Available online at www.sciencedirect.com

ScienceDirect

Procedia Engineering 100 (2015) 492 – 498

Procedia Engineering

www.elsevier.com/locate/procedia

25th DAAAM International Symposium on Intelligent Manufacturing and Automation, DAAAM 2014

Industrial Image Processing Using Fuzzy-Logic

Catalin Gheorghe Amza*, Dumitru Titi Cicic

University Politehnica of Bucharest, Splaiul Independentei 313, sector 6, Romania, 060042

Abstract

This paper concerns with the utilization of artificial intelligence borrowed techniques such as fuzzy logic for the automatic analysis of X-ray images of industrial products for defect detection. An original two stages algorithm is presented based on the feature analysis of the radiographic images obtained from the inspected product. Each object in the image is analyzed using fuzzy logic techniques. The first stage takes an automatic decision whether the current object can be classified as a defect from the geometrical point of view and the second stage takes the final decision by using "logical" criteria that is dependent on the product at hand and its quality requirements.

Peer-review under responsibility of DAAAM International Vienna

Keywords: fuzzy logic; non-destructive testing; image processing

1. Introduction

Image processing has become an integrated part of modern industrial manufacturing systems, mostly used in a variety of manual, semi- and automatic inspection processes. Such an inspection system usually acquire an image of the product that needs to be checked for quality conformance and subsequently that image is analysed either by human operators or automatically by a computer via specific image processing techniques. 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, fish, cooked products, packaged products, vessels, tins, conformance of welds and castings, 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 radiographic image [1], [2]. Depending on the quality of the acquired X-ray images or on the performance of the actual X-ray acquisition system and the X-ray absorption

* Corresponding author. Tel.: +40 744 500 803; fax: +40 21 402 9541.
E-mail address: acata1@camis.pub.ro

Peer-review under responsibility of DAAAM International Vienna
doi:10.1016/j.proeng.2015.01.404

coefficient of the inspected product, one can use various image processing techniques in order to detect possible defects. Such a method is based on the following stages:

General imaging inspection process
Step 1 **Acquire** the image or images of the inspected product
Step 2 **Image pre-processing** of the resulting image or images
Step 3 **Image segmentation**
Step 4 **Object and feature extraction** for the obtained segmented image
Step 5 **Detection of possible faults or defects** of the product
Step 6 Final product **acceptance** or **rejectance**

Image acquisition is having the means of generation of X-ray images of the inspected product and means of transmitting them to a computer. Image pre-processing implies the use of techniques for enhancing the radiographic obtained images for intermediate level image processing (contrast enhancement, background removal, noise removal, etc.) [3], [4]. Image segmentation is the most important stage of such an automated image processing system. It is simply a problem of partitioning the image into several classes of objects. Most segmentation methods currently rely on simple thresholding algorithms [5], [6], [7]. Due to the fact that usually, the inspected product has different materials with various thickness that is a function of a random variable, simple thresholding algorithms cannot be applied for segmentation of such X-ray images into objects [1], [8]; there are also various methods that are using artificial intelligence techniques such as back propagation neural networks, Kohonen neural networks or Hopfield neural networks [9], [10], [11], [12], [13]. Depending on the acquired radiographic image, the results of the segmentation should be optimum (meaning that the X-ray image is partitioned into meaningful objects for their consequent analysis). At the object and feature extraction step, the method should be able to extract and to compute some features for each object from the segmented image; the feature extraction process is highly dependent on the inspected products; if one seeks to inspect welds, then it looks for cracks, gas inclusions and then the features extracted from the images can be based on their geometrical properties, on the spatial properties or on their grey-level properties as compared to the background; if one looks to find contaminants in deboned chicken breast meat, then it looks for bone fragments that are usually very small and of a particular shape (round) hence one can only extract geometrical features from the segmented image. The final step relies on the objects and its features extracted previously. It is a classification problem or in more general terms a pattern recognition (PR) problem [14]. The method is an issue of classifying each object as being normal product or a defect. Once the features are extracted from an object, the simplest way is to compare them with the information already stocked within a knowledge database (or a simple look-up table). The knowledge base is usually designed using expert observations. Sample images are analysed by human experts and the information is saved in a useful format in an expert database. The methodology is presented in Figure 1.

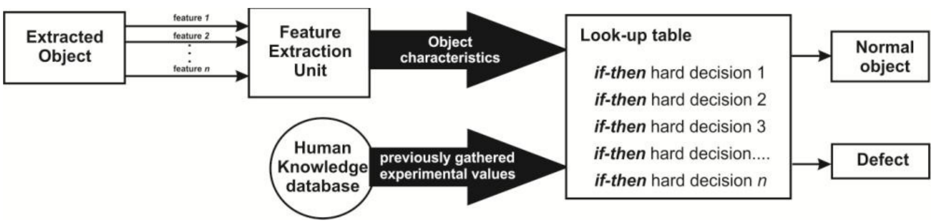

Fig. 1. Classical approach to object classification.

The main disadvantage of this approach is that it uses predefined hard *if-then* decision. The implemented look-up table consists of already stored patterns gathered thorough experiments and based on human knowledge. Small variations from those already stored patterns will render unreliable results. For instance, at this later stage of the inspection system, noise can appear in the feature extraction process, therefore altering a feature's values. This is either the result of poor segmentation or the results of image corruption during the image acquisition stage or due to transmission over cables of video signals often affected by the presence of electromagnetic fields, or bad shielding of cables. This paper concerns with step 5 of the image-processing system – the detection of possible faults or defects from the already segmented X-ray image. It presents a solution to this problem by implementing a two stage fuzzy logic method for object classification.

2. Fuzzy approach

Fuzzy logic (FL) is an easy and convenient approach for mapping an input space (referred as a universe of discourse) to an output space. In other words, mapping inputs to their corresponding outputs, such as in a general PR system where the inputs can be the patterns and outputs are the classification classes. Applying a FL approach to an image processing system brings FL properties such as:

- great flexibility, due to the ease of modifying or adding more functionality to the system;
- great tolerance of imprecise data;
- experience of human experts can be used as a scaffolding for FL;
- FL is based on natural language; natural language has evolved over the centuries to be convenient, easy and efficient, therefore it is safe to assume that FL is also easy to use when compared to other methods such as NNs.

FL is based on common sense statements. Natural language that has meaning both to the human user and the machine is used by FL as a technique to bridge the gap between people and machines. The proposed architecture consists of two Mandami-type fuzzy filtering modules and two feature extraction units (Fig. 2).

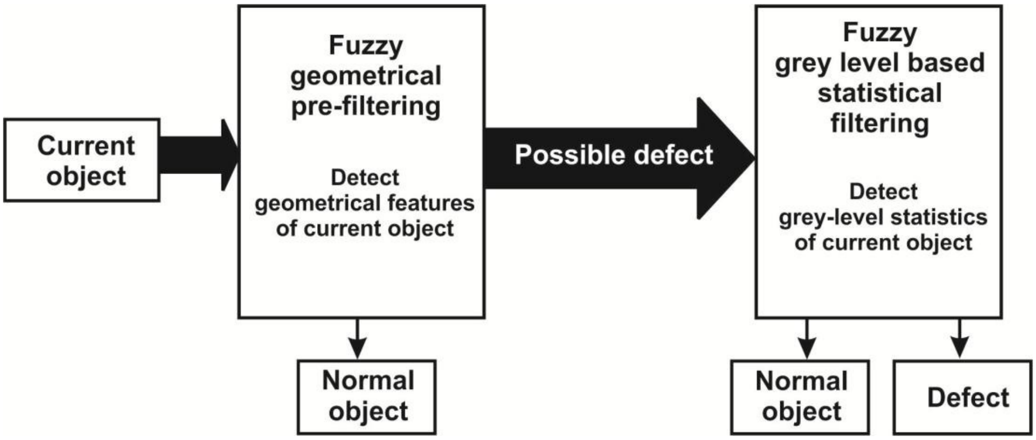

Fig. 2. Proposed fuzzy architecture.

The first feature extraction unit extracts the geometrical characteristics of the current object. Using these features, the fuzzy geometrical pre-filtering unit computes the probability of being a foreign-body for the currently analysed object. Then, the second features extraction unit computes the object's grey-level based properties. Based on the probability output of the first fuzzy module, the fuzzy grey-level based statistical filtering module takes the final decision about the current analysed object. In other words, the first module decides whether an object or area corresponds as being a defect from the geometrical point of view. Its output is not inputted into the second fuzzy module. It 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 defect. Otherwise, the next object is analysed and the process continues until all objects are analysed or one object is found to be a defect (at least one defect is found in the inspected product).

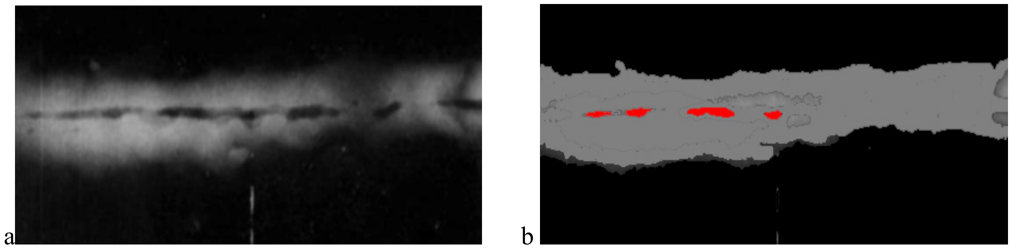

Fig. 3. (a) Sample of weld X-ray (b) Segmented image.

3. Experimental results

A great variety of X-ray equipment currently available offers a comprehensive range of penetrating power that can satisfy virtually any industrial requirement. These applications can range from irradiation studies, electronic circuitry and alloy casting inspection right through to the inspection of welded heavy steel structures. Among the applications of X-ray imaging inspection techniques are the inspection of welds. Weld metal defects are normally caused by a combination of high stresses across the weld and metallurgical weakness of the filler metal. These defects can either appear during the welding process or after. There are a number of types of weld defect categories:

- gas pores, defects that occur as a result of gas entrapment in the molten metal during a weld or through improper cleaning of the joint during preparation of the weld;
- incomplete fusion and penetration, that can arise from poor welding conditions. Fusion refers to the degree to which base metal surfaces are fused to their metal filler, while penetration refers to the degree to which metal surfaces have been melted together to form the throat of a weld;
- cracks may occur in either the weld or base metals being joined. There is a wide variety of crack types (transverse, longitudinal and so on), each with sub-definitions.

As far as defect detection goes, it is possible to reliably recognize all these defects using X-ray inspection techniques. Segmentation is performed using a Hopfield Neural Network architecture as proposed in [15], [16]. After segmentation, the high-level detection process has to take into consideration all possible defects and to take a final decision. The geometrical pre-filtering fuzzy logic module is not used, since the difference between the average grey-level value of a possible defect and its surrounding background is high. However, the size of an object is important. Therefore, only one fuzzy module can be used that combines the geometrical attributes of the object and its grey-level characteristics.

3.1. Fuzzy measures definition

A first step was to define the standard fuzzy sets describing the geometrical properties of the generated areas. From each region, five features are extracted. The first and the most important is the number of pixels contained in the current object that is analysed: **AREA**. **PERIMETER** is another important computed measure. It consists of the number of pixels at the edge of the region in question. The **SHAPE** feature is a measure of the shape of an individual region. The compactness of a shape is derived from the ratio of the perimeter of the shape divided by its area:

$$SHAPE = \frac{PERIMETER}{AREA} \tag{1}$$

The **ROUNDNESS** measure [15] is defined as follows: if a region is a circular one then it has a high roundness measure; if it is an ellipse or of a different shape then 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. 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):

$$ROUNDNESS = 1 - \frac{A_1 + A_2}{2 \cdot AREA} \tag{2}$$

These measures are defined as fuzzy sets using trapezoidal membership functions [15].

If one wants to inspect welds for cracks then from the geometrical point of view it should look for long object, with a low value of SHAPE, a high value for PERIMETER and a low value for ROUNDNESS. All these are valid only if the size of the object is not too large (AREA measure is not too large) so that the current object is actually the background. Thus, the input measures for the proposed geometrical pre-filtering module are:

- The physical area size of the current object (measured in pixels) AREA (with fuzzy sets SUITABLE, NOT-SUITABLE), variable that can be regarded as the total number of pixels in the current object;
- The perimeter of the current object – PERIMETER (with fuzzy sets LONG, SHORT);
- The shape of the current object - SHAPE(with fuzzy sets IRREGULAR, SMOOTH);
- The measure of the current object round shape – ROUNDNESS(with fuzzy sets HIGH, LOW)

The system output is (like in other inspection cases) of a bivalent nature: either DEFECT or NORMAL/BACKGROUND material. The Mamdani fuzzy inference system for the geometrical pre-filtering module consists of the following fuzzy rules:

1. *if AREA is SUITABLE and PERIMETER is LONG then OUTPUT is DEFECT*
2. *if AREA is SUITABLE and PERIMETER is SHORT then OUTPUT is NORMAL/BACKGROUND*
3. *if AREA is SUITABLE and ROUNDNESS is LOW then OUTPUT is DEFECT*
4. *if AREA is SUITABLE and SHAPE is SMOOTH then OUTPUT is DEFECT*
5. *if AREA is NOT-SUITABLE then OUTPUT is NORMAL/BACKGROUND*

The first fuzzy module will only detect whether the current object might be a defect from the geometrical point of view. Thus, the current object is used within the second fuzzy module. The functionality of the second fuzzy module is similar to the geometrical fuzzy module. Its input measures are:

- the mean intensity between the object and a rectangular area that surrounds it – DIFFERENCE(with fuzzy sets SMALL, LARGE); a surrounding rectangle was defined for computing the difference measure
- the difference between the mean intensity for the region and the mean intensity for the neighborhood of the same area - TOGETHERNESS (with fuzzy sets CLOSE and LOOSE) of the region; this means that small grey-level variations within the current object (homogenous object) will lead to a high value for TOGETHERNESS [14]

$$TOGETHERNESS = \sqrt{\frac{\sum_{pixel(i,j)\in Area}\left(I_{pixel(i,j)} - BRIGHTNESS\right)^2}{AREA\_SIZE}} \tag{3}$$

One is now looking to find objects that have a high value for DIFFERENCE and a high value for the TOGETHERNESS:

1. *if DIFFERENCE is LARGE and TOGETHERNESS is HIGH then OUTPUT is DEFECT*
2. *if DIFFERENCE is SMALL and TOGETHERNESS is CLOSE then OUTPUT is NORMAL/BACKGROUND*
3. *if TOGETHERNESS is LOOSE then OUTPUT is NORMAL/BACKGROUND*

The above method was implemented on a Borland Delphi programming environment and run on a PC computer with 4 GB RAM and with a Intel i7 processor operating at 3.2 GHz. The implemented method was tested on a batch of 33 X-ray images taken from various sheet welds. The performance accuracy obtained was compared both using a classical look-up table and using the proposed method. As explained before, noise can appear in the feature extraction process, therefore altering a feature's values. Using simulation, different levels of noise were used to corrupt the input vectors. The method used consists of modifying the input vectors with a predefined percentage called noise level. That means that all values of all testing vectors were modified with a fixed percentage. If the noise level was set at 5%, then all test vectors values were modified either with a 5% increment or a 5% decrement. The same process was applied for different values for the level of noise. As expected, when the noise level is quite low, the performance of the classical method remains almost unchanged. However, when the noise level increases, the performance decreases exponentially. In case of the proposed fuzzy methods, the results obtained are good even in the presence of noise, as one can see from Table 1 and Fig. 4.

Table 1. Performance over noise levels.

Method/Performance	Noise level 0%	Noise level 3%	Noise level 5%	Noise level 10%	Noise level 20%	Noise level 30%
Look-up table	86.3%	85.2%	72.3%	64.6%	50.3%	32.7%
Fuzzy logic approach	90.71%	90.41%	89.51%	88.21%	79.51%	64.91%

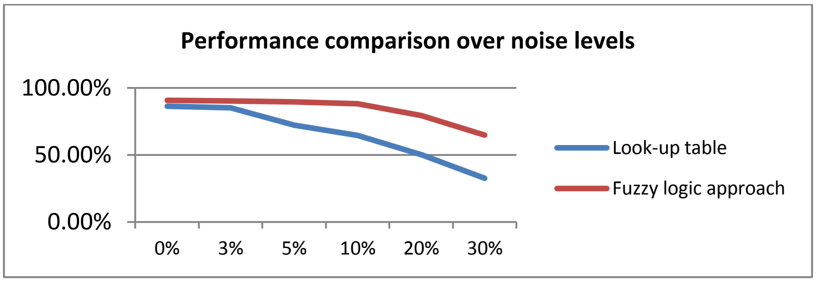

Fig. 4. Performance comparison of the proposed algorithm in the presence of noise.

Conclusion

Classical and artificial intelligence methods have been investigated in the context of image analysis. As shown, once the X-ray image is segmented, irrespective of the method used, the result needs to be further analysed. Each object is extracted and analysed and a decision needs to be taken whether that object represents a normal part of the product or a defect. This paper concerns with a fuzzy-logic approach for the automatic analysis of the segmented objects. As proven when compared to other classical methods (such as a look-up table), the reliability and performance of the proposed method is higher. Since the architecture is based on FL it is quite tolerant to imprecise input data, making the proposed methods quite insensitive to noise. Further work is required in work to minimize the number of parameters required for the proposed architecture (the number of fuzzy sets). Moreover, one might want to automatically establish the fuzzy sets for the fuzzy variables used in the FL modules, and this aspect is currently under investigation.

References

[1] Amza, C., G., Intelligent X-ray Imaging Inspection System for the Food Industry, PhD Thesis, De Montfort University, Leicester, United Kingdom, 2002.

[2] Connolly, C., X-ray systems for security and industrial inspection, *Sensor Review*, Vol. 28 Iss: 3, pp.194 – 198, 2008Otsu, N., A threshold selection method from grey-level histograms, IEEE Trans. On systems, man and Cybernetics, vol. SMC-9, no.1, pp.62-66, 1979.

[3] Pascu, N.E.; Dobrescu, T.; Opran, C.; et al., Realistic Scenes in CAD Application , 24th Daaam International Symposium On Intelligent

Manufacturing And Automation, 2013 Procedia Engineering Volume: 69, pp 304-309.

[4] Rakvin, M.; Markucic, D.; Hizman, B., 24th Daaam International Symposium On Intelligent Manufacturing And Automation, 2013, Procedia Engineering, Volume: 69, pp. 1216-1224.

[5] Otsu, N., A threshold selection method from grey-level histograms*, IEEE Trans. On systems, man and Cybernetics*, vol. SMC-9, no.1, pp.62-66, 1979.

[6] Ch.Hima Bindu, An Improved Medical Image Algorithm Using Otsu Method, *International Journal of Recent Trends in Engineering*, Vol 2, No. 3, November 2009.

[7] C.K.Leung, F.K.Lam, Maximum segmented image information thresholding, Graphical Models and Image Processing, vol.60, no.1, pp.57-76, 1998.

[8] J.N. Kapur, P.K.Sahoo, A.K.C. Wong, A new method for gray-level picture thresholding using the entropy of the histogram, Computer Vision, Graphics and Image Processing , vol. 29, pp.273-285, 1985.

[9] Amza, C.G., Tasca, G., Segmentation of Industrial X-ray images, Proceedings of the 4th WSEAS International Conference on Computational Intelligence CI'10, Bucharest, Romania, 2010, pp.54-59.

[10] N.R. Pal, S.K. Pal, A review on image segmentation techniques, Pattern Recognition, vol.26, no.9, pp.1277-1294, 1993.

[11] Amza, C.G., Amza, G., Popescu D., Image segmentation for industrial quality inspection, rev. Fiability and Durability, Supplement no.1/2012, Ed. "Academica Brancusi", Targu Jiu, pp.126-132, 2012.

[12] Popescu. D., Amza C.G., Laptoiu D., Amza G., Competitive Hopfield Neural Network Model for Evaluating Pedicle Screw Placement Accuracy, Strojniški vestnik - Journal of Mechanical Engineering, 58(2012)9, pp509-516, 2012, ISSN 0039-2480.

[13] J.E. Koss, F.D. Newman, T.K. Johnson, D.L. Kirch, Abdominal organ segmentation using texture transforms and a Hopfield neural network, IEEE Transactions on Medical Imaging, vol.18, no.7, pp.640-648, July 1999.

[14] Chen, C., Statistical Pattern Recognition, Hayden, Washington, 1973.

[15] Cicic D.T., Amza, C.G., Popescu, D., Anania, D., Automated stand for non-destructive testing evaluation of metal products, in "Applied Mechanics and Materials Vol. 371, pag 401…405, ISSN ISSN 978-3-03785-786-1 Applied Mechanics and Materials Vol. 371 (2013) pp 401-405 © (2013) Trans Tech Publications, Switzerland doi:10.4028/www.scientific.net/AMM.371.401.

[16] Amza, C.G., Nitoi, D.F., Enciu, G., Automatic Image Processing For Welding Inspection, in Proc. of the 1st International Conference on Industrial and Manufacturing Technologies (INMAT '13), Vouliagmeni, Athens, Greece, May 14-16, 2013, pp.153-158, ISSN 2227-4596.