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# Development of Neural network based Plasma Monitoring System and simulator for Laser Welding Quality Analysis

Kwon Jangwoo\*, Son Joongsoo\*\*, Lee Myungsoo\*, Lee Kyungdon\*\*

\*Dept. of Computer Eng. Tongmyong Univ. of Info. Tech.

\*\*Dept. of Design Technology, IAE/Dept. of Systems Eng., AJOU Univ.

\*\*\*Dept. of Design Technology, IAE

## Abstract

Neural networks are shown to be effective in being able to distinguish incomplete penetration-like weld defects by directly analyzing the plasma which is generated on each impingement of the laser on the materials. The performance is similar to that of existing methods based on extracted feature parameters. In each case around 93% of the defects in a database derived from 100 artificially produced defects of known types can be placed into one of two classes: incomplete penetration and bubbling. Especially we present simulator for weld defects classification and data analysis. The present method based on classification using plasma is faster, and the speed is sufficient to allow on-line classification during data collection.

## I. INTRODUCTION

The inspection of welded components often requires the collection of data from a few meters of weld, followed by a rigorous characterization to detect significant defects. This characterization is at present performed largely by human operators, often after the data collection from the weld has been completed. The human eye is unparalleled in its ability to recognize significant patterns after a period of suitable training and experience. However, even the best operators suffer from fatigue and loss of concentration, so human error cannot be neglected. Automated characterization offers the possibility of an impartial, standardized performance 24 hours a day.

In this paper, we will discuss how neural networks may be used to assist in the automation process, by providing a rapid and accurate classification of a number of different defect types. In Section 2, we discuss the theoretical background, defining the several intrinsic transitions that form weld nugget during laser welding. A feature vector extraction is presented in section 3. In section 4 we present a plasma detection signal processing technique for an on-line

system. There we describe an optical technique applied in conjunction with a signal processor and a PC for ascertaining information from the plasma that is generated on each impingement of the laser on the materials. A CO<sub>2</sub> laser with a velocity of 5m/min and an average power of 4KW was used for the welding. An UV sensor is used to detect the high-intensity plasma given off from the material during welding. The signal is then amplified, filtered, and quantified in terms of the spectral density distribution of the signal. The information is then used to characterize the weld quality. In section 5, we present the classification method using neural networks. The classification rates of neural networks with different numbers of hidden neurons for classifying weld defects are presented in section 6. We draw some final conclusions in section 7.

## II. THEORETICAL BACKGROUND

During laser welding the formed weld nugget experiences several intrinsic transitions. These transitions are recrystallization, melting, vaporization, and solidification. Under normal welding conditions, melting and vaporization are the most viable stages that can be

related to weld integrity. The detection technique is based on measurements from the observed vaporization, it is appropriate to justify the relationship between melting, vaporization, and the observed measurements. Intuitively, it is apparent that a relationship between melting and vaporization does exist; however, the extent of this relationship is uncertain. To achieve melting at the inner surfaces of a material of some thickness, a considerable amount of vaporization is generated during the welding process. This vaporization is given off in the form high-intensity plasma. The plasma is detected by an UV sensor that converts the light energy into electrical energy, from which information pertaining to the weld quality is extracted by measuring the electrical energy.

### III. FEATURE VECTOR EXTRACTION

The action of the UV sensor is to convert the spasmodic light energy into an electrical signal. The sensor's response is a continuous signal going through positive and negative peaks of varying amplitude and frequency; hence, the signal is both amplitude and frequency modulated. The rise and fall times of the UV sensor is within nanoseconds; consequently, its response to the plasma is almost instantaneous, leaving no trailing effect. Therefore, the resulting signal is a true representation of dynamic behavior of the plasma. For this study spectral density distribution is chosen as feature vector. Spectrum density distributions for classifying the types of weld defects are calculated in DSP unit. These are sent to the input layers of the MLP. Fig. 1 to Fig. 3 shows spectral distribution for each collection of data after the FFT algorithm is applied. As shown in these figures they have different spectral density distribution characteristics. The overall procedure from feature extraction to defects classification is shown in Fig. 4

### IV. PLASMA DETECTION AND SIGNAL PROCESSING

The overall system is shown in Fig.4. The plasma from the welded parts is detected using the UV sensor.

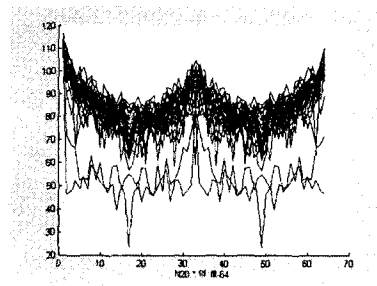


Fig.1. Frequency response characteristics showing a good weld

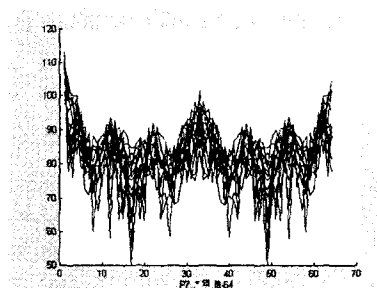


Fig.2. Frequency response characteristics showing incomplete penetration weld

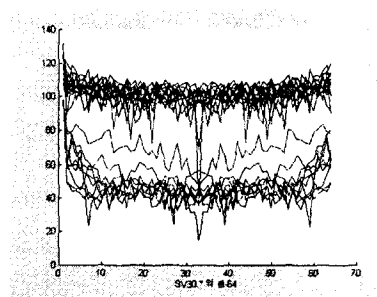


Fig. 3. Frequency response characteristics for void weld

The UV sensor is a B1961 ultra violet sensor made by HAMAMATSU with an operating wavelength range between 190 and 550 nm. The beam from the plasma to the UV sensor is focused using a lens as shown. The output of the UV sensor an electrical signal, is amplified and filtered with a 4-kHz low-pass filter. To extract the feature vector, the signal from the amplifier is passed through an analog-to-digital

converter on a DSP unit which in turn converts the incoming analog signal into a series of digital pulses. These digitized pulses are then calculated into spectral information through a fast Fourier transformation before they are transferred to a computer. In Fig. 5 the layout of data acquisition and DSP unit is shown. The transfer of data from the DSP unit to the computer is done at every 2048 of points data (about 200 ms.) The trigger source to this circuit is provided externally by the laser control system. This pulse, a negative going with transition from 5 to 0 V, is used as the input to the DSP unit

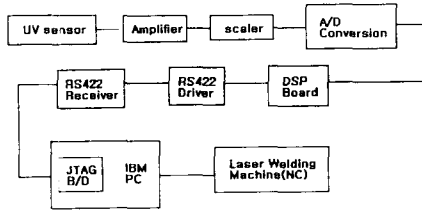


Fig. 4. Overall system

A pair of IEEE 422 line drivers are used in the transmission of this signal. During the time the weld signal is being generated, the analog-to-digital converter is enabled. The result is a series of digital pulses corresponding to the area of the signal envelope. These pulses are fed to the DSP core to calculate spectral information before it is transferred to the computer.

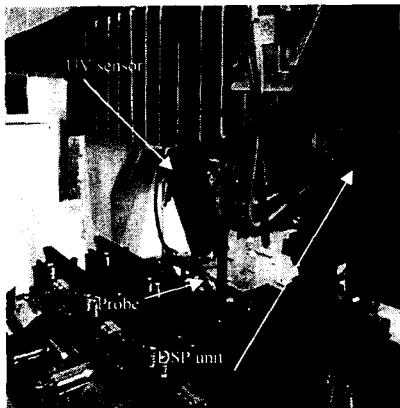


Fig. 5. Data acquisition part and DSP unit

### V. CLASSIFICATION USING NEURAL NETWORKS

Here we briefly introduce the type of neural network used in the present application to classify defect types from the spectral density distribution calculated in DSP unit. In this application the neural net is used as a classifier of suitable features extracted by classical methods. In this study the most widely used artificial neural network, the multi layer perceptron (MLP) is chosen. For example one neuron may be allocated to turn on for an incomplete penetration defect while another is activated when an void defect is presented as an input. The Error-back-propagation learning algorithm is used to adjust each weight in a direction guaranteed to reduce the overall error. Proper structure of MLP has 65 neurons for the input layer, 50 neuron for the hidden layer and 3 neurons in the output layer.

### VI. EXPERIMENTS

On line welding defects monitoring process is shown in fig. 6. Top window stands for laid materials for welding. The classified results displayed on left bottom window in text.

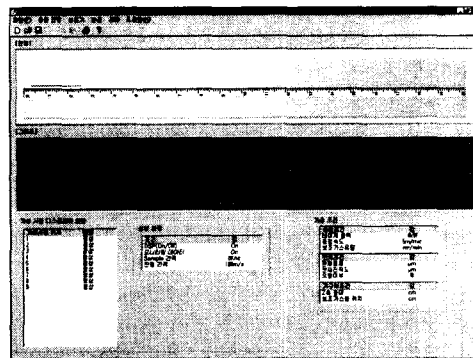


Fig.6 Main screen of monitoring system.

we prepared user also other classifiers like Fuzzy and probabilistic classifier to choose better one. The user interface mode to choose classifier is shown in Fig. 7

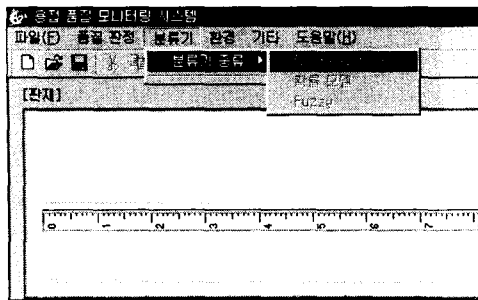


Fig.7 Classifier select mode.

We also examined the performance of the different numbers of hidden neurons on the real feature space data obtained as described above. Many of the classification methods contained parameters which could be varied to obtain an optimum classification, and methods such as the Fuzzy classification algorithm performed well at some part. The MLP method was generally good over the whole range. In Fig. 9 success rates in a varying number of hidden neurons is shown. As it appears in Fig. 8, the success rates with 50 hidden neurons is better than that of 20 and 30. The laser welding process for this study is shown in Fig. 8.

### VII. CONCLUSIONS

Neural networks classifiers have been applied to the problem of detecting, incomplete penetration and bubble defect from plasma data. Success rates of over 90% have been obtained from it. A MLP can describe the arbitrary boundaries between the clusters in feature space.

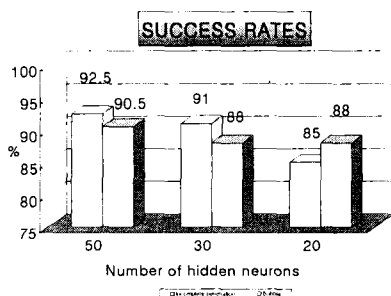


Fig. 8. Laser welding process

A clear potential advantage of neural network methods in general is their speed in carrying out classification. This is a significant advantage in on-line weld defects classification. An MLP approach must be tuned in to a number of layers and number of neurons in each layer. Trial-and-error methods were chosen to find the most accurate model for this study.

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