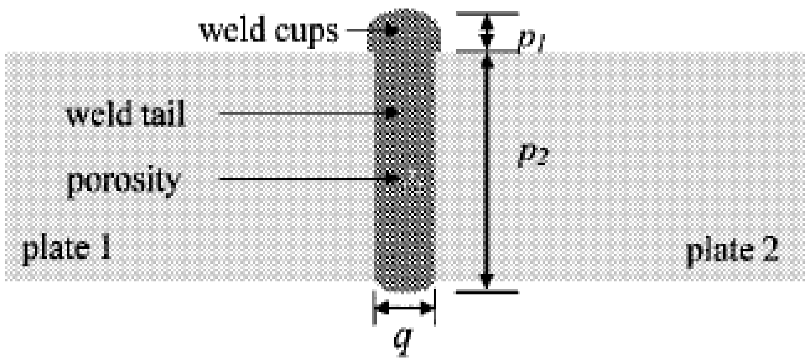

Fig. 3 Parameters used for characterization

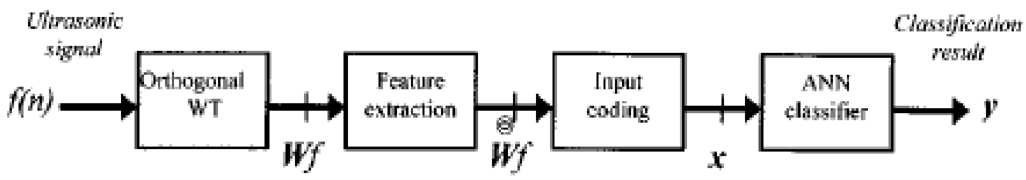

Fig. 4 Process of ultrasonic feature extraction and classification

Figure4. presents an idea of sequential processes performed which ultimately resulted in above 90% accuracy for 122 ultrasonic signals with data set D_1 and 92% accuracy from dataset D_2.

Resistance spot welding platform was considered in paper [6] where weld quality was determined by observing the resistance variation in the primary of the weld machine. While resistance variations were mapped into a bipolarized vector for pattern recognition, hop field neural network was used to classify the welding quality.

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The paper could prove a good agreement between the obtained quality parameters and tensile shear strength. Figure 5 shows the electrical equivalent of the welding circuitry using SCR (Silicon controller rectifier), where R_p is the primary resistance of interest.

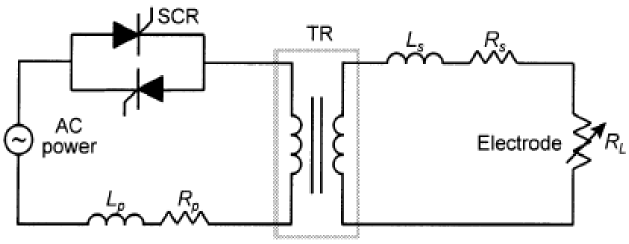

Fig. 5 Equivalent circuitry of welding machine

The resistance data was mapped into 6x10 vectors which are divided into five classes. Class I and class II were taken as poor weld quality, class III, class IV and class V shows good welds. This paper opens a new gateway to consider only the resistance values instead of any other measurement methods used on the conventional methods of metal welding.

In order to ensure a quality welding in the areas of aerospace, automotive sectors and nuclear plant constructions, arc welding and laser welding had been introduced in the scenario by the research community. Such arc weld tests conducted on steel are reported in [7] while using temperature profile obtained from plasma spectra is used to extract feature vectors using Principal Component Analysis (PCA). Sequential classification using NN could prove a better correlation between the ANN outputs and temperature profiles.

A vision based inspection system had been introduced in [8] to inspect the weld bead to maintain the weld quality. Figure 6 shows the vision sensor and welding arrangement which attempts to monitor the processes online. The performance of the system is shown in terms of standard deviation is about 0.35mm and 0.25mm in horizontal and vertical direction respectively, false positive rate of 3.2% and false negative rate of 5.6%.

A combination of artificial intelligent methods were used in [9] to provide better accuracy in determining welding quality. Neuro-fuzzy model was constructed to predict and classify the fused Zone Levels of Imperfections in Ti6Al4V Alloy Butt Weld. A flow diagram shown in Fig.6 explains the complete process.

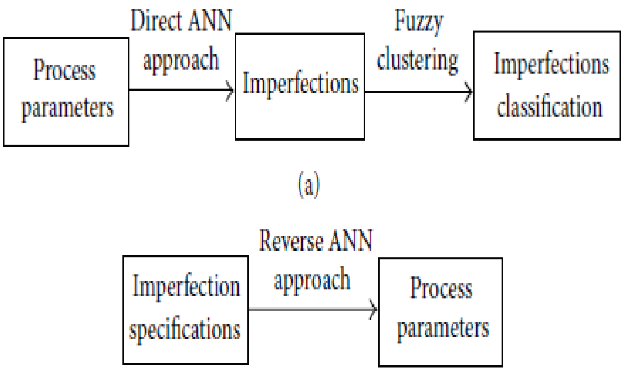

Fig. 6 Process flow used in [9]

The calculation of a single score for the quality comparison between the welds was presented. It followed the-smaller-the-better criterion. Both the prediction and the classification of the imperfections were based on a structured and objective model, which was built straight from experimental data. This Neuro-fuzzy method gives the opportunity to predict the quality of the fused zone which can make the titanium welding more suitable for the severe standard of the aeronautical and modern automotive industries for the weld imperfections.

While observing in major number of researches on weld flaw detection and weld quality improvements, data mining methods have been invariably which adds a better intelligence to the system which supports the views given in [10]. In literature [11], Faiza Mekhalfa et al present through their experimental study, the use of support vector machines (SVM) in the automatic classification of weld defects in radiographic images. SVM classification method can achieve high accuracy percent and is found to be faster than Multilayer Perceptron Artificial Neural Network (MLP-ANN).

In all the quality inspection works involving data mining methods produce revolutionary performances in terms of overall minimization of poor quality welds. Irrespective of the source of imaging methods, whether it could be images or 1D waveforms obtained it is seen that the accuracy of this flaw detection process mainly depends on classification methods. Hence it is highly recommended by the author of this survey to work on enhancement in classification methods.

II. MATERIALS AND METHODS

In the proposed weld flaw detection and classification, chaotic metrics such as Lyapunov exponents, Kolmogorov-Sinai entropy density, Kurtosis and Skewness have been used for better classification accuracy. X-ray images from 'GRAMI' database have been used to prove the robustness of the proposed methods.

Chaotic systems are very sensitive to the initial conditions. Hence dynamical weld process and its associated weld quality could be captured through the following metrics of chaotic systems. Actually, these metrics are useful to find whether the dynamic system is in chaos or not. The following presentation briefs the mathematical background of Lyapunov Exponents (LE) and Kolmogorov Sinai (KS) entropy density metrics.

a) Lyapunov Exponents

Lyapunov exponents are very useful in analyzing the dynamical systems. The sensitivity of divergence or convergence of trajectories in phase space with respect to the initial conditions is measured through Lyapunov exponents (LE). A system with at least one positive exponent is considered to be in chaotic region. LE is a measure of how diverse the lattices during each time iteration and it is given by Equation (1)

$$\lambda(i) = \lim_{n\to\infty} \frac{\log|\sigma(i)|}{n} \quad (1)$$

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Where n refers iterations and λ(*i*) is LE. λ(*i*) are calculated from the eigenvalue $\sigma(i)$ of R_n.

R_n is calculated using Equation (2) from the initial values of the lattices from the construction of Jacobian matrix J_n as done in [12] in each iteration. Then we define

$$R_n = \prod_{k=1}^{n} J_k \quad (2)$$

After calculating the LE values, those lattices have positive values are understood to be in chaotic region. In this work, lattice values are nothing but 1D row vector obtained from the test images. The sum of Lyapunov exponents reveals the damping nature of a system and any changes in damping could be monitored with Lyapunov exponents [13].

Calculation of Lyapunov exponents are done in many methods, the one given in Equation (3.2) is related to discrete time system. Few other approaches to calculate LE, for a continuous time series are reported below. Computing the Lyapunov exponents and Instantaneous Lyapunov exponents (ILEs) utilized phase space and tangent space approach in [13]. In an algorithm developed in [14] Short Term Averaged Lyapunov exponents (SLEs) are introduced. This is needed when the experimental data (time series) gives inaccurate ILEs from a time series due to computational errors. A similar concept to the SLEs, the LLE (Local Lyapunov Exponents) was proposed by Abarbanel et al. in [15].

It is convinient to model a dynamical continuous time system by ordinary differential equations which is of the form given in Equation (3) and Equation (4)

$$\frac{dx}{dt} = f(x_1, x_2, x_3 \ldots\ldots x_n) \quad (3)$$

$$= \left[\frac{dx_1}{dt}, \frac{dx_2}{dt}, \ldots\ldots \frac{dx_n}{dt}\right]^T \quad (4)$$

where $x=[x_1,x_2, ..x_n]^T$

The above equation gives a set of trajectories in phase space. The i_{th} Lyapunov Exponent is calculated as given in Equation (5)

$$\lambda_i = \lim_{t\to\infty} \frac{1}{t} \ln \frac{P_i(t)}{P_i(0)} \quad (5)$$

Where, the Eigen values are ordered from largest to smallest. Since the integration time is of infinite, it is practically not possible for infinite time series. Hence, LE calculation based on finite number of iterations is given below in Equation (6)

$$\lambda_i = \frac{1}{t} \ln \frac{P_i(t)}{P_i(0)} \quad (6)$$

LE gives a better idea on how the nearby orbits diverge due to initial conditions. The method of calculating Lyapunov exponents have been already dealt in almost similar methods as given in [16]-[19].

b) Kolmogorov-Sinai Entropy Density

The spatiotemporal chaotic system of the proposed system can be considered as *L* dimensions dynamics, the Kolmogorov–Sinai entropy of the *L* dimensions dynamics is the sum of positive Lyapunov exponents. Without loss of generality, the Kolmogorov–Sinai entropy density is employed here to eliminate the effect of number of lattices, which is presented in Equation (7) as follows

$$h = \frac{\sum_{i=1}^{L} \lambda^+(i)}{L} \quad (7)$$

Where, *h* is the KSE density and the numerator is the sum of positive values of LEs. [20].

c) Kurtosis

Kurtosis is a measure of whether the data are peaked or flat relative to a normal distribution. The formula for the kurtosis of the gray levels is

$$Kurtosis = \frac{(M*N)*(M*N+1)}{(M*N-1)*(M*N-2)*(M*N-3)} * \left\{\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}\left(\frac{u(x,y)-\pi}{std}\right)^4\right\} - 3\,\frac{(M*N-1)^2}{(M*N-2)*(M*N-3)} \quad (8)$$

Where *M* and *N* are the number of rows and columns of the X-ray digital image, *std* is the standard deviation [21].

d) Skewness

Skewness is a measure of the asymmetry of the data. The formula for the skewness of the gray levels is

$$Skewness = \frac{M*N}{(M*N-1)(M*N-2)} \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} * \left(\frac{u(x,y)-\pi}{std}\right)^3 \quad (9)$$

Where *M* and *N* are the number of rows and columns of the X-ray digital image, *std* is the standard deviation [21].

The proposed work uses a Gaussian map. In mathematics, the Gauss map (also known as Gaussian map or mouse map), is a nonlinear iterated map of the reals into a real interval given by the Gaussian function:

$$X_{n+1}=\exp(-\alpha\, x_n^{2})+\beta \quad (10)$$

Where α and β are real parameters.

The lattice values obtained using α=5.9 and β = -0.5, as these values ensure the chaotic behavior of the system.

III. RESULTS AND DISCUSSION

- **Specificity**

It is the ratio between the total T_P decisions to the number of actual positive cases. It is given by equation (11).

$$Sensitivity = \frac{TP}{(TP+FN)} \quad (11)$$

- **Specificity**

It is the ratio between the total T_N decisions to the number of actual negative cases. It is defined by Equation (12).

$$Specificity = \frac{TN}{(FP+TN)} \quad (12)$$

- **Accuracy**

It is the ratio of the summation of True positive and True negative cases and the total samples in the classification problem. It is defined by Equation (13).

$$Accuracy = \frac{TP+TN}{(TP+FN+FP+TN)} \quad (13)$$

Table 2 presents the performance of the system on GD X-ray image database.

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Table 2. Accuracy performance

S. No.	Sensitivity (%)	Specificity (%)	Accuracy (%)
1	89.89	86.67	89.66
2	97.93	99.75	97.94
3	99.74	94.74	99.73
4	99.51	88.17	99.48
5	99.44	100	99.44
6	98.83	95.98	98.82
7	95.72	87.73	95.42
8	99.48	100	99.48
9	89.61	98.03	90.10
10	98.61	100	98.62
Average	96.88	95.11	96.87

IV. CONCLUSION

The basic principle being the analysis of reflected data from the welding zone, a better classification method would produce a more accurate performance. Since image processing is performed to mine the features, it needs sufficient preprocessing stages. The present implementation is based only on the Lyapunov exponents calculated from each image. The average accuracy obtained is about 96.87%.

The future extension of the algorithm is to be the reduction in flaw detection time and overall classification time. The algorithm to be designed should obviously consume less time, so that it is suitable to be used for online applications. After a detailed survey made on earlier literatures including Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony optimization (ACO). The classification performance could be improved with two well-known evolutionary multi-objective algorithms, non-dominated sorting based multi-objective genetic algorithm II (NSGAII) and strength Pareto evolutionary algorithm 2 (SPEA2). These algorithms would play efficient roles to filter and optimize the feature selection process. Totally two multi-objective filter based feature selection algorithms have been developed. Mutual information and entropy has been used as filter evaluation criteria. The proposed work has been tested with decision tree to evaluate the classification performance.

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