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Classification of Welding Defects Using Gray Level Histogram Techniques via Neural Network

تصنيف عيوب اللحام باستخدام تقنيات المنحنى التكراري للدرجات الرمادية في الصور عبر الشبكات العصبية

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الخلاصة

صاحب التطور التكنولوجي الاحتياج للحصول على لحام ذو جودة عالية. فالصناعات الهامة مثل الصناعة النفطية و السيارات و الطيران و غيرها من الصناعات الهامة تعتمد على عمليات لحام نثق بها، فأي انهيار ينتج عن لحام غير سليم قد يعني خسارة كبيرة في الأرواح و الأموال. يهدف هذا البحث إلى تقديم نظام آلي للكشف عن عيوب اللحام والتعرف عليها وتصنيفها بالاعتماد على تطبيق تقنية المنحنى التكراري لدرجات الصور الرمادية. ويتم ذلك من خلال مرحلتين أساسيتين. في المرحلة الأولى، تم تطبيق تقنيات معالجة الصور، بما في ذلك من تحويل الصور الملونة إلى درجات الرمادي، وتنقية (فلترة) الصورة، وكذلك تغيير حجمها لتهيئة صور اللحام المصورة بالأشعة السينية. أما في المرحلة الثانية، فقد تم بناء برنامج حاسب آلي بالاعتماد على برنامج (Matlab) يعتمد على الشبكات العصبية الاصطناعية يهدف إلى الكشف عن عيوب اللحام و تحديدها. ويمكن لهذا النظام الآلي المقترح أن يكشف و يصنف ستة أنواع من عيوب اللحام الأشهر من خلال الممارسة العملية و هي ***المسام- القطع أسفل الحافة – نقص الانصهار – التشقق – الشوائب - الفجوات***، بالإضافة إلى تصنيف حالة عدم وجود عيب. وقد اتضح من النتائج أنه يمكن أن يعول على هذه الطريقة، حيث وصلت نسب تعيين العيوب وكذلك حالة عدم وجود عيب إلى حوالي 94.3%.

Abstract

Technological development accompanied the need to get a high-quality welding. The important industries such as oil and auto industries and other important industries need to rely on reliable welding operations; collapse as a result of this welding may mean a great loss in lives and money. This paper aimed to produce an automatic system to detect, recognize and classify welding cases (defects and no defects) in radiography images was described depending upon image histogram technique. Two main steps to do that, In the first step, image processing techniques, including converting color images to gray scale, filtering image, and resizing were implemented to help in the image array of weld images and the detection of weld defects. The second step, a proposed program was build in-house depending upon Matlab to classify and recognize automatically six types of weld defects met in practice, it is ***Porosity – Undercut – Lac of fusion – Crack – Slag –Cavity***, plus the non-defect type. It was clear from the results that it can rely on this method significantly, reaching rates as well as the appointment of defects and no defects to about 94.3%.

Key words

Welding defects - Neural network - Computer vision - X-ray - Image histogram

1 Introduction

Quality control of manufactured products has become one of the main objectives of production processes. Inspection of welded structures is essential to ensure that the quality of welds meets the requirements of the design and operation, thus to assure safety and reliability. Although it is one of the oldest techniques of non-destructive inspection, radiography is still accepted as essential for the control of welded joints in many industries such as the petroleum, nuclear, naval, chemical, and aeronautical.

It is particularly important for critical applications, where weld failure can be catastrophic, such as in pressure vessels, load-bearing structural members, and power plants [1].

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The reliable detection of defects is one of the most important tasks in nondestructive tests, mainly in the radiographic test, since the human factor still has a decisive influence on the evaluation of defects in the film. Radiographic inspection is a well-established testing and quality control method to detect weld defects [2].

Flaws resulted from welding operations are detrimental to the integrity of the fabricated artifacts/structures. Commonly seen weld flaws include lack of fusion, lack of penetration, gas holes, porosities, cracks, inclusions, etc. Of course, some flaw types might appear more often than others for a particular welding process. To maintain the desirable level of structural integrity, welds must be inspected according to the established standard. The results of weld inspection also provide useful information for identifying the potential problems in the fabrication process, which are necessary for improving the welding operations. In the current industrial practice, weld inspection is often carried out by certified inspectors; Previous studies shows that the capability of improving inspection systems depending on computer-aids through radiographic images to improve the objectivity and productivity of weld inspection operations [3].

2 Classification of welding defects

The method of welding defect classification could be including feature extraction [1-8], thermal image analysis and ultrasonic inspection [9-11], and image histogram [12-16].

2.1 Feature extraction

An automatic detection system to recognize welding defects in radiographic images was described by Vilar et al. [4]. They aimed to analyze ANN modifying the performance function for different neurons in the input and hidden layer in order to obtain a better performance on the classification stage.

In addition, an automatic system was described by Zapata et al. [1, 2], to detect, recognize, and classify welding defects in radiographic images and to evaluate the performance for two neuro-classifiers based on an artificial neural network (ANN) and an adaptive-network-based fuzzy inference system (ANFIS). An expert vision system for automatic inspection is introduced by Shafeek et al. [5-6], to detect and to assess the welding defects of gas pipelines from the radiographic images. This system has many advantages such as enhancing the captured images and eliminating the loss of image details, so this system is considered very effective where it helps in appearing the defects more clearly.

An automatic control and inspection of welding defects is introduced by Yahia et al. [7], using edge detection method of radiographic images, based essentially on the use of a multilayer perceptron, aiming to classify and to increase the successful recognition default percentage. A new approach for feature extraction from radiography images acquired with gamma rays was proposed by Kasban et al. [8], in order to detect weld defects. Neural networks are used for feature matching in the proposed approach. The experimental results show that the proposed approach can be used in a reliable way for automatic defect detection from radiography images in the presence of noise and blurring.

2.2 Thermal image and ultrasonic inspection

Due to the high frame rates and temperature resolution of currently available infrared cameras, Sreedhar et al. [9] believed that infrared thermo-graphy can be a practical weld-monitoring option capable of providing reliable assessment comparable to more elaborate off-line assessment. An infrared video sequences from the cooling step of the pipeline welding procedure were collected by Kafieh et al. [10]. In addition, Fortunko [11] described an ultrasonic inspection technique for detecting elongated defects in butt-weldments. The technique is used to detect an incomplete fusion defect with a through-wall depth of 0.5 mm and to monitor crack growth in the heat affected zone under tension-tension fatigue loading.

2.3 Image Histogram

A feature selection methodology is proposed by Garcia-Allende et al. [12], to solve the uncertainty regarding the selection of the optimum spectral band, which allows the employment of the line-to-continuum method for on-line welding diagnostics.

Field test results have been conducted to demonstrate the feasibility of the solution. Daillant et al. [13], proposed a complete acquisition and processing line of weld radiographies, from which must be highlighted cavity shaped defects. They presented a study of three trend removal methods allowing improving the signal/noise ratio of the edges pictures. The segmentation is derived from the edges picture by the mean of a constrained watershed algorithm. A new approach that allows automatic weld defect detection and classification based in the combined use of principal component analysis and an artificial neural network is proposed by Mirapeix et al. [14]. Arc-weld tests on stainless steel were reported, showing a good correlation between the ANN outputs and the classical interpretation of the electronic temperature profile. Therefore and due to the problems associated with manual detection, this work aims to classify automatically welding defects using image histogram method via neural network.

3Theoretical background

This work depends on theoretical background to enhance the practical part of it, which consists of welding and its defects, computer vision and its related process, pre-processing for image, and artificial neural network.

3.1 Welding and welding defects

Industries, such as power plants, oil refineries, chemical plants, food processing plants depends on networks of pipe-lines. Today, most pipes are joined by welding, but this was not always true, for until about 35 years ago pipe was joined by screw threads or by bolted flanged joints. Welding now considered the best method for connecting pipe, is used even in the most demanding high-pressure and high-temperature service.

Only high quality pipe welds are acceptable in modern industry; for the failure of a pipe weld not only can disrupt the operation of a plant, it can be the cause of a serious accident with the possible loss of life and property [15]. Arc welding is a welding process in which the heat is generated by an electric arc between an electrode and the work. In DC welding, the work is generally the positive pole with the electrode the negative pole, but reverse polarity may be used in which the work is the negative pole and the electrode is the positive pole. Welding pipelines is important process to join pipelines and its accessories, defects due to welding could occur and needs for methods to test welding process is a must to achieve quality control and quality assurance. The advantages of this process are:

a) most efficient way to join metals;
b) lowest-cost joining method;
c) affords lighter weight through better utilization of materials;
d) joins all commercial metals;
e) Provides design flexibility.

Welding discontinuities may be divided into three board classifications: Design related, welding process related and metallurgical related. Include problems with design or structural details, choice of the wrong type of weld joint for a given application, or undesirable changes in cross section.

Defects due to process itself are: undercut, slag inclusions, overlap, and porosity, tungsten inclusions, backing peace left on shrinkage voids, oxide inclusions, lack of penetration, craters, melt-through, spatter, arc strikes, under fill, and lack of fusion [16].

3.2 Computer vision and image process

Developments in image processing, computer vision, artificial intelligence and other related fields have significantly improved the capability of visual inspection techniques.

It was reported that about 60–90% of all existing machine vision applications were classified as automated visual inspection [6].

Images are stored in computers as a 2-dimensional array of numbers. The numbers can correspond to different information such as color or gray scale intensity, luminance, chrominance, and so on. Before we can process an image on the computer, we need the image in digital form.

Chakrabarti et al. [17] developed a sophisticated 24-parameter model that is an even better match to the processing performed in today's cameras. Image processing is the first stage in most computer vision applications, namely the use of image processing to preprocess the image and convert it into a form suitable for further analysis.

The aim of industrial machine vision systems is to replace human inspectors for visual inspection processes. High resolution cameras, advancement in computer hardware and high-performance software algorithms fuel the application of machine vision in many fields. Based on the application of machine vision systems, they are grouped into three groups: measurement, guidance and inspection. Inspection systems determine whether an object or a scene matches a preset description.

3.3 Image pre-processing

3.3.1 Median filtering (Noise reduction)

Digital image processing techniques are employed to lessen the noise effects and to improve the contrast, so that the principal objects in the image can be more apparent than the background. The gray level values of the noise pixels are much higher than those of their immediate neighbors. As noise is characterized as high frequency values, low-pass filtering methods, like a median filter, can be used to effectively remove the noise pixels. Median filter is a spatial filtering operator; it uses a 2D mask applied to each pixel in the input image.

The median filtering allows mainly the attenuation/elimination of noise. Indeed the acquired images should pass through a stage of image filtering in order to remove distracting and useless information [8]. The application of a low-pass filter is used to remove noise in radiographic images. The median filter is a nonlinear filter used to remove the impulsive noise from an image [9-11]. This filter performs better than the major averaging filters because it can remove noise from inputting images with a minimum amount of blurring effect.

3.3.1 Contrast enhancement

Radiographic images usually have poor contrast and a lack of detail. The target of the contrast enhancement is to improve the radiographic images quality by highlighting the useful information while leaving the unimportant information intact. In the original radiographic image, the distribution of gray levels is highly skewed towards the darker side. Defects in these areas can hardly be recognized; therefore, it is desirable to stretch the histogram distribution to an evenly distributed one, like a rectangular shape instead of a skewed shape. The histogram equalization algorithm proportionally modifies the original gray level values to the range of 0 and 255.

3.3.2 Image histogram

Histogram is a graph showing the number of pixels in an image at each different intensity value found in that image, as shown in Fig.1.For an 8-bit gray scale image, there are 256 intensity values are possible. The intensity histogram features are first order statistics. The histogram is plotted from the image and from the histogram a four features are extracted that can discriminate between different classes of x-ray images. Four features such smoothness, uniformity, third moment and entropy is calculated using intensity histogram graph. The histogram graph is constructed by counting the number of pixels at each intensity value [19].

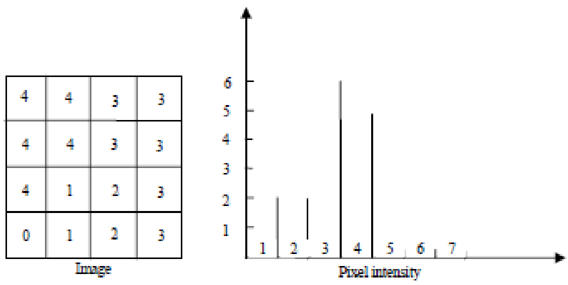


Fig. 1. Sample image with histogram.

3.4 Artificial Neural Network (ANN)

A neural network is an interconnected assembly of simple processing elements, units or nodes, whose functionality is loosely based on the animal neuron. The processing ability of the network is stored in the inter-unit connection strengths, or weights, obtained by a process of adaptation to, or learning from, a set of training patterns. Recently, there has been an increased interest on the neural researches; in the next some of those researches as an example for detecting welding defect by using neural network.

ANNs are machine learning programs based on neuron like building blocks similar to the neurons in the human brain. Most of the research and applications of neural networks involves feed-forward networks trained by the back-propagation algorithm. These ANNs usually undergo a training phase by feeding it a set of inputs with known outcome, and then back-propagating the known results to adjust the weights among the neural elements. After many iterations of training, called epochs, the NN is able to detect subtle patterns in large data sets and make predictions based on what it has learned through past observations [18]. Feed forward neural network architecture was selected based on the flexibility and applicability of the approach in a variety of problems [20]. The network shown in Fig.2 can be described as follows:

Back-propagation: The back-propagation (gradient descent) algorithm and the more sophisticated variants described, are used for training.

Multilayer: The neurons are arranged in layers, with input, hidden and output layers.

Perceptrons: The neurons each have a transfer function, either hard limit, linear, sigmoid or tanh.

Supervised: The networks are trained with an example set of galaxies classified by humans.

Feed forward: The training has no effect on the input parameters, just the weights and biases.

Static: There is no time dependence in the network.

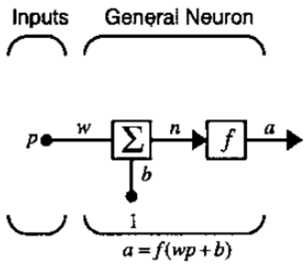


Fig. 2. Network procedure.

Where: p is an input, weight ($w = w_p$) and b is the bias (offset). Iit's like a weight except that it have a constant input of 1. A neuron may have or may not have a bias. Summer output (*n*) (net input), transfer function (activation function) (*f*) is chosen by the designer, neuron output (*a*), and w and b are adjustable scalar parameters of the neuron (by a learning rule).

4 Experimental methodology

The quality of radiographic images is related to the technique employed, as well as of the inspected material, as well as the choice of a standard filter for noise elimination. Film digitizing is a critical part of the weld recognition system. Hence, selecting optimized resolution of scanning and acceptable quality of digitizing plays an important role in whole system performance.

The radiographic films can be digitized by several systems according to ASME V [10]. The more common way of digitization is through scanners, which works with light transmission – usually called transparency adapters. Another method also used is image acquisition by camera CCD (Charge Couple Device).

In this case, the film is placed in a light box and the camera captures the digital image and transmits it for a computer.

The system which described in this research is an inspection system for welding defects. The main elements of machine vision system are as follows:

a) image acquisition system,
b) lighting system, and
c) Data processing system, as shown in

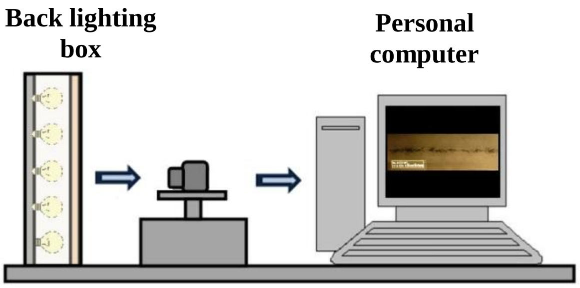


Fig.3

Fig. 3 welding defect's capturing system.

In this work, a digital camera (Panasonic DMC-LS70) is fixed in the tripod and positioned to view normal to a back lighting box. The samples were placed in front of the camera keeping the relative position and zoom level unchanged.

In order to improve the reliability in the results, radiographs from IIW (International Institute of Welding) were used in a total of 38films. These patterns have indications of the most frequent classes of defects in welded joints, such as cavity, undercut, porosity, lack of fusion, slag, crack, and no-defect.

Thirty eight images with resolution 3072 × 2304 and file size 2.96 MB in JPG format were captured. The used lighting method is background lighting.

Desktop computer with Intel Core2 Duo processor and 4 GB RAM was used for processing the data. Coding and processing were carried out in MATLAB R2012b software.

4.1 Preprocessing of the images

After digitization of the films, it is very common to use a preprocessing stage, seeking mainly the attenuation/elimination of noise and contrast improvement.

The application of low pass filters is the more frequently used tool to remove noise in a radiographic image [21, 22].

4.2 Histogram Features

Observing the magnitude of the pixel values, it is found that the range of intensity varies from class to class. A better graph to show the range of variation is the histogram plot. The information derived from a histogram plot can be used as features for visual inspection.

A representative samples (images for each case) was taken, and the corresponding histogram was plotted.

Table 1 shows the output of produced program for 7 samples of welding defects and their images with their histograms.

4.3 Procedures of the work

Collection of radiograph weld defect patterns from IIW (International Institute of Welding) each contains one or more welding defects were used in this work. The following procedures, as shown in Fig.4, were applied as mentioned in the following points.

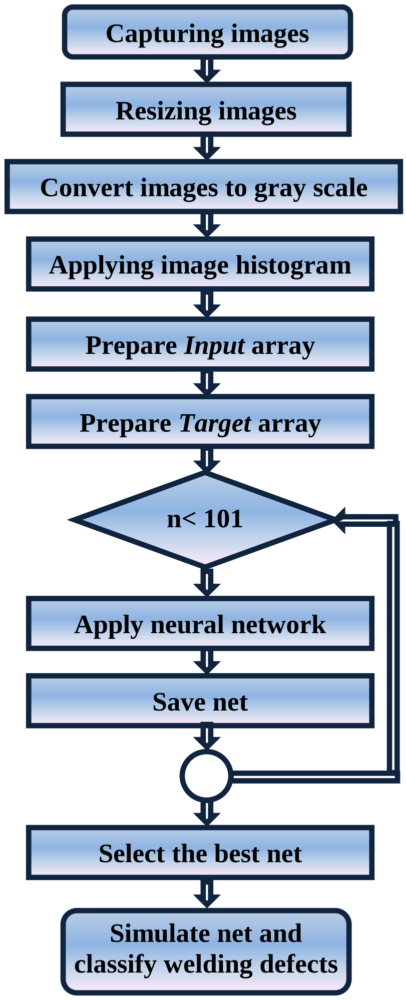
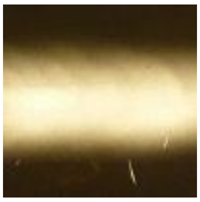
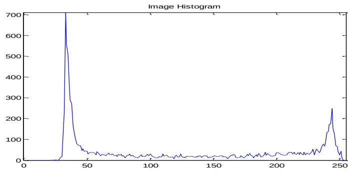
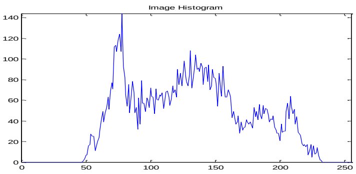
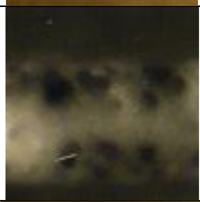
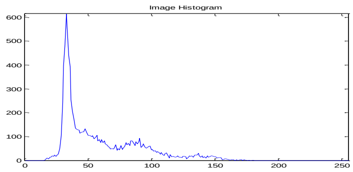
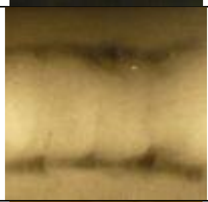
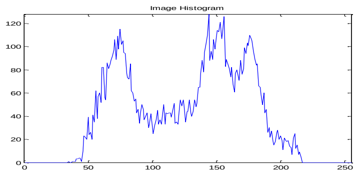
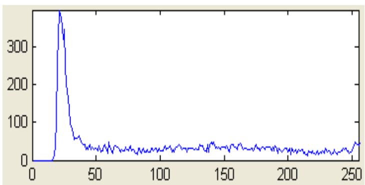
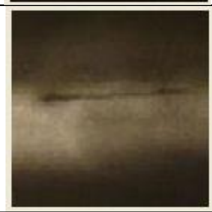
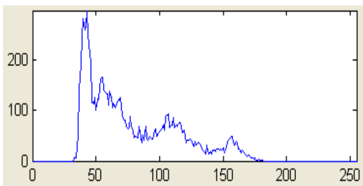


Fig. 4. Block diagram of the procedure.

Table 1: x-ray images of welding defects and no defects.

No.	Defect type	Image number	Image	Histogram
1	No defect	T0037		
2	Lack of fusion	T0067		
3	Porosity	T0129		
4	Undercut	T0215		
5	Cavity	T0242		
6	Slag	T0195		
7	Crack	T0010		

1.Thirty eight radiographic films represent seven cases of welding defects were collected in order to apply the proposed method of welding defect classification.
2. Radiographic films were holding on a backlighting then an image was acquired by a digital camera and saved to a file.
3. All radiographic images were cropped and resized using a commercial program from the captured image to form a total of 222 images. These images were classified to seven cases as mentioned before.
4. In order to evaluate the effect of image resolution, these images were resized to be 100×100 pixels, 70×70 pixels, and the 50×50 pixels.
5. These images were loaded by software written specially for that work using Matlab package, to convert the colored images to gray scale image, and then filtered by a suitable method (Median filter).
6. Image histogram was performed for each image using Matlab image processing toolbox and stored in an array called *input* array.
7. Target array was created so as each case was represented in one row. For example, case one 'Crack' is defined as: [1 0 0 0 0 0 0] and in case of two defects as case one and case four the array is defined as: [1 0 0 1 0 0 0]. The output dataset is an array of 222×7 (222 image × 7 cases) as follows:

$$T = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

8. A feed forward neural network with error back propagation algorithm was adopted for the neural network system as in Fig.5. Here it is used to classify welding defects through captured images.

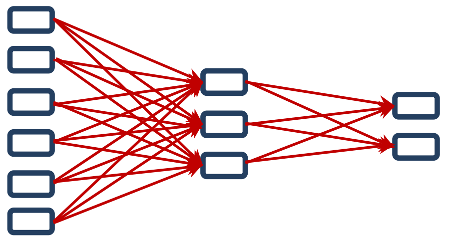


Fig. 5. Neural Network Architecture.

9.Input/output datasets were used to train the network. A procedure was employed to optimize the hidden layer neurons and select the transfer function for which a program was generated in Matlab package.
10.About 100 training process were performed and the best net was extracted and saved for later use. The best net elected as the results of its output have the heist percentage value of successful prediction.
11. A program was built especially for the classification of welding defects named Welding Defects Inspection using Neural Network Program "*WDINProg*". This program was built using Matlab Software Packages. Fig. 6 shows the main interface of the program.

The Matlab Neural Network Toolbox is one example of such a toolset, and it is available in a standard form to all. High performance computers would enable more runs and shorter training times. Feed-forward artificial neural networks allow signals to travel one way only – from input to output. There is no feedback (looping), i.e. the output of any layer does not affect the same or earlier layers. Feed-forward artificial neural networks tend to be straightforward networks that associate inputs with outputs.
Figure 6 shows the graphical user interface of the *WDINProg* that used for detecting welding defects using image histogram method. The *Input Net Name* section (a) represents a drop-down selection of all available pre-created nets. In section (b), the user can load an x-ray image to estimate the defects (if exists), then showing the results as illustrated. Section (c) shows a brief information about image histogram,

whereas, section (d) shows the current image information (Name and size). The user can only load any image (e) to display the selected image as original, gray-scale and enhanced forms (f). Therefore, image histogram was calculated and plotted in section (g).

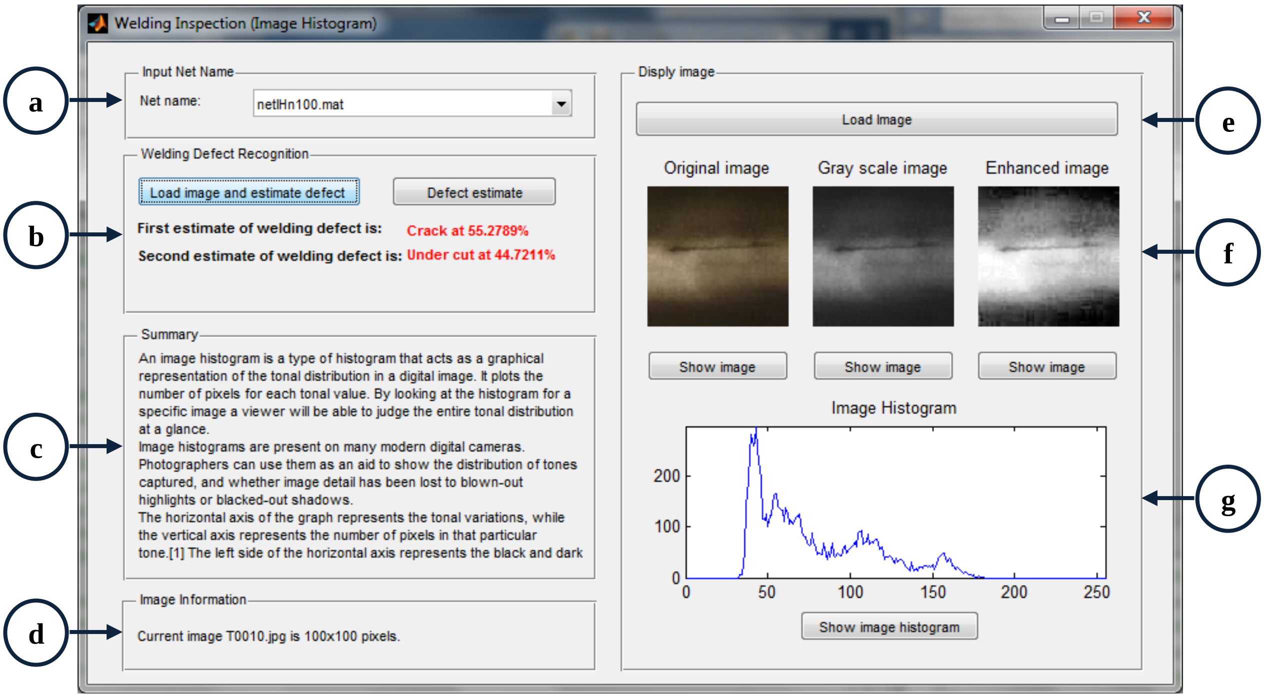


Fig. 6. Detection of weld defects by *WDINProg.*

5 Results and Discussion

In the present work, six parameters are defined for discrimination of six classes of defects: lack of fusion (LF), porosity (PO), undercut (UC), cavity (CA), slag (SL) and crack (CR). The amount of used data was composed by 33 of cavity, 36 of undercut observations, 15 of porosity, 50 of lack of fusion, 23 of slag and 26 of crack, in addition to 39 images with no defect which it is the seven classes.

Figure7shows the relationship between the percentages of the program's succession the detection of defects (cavity). It is clear that the lack of percentages when determining only one defect(cavity), which ranges from 69.7% to 87.9%, depending on the size of the image (50×50, 70×70, 100×100) pixels. In the case of the detecting more than one defect (provided that cavity is one of them), the percentage is raised and ranged between 90.9% and 100%. This improvement is due to two different algorithms that used in the programs. The first one depends on the detecting only one defect, regardless if there are more than one defect or not.

The second algorithm detects more than one defect (Defined a maximum of three defects), sorting them in descending order according to the expected degree of presence of these defects. This is due to some of the images that do not contain only one defect, but can be contain more than one type of welding defects.

As mentioned before, the program depends on the classification upon algorithms for possible defects and arranged in descending order according to the expected ratios of the impact of disadvantage, and thus may be a defect under study (here cavity) comes in the order of second or third of the total defects in the image. For this reason, it is found the low success percentage when studying only one defect than studying more than one defect.

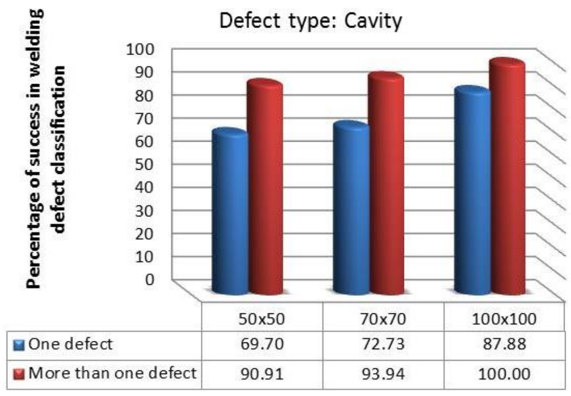


Fig. 7. Percentage of success in cavity welding defect classification.

Similarly, Fig. 8 shows the success percentage in detecting porosity defects. In case of detecting only one defect ranges from 73.3% to 86.7% and the detection of more than one defect ranges between 93.3% and 100% depending on the size of the image.

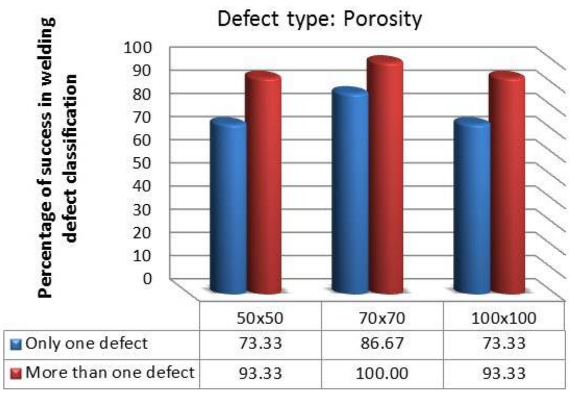


Fig.8. Percentage of success in porosity welding defect classification.

Figure 9 shows the success percentage in detecting undercut defects. In case of detecting only one defect ranges from 77.78% to 80.56 % and the detection of more than one defect ranges between 91.67% and 97.22% depending on the size of the image.

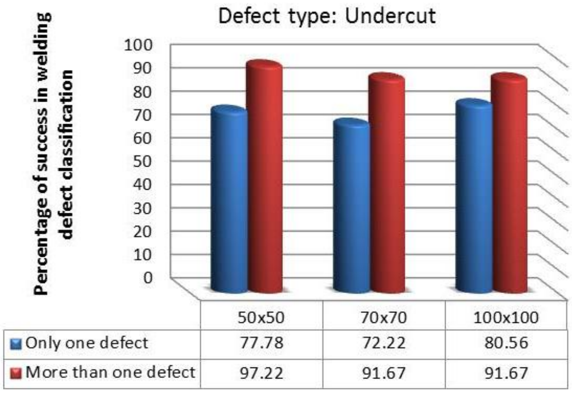


Fig.9. Percentage of success in undercut welding defect classification.

Similarly, Fig. 10 shows the success percentage in detecting lack of fusion defects. In case of detecting only one defect ranges from 62% to 80% and the detection of more than one defect ranges between 88% and 90% depending on the size of the image.

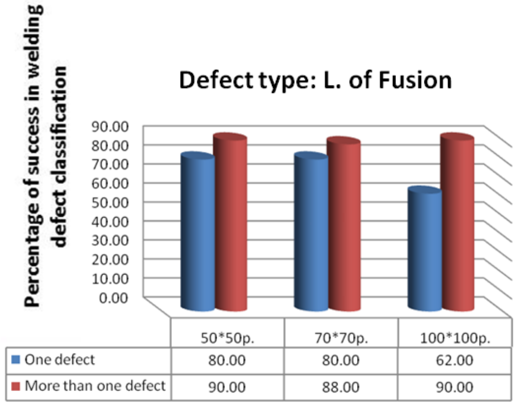


Fig. 10. Percentage of success in L. of Fusion welding defect classification.

Figure 11 shows the success percentage in detecting slag defects. In case of detecting only one defect ranges from 52.17%to 91.3% and the detection of more than one defect reached 95.65% depending on the size of the image.

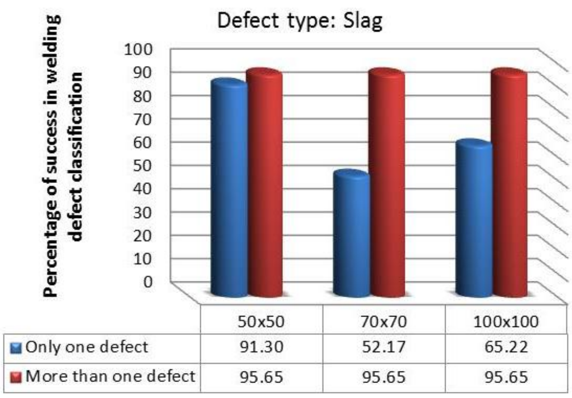


Fig.11. Percentage of success in slag welding defect classification.

Similarly, Fig.12 shows the success percentage in detecting crack defects. In case of detecting only one defect ranges from 38.46% to 57.69% and the detection of than one defect ranges between 96.15% and 100% depending on the size of the image.

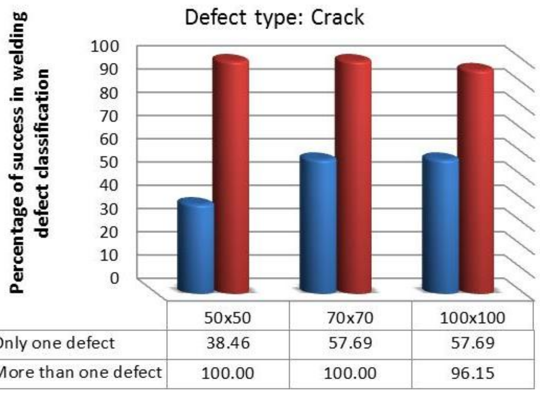


Fig.12. Percentage of success in crack welding defect classification.

Figure13shows the success percentage in detecting no defects. In case of using algorithm that depends on detecting only one defect, it ranges from 89.74% to 94.87% and the detection of more than one defect ranges between 94.87% and 100% depending on the size of the image.

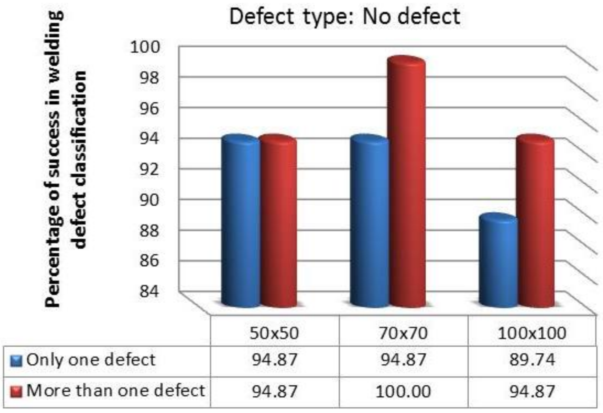


Fig.13. Percentage of success in welding no defect classification.

The results have been studied, as illustrated in Table 2, by calculating mean valuesfor the percentages of success in the detect of six defects and no defect for both methods (one defect and more than one defect) were calculated standard deviation in each case, depending on the size of the image and the previously mentioned and is (50×50, 70×70,100×100) pixels. For example, in the case of cavity defects found that the success percentagewere76.8% and its standard deviation of 9.7in the case of the detect of only one defect. In the case of the detecting of more than one defect the success percentage were 95% and its standard deviation of 4.6. In the end of this study, it Were calculated overall average success percentages in detecting all cases and the success percentage was 75.4% and its standard deviation ±1.1 in order to discover the one defect. In the case of the discovery of more than one defect success percentage has risen to 94.3% and its standard deviation ± 0.3.

Table 2: the average and the standard deviation for each case.

Defect type	One defect	More than one defect
Cavity	76.8±9.7	94.9±4.6
Undercut	76.9±4.2	93.5±3.2
Porosity	77.8±7.7	95.6±3.8
Lack of fusion	74.0±10.4	89.3±1.2
Slag	69.6±19.9	95.7±0.0
Crack	51.3±11.1	98.7±2.2
No defect	93.2±3.0	96.6±3.0
Total	75.4±1.1	94.3±0.3

Conclusion

From the previous work outcomes appears and summarizing in the following.

Design and build a program to detect and to classify the welding defects based on x-ray images and relying on artificial neural net works and image analysis processes, and depends on the design and program of two ways: (a) depends on the discovery of a defect, and only one in the image, (b) the discovery of more than flawing in the image, and have found the following:

1. The effect of varying the size of the image on the degree of success of defects for all cases, and has turned out that the detection of defects does not depend on the size of the image.
2. It has turned out that the average college success percentages when detected on only one defect was 75.4 % ± 1.1.
3. As it turns out that the average college success percentages when detected at more than one defect was 94.3% ± 0.3.

4. Led the development of the program for detects of more than one defect to a significant increase in the percentages of detection of different cases

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