Fuzzy Hyperbolization Image Enhancement and Artificial Neural Network for Anomaly Detection

Sri Hartati, Agus Harjoko, and Brad G. Nickerson

Abstract—A prototype of an anomaly detection system was developed to automate process of recognizing an anomaly of roentgen image by utilizing fuzzy histogram hyperbolization image enhancement and back propagation artificial neural network.

The system consists of image acquisition, pre-processor, feature extractor, response selector and output. Fuzzy Histogram Hyperbolization is chosen to improve the quality of the roentgen image. The fuzzy histogram hyperbolization steps consist of fuzzyfication, modification of values of membership functions and defuzzyfication. Image features are extracted after the the quality of the image is improved. The extracted image features are input to the artificial neural network for detecting anomaly. The number of nodes in the proposed ANN layers was made small.

Experimental results indicate that the fuzzy histogram hyperbolization method can be used to improve the quality of the image. The system is capable to detect the anomaly in the roentgen image.

Keywords—Image processing, artificial neural network, anomaly detection.

I. INTRODUCTION

ROENTGEN image in the form of a film is commonly used in the process of medical diagnosis of disease. But often the quality is so low that body tissue does not clearly visible. Thus, it becomes difficult to determine the anomaly in the image. To overcome this difficulty, it is necessary to convert the roentgen image into digital image. The digital image allows digital image processing techniques be applied to the image to improve the anomaly detection accuracy.

The proposed method consists of a number of steps. First, the digital roentgen image is processed to improve the image contrast. The improvement to the image contrast was carried out using the fuzzy histogram hyperbolization (FHH) method with the hedges operator [8], since the transformation of the gray level image is logarithmic and it is in accordance with the human vision system. Following the image enhancement, features are extracted from the image. These features are then input to the artificial neural network to determine if an anomaly is present.

II. FUZZY HYPERBOLIZATION IMAGE ENHANCEMENT

Fuzzy image enhancement is based on gray level mapping into a fuzzy plane, using a transformation function. The aim is to generate an image with higher contrast than the original image by giving a larger weight to the gray levels that are closer to the mean gray level of the image rather than to those that are farther from the mean. In recent years, many researchers have applied the fuzzy set theory to develop new techniques for contrast improvement [3, 5]. An image *I* of size $M \times N$ and L gray levels can be considered as an array of fuzzy singletons, each having a value of membership denoting its degree of brightness relative to some brightness levels. For an image *I*, the notation of fuzzy sets can be written as:

$$I = \bigcup_{mn} \frac{\mu_{mn}}{g_{mn}} \tag{1}$$

where g_{mn} is the intensity of $(m, n)^{th}$ pixel and μ_{nm} is its membership value. The membership function characterizes a suitable property of image (e.g. edginess, darkness, textural property) and can be defined globally for the whole images or locally for its segments. In recent years, some researchers have applied the concept of fuzziness to develop new algorithms for image enhancement has been applied. The principle of fuzzy enhancement scheme is illustrated in Fig. 1.



Fig. 1 Fuzzy histogram hyperbolization image enhancement

The idea of histogram hyperbolization, and fuzzy histogram hyperbolization is described in [1,5]. Due to the nonlinear human brightness perception, this algorithm modifies the membership values of gray levels by a logarithmic function. The algorithm works in the following sequence: setting the shape of membership function, setting the value of the fuzzifier β , calculation of membership values μ_{nm} , and modification of the membership values by β and finally generation of new gray levels. The choice of the membership

S. Hartati is with the Electronic and Instrumentation Lab, FMIPA, Gadjah Mada University, Yogyakarta, Indonesia 55281 (phone: 62-274-545185; e-mail: shartati@ugm.ac.id).

A. Harjoko is with the Electronic and Instrumentation Lab, FMIPA, Gadjah Mada University, Yogyakarta, Indonesia 55281 (phone: 62-274-545185; e-mail: aharjoko@ugm.ac.id).

B. G. Nickerson is with the Faculty of Computer Science, University of New Brunswick, Fredericton N.B, Canada E3B 5A3 (phone: 215-506-453 466; e-mail: bgn@unb.ca).

function is very important, as the membership function characterize a certain property of the image (edginess, darkness, textual property).

A. Image Fuzzification

The image fuzzification transforms the gray level of an image into values of membership function [0...1]. Two types of transformation functions were used, namely the triangle membership function, and Gaussian membership functions. A triangular membership functions is shown in Fig. 2 and it's equation is written equation (2).

Triangular

$$\begin{pmatrix}
0 & x \le a \\
\frac{x-a}{b-a} & a \le x \le b \\
\frac{c-x}{c-b} & b \le x \le c \\
0 & x \ge c
\end{pmatrix}$$
(2)

In equation (2), a is equal to 0, c is equal to 255, and b varies. The Gaussian membership function is shown in the Fig. 2b, and is characterized by two parameters $\{c, \sigma\}$. The equation for the Gaussian membership function is written in equation (2)

$$Gaussian(x;c,\sigma) = e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2}$$
(2)

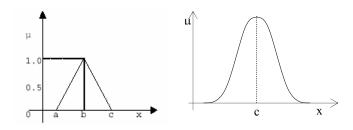
B. Modification of Membership Function

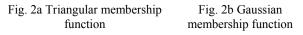
This process is needed to change the values of the membership functions resulted from the fuzzification process above. In this algorithm, the shape of the membership function is set to triangular to characterize the hedges and the value of the fuzzifier β . The fuzzifier β is a linguistic hedge such that $\beta = -0.75 + \mu 1.5$ [3], so that β has a range of 0.5 to 2. The modification is carried out to the membership values by a hedges operator [7]. The operation is called dilatation if the hedge operator β is equal to 0.5 and is called concentration if β is equal to 2.

If A is a fuzzy set and it is represented as a set of ordered pairs of element x and its membership value μ , then A^{β} is the modified version of A and is indicated by equation

$$A^{\beta} = \int_{X} \left[\mu_{A}(x) \right]^{\beta} / x \tag{3}$$

The hedge operator operates on the value of membership function as fuzzy linguistic hedges. Carrying hedge operator may result in reducing image contrast or increasing image contrast, depending on the value of β . The hedge operators can be used to change the quality of the contrast of a digital image.





A. Image Defuzzification

After the values of fuzzy membership function are modified, the next step is to generate new gray level values. This process uses the fuzzy histogram hyperbolization. This is due to the nonlinearity of human brightness perception. This algorithm modifies the membership values of gray levels by a logarithmic function:

$$g'_{mn} = \left(\frac{L-1}{e^{-1}-1}\right) \left[e^{-\mu_{mn} (g_{mn})^{\beta}} - 1\right]$$
(4)

where μ_{mn} (g_{mn}) is the gray level in the fuzzy membership values, β is the hedge operator, and g'_{mn} is the new gray level values.

III. ANOMALY DETECTION

The abnormality detection system developed in this research has components as shown in Fig. 3.

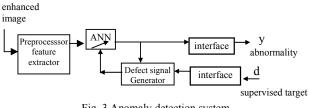


Fig. 3 Anomaly detection system

The pre-processor carries out an image enhancement process in order to enhance the image contrast, since it is useful when area for the image that is of particular importance has only subtle changes in pixel intensity. In these cases, it may be difficult for the human eye to make out the structures clearly, especially if the image is being displayed on a low quality screen. By exaggerating the changes in pixel intensity the image may become easier to interpret [1,2,3,4]. Applying the contrast enhancement filter will improve the readability of areas with subtle changes in contrast but will also destroy areas of the image where the intensity of the pixels is outside the range of intensities being enhanced.

The feature extractor extracts features in the digital roentgen image. For this purpose, Sobel operator [5] is employed. A threshold is applied to the resulted image to determine edges of the anomaly. In order to improve the

resulted image an edge linking process is applied [5]. The edge linking removes false edge indicators.

The supervised ANN is utilized to detect anomaly found in the image. An appropriate artificial neural network (ANN) model is needed to make an efficient computation. One way to keep the computation efficient is by keeping the number of nodes in the layers of ANN small. For that purpose, the result of the edge linking is threshold to yield a binary image. The histogram of the binary image is input to the ANN.

The ANN architecture for defect detection system is feed forward ANN, which consists of two nodes in the input layer, two processing layers with two nodes on each layer, and an output layer with two nodes. This adopted network has a fully connected topology, and consists of (2x2) synaptic weights. This network is trained using a set of roentgen images with and without anomaly as discussed in [4,6].

IV. EXPERIMENTAL RESULTS

A. Results of Image Enhancement

The system was tested by conducting several experiments and the improvement in contrast of image using the triangular and the Gaussian membership function with different values of β . Fig. 4a shows an example of digital roentgen image before enhancement. Fig. 4b shows the result of improvement of the contrast digital roentgen image using triangular membership functions with $\beta = 0.5$.



Fig. 4a Before image enhancement

Fig. 4b After image enhancement using triangular fuzzy set and $\beta = 0.5$

Table I shows the statistical data of the roentgen image before and after image enhancement. This table shows that the fuzzy histogram hyperbolization method can be used to improve the contrast of digital images. For the image with the condition of the gray level located in the vicinity of a particular value (86,374), FHH with the gaussian membership function produces the image with greater contrast than using the triangle membership function. This is due to the spread of gaussian membership function. The spread of the resulted gray level distribution can be seen from the value of the standard deviation which is bigger. With the greater standard deviation of the gray level of image, the contrast of the image will be the better.

 TABLE I

 Statistical Data of an Image before and after Image Enhancement

| Original image | | After image enhancement | | | | | |
|--------------------------|---------|-------------------------|---------|---------|-------------------|---------|---------|
| | | Triangular | | | Gaussian | | |
| | | hedge (β)operator | | | hedge (β)operator | | |
| | | 0.5 | 1 | 2 | 0.5 | 1 | 2 |
| Mean of gray level | 86.3741 | 224.310 | 195.741 | 149.970 | 183.569 | 143.018 | 101.541 |
| Standard deviation | 43.8093 | 20.5355 | 37.5721 | 58.9221 | 63.0731 | 81.2258 | 88.1804 |

The level of contrast of the image as a result of contrast improvement depends on the used hedges operator. The experimental results show that using triangular membership functions, with β equals to 0.5, 1, and 2 respectively, results in image with better contrast having an average gray level of 224.31, 149.97 and 195,741.

The Gaussian membership function generated with the value of β equals to 0.5, 1 and 2 results in the average gray level values 183.569, 143.018 and 101.541 respectively. The results show that the greater β the higher the contrast image become. In fuzzy concept, the use of hedges operator is to change the value of the linguistic variable. If the value of β is 1, the image is considered medium contrast, the results of improvement with $\beta = 0.5$ is less contrast, the results of image improvement with $\beta = 2$ is more contrast.

B. Results of Anomaly Detection

Once the image features are extracted, the anomaly is detected with the ANN. Fig. 5 shows the case where no anomaly is not found (in Indonesian language, "TIDAK ADA KELAINAN" means "NO ANOMALY"). Fig. 6 shows the case where an anomaly is detected. The position of the anomaly of the image is shown in rectangular. Fig. 7 shows that the proposed method is translation invariant. This system is able to detect the anomaly, even if the shifted in different position.



Fig. 5 Results of anomaly detection. Anomaly not found



Fig. 7 Results of anomaly detection. Anomaly found

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V. CONCLUSION

The results of anomaly detection show that Fuzzy Histogram Hyperbolization (FHH) was successfully used for the improvement of quality of roentgen digital image. The level of contrast image can be arranged with the operator by selecting the hedges value. If most of the gray level values are around a particular value, then the Gaussian membership function provides a better contrast than the triangular membership functions. Anomaly detection is also running well when the anomaly in the test image is shifted relative to the image reference.

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REFERENCES

- [1] S. Banks, *Signal Processing, Image Processing and Pattern Recognition*, Prentice Hall International, 1995.
- [2] A.Harjoko, S.Hartati, A Defect Detection Method for Quality Control in Ceramic Tile Industry, *Proceedings The First Jogja Regional Physics Conference, Section E Geophysics and Applied Physics.*, Yogyakarta, 2004.
- [3] E. Hassanien, A. Badr, A Comparative Study on Digital, Enhancement Algorithm Based on Fuzzy Theory, *Studies in Informatics and Control*, *Vol 12, No.1*, 2003.
- [4] S.Haykin, *Neural Network: A Comprehensive Foundation*. New Jersey: Prentice Hall, 1999.
- [5] P. Gonzales, *Digital Image Processing*, Addison-Wesley, New York, 1990.
- [6] F.O,Karray, C.Silva, Soft Computing and Intelligent Systems Design Theory, Tools and Applications, Pearson Addison Wisley, 2004.
- [7] J.R. Jang, C.T Sun., Neuro-Fuzzy and Soft Computing a Computational Approach to Learning and Machine Intelligence, Prentice Hall, Inc., New Jersey, 1997.
- [8] HR. Tizhoosh, M. Fochem, Image Enhancement with Fuzzy Histogram Hyperbolization, Proceeding of EUFIT'95, vol.3, 1695-1698, 1995.