Intelligent X-Ray Imaging Inspection System for Composite Materials with Polymeric Matrix

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Due to the required high demands of quality products and to higher productivity rates, automated inspection systems have to be implemented in the industry. These inspection systems have to be reliable, fast, robust and flexible in their functionality in order to meet the high demands of the industry. An X-ray image of the product is taken and analysed by the system. The most important stages of the inspection process are the segmentation of the image into meaningful objects and the consequent analysis of these. This paper presents a Competitive Hopfield Neural Network (CHNN) for the segmentation of dual-band X-ray images of inspected product and a high-level detection of foreign bodies/defects based on fuzzy logic.

Keywords: composite materials, image segmentation, Hopfield neural network, dual-band image, X-ray image, fuzzy logic

Image segmentation is the first and the most important step in a contaminant/defect detection/inspection system used in the industry. Whereas such a system is used for detection of metallic or non-metallic contaminants (e.g. glass, bones and stones, for detection of defects of raw or prepared meat, detection of crack in weldings and casts, detection of defects in electronic components, etc.), it usually involves some means of acquiring one or more images of the inspected product. The most important type of image used in commercial inspection systems is the X-ray image [1,2]. Due to the difference between the absorption coefficients of radiation of the product and contaminants or defects a human expert can decide whether the product passes the inspection process or not. In the automated systems, a very important task is the segmentation process (partitioning the X-ray image into meaningful objects). Most segmentation methods currently rely on simple thresholding algorithms [3-6]. After the segmentation process, a high-level detection is necessary in order to finalise the inspection task. It is the process of deciding whether objects resulting from the segmentation are foreign bodies or not.

Composite materials consist of two or more materials combined in such a way that the individual materials are easily distinguishable. A common example of a composite is concrete. It consists of a binder (cement) and a reinforcement (gravel). The individual materials that make up composites are called constituents. Most composites have two constituent materials: a binder or matrix, and a reinforcement. The reinforcement is usually much stronger and stiffer than the matrix, and gives the composite its good properties. The matrix holds the reinforcements in an orderly pattern. Because the reinforcements are usually discontinuous, the matrix also helps to transfer load among the reinforcements [7]. In the present study, a composite material was obtained using a polymer resin and a hardener as the reinforcement.

The problem of inspection of the composite materials is one of detection of non-uniformities in the X-ray images taken from the material. These uniformities can appear due to uneven mixing of the constituents polymers and hardeners, and therefore, one can find areas that contain only hardeners, or only polymers or uneven distribution of those across the full body of material [8,9,10]. Since the resulting composite material has to have an uniform viscosity the resulting X-ray image has to be uniform from the grey-level point of view. Possible air bubbles or non-uniformity [10] of the composite material will appear on the image as areas with either a higher contrast or a lower contrast than the surrounding background.

This paper concerns the use of a CHNN for the segmentation process of a dual-band image (an image consisting of a high-energy and low-energy X-ray images or views) and a fuzzy logic high-level detection of foreign bodies/defects embedded within the products.

Proposed inspection system

The proposed system, an implementation of a general pattern recognition (PR) system [11] comprises the following units or systems (figure 1):

· Image acquisition system – means of generation of X-ray images of the inspected product and means of transmitting them to a computer;

· Image pre-processing system – techniques for enhancing the X-ray images for intermediate level image processing (contrast enhancement, background removal, noise removal, etc.);

· Image segmentation system – aCHNN module that partitions the X-ray image into meaningful classes for further higher level inspection;

· Object extraction unit – extracts objects from the previously segmented image;

· Feature extraction system: comprises two modules that extract geometrical features and grey-level based statistical features respectively, of each extracted object;

· High level detection system – a fuzzy logic based system for the higher inspection level; it consists of two fuzzy modules that use fuzzy inference systems based on rules about the above mentioned extracted features.

A summary of the inspection process is presented below:

General X -ray imaging inspection process

Step 1. **Acquire the X-ray image** or images of the inspected product;

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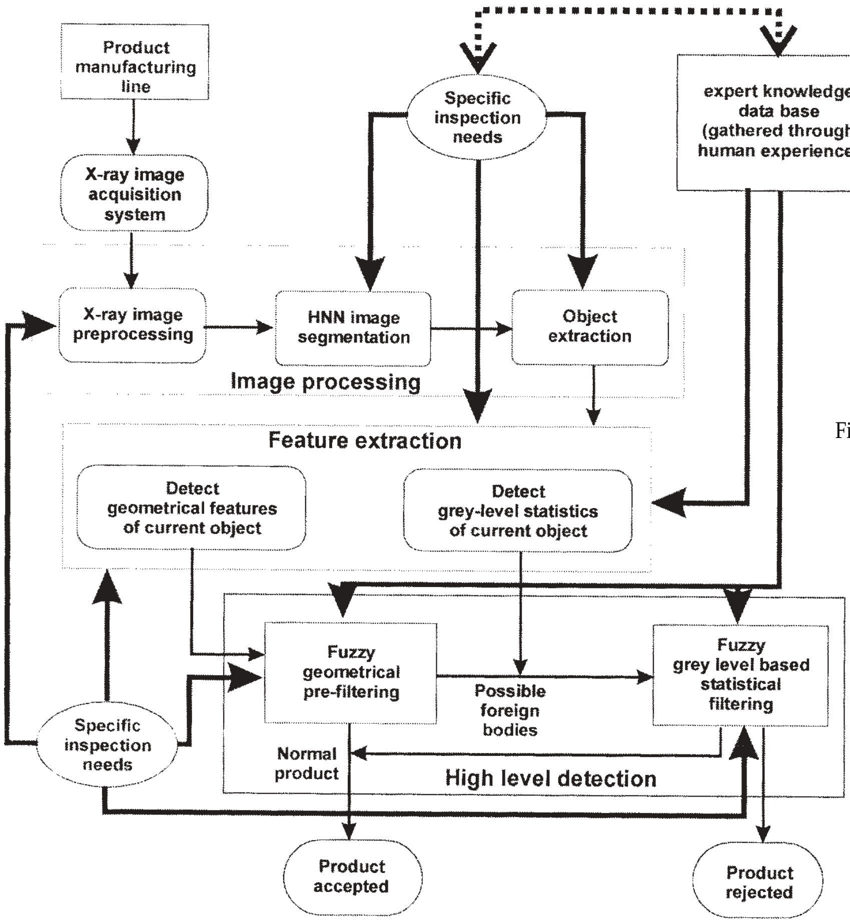

Fig. 1 X-ray imaging inspection system incorporating human and end-user specific inspection needs

Step 2. **Low-level image processing** of the resulting image or images;

a)X-ray image or images **pre-processing**;

b)X-ray image **segmentation** using a Hopfield Neural Network (HNN):

c) Object extraction for the obtained segmented image

Step 3. **High-level detection of possible faults or defects** of the product (a defect is considered here as a generic notion; it represents any possible problems with the inspected product that can make it not useful for its designed purpose):

a)Feature extraction for the extracted objects

b)High-level fuzzy logic based detection of possible faults or defects

Step 4. Final product **acceptance or rejection**

Human experience has to be incorporated into the design of such a system. The knowledge obtained using experiments by human experts is gathered into a common database that is used along the entire inspection system. The knowledge database contains data about the inspected product (such as physical and chemical characteristics), data about the possible faults and defects (such as the presence of foreign bodies and their characteristics, cracks, porosities, etc.) and any other information direct or indirect related to the inspection process. Based on the product knowledge gathered through human experience, the system must be able to extract the appropriate features from the segmented objects in order to facilitate the high-level detection process. This task makes use of the same database, as well.

The end-user has to be able to incorporate preferences in the inspection process. As a result, a module for specific inspection needs is used to obtain flexibility from the end-user point of view, as depicted in figure 1. The user preferences have to be taken into account in most of the inspection stages, from the low-level image pre-processing to the high level detection of faults. In the image processing part of the system, user preferences come heavily into play, starting with the pre-processing unit where a user wants a specific way of enhancing of the X-ray images to suit its needs. Image segmentation takes into account what the user wants to detect. For instance, when detecting foreign bodies from a composite material, segmentation into two classes will miss a large number of possible foreign bodies due to the random thickness of the inspected product. Another method that the user wants to control is how the objects are extracted. Therefore, in order to suit their specific needs, the end-user has to control the high-level detection process. At all times, to achieve more flexibility of the system, there is a two-way communication link between the 'product expert knowledge database' module and the 'end-user specific inspection needs' module. The link makes sure that human knowledge gathered through experience and the user needs are mixed and used either sequentially or in parallel in order to obtain the optimum system's performance.

Image segmentation by using a CHNN

HNN was proposed in 1985 by Hopfield as a way of solving optimisation problems. In a HNN each neuron is linked to another and weights are symmetrical, i.e. $w_{ij}=w_{ji}$, where w_{ij} represent the weight of connection between neuron i and j. There are no input or output neurons, but rather all the neurons look and act exactly the same. Inputs are applied to all neurons at the same time. The network for the optimisation application tends to relax into stable states that minimises an energy function of a Lyapunov form [12-14]:

$$E=-\sum_{i=1}^{N}\sum_{j=1}^{N}w_{ij}v_iv_j-\sum_{i=1}^{N}I_iv_i \qquad (1)$$

where N is the number of neurons, v_i is the output of the i^{th} neuron , and I_i is the external input for the i^{th} neuron term. Hopfield demonstrated that HNN relax into a stable state tending to minimise its corresponding energy function.

The strategy used by the majority of the authors comprises two steps: firstly, to find a binary representation for the segmentation solution, so that it can be mapped into a HNN stable state; and secondly, to define the energy function whose minimisation will lead to an optimum solution to the problem.

The problem of segmenting an image of *n by n* pixels into *k* classes is to choose a suitable architecture for the HNN. In this study, we follow the ideas proposed in [15-16]. The solution of the segmentation process using a binary representation can be mapped using a grid of *P* rows of *k* neurons. The columns of this architecture represent the classes in which the image has to be segmented. The rows correspond to the objects that have to be assigned to a class according to some constraints. An approach taken in [14] is to use a grid of *P* by *k* neurons, where *P* is the total number of pixels in the image. Thus, the number of neurons in this approach is n x n x k. This means that, in the present case, an image with 536 . 536 pixels that needs to be segmented into 10 classes would need a HNN with 2,872,960 neurons. The computations associated with the behaviour of such a neural network are very complex and unsuitable for a real time application.

The complexity of such an approach can be decreased severely as in [17]. Their HNN consists of a similar grid of *N* by *k* neurons, but in this case *N* is the number of grey-level values found in the input image (fig. 2). The number of neurons decreases dramatically to *Nxk*. In the present case, for 10 classes and for all 255 grey-level values present in the image one only deals with 2550 neurons. This makes this architecture not only manageable from the point of view of computations involved, but also independent of the size of the image.

An energy function associated with a HNN must comprise terms for image segmentation constraints $E_{systactic}$ or syntax energy i.e. to ensure that no grey-level or pixel can belong to two classes at the same time, and terms for goodness of segmentation, $E_{semantic}$ or the semantic energy:

$$E = E_{syntactic} + E_{semantic} \tag{2}$$

Using the binary mapping mentioned above, the segmentation constraints can be summarised as follows: only one neuron per row can be active (output is 1); this puts each grey-level into one class (left term of equation (3)); the sum of outputs of all neurons in one row is 1, thus ensuring the fact that each grey-level belongs to only and only one class (right term of equation (3)):

$$E_{systactic} = \alpha \sum_{x=1}^{N} \left(\sum_{i=1}^{k} v_{xi} - 1 \right)^2 + \beta \sum_{x=1}^{N} \sum_{i=1}^{k} \sum_{\substack{j=1 \\ j \neq i}}^{k} v_{xi} v_{xj} \tag{3}$$

where α and β are constant values

The goodness of segmentation has to be measured by the following properties. Firstly, segments have to be uniform and homogenous with respect to grey-level values. Secondly, adjacent regions or segments have to have significant differences with respect to their uniformity (in this case the grey-level values). Thus, the semantic energy is defined in this case as the sum of square distances from each grey-level to the centre of its class. By minimizing the energy, these distances decrease to a minimum leading to a solution for the segmentation. Due to the fact that two images are taken for each product, one high-energy X-ray and one low-energy X-ray image, a semantic energy for both images has to be defined as follows:

$$E_{semantic_1} = \vartheta \sum_{x=1}^{N_1} \sum_{y=1}^{N_1} \sum_{i=1}^{k} \frac{1}{\sum_{y=1}^{N} hl_y v_{yi}} v_{xi} DIS_{xy} hl_y v_{yi} +$$

$$+ \delta \sum_{x=1}^{N_2} \sum_{y=1}^{N_2} \sum_{i=1}^{k} \frac{1}{\sum_{y=1}^{N} hh_y v_{yi}} v_{xi} DIS_{xy} hh_y v \tag{4}$$

where N_1 , N_2 are the number of grey-levels present in the low-energy and high-energy image respectively, ϑ and δ are constants and hl_y and hh_y are the histogram values of the *y* grey-level for the low-energy band and high-energy band image respectively.

An important aspect in the process of defining the semantic energy is choosing the appropriate measure of distance DIS_{xy}. This represents the distance between grey-level l_x and grey-level l_y. Because the present method is actually a cluster analysis algorithm, a good segmentation can be defined by having spherical or hyperspherical distribution of clusters. Thus, the distance used is the squared Euclidian distance that will allow hyperspherical distribution of clusters:

$$DIS_{x,y} = d_{l_x, l_y} = (l_x - l_y)^2 \tag{5}$$

A simplification of the energy equation can be achieved using a Winner Take All (WTA) scheme transforming HNN into a competitive architecture (CHNN). The input-output function for a neuron is modelled as to satisfy the constraints of the energy function. For every row, only one neuron can be active. The neuron that receives maximum input from all other neurons is declared winner and its

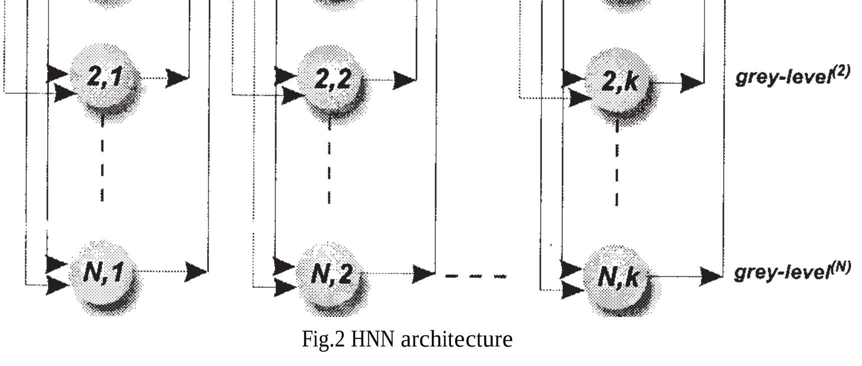

Fig.2 HNN architecture

output is set to 1; the output of the rest of neurons for the same row is set to zero:

$$V_{\substack{x,i\\x=1..N\\i=1..k}} = \begin{cases} 1, & \text{if } u_{x,i} = \max\left(v_{\substack{x,i\\i=1..k}}\right) \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

In other words, only one neuron is assigned 100% to a class. This satisfies the syntactic energy terms, therefore the energy equation (4) can be simplified to:

$$E = \sum_{x=1}^{N} \sum_{y=1}^{N}\sum_{i=1}^{k} \frac{1}{\sum_{v=1}^{N}(hl_y + hh_y)V_{yi}} V_{xi} DIS_{xy}(hl_y + hh_y)V_{yi} \tag{7}$$

where $N = max(N_1, N_2)$.

Comparing equation (7) with the definition of the Lyapunov energy (1) one can compute the updating equation for the interconnection weights when no bias or threshold is present:

$$w_{\substack{(x,i)(y,j)\\x,y=1..N\\i,j=1..k}} = -\frac{1}{\sum_{y=1}^{N}(hl_y + hh_y)V_{yi}} V_{xi} DIS_{xy}(hl_y + hh_y)V_{yi} \tag{8}$$

where V_{xi} and V_{yi} are the binary values for the output of neurons *(x,i)* and *(y,i)*. Because the number of weights that needs to be updated is considerable, using the weights updating formula (8), an equation for the total input to the neuron *(x,i)* is obtained:

$$v_{xi} = -\frac{1}{\sum_{v=1}^{N}(hl_y + hh_y)V_{yi}} \sum_{y=1}^{N} DIS_{xy}(hl_y + hh_y)V_{yi} \tag{9}$$

An algorithm was designed and implemented using the above equations.

Therefore, HNN segmentation has to be performed into two classes: one class for the defects and the other one for the normal material. Once the segmentation process is finished, objects are extracted from the segmented image. These objects were then analysed and a final decision is taken whether they are or not defects by the high-level fuzzy logic detection system.

Object extraction

The object extraction process extracts the objects from the segmented image. For each segmentation level (or class), a backtracking algorithm was designed and implemented for the object extraction. It consists of a function that requires a starting point (pixel) of the current object to extract. Then, all pixels adjacent to the starting pixel are tested for similarity. If a pixel is found to be the same grey-level as the object, then it is marked respectively. Otherwise the process is stopped. The algorithm recursively searches for neighbour pixels from right to left for instance and it continues to do so until a dead end is reached; then the function "backtracks" its way to the starting point and the process continues for considering pixels from left to right and so on.

When the function has marked all the pixels of an object, features are extracted from it and further high-level classification is performed. As explained before, if the object analysed is found to be a foreign body, then the entire inspection process is stopped and the product is rejected. Otherwise, the object is simply erased for the analysed class and another one is extracted using the same backtracking technique.

Fuzzy logic (FL) high-level detection

A FL-based PR system for the food inspection process is presented in figure 3. As with all implementations of PR systems, it must contain an object and feature extraction unit and a classifier. The classifier is a FL-based called *fuzzy inference system* [19,20]. This classifies the current object as a foreign body or normal meat.

The architecture consists of two fuzzy filtering modules and two feature extraction units (figure 4). The first feature extraction unit extracts the geometrical characteristics of the current object. Using these features the first module decides whether an object or area corresponds to a foreign body from the geometrical point of view. Its output is analysed and a decision is taken whether the system has to continue the analysis process. Thus, the second module is used only if the output of the first module confirms the possibility of the current area being a foreign body. It consists of a second fuzzy inference system using statistical grey-level characteristics of the region in question. If the object corresponds to the statistical grey-level foreign body criteria, the food product is rejected. Otherwise, the next object is analysed and the process continues until all objects are analysed or one object was found to be a foreign body. During development, the process of detection of foreign bodies carries on no matter how many are found. The reason behind this is so that the performance of this approach can be measured.

A first step was to define the fuzzy sets describing the generated areas geometrical properties (table 1). From each region, four measures were taken. The first and the most important one is the number of pixels contained in that area: **AREA_SIZE**. This measure was defined as fuzzy sets using a trapezoidal membership function. **PERIMETER** was another important measure computed. It consists of the number of pixels at the edge of the region in question. The **SHAPE** [24] feature is a measure of the shape of an individual region.

The compactness of a shape is derived from the ratio of the perimeter length of the shape divided by its area:

$$SHAPE = \frac{PERIMETER}{AREA} \tag{10}$$

The **ROUNDNESS** measure [21, 22, 24] is defined as follows: if the region is a circular one then it has a high roundness measure, if it is an ellipse or of a different shape it has a low roundness measure. In defining this concept a reference circle was used with its centre in the centre of gravity of the current region and with a similar area size.

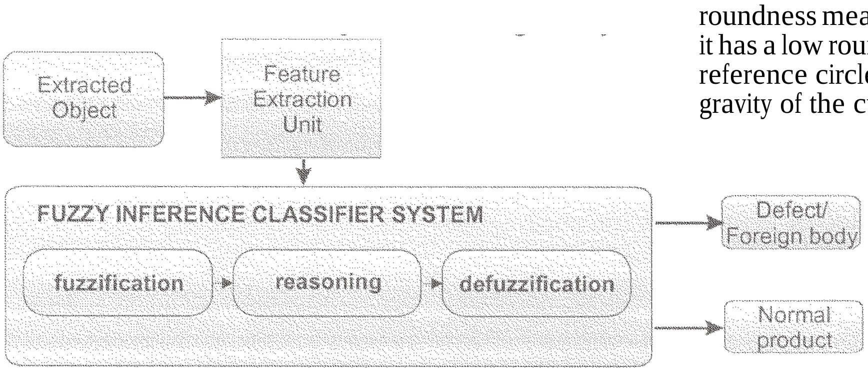

Fig.3. General FL-based PR system for the food inspection process

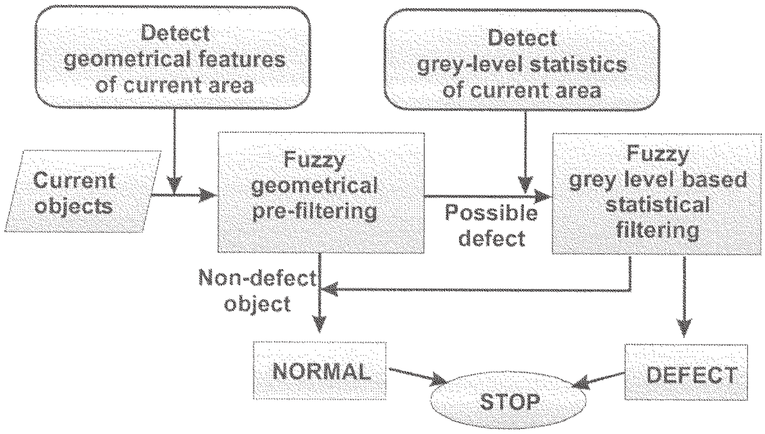

Fig.4 Proposed fuzzy filtering system

Table 1
LINGUISTIC VARIABLES DEFINED FOR THE SYSTEM

Geometrical features	Grey-level based features
AREA_SIZE: tiny, small, medium, big, large PERIMETER: short, long SHAPE: smooth, irregular ROUNDNESS: low, medium, high	LOCATION: edge, middle DIFFERENCE: big, small, negative

Therefore the concept was defined as the difference between the two areas (pixels that do not belong to the region but belong to the reference circle-A_1; and pixels that belong to the region but do not belong to the reference circle-A_2):

$$ROUNDNESS = 1 - \frac{A_1 + A_2}{2 \cdot region\_area} \qquad (11)$$

The system was implemented for several X-ray images with or without defects (fig. 5). In all cases one has to take into account the fact that the composite material always had a lower thickness near the edges and that should not be considered as faults.

The basic principle for the fuzzy rules was: if the average grey-level difference between current object and its surrounding background is high and it is not on the edge of the image then the object is a defect; otherwise, the object is normal material. In this case, the fuzzy pre-filtering module informs the user of some physical measurements of the defects or foreign bodies (such as area size and the shape of the possible defect). Thus, the user can specify specific inspection needs such as rejection of all products with non-uniformities larger than a certain threshold.

The second fuzzy grey-level statistics module had two input measures: LOCATION (with two fuzzy sets: EDGE and MIDDLE) on the image of the current object and the DIFFERENCE (with two fuzzy sets: LOW and HIGH). The

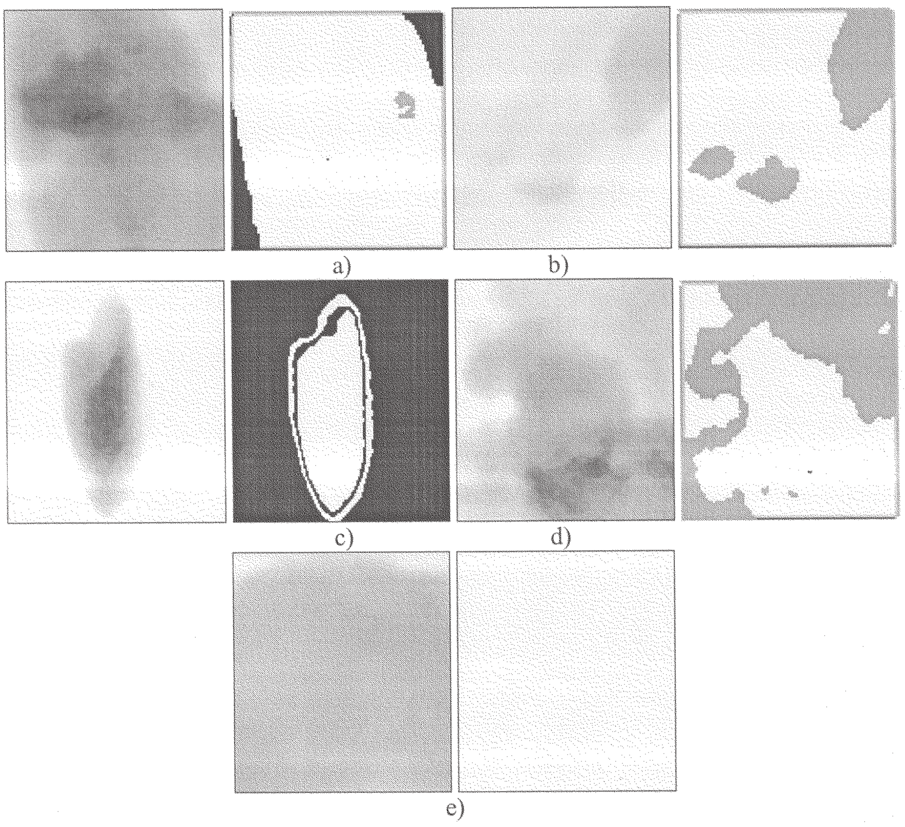

Fig.5 X-ray images of composite materials and their corresponding system-output; objects in red are reported as defects
a),b),c),d) composite materials with defects;
e) composite materials without defects

second measure is defined as the difference between the mean intensity for the region and the mean intensity for the neighbourhood of the same area. Both high- and low energy images were used when computing those two measures. The output of the system had two fuzzy sets: DEFECT for when an object is classified as a defect and MATERIAL when the object is classified as normal material. There were four fuzzy rules for the implemented Mamdani-type fuzzy inference system [20]:

1.if DIFFERENCE is HIGH and LOCATION is MIDDLE then OUTPUT is DEFECT

2.if DIFFERENCE is LOW and LOCATION is MIDDLE then OUTPUT is MATERIAL

3.if DIFFERENCE is HIGH and LOCATION is EDGE then OUTPUT is MATERIAL

4.if DIFFERENCE is LOW and LOCATION is EDGE then OUTPUT is MATERIAL

The algorithm was tested on 132 images and its performance was measured as being 91.34% in accuracy with 0.55% false negatives (cases reported by the system as being normal products while in reality they were products with defects/foreign bodies) and 8.11% false positives (cases reported by the system as being rejected while in reality they were normal products).

Conclusions

This paper concerns using a Hopfield Neural Network in conjunction with a Winner Take All mechanism for segmentation of dual-band X-ray images of composite materials with polymeric matrix and consequent high-level detection of foreign bodies/defects using fuzzy logic. The proposed system is robust and flexible with regards to its functionality and achieves an acceptable performance.

Segmentation with a HNN achieves good results in terms of the correct segmented objects. The corresponding energy function is dependent only on the global distribution of grey-levels present in the input images and no spatial constraints are introduced. Thus the number of nodes in the HNN architecture is independent upon the image size. Due to the lack of clarity of the images, it was demonstrated that using dual-images offers better results as opposed to single-image segmentation. Complementary information from both components of the dual band high and low energy images, was used in the definition of the energy function so that improved segmentation was obtained.

Future work will concentrate on minimizing even further the computational overhead involved. Automatic generation of the number of classes for the segmentation process that now needs to be known *a priori*, is currently under investigation. Furthermore, spatial constraints can be added to the definition of the energy function in order to improve the network performance. The present architecture can be easily extended to colour-image segmentation and analysis and it has a great deal of potential for hardware implementation (VLSI parallel hardware implementation).

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