A NOVEL TOOL FOR AUTOMATED EVALUATION OF RADIOGRAPHIC WELD IMAGES

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Abstract : Radiography is one of the oldest and the most widely used NDT method for the detection of volumetric defects in welds and castings. Once a radiograph of a weld or a casting or an assembly is taken, the radiographer examines the same. The task of the radiographer consists of identifying the defects and quantitatively evaluating the same based on codes and specifications. Radiographic interpretation primarily depends on the expertise of the individual radiographer. To overcome the subjectivity involved in human interpretation, it is thus desirable to develop a computer based automated system to aid in the interpretation of radiographs. Towards this goal, the authors have developed a flowchart chalking out the various stages involved. Typical weld images of tube to tubesheet weld joints were digitised using high resolution digitiser. The images were segmented and 52 invariant moments were computed to be used as features. The results of these are presented in this paper. Once the features (invariant moments) are extracted and ranked, a neural network classifier based on error back-propagation has to classify the (top ranking) features and evaluate the image for acceptance or rejection.

Introduction : Radiography is one of the oldest and the most widely used NDT method for the detection of volumetric defects in welds and castings. Though imaging plates and real time systems based on image intensifiers and flat panel detectors are available, more than 75% of the radiography is still being carried out using films. The basic advantage of films is their higher resolution and their flexible usability for any kind of job – be it straight or curved. Once a radiograph of a weld, a casting or an assembly is taken, the radiographer examines the same for identifying the defects and quantitatively evaluating the same based on codes and specifications. Radiographic interpretation primarily depends on the expertise of the individual radiographer. The task can become complicated when the radiographic contrast and sensitivity is poor, making interpretation quite difficult. Human interpretation of radiographs is also subjective and labor intensive. When a number of radiographs are to be interpreted by a single person within a stipulated time, operator fatigue can result in inconsistent and biased evaluations. Apart from all these, interpretation of radiograph is a science and art and depends much on the experience and capabilities of the operator. It is thus desirable to develop a computer based automated system to aid in the interpretation of radiographs. Such a system would ensure uniformity and thereby reliability in the interpretation of radiographs. An extensive database pooling the resources of the experts would be needed for effective interpretation. Such a database would serve as a repository of knowledge for the future. Review of literature indicates that limited work has been done in this particular area. T.W.Liao et. al have used MLP neural network and case based reasoning for the detection of welding flaws [1-3], Nacereddine nafaa et. al [4] have used geometric invariant moments to construct a set of weld defect descriptors in X-ray images and developed a classifier based on multiplayer feed forward neural network. At the authors lab, ANN, has been successfully applied for the classification of defects in eddy current testing and for the prediction of temperature / strain rate during tensile deformation of AISI 316 SS[5,6].

As part of the technology development program, efforts have been initiated at the authors lab for the development of a computer based automated radiographic evaluation system for the interpretation of the microfocal radiographs of the tube to tubesheet weld joints of the steam generator of prototype fast breeder reactor. In this paper, we outline the approach being adopted for the development of such a system. The preliminary result of feature classification based on geometric invariant moments using the DESKPACK [7] System Software (developed at the author's laboratory) is presented.

The Approach : The three essential functions that a computer based automated weld evaluation system has to perform is feature extraction, classification and evaluation. Figure 1 below indicates the typical flow chart that has been adopted in the present case.

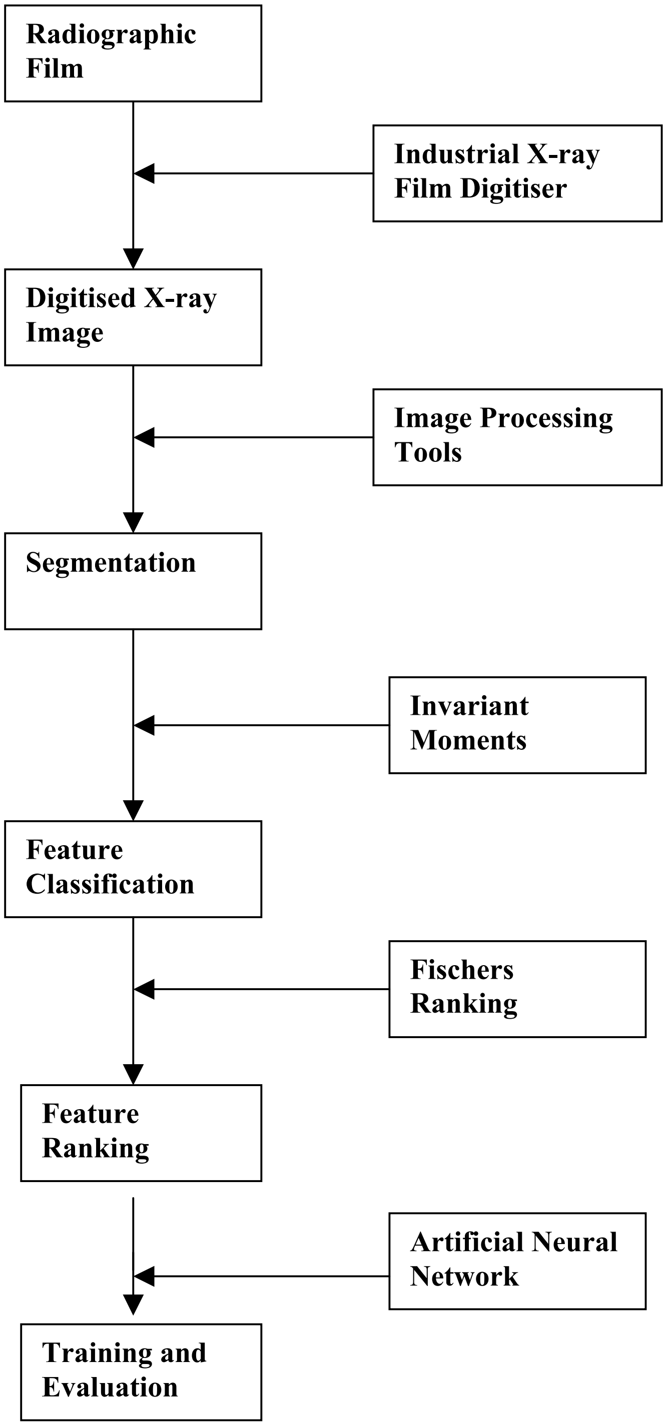

Figure 1 Typical Flow Chart indicating the sequence of steps for realizing an automated defect classification and analysis using MLP based ANN

The first step in automated defect analysis is the digitization of the radiographic film. Choice of appropriate digitiser is very crucial as this decides the resolution and the reproducibility of the fine features in the radiograph. In the present work, a large number of weld radiographs pertaining to the tube to tubesheet welds of steam generator and evaporator fabricated as part of technology development program were chosen. These were digitized using LS 85 film digitiser. This is a laser film digitiser capable of converting radiographic film images of sizes upto 14” x 17” to high resolution digital images of upto 5120 pixels x 6140 lines [3]. A typical digitised radiographic image of tube to tube sheet weld used in the present experimental work is shown in Figure 2.

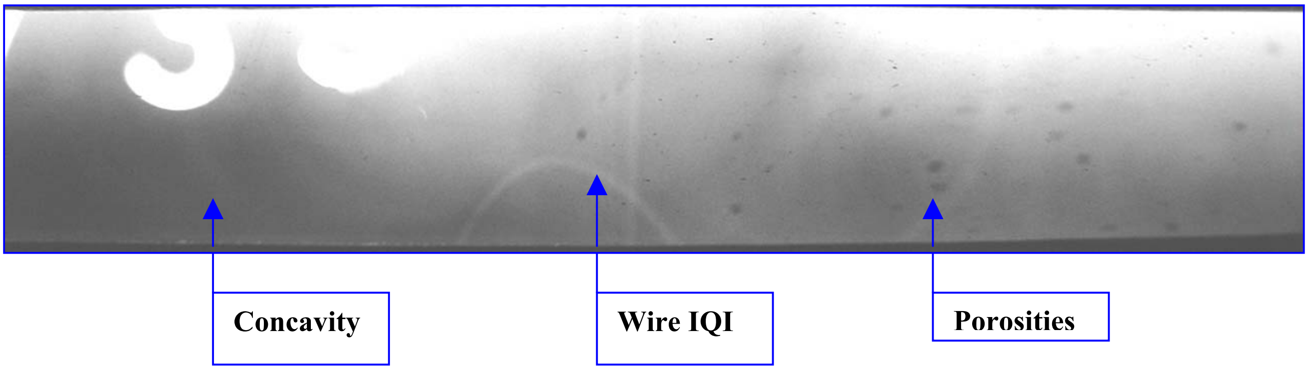

Figure 2 : Typical digitised radiographic image of tube to tubesheet weld.

To facilitate better feature classification, the radiographic image was segmented into smaller images of size 128 x 128 pixels using the conventional image processing tools. While segmenting the image into smaller ones, care was taken to ensure overlap between one image and the succeeding image. From a single radiograph about 40 segmented radiographs were generated.

Feature Classification through Geometric Invariant Moments : The biggest challenge in the development of automated defect recognition system is the feature identification. Radiographic images of the same defect like porosity can vary in size, shape and density. Irrespective of these variations, the software and methodology so chosen should be capable of identifying it as a porosity. For effective feature identification, it is essential that at the input stage, a large number of radiographic images pertaining to that particular defect is characterised. Feature classification can be accomplished earlier using a variety of methods such as pattern recognition, fractal based concepts etc. In the present case, we have used geometric invariant moments as features to be computed from the weld images. The main advantage of using the moments is their invariance to geometric transformations (translations, rotation, scale change etc.) This is very important in the present application since the aim of automated defect recognition is to identify the different types of weld defects irrespective of their orientation, size or position.
Hu [8] had introduced moments as image recognition features. He had derived a set of seven moments using non-linear combinations of normalized central moments, which has the desirable property of being invariant under translation, scaling and rotation. According to this, the central moment of any image is given by

$$\mu_{pq} = \frac{1}{N}\sum_{i=1}^{N}(u-\vec{u}_i)^p(v-\vec{v}_i)^q \qquad \text{---------------(1)}$$

where N is the number of pixels in the image and u,v are the mean values of the image co-ordinates U and V. The set of seven invariant functions based on the second and third order moments that can be used as a feature vector are given below

$$\left.\begin{array}{l} *M_1 = \mu_{20} + \mu_{02} \\ *M_2 = (\mu_{20} - \mu_{02})^2 + 4\mu_{11}^2 \\ *M_3 = (\mu_{20} - 3\mu_{12})^2 + (3\mu_{21} - \mu_{03})^2 \\ *M_4 = (\mu_{30} + \mu_{12})^2 + (\mu_{21} + \mu_{03})^2 \\ *M_5 = (\mu_{30} - \mu_{12})(\mu_{30} + \mu_{12}) \bullet [(\mu_{30} + \mu_{12})^2 - 3(\mu_{21} + \mu_{03})^2] + \\ (3\mu_{21} - \mu_{03})(\mu_{21} + \mu_{03}) \bullet [3(\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2] \\ *M_6 = (\mu_{20} - \mu_{02})[(\mu_{30} + \mu_{12})^2 - (\mu_{21} - \mu_{03})^2] + 4\mu_{11}(\mu_{30} + \mu_{12})(\mu_{21} + \mu_{03}) \\ *M_7 = (3\mu_{21} - \mu_{03})(\mu_{30} + \mu_{12}) \bullet [(\mu_{30} + \mu_{12})^2 - 3(\mu_{21} + \mu_{03})^2] - \\ (\mu_{30} - 3\mu_{12})(\mu_{21} + \mu_{03})[3(\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2] \end{array}\right\} \text{--- (2)}$$

It is better to make these moments, size invariant too. For any function ‘x’ and ‘y’ we have

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} a,0 \\ 0,a \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \qquad \text{------(3)}$$

where ‘a’ is a constant. For the moment functions, we have

$$\mu'_{pq} = a^{p+q+2} \mu_{pq} \qquad \text{------(4)}$$

Eliminating ‘a’ between the zeroth order relation, one obtains,

$$\mu'_{00} = a^2 \mu_{00} \qquad \text{-------(5)}$$

Similitude moment invariants are

$$\frac{\mu'_{pq}}{\mu'_{\frac{(p+q)}{2}} + 1} = \frac{\mu_{pq}}{\mu'_{\frac{(p+q)}{2}} + 1} \quad \text{where p+q =2,3} \qquad \text{----- (6)}$$

Thus, the moment can be made invariant to translation, rotation and sizing.

Results and Discussion : In the present case a total of 52 moments were used for feature extraction. The segmented radiographic images were subjected to these 52 moments. Typical feature plots for a plain weld and weld with different features including defects are given in figures 3-7. The segmented weld that was analysed is also embedded in the figures.

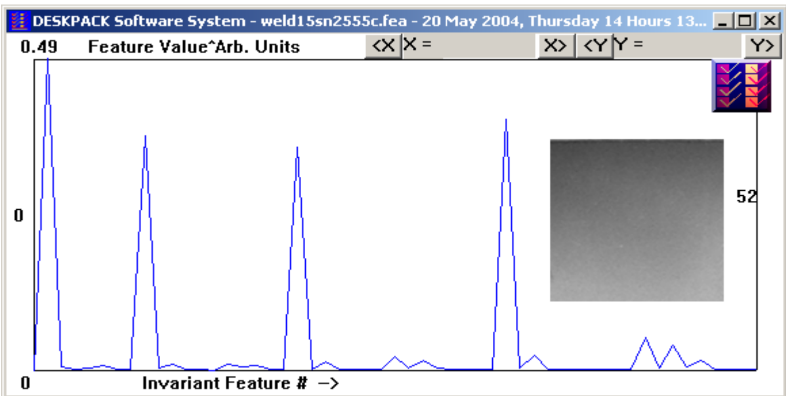

Figure 3: The 52 Invariant Image Features for a plain weld

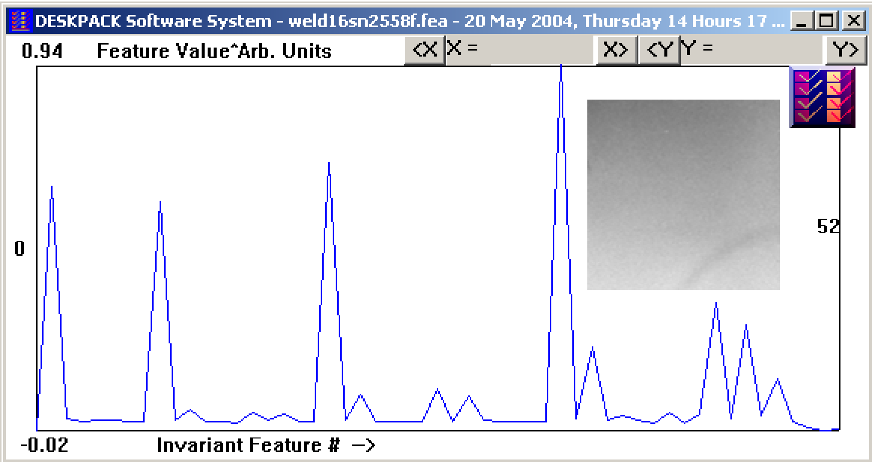

Figure 4 : The 52 Invariant Image Features for a weld image with wire

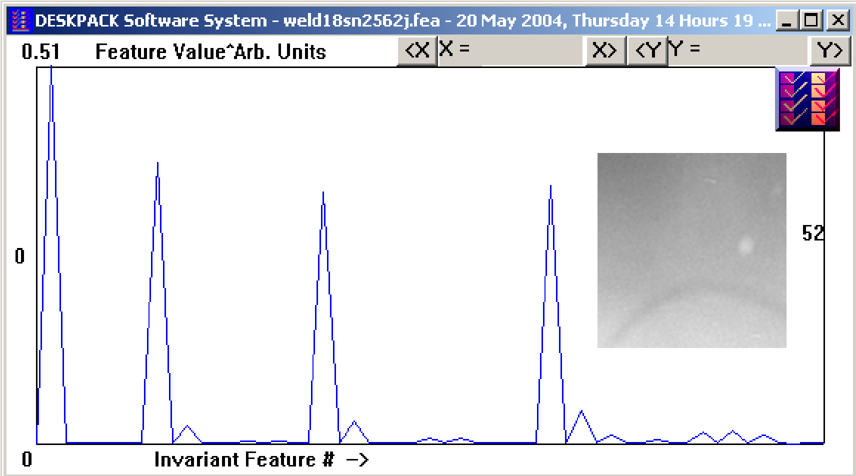

Figure 5: The 52 Invariant Image Features for a weld image with a wire and a porosity present

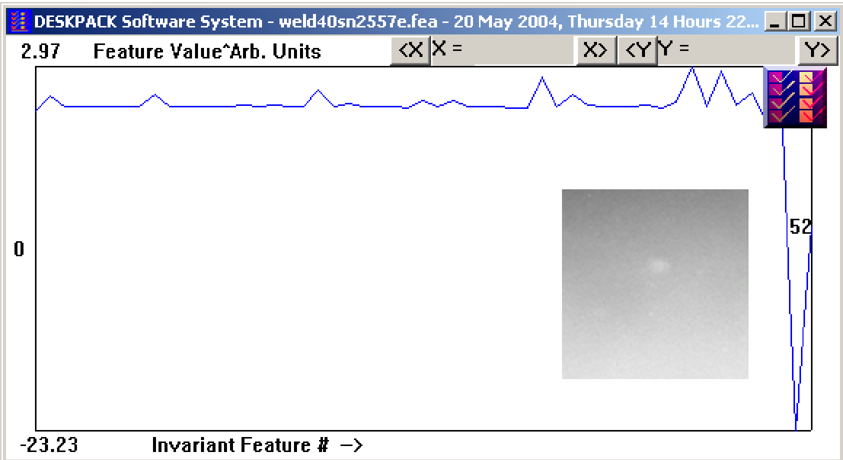

Figure 6: The 52 Invariant Image Features for a weld with a single porosity

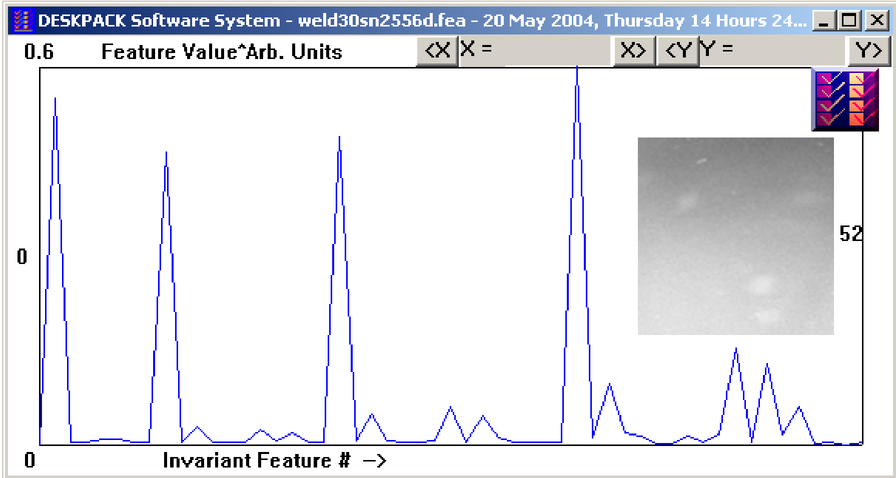

Figure 7: The 52 Invariant Image Features for a weld image with multiple porosities

Feature classification in these welds was complicated by the uneven background and the density variations. Three main reasons for the variations in the density are (1) variations in the thickness of the weld (2) radiation beam angle – since a backward throw probe with a beam angle of – 5 ^{o} to -60^{o} x 360 ^{o} was used for weld radiography to ensure complete coverage of the weld, the varying distance of the weld from the focal spot result in density variations and (3) statistical variations in the number of photons emitted during the radiography process. While the second factor can be taken care through appropriate background subtraction techniques, the first and the third factors are difficult to handle. Analysis of more than 50 segmented radiographs using the 52 moments clearly indicate that it is possible to delineate the defects in the presence of other weld features clearly.
Feature extraction is the first and crucial step in automated recognition. The next step envisaged in this process is feature selection. Feature selection is the process of selecting the best subset (of features) from amongst the entire initial set which would achieve the best classification result. To arrive at an optimized feature selection, the first step is feature ranking, wherein all the features in the total feature set of one domain are ranked with respect to their potential to discriminate the patterns under study. In this study, feature ranking has been done by an integral mechanism using a combination of the inter- and intra-class distances and the use of the Fisher approach [9]. The Fisher approach is based on projection of d-dimensional data onto a line oriented to maximize data partitioning and produces a set of linearly independent features that are ordered in accordance with a criterion called Fisher weighing, which is a measure of a feature's ability to discriminate categories. Once the ranking has been achieved, the problem is simplified and using MLP based ANN it is possible to train the NN for the various defects based on the features extracted. With quantitative estimation of the defect sizes and comparison with the specifications given in the codes and standards, we have a full fledged automated defect recognition system. These results would be presented during talk.

Conclusion : In this paper, **52** geometric invariant moments has been used for feature extraction from the images of the weld. The main advantage of using the moments is their invariance to geometric transformations (translations, rotation, scale change etc.). Compared to the seven moments that have been used earlier by other authors, the authors have used 52 moments which has resulted in better feature selection process. Using the Fischers ranking criteria and MLP based ANN it now becomes possible to realise a automated defect recognition system.

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