Chapter 1

Introduction

1.1 Preamble

Digital image processing is an area characterized by the need for extensive experimental work to establish the viability of proposed solutions to a given problem (Gonzalez and woods, 2010). Interest in digital image processing methods stems from two principal application areas: improvement of pictorial information for human interpretation; and processing of image data for storage, transmission and representation for autonomous machine perception (Gonzalez and Woods, 2002).

The progress in computer science and the artificial intelligence techniques have allowed the defect detection and classification to be carried out by using digital image processing and pattern recognition tools (Mekhalfa et al., 2007).

Interest in digital image processing methods stems from two principal application areas. The first application is improvement of pictorial information for human interpretation and the second application is processing of image data for storage, transmission and representation for autonomous machine perception. One of the first applications of digital images was in the newspaper industry, when pictures were first sent by submarine cable between London and New York. Introduction of the Bartlane cable picture transmission system in the early 1920s reduced the time required to transport a picture across the Atlantic from more than a week to less than three hours. Specialized printing equipment coded pictures for cable transmission and then reconstructed them at the receiving end (Gonzalez and woods, 2010).
Today, there is almost no area of technical endeavor that is not impacted in some way or other by digital image processing.

- Industry: inspection/sorting, manufacturing (robot vision)
- Environment: strategic surveillance (hydro-dams, forests, forest fires, mine galleries) by surveillance cameras, autonomous robots
- Medicine: medical imaging (ultrasound, MRI, CT, visible)
- Culture: digital libraries, cultural heritage preservation (storage, restoration, analysis, indexing)
- Television: broadcasting, video editing, efficient storage
- Education & tourism: multi-modal, intelligent human-computer interfaces, with emotion recognition components
- Security/authentication (face and iris recognition, signature verification)

The radiography is a reliable and tested method of nondestructive diagnostics and has evolved during past 100 years from the moment of the discovery of mysterious rays by Wilhelm Konrad Roentgen in 1895 and is close to perfection today. These rays are called Roentgen rays or X-rays. This method has broad applications in medical and industrial imaging. Experts are able to identify most types of defects in the images produced by this method. The method is based on the fact that the defective areas absorb more energy and thus the defects appear darker in the image (Hayes, 1997).

Applications of radiography images include medical radiography and industrial radiography. If the object being examined is living, whether human or animal, it is regarded as medical all other radiography is regarded as industrial radiographic work.

Medical radiography is used in many types of examinations and procedures where a record of a static image is desired. Some examples include: Dental examination, Verification of correct placement of surgical markers prior to invasive procedures, Mammography, Orthopedic evaluations, Spot film or static recording during fluoroscopy, Chiropractic examinations and etc.
Industrial radiography is used commonly in the following applications: gas and oil pipelines, boilers, pressure vessels in chemical plants, vehicles, aircraft, metal production and etc.

Meanwhile, in recent years an active trend for transition from upgrading of the traditional radiographic systems to the development of the digital radiographic systems is more common. This development is due to a series of technical, economical and ergonomic (related to the working process) reasons. Over the last 40 years, there has been a large amount of research attempting to develop an automatic (or semiautomatic) system for the detection and classification of weld defects examined by radiography.

The first experiments to detect weld defects using X-rays took place at the laboratory scale at Yale University in 1896, barely one year after the discovery of X-rays. However, it was in 1927 that the first industrial X-ray equipment was developed to carry out these inspection tests on a larger scale. After getting the radiographs, the inspection is done by visual interpretation of the X-ray images, which show radiation energy attenuation as it goes through the object that is being studied. Inspection by X-rays became so important that in 1931, the American Society of Mechanical Engineering (ASME) accepted its use for weld quality control in steam boilers (ASME, 2007). Then, during the Second World War, it was used extensively for the inspection of ships, submarines and airplanes. It is estimated that in 1950s in Western Germany about 50% of all welds in steel constructions were inspected using X-rays. Even though it is true that in the 1960s there was clarity in relation to quality control programs for welds, it was only in 1975 that a weld radiograph was digitized for the first time and that meant the beginning of automatic visual inspection of welds based on digital image processing techniques (Da Silva and Mery, 2007).

Welding is the most efficient way to join metals. It is also the only way to join two or more pieces of metal to make them act as one piece. Welding is widely used to manufacture or repair all products made of metal. Welds are encountered in many
structures such as gas and oil transmission pipelines, nuclear power reactors, aircrafts, automobiles and ships.

Weld defects are produced by material stress, fatigue and environmental changes as well as the manufacturing process.

Nowadays, industrial radiography of welds is widely used for the detection of defects in the petroleum, chemical, nuclear, naval, aeronautics, civil construction industries, etc. It is well known to those involved with welding that a high degree of reliability or joint integrity does not come easily. Indeed defects can, and do, occur in welded joints.

Radiographic testing usually requires exposing film to X-ray or gamma rays that have penetrated a specimen, processing the exposed film and interpreting the resultant radiograph. There are many variables in these procedures and successful completion of any test is dependent upon understanding and control of the variables. There are basically two large types of research areas in this field: Image processing, which consists in improving the quality of radiographic images and segmenting regions of interest in the images and Pattern recognition, which aims at detecting and classifying the defects segmented in the images. Because of the complexity of the problem of detecting weld defects, a large number of techniques have been investigated in these areas.

In this thesis, we explore Two Dimensional Left Median Filter (2DLMF) method for the reduction of noise and we compare the performance of 2DLMF with some other standard methods. We propose a method for segmentation of weld defects and compare the performance of this method with region growing. Finally, we focus on welding defects detection using developed classification technique applied to the radiographic images of weld.

In the following sections, we present the overview and application of radiographic technique, welding, non-destructive testing (NDT). Then we explain architecture of this research and related works. Afterwards we present the current research objectives. Finally, the outline of the thesis is given.
1.2 Overview and Applications

Here we discuss in detail the radiographic image characteristics: process of welding and the use of X-rays for detect defection in welded joints.

1.2.1 Radiographic technique

X-rays and gamma rays possess the capability of penetrating materials, even those that are opaque to light. In passing through matter, some of these rays are absorbed. The amount of absorption at any point is dependent upon the thickness and density from the matter at the point; therefore, the intensity of the rays emerging from the matter varies. When this variation is detected and recorded, usually on film, a means of seeing within the material is available. Penetration and differential absorption characteristics of radiant energy can be used to examine material for internal discontinuities. Figure 1.1 illustrates the absorption characteristics of radiation as used in the radiographic process. The specimen absorbs radiation but, where it is thin or where there is a void, less absorption takes place. The latent image produced in the film as the result of the radiation passing through the specimen becomes a shadow picture of the specimen when the film is processed. Since more radiation passes through the specimen in the thin and void areas, the corresponding areas of the film are darker (NASA, 1983).

The penetration and absorption capabilities of X and gamma radiation, in the process of radiography is used to test a variety of non-metallic products and metallic products such as welds, castings, forgings, and fabrications. Since it is capable of revealing discontinuities (variations in material composition or density) in a variety of dissimilar materials, radiographic testing is one of the primary nondestructive test methods (NASA, 1983). The radiographic testing continues to be in practice today and is considered more effective in detection and classification of defects.
1.2.2 Welding

In order to understand the concept of welding, we must first define joint and weld. A joint is the junction of members or the edges of members that are to be joined or have been joined. Welds in material are produced either by heating materials to the welding temperature, with or without the application of pressure, or by applying pressure alone, again with or without the use of filler metal.

Welding is a fabrication or sculptural process that joins materials, usually metals or thermoplastics, by causing coalescence. This is often done by melting the work pieces and adding a filler material to form a pool of molten material (the weld pool) that cools to become a strong joint. Sometimes pressure is used in conjunction with heat, or by itself, to produce the weld. This is in contrast with soldering and brazing, which involve melting a lower-melting-point material between the work pieces to form a bond between them, without melting the work pieces. Several types of weld joints exist, such as butt, corner, edge, lap and tee joints are shown in Figure 1.2.
1.2.3 Welding Defects

A weld defect is a physical characteristic in the completed weld that reduces the strength and/or affects the appearance of the weld. Figure 1.3 shows five types of weld defects: external undercut (undercut), incomplete fusion, lack of penetration, tungsten inclusion and gas porosity (porosity). Tungsten inclusion defect appear bright and other types appear dark in radiographic images. Undercut, incomplete fusion and lack of penetration are linear in shape and other defects are round in shape.
External Undercut  Incomplete Fusion  Lack of Penetration

Tungsten Inclusion  Porosity

Figure 1.3: Radiographic images of weld defects
1.2.4 Non-Destructive Testing

Specimens tested by destructive test methods usually become bent, twisted, notched, chipped or broken during the testing and hence become worthless for further use. Consequently, destructive testing can test only a certain portion of the articles fabricated and it must be assumed that the remainder is equal in quality to those tested. Nondestructive testing (NDT) is a wide group of analysis techniques used in science and industry to evaluate the properties of a material, component or system without causing damage. Because NDT does not permanently alter the article being inspected, it is a highly-valuable technique that can save both money and time in product evaluation, troubleshooting and research. Common NDT methods include Radiographic, Ultrasonic, Magnetic particle, Liquid penetrant and Eddy current testing. Each method has peculiar capabilities and limitations qualifying it for specific uses. In each instance of NDT, it is necessary to analyze the test specimen and determine which test method will best obtain the desired results. In many instances, more than one method may be required (NASA, 1983). NDT is a commonly used tool in Mechanical, Electrical, Civil, System and Aeronautical Engineering and also in Medicine and Art.

1.2.4.1 Radiographic Testing (RT)

Radiographic testing or industrial radiography, is a nondestructive testing (NDT) method of inspecting materials for hidden defects (flaws) by using the ability of short wavelength electromagnetic radiation to penetrate various materials (Hellier, 2003).

Radiography is the use of X-rays to view a cross sectional area of a non-uniformly composed material. By utilizing the physical properties of the ray an image can be developed displaying clearly, areas of different density and composition. A heterogeneous beam of X-rays is produced by an X-ray generator and is projected toward an object. According to the density and composition of the different areas of the object a proportion of X-rays are absorbed by the object. The X-rays that pass through are then captured behind the object by a detector (film sensitive to X-rays or a digital detector) which gives a 2D representation of all the structures superimposed
on each other as shown in Figure 1.4. In tomography, the X-ray source and detector move to blur out structures not in the focal plane.

![Diagram showing radiation source, penetration radiation, section view of welded specimen, film, and defect image.](image)

Figure 1.4: Non-destructive testing, Radiography method

Weld defects are characterized by a local variation in material density, which manifests itself as a local intensity variation in the resulting radiographic image.

**1.2.4.2 Ultrasonic Testing (UT)**

In ultrasonic testing, very short ultrasonic pulse-waves are launched into materials to detect internal defects (flaws) or to characterize materials. The technique is also commonly used to determine the thickness of the test object, Figure 1.5. In ultrasonic testing, an ultrasound transducer connected to a diagnostic machine is passed over the object being inspected (Hellier, 2003).
There are two methods of receiving the ultrasound waveform, *reflection* and *attenuation*. In reflection (echo) mode, the transducer performs both the sending and the receiving of the pulsed waves as the "sound" is reflected back to the device. Reflected ultrasound comes from an interface, such as the back wall of the object or from a defect within the object. The diagnostic machine displays these results in the form of a signal with amplitude representing the intensity of the reflection and the distance, representing the arrival time of the reflection. In attenuation (transmission) mode, a transmitter sends ultrasound through one surface, and a separate receiver detects the amount that has reached it on another surface after traveling through the medium. Imperfections or other conditions in the space between the transmitter and receiver reduce the amount of sound transmitted, thus revealing their presence.

![Diagram](image.png)

Figure1.5: Non-destructive testing, Ultrasonic method
1.2.4.3 Magnetic Particle Inspection (MPI)

Magnetic particle inspection is a non-destructive testing (NDT) process for detecting surface and subsurface discontinuities in ferrous materials. The process puts a magnetic field into the part. The piece can be magnetized by direct or indirect magnetization. Direct magnetization occurs when the electric current is passed through the test object and a magnetic field is formed in the material. Indirect magnetization occurs when no electric current is passed through the test object, but a magnetic field is applied from an outside source Figure 1.6 (Hellier, 2003).

![Figure 1.6: Non-destructive testing, Magnetic particle method](image)

The presence of a surface or subsurface discontinuity in the material allows the magnetic flux to leak. Ferrous iron particles are applied to the part. If an area of flux leakage is present the particles will be attracted to this area. The particles will build up at the area of leakage and form what is known as an indication of detector for surface defects.
1.2.4.4 Liquid Penetrant Inspection (LPI)

Liquid penetrant inspection also called Dye penetrant inspection (DPI) or Penetrant testing (PT), is a widely applied and low-cost inspection method used to locate surface-breaking defects in all non-porous materials (metals, plastics or ceramics). LPI is used to detect casting, forging and welding surface defects and leaks in new products and fatigue cracks on in-service components Figure 1.7 (Hellier, 2003).

Figure 1.7: Non-destructive testing, Liquid penetrant method

LPI is based upon capillary action, where low surface tension fluids penetrate into clean and dry surface-breaking discontinuities. Penetrant may be applied to the test component by dipping, spraying or brushing. After adequate penetration time has been allowed, the excess penetrant is removed, a developer is applied. The developer helps to draw penetrant out of the flaw where a visible indication becomes visible to the inspector.

1.2.4.5 Eddy-Current Testing (EDT)

Eddy-current testing uses electromagnetic induction to detect defects (flaws) in conductive materials. There are several limitations, among them: only conductive materials can be tested, the surface of the material must be accessible, the finish of the material may cause bad readings, the depth of penetration into the material is
limited and flaws that lie parallel to the probe may be undetectable Figure 1.8 (Hellier, 2003).

Figure 1.8: Non-destructive testing, Eddy current method

In a standard Eddy current testing, a circular coil carrying current is placed in proximity to the test specimen (electrically conductive). The alternating current in the coil generates changing magnetic field which interacts with test specimen and generates Eddy current. Variations in the phase and magnitude of these Eddy currents can be monitored using a second 'search' coil or by measuring changes to the current flowing in the primary 'excitation' coil. Variations in the electrical conductivity or magnetic permeability of the test object or the presence of any flaws will cause a change in Eddy current and a corresponding change in the phase and amplitude of the measured current. However, Eddy current testing can detect very small cracks in or near the surface of the material.
1.2.5 Advantages and limitations of radiographic testing

We mention here some plus and minus points of radiographic testing.

1.2.5.1 Advantages

Some of the advantages of radiographic testing as a quality assurance procedure are as follows:

1. Can be used with most materials

2. Provides a permanent visual image record of the test specimen on film and can be viewed when desired

3. Reveals the discontinuities of a material

4. Discloses fabrication error and often indicates necessary corrective action

5. Reveals assembly errors

1.2.5.2 Limitations

There are both physical and economic limitations to the use of radiographic testing. Geometric exposure requirements make it impracticable to use radiographic testing on specimens of complex geometry. When proper orientation of radiation source, specimen and film cannot be obtained, radiographic testing is of little use. Similarly, any specimen which does not lend itself readily to two side accessibility cannot be inspected by this method. Since radiographs are patterned by material density differences in the specimen, they are of little value in detecting small discontinuities parallel to the lines of radiation. Laminar type discontinuities are, therefore, often undetected by radiographic testing. If laminar type discontinuities are suspected in a specimen, the radiation source, the specimen and the film must be oriented to present the greatest possible discontinuity density to the rays. The greatest dimension of the suspected discontinuity must be not parallel to the radiation beam. Safety considerations imposed by X-ray and gamma ray use must also be considered as a limitation. Compliance with safety regulations, mandatory in
radiographic testing, is time consuming and requires costly space utilization and construction practices. Radiographic testing is a relatively expensive means of nondestructive testing. It is most economical when it is used to inspect easily handled material of simple geometry with high rates of test. It is expensive when it is used to examine thick specimens that require equipment of high energy potential (NASA, 1983).

1.3 Architecture of the this research

The initial stage of our welding defect detection system is 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 become more apparent than the background. In the second stage, we detected defect and non defect segments of the images. Finally, our procedure can detect five types of weld defects by using pattern recognitions techniques. These processing steps in defect detection of classification are shown in figure 1.9.

![Architecture of the this research](image-url)
1.3.1 Preprocessing

The digital radiographic images are contaminated with noise and are also blurred. In order to improve the image for observation and accurate analysis, various digital image processing techniques can be applied. Noise is introduced as a result of the electronic circuitry of cameras or during transmission of images (Aboshosha et al., 2010). A large number of linear and non-linear filtering algorithms have been developed to reduce noise from corrupted images to enhance image quality. A lot of filtering methods are available to eliminate salt and pepper noise.

Noise removal is required for improving the quality of the image in order to better recognize the defects. Different noise removal filters such as mean, median are used (Rale et al., 2009). In digital image processing, filtering is the most common and basic operation, because the results of filtering directly influence all the following operations such as edge detection, image enhancement, etc (Fu et al., 2010).

1.3.2 Segmentation

Segmentation subdivides an image into its constituent regions or objects. The level to which the subdivision is carried depends on the problem being solved. That is, segmentation should stop when the objects of interest in any application have been isolated (Gonzalez and Woods, 2002).

Image segmentation plays an important role in the field of image understanding, image analysis and pattern identification. The foremost essential goal of the segmentation process is to partition an image into regions that are homogeneous (uniform) with respect to one or more self characteristics and features (Saikumar et al., 2012).

1.3.3 Classification

Image classification is one of classical problems of concern in image processing. The goal of image classification is to predict the categories of the input image using its features. It is the systematic arrangement of entities into categories according to differing characteristics.
The nature of automatic defect classification is a procedure of pattern recognition. The classification is a processing step, which is decoupled from the feature definition and extraction. A classifier can predict a class label of the input object. Actually, classifier performance depends greatly on the characteristics of the data to be classified. Typically, any trainable classifier uses a reference set of manually classified samples. These samples are referred to as the training sets. The quality of the results for such a classifier depends mainly on two factors: the quality of the aforementioned feature set and the quality of the training set (Xue-wu et al., 2010).

1.4 Related work

Here we discuss some recent research work on the three steps of image analysis namely; Preprocessing, Segmentation and Classification for general image and in particular the radiographic images of weld joints.

1.4.1 Preprocessing

There are different methods for removing salt pepper and blur noise. One of the simplest ways to remove is by windowing the noisy image with a conventional median filter (Gonzalez and E.Woods, 2002). However, the result of conventional median filter could be blurring of images. This is replaces each pixel with the median pixel in the filtering window regardless whether it is a noise or noise-free pixel. With respect to the reduction of noise and contrast enhancement in spatial domain researches found Median Filter and Histogram processing to be useful (Da Silva et al., 2002b; G. Wang and Liao, 2002; Carrasco and Mery, 2004; Padua et al., 2004; Nacereddine et al., 2005b; Alghalandis and Alamdari, 2006; Carrasco and Mery, 2007; Sargunar and Sukanesh, 2010).

Chen and Wu (2001) proposed the adaptive impulse detector with center-weighted median (ACWM) filter to effectively remove salt pepper noise. Similarly (Luo, 2006) proposed an efficient detail-preserving approach (EDPA) based on alpha-trimmed mean statistical estimator. Then, an efficient edge-preserving algorithm (EEPA) was introduced in the removal of salt pepper noise without degrading fine details of the image (Chen and Lien, 2008). These methods perform well when an
image was corrupted with 50% of salt pepper noise or lower. On the other hand, the decision-based algorithm (DBA) filter in (Srinivasan and Ebenezer, 2007) and the open-close sequence (OCS) filter based on mathematical morphology (Ze-Feng et al., 2007) were shown to be able to filter high-density of salt pepper noise corruption, but at the expense of fine image details and high computational time (Zhang and Xiong, 2009).

A welding defect classification method were proposed by (Da Silva et al., 2002b), in image preprocessing, the quality of the image was improved using a median filter and a contrast enhancement technique. After that the evaluation of the characteristic parameters following a relevance criterion in discriminating welding defect classes by using a linear correlation coefficient matrix was then used.

Portilla et al. (2003) described a method for removing noise from digital images based on a statistical model of the coefficients of an over-complete multiscale oriented basis.

Xiao-guang et al. (2005) presented a method of generalized fuzzy enhancement, which overcomes effectively the shortcomings (less of information of middle and low gray levels) in the method which had been developed by Pal and King (1981), making the edge of processed image distinctive. Further Xiao-guang et al’s method keeps better object information of low gray and enhances radiographic testing weld image better, improving contrast ratio. The generalized fuzzy enhancement used in enhancement of radiographic testing weld image has a satisfactory result.

A new method for nonlinear filtering of images based on trace transform was suggested by Nikiforova and Fedotov (2006). The method can be used to reduce noise, quantize images and construct their polygonal approximations. The efficiency of the method is confirmed by the results of experimental tests of a system recognizing weld defects. The system was tested by recognizing more than one and a half thousand X-ray photographs of real welds. The test results confirmed the high efficiency of defect recognition in welds.
Rommi et al. (2006) proposed a recursive filter for effective suppression of impulse noise. The proposed work estimated the noise corruption level and the position of impulses in the first stage. The appropriate filter parameters for a detail preserving restoration of the corrupted pixels are determined based on these estimations. The filtering process assumes a Gaussian spatial profile in the neighborhood of corrupted pixel and interpolates accordingly. A normalized, truncated, trimmed and scaled Gaussian weighting function is proposed for the coefficients of interpolation.

Xiaowei et al. (2009) presented an approach of adaptive enhancement of X-ray weld image. The extraction of the welding image region has been achieved by using brightness projection. According to the characteristics of the human vision, the image of welding region enhanced adaptively and the dynamic brightness range of image defects expanded. Experimental results have shown that enhanced welding image has clearer details for human vision.

Weixin et al. (2009) presented a new Hopfield neural network based method to enhance X-ray image of thick steel pipe welding, and illustrates its effectiveness in practical applications.

A new detection method using fuzzy support vector machine (FSVM) and Beamlet transform was proposed by Sun et al. (2009). In the preprocessing stage, they used wavelet transform and morphological methods to de-noise and eliminate the image background, which will enhance the defect features.

Pérez et al. (2009) described an automatic detection system to recognize welding defects in radiographic images. They implemented image processing techniques, including noise reduction, contrast enhancement, thresholding and labeling to recognize weld regions and the detection of weld defects.

Toh and Isa (2010) presented a novel two-stage noise adaptive fuzzy switching median filter (NAFSM) for effective removal of salt-and-pepper noise. The proposed filter was able to suppress high-density of salt-and-pepper noise, at the same time preserving fine image details, edges and textures well. In addition, it did not require any further tuning or training of parameters once optimized. By carefully
considering the tradeoff between the complexity of the filtering algorithm and the performance of the filter, the proposed NAFSM filter was able to yield good filtering results with efficient processing time.

An effective adaptive median filter algorithm based on modified Pulse Coupled Neural Network (PCNN) model was presented by Jiang and Shen (2010). The adaptive median filter algorithm was achieved by detecting the pollution level, ascertaining the specific location of the noise and determining the size of the median filtering window adaptively. Their results exhibited improvement in the accuracy of noise detection and the fidelity of image filtering, and have a better performance on different noise densities.

Minxia and Meng (2011) presented a new adaptive wavelet threshold de-noising method based on genetic algorithm optimization. The method can remove image noise effectively and keep the image details. The method of multi-scale morphology can enhance local contrast, highlight the characteristics of edges and details of image and improve the image quality. Thus, image preprocessing is very effective and making the image segmentation better. The experimental results indicated that the algorithm can achieve satisfactory results and with almost no false target, which provides accurate basis for flaw type recognition.

Han et al. (2011) proposed an effective noise reduction filter for real-time X-ray image processing. They analyzed the relationship between noise variance and grayscale value in real-time X-ray image and found a linear relation. They proposed a modified Adaptive Local Noise Reduction filter to reduce image noise while keeping information of small defects. Results have shown that the proposed noise reduction algorithm was better than original local noise reduction filter and median filter and avoid the conflict between the noise reduction and preservation of image details, particularly in the area of defects.

A gray-level mapping transformation function was presented by Mu et al. (2013) to enhance radiographic image. They compared the image enhancement of presented method by histogram equalization, linear strength and logarithmic transformation.
This algorithm reduced the MAE and MSE by 75% and 94% respectively, improved the PSNR, SSIM and CC by 17.6, 1.8 and 0.2 times.

1.4.2 Segmentation

Algorithms used for detecting discontinuities in weldment usually comprise a number of steps. These steps may constitute preprocessing, segmentation and classification. The segmentation step is crucial as the result from this stage strongly influence the final quality of interpretation. In this step, locations and features of the objects of interest like welding defects are extracted and separated from the background. Usually, welding defects in radiographic images have lower intensity than non-defective area that makeup the background. It is sufficient to use this feature to identify defects as the intensity difference is large. The intensity of an area is essentially based on the gray level of pixels in it. The process of partitioning images in to objects and background based on pixels’ gray level values is called thresholding. This is a widely used technique that has been studied and used extensively.

Murakami (1990) described the segmentation techniques for detecting weld defects in radiographs using various types of filters such as smoothing filters, bridge filters, Kirsch, Prewitt, Sobel operators on contrast filters. He gave an example of segmented radiograph applying a sequence of these filters. The result was efficient for detecting the porosity defect. An important disadvantage of this method was that the sequence of filters used was different for each type of radiographic image.

A real-time radiography configuration for the automatic inspection of welds described by Gayer et al. (1990). The optimal geometrical imaging configuration are evaluated and discussed in relation to conventional film radiography. For the automatic inspection of X-ray images, a two-step analysis was adopted: a fast search for defective regions, followed by fine identification and location of defects. Two different algorithms, based on the relative irregular behavior of a defect, were developed for the fast search procedure. The second step, fine identification, achieved by a sequential similarity detection algorithm and by a thresholding
algorithm. The different methods were applied to various X-ray images of welds and the automatic inspection was evaluated and compared with visual inspection.

Two networks were combined by Lawson and Parker (1994) to locate the defect. In the first step, a multi-layer perceptron back propagation network was utilized to locate the weld region based on the gray level and spatial structure of the input image. Then, in the second step, the multi-layer perceptron was trained on a test set of segmented image by a conventional adaptive threshold method to detect the defect area in the image.

In 2002, G. Wang and Liao implemented background subtraction and histogram thresholding in the segmentation phase of line weld defect detection. 12 numerical features were extracted and used to classify the defects using fuzzy k-nearest neighbor and multi-layer perceptron neural networks.

Carrasco and Mery (2004) segmented regions identified by means of binary thresholding, filters taken from morphological mathematics have used to eliminate over-segmentation and used the Watershed transform to separate internal regions. The results of the study have generated an area underneath the ROC (Receiver Operating Characteristic) curve of 0.93 in a set of ten images. The best operational point reached corresponds to a detection rate of 88% and a false positive rate of 9.4%. Also in (2004) they have developed a segmentation method based on noise attenuation filters, morphological mathematical operators, edge detection techniques such as the Canny filter, the watershed transform, and the distance transform.

Li et al. (2004) proposed the development of an adaptive segmentation algorithm through genetic algorithms (GA) (Simunic and Loncaric, 1998). One of the major problems of segmentation is the determination of an appropriate threshold value that allows the separation of the relevant objects from the background. One of the most widely used methods is that of (Otsu, 1979), because it determines an optimum threshold value for two classes. Unfortunately, the weld images contain more than two classes due to the surface of the object, light interference, etc. The results indicate that the designed method was adaptive and efficient at generating segmentation in welded joints.
Shafeek et al. (2004a) presented a vision system that consists of image capturing from the radiographic film, detection of the welding defects of gas pipelines, calculation of defect information such as length, width, area and perimeter.

A comparative study of non-parametric histogram thresholding for automatic extraction of weld defect investigated by Nacereddine et al. (2005a). Four methods based on within class variance minimization, the minimum error of clustering, the class entropy maximization and the moment preservation were implemented and the result have shown that entropy maximization gave the best result.

Wang and Wong (2005b) proposed an adaptive wavelet thresholding and histogram equalization to improve the quality of the radiographic image. Three level thresholding, which is based on maximum fuzzy entropy adapted to classify the image into three regions namely the black, gray and white. The optimal threshold was obtained using genetic algorithm.

Fuzzy c-means algorithm used by Wang and Wong (2005a) as a welding defect segmentation method. The method consisted of three steps: First, the top-hat and bottom-hat filters are applied. Second, an adaptive wavelet thresholding filter proposed by Donoho (1995) was applied. The purpose of this filter was to eliminate the noise present in the signal while preserving the characteristics of the signal. According to (Chang et al., 2000b), this filter retained the sharpness of the edges of the defects better than the median filter. Third, they used a fuzzy c-means (FCM) clustering algorithm. The clustering allowed the assignment of a class depending on the degree of similarity present in the patterns in the defect. One of the advantages of using this technique is that it allows the use of any number of characteristics and assign them to any number of classes, in addition to being applicable to instances in an unsupervised way. According to Wang and Wong, this technique has a more efficient performance compared to the method of Otsu, so the fuzzy c-means algorithm can detect a greater number of flaws in the welds.

Movafeghi et al. (2005) proposed improving the quality of the digitized radiographic images to intensify the location and recognition of the defects. The research proposed the independent use of three techniques, two in the spatial domain filters
through morphologic mathematics and pseudo-color and one in frequency domain, the wavelet filter. This methodology has been used in radiological applications in mammography by Wang and Karayiannis (1998). The results indicated that the morphologic mathematics technique has the best performance, with sensitivity ($S_n=90\%$) and 1-Specificity ($1-S_p=0\%$). According to the authors, the application of wavelets has greater complexity and must have supervised training.

\[
S_n = \frac{TP}{TP + FN} \quad 1 - S_p = \frac{FP}{TN + FP}
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where TP is the number of true positives (correctly detected defects), TN is the number of true negatives (correctly detected no-defects), FP is the number of false positives (false alarms, or no-defects detected as defects), and FN are false negatives (flaws detected as no-defects). Ideally, $S_n = 1$ and $1-S_p = 0$, which means that all defects were found without any false alarms.

Anand and Kumar (2006) adopted Canny operator to detect the defect boundaries and then fixed the boundaries using morphological image processing. Afterward, Anand and Kumar (2009) introduced a new two stage water segmentation to reduce over segmentation in detecting flaws in weldment images. In the first stage, the watershed transformation was adopted for segmentation and resulting image was obtained. The Otsu thresholding applied and converted into a binary image. The morphological and top hat transform was utilized onto the binary image to separate the overlapping defects. In the second stage, the watershed segmentation was used to obtain well defined boundaries while removing the over segmented regions.

Alghalandis and Alamdari (2006) described a method for automatic recognition and separation between defective and non-defective radiographic images of welds. A new structure of neural network classifier in combination with binary logic was introduced. Experimental results have shown that this new hybrid neuro-logic structure gave better recognition performance, especially when ANNs were confused by film defect information during training stage. Neuro-logic structure has the ability to reject film defects by its logical part with no need for training the film defects. It is important because direct training of the film defect information to
neural networks, reduces the recognition efficiency. For better recognition performance adaptive preprocessing and local binarization techniques are used for image enhancement and segmentation then features are extracted from regions identified as zoned block.

Felisberto et al. (2006) adopted genetic algorithm to find a suitable parameters values such as position, width, length and angle that are best defined in a window and matched it with the model of the defective sample. However this method was more suitable for detecting weld bead stretches that are linear or almost linear rather than the curved welds.

An automated welding fault segmentation algorithm was presented by Carrasco and Mery (2007) using a set of digitized radiographic images. They used the filters provided by morphological mathematics to eliminate segmentation and used the watershed transform to separate the internal regions. The results of the study have generated a general ROC curve on a set of 10 images with an area $A_z=93.6\%$. The ROC curve makes it possible to evaluate the performance of the detection process at different points of operation (as defined for example by means of classification thresholds). The area under the curve ($A_z$) is normally used as a measure of this performance as it indicates how flaw detection can be carried out: a value of $A_z = 1$ indicates an ideal detection, while a value of $A_z = 0.5$ corresponds to random classification.

Histogram concavity threshold approach was employed by Saravanan et al. (2007) to segment the defects. The proposed method was compared with maximum entropy thresholding and Otsu methods. The proposed method yields a better result compared to both of the conventional thresholding methods. The histogram concavity-based thresholds provided segmentation of pores, crater crack and external undercut in welds.

Yazid et al. (2007) introduced a system to detect circular discontinuities that are present in the weld joints. The system utilizes separability filter to identify the best object candidates and the Circular Hough Transform to detect the presence of circular objects. The algorithm generated satisfactory result in recognizing circular
discontinuities in the radiographic images. However, the limitation of this approach is its difficulty in detecting defects, which are not circular.

A new algorithm for segmenting X-ray images of welding was presented by Weixin et al. (2007) to detect air hole defects. The algorithm was based on multi-layer Hopfield neural network and its noise-reduction ability was high. The algorithm could even segment images with edge-blurred and when background is not intact and it could be programmed easily.

Fong et al. (2007) presented a methodology that produces a flaw map to plot and obtain the welding defect. The flaw map with adjustment of contrast and brightness level used to segment the defects from the welding regions. Since the intensity levels of defects in the radiographic images were lower than the neighboring regions, troughs can be used to characterize the defect and were plotted in the flaw map.

A method based on multiple threshold and support vector machine was introduced by Wang et al. (2008) to classify the welding defect. In every block that contained the defect, Hough Transform performed to remove the noisy pixels and obtain an accurate segmentation and location of the defect.

Runshi et al. (2008) proposed a method of background subtraction based on partial surface reconstruction. They identified the possible defect positions by gray-level wave analysis and then weld background was estimated by reconstruction of these areas. This segmentation method has been employed in real-time X-ray automatic inspection system. Results have shown that false alarm and missed detection were decreased effectively and the defect shape was more accurate.

A defect segmentation using background subtraction and rank leveling was introduced by Soo et al. (2008). Comparison has made between the rank leveling and polynomial surface fitting for background estimation. The proposed method indicates a better result to isolate the defects.

Sun et al. (2009) used FSVM to recognize and locate the rough region containing crack defects.
Vilar et al. (2009) utilized several methods including noise reduction, contrast enhancement, Otsu thresholding and labeling to assist the recognition of the weld regions and the detection of the weld defects.

Mahmoudi and Regragui (2009a) presented a new segmentation method of digitized weld radiographic images which was based on thresholding techniques and compared it with a multiple thresholding and Support Vector Machines based method. The results have shown that, the algorithm was faster, effective and practical, which is a necessary step before characterizing defects.

A new method for segmenting digitized radiographic images was proposed by Mahmoudi and Regragui (2009b). In the pre-process stage, they used histogram analysis and contrast highlighting by a homomorphic filtering. They isolated the weld bead by performing global thresholding using Otsu’s method on the resulting image. The last stage consists of applying an appropriate local thresholding technique based on integral images that performs the final segmentation.

Region-based hierarchical segmentation approach was proposed by Liling and Yingjie (2009) to detect defects on welding radiographic images. The image segmented into a set of regions by using graph-based minimal cut method. Then the initial partition was done in hierarchical way by using diffusion-based method, where the diffusion parameter can be automatically determined from successful segmentation of defects. Finally, the boundaries of defects are extracted and corresponding necessary information were computed by using boundary tracing algorithm. They tested 84 welding radiographic images which contain 63 defects of various kinds, all of the test images from the same parts, and the test results have shown that the successful defect detection rate by proposed approach to be up to 97.2%

An effective algorithm for the slim line defects detection in low contrast digitized X-ray film images was developed by Jiaxin et al. (2009). They segmented the line defect preliminarily from the uneven background by adaptive local threshold column by column, and then adapted modified local Hough transform to get the final segmentation result of line defects. Results have shown success in detecting low
contrast slim line defects and other line defects. The proposed algorithm permits reliable and flexible slim lines detection in weld X-ray images.

Goumeidane et al. (2009) described a new approach for weld defects boundary extraction in radiographic images, based on a statistical pressure snake. Experiments on radiographic images have shown the ability of the model to give a good estimation of the contours by fitting most concavities.

Simple thresholding Gaussian mixture model for segmentation was implemented by Sargunar and Sukanesh (2010). Background and noisy pixels were segmented into one class and the input image features which consist of the spots or crack were segmented into another class, without any pixel belonging into two classes.

Sauvola local thresholding and graph based segmentation was utilized Valavanis and Kosmopoulos (2010) to segment the weld defect from the background. Then, the defects were classified using multi-class support vector machine and neural network classifiers.

Vaithiyanathan et al. (2011) performed Watershed, Hough Transform and Region Growing segmentation. They presented a detailed survey on various segmentation methods used for detecting various types of weld defects. From the results it can be clearly concluded that a specific type of segmentation algorithm was suitable for a particular type of weld defect. Region based technique was more suited for detection of porosity weld defect which produced better result than that of Watershed method without over segmentation. For Lack of penetration (LOP) defect in weldments, Hough transform segmentation technique was very efficient to detect line defects. Watershed segmentation applied for detecting Oxide inclusion weld defect results in a good quality segmented image better than other segmentation methodologies.

Halim et al. (2011) described a method to extract the weld defect and evaluate its geometrical feature. The boundary of defect has been extracted by converting the image into binary form. The defect boundary was detected by recognizing the black pixel of eight neighborhoods of 3x3 filtering. The coordinates of the boundary pixels
were stored and used to calculate the information of defect features. The information can be used by an interpreter to interpret a defect.

The active contour models (Snakes) for edge detection and segmentation of weld defects in radiographic images was used by Boutiche and Bessekri (2011). Gradient Vector Flow (GVF) snakes enhanced the concave object extraction capability. They proposed a Multi-Scale GVF and B-spline model to overcome the traditional GVF disadvantage. Experiments on synthetic and radiographic images are promising. They confirmed the previous results which have shown that the Multi-Scale GVF B-snake gives a better edge detection.

Rathod and Anand (2010) proposed three image segmentation techniques i.e. morphological edge detection, region growing segmentation technique, multished water segmentation implemented on NDT radiographic images of weldments for extraction of defects. Every segmentation technique had its own merits and demerits i.e. results obtained were of varying quality. Comparative study had been performed to find out the best segmentation technique for particular type of defect. Afterwards, they developed image processing algorithm for the measurement of radiographic welding defects to detect the defect areas (Rathod and Anand, 2012). They obtained length, width and area of the defects by these algorithms. This information could be useful in the classification of welding defects.

Shao et al. (2011) and (2012) proposed an adaptive and effective method based on potential weld defects tracking in real-time radiographic image sequence of a moving weld. All the potential weld defects segmented in each image of the sequence by fusion of background subtraction and gray-level profile analysis algorithms, and the modified Hough transform proposed to track potential weld defects segmented by the first step, and all the potential defects that cannot be tracked eliminated as false alarms. Experiment results shown that the proposed automatic defect detection method based on potential defect tracking was fast and effective to detect low contrast small defects without false alarms.

A new approach using surface thresholding method to detect defects in radiographic images of welding joints was proposed by Yazid et al. (2011) and Yazid and Arof
2012). In the first stage, several image processing techniques namely fuzzy c-means clustering, region filling, mean filtering, edge detection, Otsu thresholding and morphological operations methods, utilized to locate the area where defects might exist. This is followed by the construction of the inverse thresholding surface and its implementation to locate defects in the identified area. The proposed method was tested on 60 radiographic images and it obtained 94.6% sensitivity. Its performance was compared to that of the watershed segmentation, which obtained 69.6%.

1.4.3 Classification

Liao and Ni (1996) proposed a methodology for the extraction of welds from digitized radiographic images. The method was based on the observation that the intensities of pixels in the weld area distribute more like Gaussian distribution than other areas in the image. However this method has proved effective, only in segmenting linear welds. Subsequently, Liao and Tang (1997) applied a multilayer perceptron (MLP) neural network procedure for the same application, which was successfully applied to segment both linear and curved welds. Then Liao and Li (1998) developed welding flaw detection based on the fitted line profiles of a weld image and successfully detected 93% of various defects from linear welds.

In another study Liao et al. (1999) presented a fuzzy clustering based methodology for detecting welding defects from radiographic images. The performance of two fuzzy clustering methods, i.e. fuzzy k nearest neighbors (K-NN) and fuzzy c-means were studied and compared. The methodology processed each image line by line. For each line, 25 features have been selected. The fuzzy K-NN classifier found to give lower missing rate and lower false alarm rate than the fuzzy c-means classifier. Five different sets of features were tested. It was found that the set with all 25 features is the best. Currently, the system at best can achieve 6% missing rate and 18.7% false alarm rate.

Fuzzy logic classifier has also been used in weld extraction by Liao et al. (2000). Features were extracted from the intensity profiles of the weld, and then inputted into fuzzy logic system. Fuzzy k-NN and fuzzy c-means algorithm were used as pattern classifiers to recognize each peak in the intensity profile as weld and non-
weld. However, this method did not produce good results. It generated false alarm rate of 16% to 23% with fuzzy k-NN classifier and 55% to 80% with fuzzy c-means classifier. Even after post-processing procedure, false alarm rate of 10% to 28% was reported.

In 2002, G. Wang and Liao proposed a fuzzy k-nearest neighbor method based on multilayer perceptron neural network and a fuzzy expert system for the classification of welding defect types. The features used for the classification are distance from center, circularities, compactness, major axis width and length, elongation, Heywood diameter, the intensity average, and its standard deviation. They used a set of parameters to classify six possible defects and obtained the highest accuracy of 92%. In this work, 108 data sets were used for training while 12 data sets were used for testing. However, the 12 test samples used for classifying six types of defects are considered small and the success rate for individual defect was not reported. Then Li and Liao (2002) developed two fuzzy K-NN (K-nearest neighbor) based procedures for identifying welds from digitized radiographic images. The procedure comprises of two major components: feature extraction and fuzzy K-NN based pattern classification. The weld image was processed line-by-line and three features extracted for each object in each line image. The results of this study indicate that the fuzzy K-NN based procedures produce a high successful rate of recognition for both applications. The test results have shown that 93.2% welds could be successfully extracted from radiographic images.

Liao (2003) proposed a fuzzy k-nearest neighbor method based on multilayer perceptron neural network and a fuzzy expert system for the classification of welding defect types. The features used for the classification are distance from center, circularities, compactness, major axis width and length, elongation, Heywood diameter, the intensity average, and its standard deviation. Liao (2004) developed a fuzzy reasoning based expert system for the classification of welds in radiographic images. First, each object in radiographic image was identified and described with a three feature vector. The fuzzy rules are extracted from feature data one feature at a time based on a modified fuzzy c-means algorithm. The
performance of the fuzzy expert system is also found to be better than that of multilayer perceptron neural networks.

Liao (2008) presented the details of a study carried out to investigate the effectiveness of 22 data preprocessing methods for dealing with the imbalanced data problem inherent to the classification of six different types of weld defects. The one-against-all scheme adopted to carry out multi-class classification and three algorithms including minimum distance, nearest neighbors and fuzzy nearest neighbors were employed as the classifiers. The test results indicated that: nearest neighbor classifiers outperform the minimum distance classifier; some data preprocessing methods did not improve any criterion and they vary from one classifier to another; the combination of using the Hierarchical Clustering K-Means (AHC_KM) data preprocessing method with the 1-NN classifier was the best because they together produce the best performance in six of eight evaluation criteria and even in the most difficult weld flaw type to recognize namely crack.

A computer-aided radiographic weld inspection system was developed by Liao (2009). They proposed two versions of ant colony optimization (ACO) - based algorithms for feature selection and experimentally proved their effectiveness in improving the accuracy of detecting weld defects and the accuracy in classifying weld defect types. The performances of ACO-based methods were compared with that of no feature selection and that of sequential forward floating selection, which was a known good feature selection method. Four different classifiers, including nearest mean, k-nearest neighbor, fuzzy k-nearest neighbor and center-based nearest neighbor were employed to carry out the tasks of weld defect identification and weld defect type classification. Their results have shown that both the 1NN and fuzzy 1NN classifiers were the best for this data set when feature selection was applied. The lowest classification error of 9.3% was achieved regardless of features selection method.

Kaftandjian et al. (1998) proposed a background subtraction based and histogram threshold approach to segmentation of aluminum weld defects. The results obtained
in the case of radioscopic images show that lack of penetration were correctly detected, as porosities.

Jacobsen et al. (1998) presented a study about the detection of cracks and undercuts. A lot of features were computed on each column of the image, in the direction perpendicular to the weld seam. The performance was good as compared to a human operator, but learning required a huge set of defects and the method was based on the assumption that the defects are elongated in the direction of the weld.

Nafaâ et al. (2000) presented artificial neural network based approach for the classification of 2D dimensional weld defect images which is in variant to translation, scale and rotation of region of defect. ANN approach employing supervised learning represented by a multilayer ANN was utilized. The error backpropagation algorithm was used for the training of the multilayer ANN. Through experimentation with the defect-images for the classification problem, they have shown the feasibility of the proposed feature extraction and neural network paradigms, which are very promising in radiography inspection of welding joints.

Lashkia (2001) proposed a more effective method based on fuzzy theory. With the proposed algorithm, images were filtered by applying fuzzy reasoning using local image characteristics. The proposed algorithm was applied to detect internal weld defects from radiographic films, which were taken from steel butt weld parts. Results show success in detecting defects at a similar level to human vision. A comparison between a visual and an automatic evaluation demonstrates the efficiency of this method.

A method to obtain the best hierarchical and non-hierarchical linear discriminators was presented by Da Silva et al. (2001) for classification of the principal welding defects. They used a neural network technique for implementation. The results obtained in this work were good for the proposed case. Even with non-hierarchical linear classifiers alone, it was possible to reach promising indices of successes in the classification of some of the welding defects more frequently found in radiographic inspection. These indices were still better when a classification algorithm based on a hierarchical criterion was used. Da Silva et al. (2002a) extended their earlier work,
also presented statistical tools to estimate the probabilities of correct classification using linear classifiers and aiming at their generalization. The results obtained confirm the efficiency of the methodology due to the high indices of probability of correct classification which were obtained. Then Carvalho et al. (2003) described a technique to evaluate the relevancy of some features to classify the main classes of weld defects on industrial radiographs. Furthermore, these features were used on a nonlinear pattern classifier as input vector to classify the weld defects: undercutting (UC), lack of penetration (LP), porosity (PO) and slag inclusion (SI). The employed technique is the linear correlation between the defect features and the classes of defects. The nonlinear classifier has been implemented by neural networks. The new results obtained by this work proved of the efficiency of the technique. In later study Da Silva et al. (2004) implemented non-linear classifiers by artificial neural networks aiming principally to increase the percentage of defect recognition success obtained with the linear classifiers. In another work, Da Silva et al. (2005) presented the methodologies to estimate the classification accuracy of the non-linear classifiers implemented using artificial neural networks.

A method for the automated recognition and classification of welding defects was presented by Sofia and Redouane (2002), in which detection follows a pattern recognition methodology. They used a watershed algorithm and morphological operations for segmentation and \( k \)-nearest neighbor for classification. The achieved a good detection rate.

Mery and Berti (2003) presented a new approach to detecting weld defects from digitized films based on texture features. They described two groups of widely used texture features, those based on the co-occurrence matrix and other based on 2D Gabor functions. They have used the polynomial, Mahalanobis and nearest neighbor classifiers. The best performance was obtained with the polynomial classifier, where 91% of the existing flaws were detected with only 8% of false alarms observed.

Gauss and Worn (2003) applied inspection criteria specified in the standards that include the measurement of the height and cross sectional area of the weld together with detection of porosity density and undercuts.
Kaftandjian et al. (2003) presented an approach that based on the combined use of Dempster–Shafer (DS) (Dempster, 1967; Shafer, 1976), theory and fuzzy sets for improving automatic detection of weld defects. The proposed approach modeled detection uncertainty in feature space through using the mass function weighted by membership degrees and fusing the features of objects using DS combination rule. The obtained results have been shown by modeling detection uncertainty, a confidence level is associated to each detected object, making the defect detection more precise and reliable. The results obtained in the case of X-ray weld inspection have shown up to 80% of defects with a credibility of about 0.55 without any false alarm.

Chang (2003) investigated the performance of multi-layer perceptron (MLP) neural networks and case based reasoning (CBR) individually as well as their combined use. It was found that better performance was possible by all the methods tested in this study than that the fuzzy clustering methods employed before.

De Moura (2003) showed how to obtain the best hierarchical and non-hierarchical linear classifiers implemented by neural networks, in order to distinguish defects (lack of fusion, lack of penetration and porosity) inserted into the testing pieces during the welding process and detected by the Time of Flight Diffraction (TOFD) technique. The position, type and dimension of each inserted defect were known by conventional ultrasonic and radiographic techniques. The results have shown the performance of the hierarchical linear classifier, for the original training data (96.25%), was better than the performance of the non-hierarchical linear classifier (85%). It also increased from 71.25% (non-hierarchical linear classifier) to 78.75% (hierarchical linear classifier) for the test data. Subsequently, Moura et al. (2004) used computational tools for signal preprocessing and pattern recognition, such as the artificial neural networks, in order to improve the classification reliability of three kinds of defects: lack of fusion, lack of penetration and porosity detected by TOFD (Time of Flight Diffraction).

Shafeek et al. (2004b) introduced a novel automated vision system to detect and assess the welding defects of gas pipelines from radiographic films. They developed
vision system which makes use of various image processing and computer vision algorithms applied to capture images of the radiographic films to recognize the defects and to make acceptance decisions according to international standards. To verify the proposed system, five clear radiographic films for each type of the defects were used. The results obtained by both the proposed system and the specialists proved that the identification tree of the defects has been successfully defined after inspecting all defects, which are predefined by the identification tree.

A neuro fuzzy method (ANFIS) for automated defect detection in aluminum castings was presented by Hernández et al. (2004a). The system was able to detect potential defects into defects and regular structures or false alarms.

Zhang et al. (2004) presented a method of automatic defect recognition in weld image based on support vector machine (SVM). Weld defects were classified by a multi classifier based on SVM combined with the tree. They compared the classifier based on multilevel SVM with the one based on fuzzy neural network (FNN) using total 84 samples in defect recognition. Experimental results have shown SVM has higher accuracy under the condition of small samples and less effect on accuracy with the decrease of training samples. This research demonstrated that SVM has 83.3% performance for the defect recognition in weld image.

A method of automatic recognition of weld defects was presented by Xiao-Guang et al. (2004). The method was based on fuzzy neural network (FNN). The weld image was first preprocessed to extract defect features. Eight characteristic parameters were selected as features and the FNN model used for defects recognition. Weld defects of different types have been processed using a three layer Neural Network and back-propagation (BP) learning algorithm. Using forty-two training samples and seven testing samples for examination, the results have shown this model can recognize weld defects with better effects.

Hernández et al. (2004b) presented a new approach for detect detection in X-ray images based on stratified dimensionality reduction and the Neuro-Fuzzy classification. Potential defects were segmented using an edge detector. They investigated two groups of features: geometric and intensity features. Neuro-Fuzzy
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classifiers have been implemented in order to establish decision boundaries in the space of the selected features which separate segmented regions belonging to two different classes (regular structure or defects). The results were compared with a statistical classifier and the performance analysis was evaluated using the area under the Receiver Operation Curve (ROC). The best performance was achieved using the simplified model in the case of the aluminum castings ($A_z = 0.9976$) and the complete model in the case of defect detection in welds ($A_z = 0.9659$).

A study to detect welding defects in radiographs was presented by Padua et al. (2004) using traverse profiles to the weld seam. The profiles were traced transversely to the weld seam of several radiographic defects. The performances of the classifiers, which were implemented using feed forward networks with learning algorithm with back propagation of error, were evaluated. Techniques of principal components of nonlinear discrimination were also used for two-dimension visualizations of the separation between two classes (Defect and Non defect). The accuracy of results obtained were about 80% with test sets.

A digital image processing algorithm based on a global and local approach for detecting defect in radiographic images was proposed by Nacereddine et al. (2005b). This algorithm was based on smoothing the image using a filter and a dynamic stretching procedure was applied to the region of interest (ROI) by a look up table transformation. Then, they extracted the defect by applying the morphological operators which eliminate small holes, spots, and connect the close regions.

Nacereddine et al. (2006) developed and implemented algorithms based on statistical approaches for segmentation and classification of the weld defects. They did a comparison between ANN and Expectation Maximization (EM) algorithm in weld defect classification. The experimental results show that the ANN performance is little better than EM.

Gao et al. (2006) developed a kind of multi-class classification method based on SVM combined with binary-tree. This method adopted one-against-all multi-class classification algorithm according to which the multi-class classifier of welding
defects was established. Use the classifier to classify six classes of defect samples and obtain better effects, which have shown this method was effective and practical.

A classification system using a large number of simulated images of weld defects was developed by Lim et al. (2007). They defined a set of shape descriptors and optimized the number of descriptors required in the classification using a statistical approach. A multilayer perceptron (MLP) model using back propagation algorithm was used for learning and classifying the defects. A total of 49 defects from the real images were used for testing the classification accuracy. The highest classification accuracy achieved by the MLP, using features extracted from the real weld images was 97.96%.

Zhang et al. (2007) proposed a SVM-based fuzzy neural network (FNN) classification algorithm for welding defects to overcome the shortcomings of the existing FNN learning algorithms. Simulation results have shown that the proposed algorithm can effectively model complex relations between defect features and classification performance for small sample sets has improved. The recognition classification ratio of defects was 90% in average.

A real-time automatic inspection algorithm of weld defects in X-ray images was developed by Du et al. (2007). Using optimized image smoothing and image information fusion based heuristic best-first search techniques, the algorithm could detect different kinds of defects in weld, such as slag inclusion, blow hole, incomplete penetration, lack of fusion and undercut etc. Experiments have shown that the algorithm was efficient, reliable and could be used for industrial purpose.

Mirapeix et al. (2007) presented an approach that allowed automatic weld defect detection and classification based in the combined use of principal component analysis (PCA) and an artificial neural network (ANN). Then Soo et al. (2008) developed an effective algorithm to segment the defects automatically from noisy weld radiographs having poor illumination using background subtraction and rank leveling. An approach that allowed automatic weld defect detection and classification based in the combined use of principal component analysis (PCA) and an artificial neural network (ANN) was presented by Mirapeix et al. (2007).
Peng (2009) discussed an effective method to extract the features of the defects by a much simple algorithm which was based on perceptron model to recognize and classify the defects. Experimental results had shown that air holes were most easily recognized defects (94.3%) and the lack of penetrations were the least easily recognized defects (90.7%).

SVM based binary decision tree for defect identification and classification was proposed by Hanbing et al. (2009). The classified results proved that the classifier method has satisfactory performance for defect classification in radiographic testing and a considerable application foreground.

A new detection method using fuzzy support vector machine (FSVM) and Beamlet transform was proposed by Sun et al. (2009). They used FSVM to recognize and locate the rough region containing crack defects. Next the crack defects have extracted through Beamlet transform in the rough region. The experimental results show that the proposed method can detect the crack defects in weldment images successfully.

Pérez et al. (2009) described an automatic detection system to recognize welding defects in radiographic images. They used an artificial neural network for weld defect classification under three regularization processes with different architectures. For the input layer, the principal component analysis technique was used in order to reduce the number of feature variables; and, for the hidden layer, a different number of neurons was used to give better performance for defect classification in both cases.

An adaptive-network-based fuzzy inference system to recognize welding defects in radiographic images was described by Zapata et al. (2010). With the aim of obtaining the best performance to automate the process of the classification of defects, of all possible combinations without repetition of the 12 features chosen, four were used as input for the ANFIS. The results were compared with the aim to know the features that allow the best classification. The correlation coefficients were determined obtaining a minimum value of 0.84. The accuracy or the proportion of the total number of predictions that were correct was determined obtaining a value
of 82.6%. Subsequently Zapata et al. (2011) evaluated the performance for two neuro-classifiers based on an artificial neural network (ANN) and an adaptive-network-based fuzzy inference system (ANFIS). The automatic system of recognition and classification proposed consists in detecting the four main types of weld defects met in practice plus the non-defect type. The accuracy for the ANN and the ANFIS automatic inspection system were determined. The accuracy or the proportion of the total number of predictions that were correct was 78.9% for the ANN. In a recent study Zapata et al. (2012) described an ANN with a modified performance function which used an automatic inspection system of welding defects in radiographic images. A set of geometrical features which characterize the defect shape and orientation was proposed and extracted between defect candidates. An artificial neural network for weld defect classification was used under a regularization process with different architectures for the input layer and the hidden layer. They analyzed this ANN modifying the performance function using a $\gamma$ parameter in its function, for different neurons in the input and hidden layer in order to obtain a better performance on the classification stage. The proposed method consists in detecting the four main types of weld defects met in practice plus the non-defect type. The correlation coefficients was determined obtaining a value of 80% for the ANN using a modified performance function with a parameter $\gamma = 0.6$.

Wang et al. (2010) developed a Support Vector Machine Classifier based methodology for identification of weld defects in radiographic images. This methodology was tested by 25 radiographic weld images, where 97% of the existing weld defects detected, with 14% of false alarm. The obtained results have shown the effectiveness of using SVM to detect defects. It outperforms k-means classifier, a linear discriminant classifier, a k-nearest neighbor classifier and a feed forward neural network in the detection of defective welds. Indeed, the proposed based on SVM detection technique has provided satisfying results.

Valavanis and Kosmopoulos (2010) presented a method for the detection and classification of defects in weld radiographs. The method has been applied for detecting and discriminating discontinuities in the weld images that may correspond to false alarms or defects such as worm holes, porosity, linear slag inclusion, gas
porosities, lack of fusion, and crack. The classifier was trained to classify each of the objects into one of the defect classes or characterize it as non-defect. Three fold cross validation was utilized and experimental results were reported for three different classifiers: Support Vector Machine 84%, Neural Network 85% and k-NN 60%.

Vilar et al. (2011) described an automatic system of radiographic inspection of welding. An important stage in the construction of this system was the classification of defects. In this stage, an adaptive network-based fuzzy inference system (ANFIS) for weld defect classification was used. The results have shown that, the correlation coefficients were determined obtaining a minimum value of 0.84. The accuracy or the proportion of the total number of predictions that were correct was determined obtaining a value of 82.6%. In this work, five independent ANFIS were developed to automate the process of classification in five types of defect, non defect, slag inclusion, porosity, longitudinal crack and transversal crack.

V.Vaithiyanathan et al. (2011) presented a Moment invariant Projection Profile based weld defect detection system. They fed the feature extracted to a Learning Vector Quantization (LVQ) for training, with four different output classes, where each class corresponds to different type of weld defects like Cluster Porosity, Slag inclusions, Lack of Penetration and Burn-Through. The results have shown that the proposed system was highly efficient in classifying different types of weld defects.

Jiaxin et al. (2011) proposed an effective method based on Support Vector Machine (SVM) to detect weld defects in real-time X-ray images. After segmentation and feature extraction, they used SVM classifier to distinguish non-defects from defects. The results have shown that the identification accuracy rate on testing set achieves 99.4%. After classification, potential defects recognized as non-defects are eliminated. Then, in the testing set, the undetected rate is 0.6% and the false alarm rate is 0.9%.

Means of geometric features was used by Hassan et al. (2012) to present a novel technique for the detection and classification of weld defects. They used Artificial Neural Network for classification between different defects. Experimental and
results have shown the accuracy of the proposed algorithm to be 91% in detecting and 96% in classifying defects separately.

1.5 Goals of the Thesis

This study has been carried out towards the development the process of radiographic images using image processing and pattern recognition techniques to detect welding defects. From the literature survey presented in the previous section, research in this area continues largely because no satisfactory results that allow the detection and classification of the totality of defects without false alarms were achieved. Additionally, it is not possible to determine which lines of investigation will improve the overall result, because each of them has room for improvement. Then the aims of the present thesis are:

1. Preprocessing stage is very important, because radiographic images are noisy and low contrast. We propose to design new noise reduction or improve existing noise reduction algorithm to radiographic images.
2. Detect the defects of welded metal using the radiographic images.
3. Classify the type of detected weld defect images.

1.6 Outline of the Thesis

Chapter 2 details the development of new noise reduction methods for radiographic images. We implement these methods for radiographic images of weld, teeth and knee cap.

In Chapter 3, a new segmentation method for defects detection in radiographic images of weld is described.

In Chapter 4, two new classification methods to classify five types of weld defects are proposed.

Finally, in Chapter 5, we present overall summary of the proposed research work followed by a list of contributions achieved during this research work. We also have highlighted some possible future research work.
In the chapters 2, 3 and 4, the newly proposed methods have been experimentally validated along with their performance comparison with several other existing approaches.