Texture Analysis for Classification of Thyroid Ultrasound Images

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***Abstract*—Ultrasonography (USG) is one of the best imaging modalities for early detection of malignancy in the thyroid gland. Computer Aided Diagnosis (CAD) plays an important role in classifying thyroid nodules. CAD is used as an objective consideration, this is due to the high subjectivity in physician's interpretation of ultrasound images that can lead to difference scanning results. This research proposes a classification of thyroid ultrasound images by using some texture features into two classes. The dataset consists of 39 ultrasound images which grouped into 25 cystic cases and 14 solid cases. An initial step of image pre-processing is conducted to enhance the detection capability. Afterwards, followed by some methods of morphological operation, that is active contours without Edges (ACWE) and histogram equalization. The feature extraction is developed based on texture analysis by using Gray Level Co-occurrence Matrix (GLCM), Histogram and Gray Level Run Length Matrix (GLRLM). Finally, Multilayer Perceptron (MLP) is used to classify cystic nodule from solid nodule. The result shows that the proposed method achieves the accuracy of 89.74%, sensitivity of 88.89%, specificity of 91.67%, positive predictive value (PPV) of 96.00% and negative predictive value (NPV) of 78.57%. This indicates that the proposed method is excellent in classifying thyroid ultrasound images.**

***Keywords*—morphological operation, histogram equalization, ACWE, GLCM, Histogram, GLRLM, MLP.**

I. Introduction

Thyroid nodules are solid or cystic lumps within the thyroid gland and commonly found in the world's population. Palpation was the common method used for thyroid nodule detection until 1980s. The Ultrasonography (USG) usage increased the number of nodules detected. USG is the most implemented method for thyroid gland screening because of its low cost, short acquisition time, absence of radiations and sensitivity in ascertaining the size and number of nodules. Moreover, USG also provides information about nodule structure and characteristics. Approximately 5% of the world's population has a palpable thyroid nodule. After the USG usage, the rate of nodules detected increased to 67% and the number of thyroid surgical operations has increased by 31% in the United States between 2006 and 2011. The prevalence of thyroid nodularity increases with age, affecting about 50% of the population older than 40 years and females [1][2][3][4].

Some researches to classify the thyroid nodule have been carried out, among other Singh *et al.* [5], are used histogram equalization for preprocessing in his study. GLCM for feature extraction and classifier by using support vector machine (SVM), k-nearest neighbor (KNN), and bayesian. It is observed that the SVM gives much better accuracy than KNN and Bayesian. While Gireesha *et al.* [6] are used anisotropic diffusion filter for the preprocessing, watershed algorithm for nodule region the segmentation, artificial neural network (ANN) and support SVM classifier are employed for the classification and GLCM for the feature extraction. The classification results are evaluated with the use of accuracy, sensitivity and specificity. It is derived that SVM classifier provides better result than ANN for discriminating benign and malignant nodules. In other side, Atcharya *et al.* [7] are used Discrete Wavelet Transform (DWT) and GLCM were extracted, and for classification process they were used KNN, Probabilistic Neural Network (PNN), and Decision Tree (DT). The result shows that combination of DWT and texture features in the KNN classifier gives best performance.

Keramidas *et al.* [8] review of feature extraction approaches for thyroid ultrasound image analysis such as gray level histogram, Muzzolinis features, co-occurrence matrix, radon transform and local binary pattern sand classifier using SVM and KNN. Both methodologies have advantages and disadvantages which are SVM is widely accepted classifier, consider very effective for pattern recognizing, machine learning an data mining but the average distance between the hyperplane and the closest training points on both sides should be maximal. Nugroho *et al.* [9] combined the active contour segmentation and bilateral filter to separate the thyroid nodule area and it showed better result with the edge of the nodules firmly and clear. Maysanjaya et al [10] compare six types of the ANN methods such as radial based function (RBF), learning vector quantization (LVQ), back propagation algorithm (BPA), artificial immune recognition system (AIRS), and perceptron. MLP methods produce the most accurate result for thyroid case classification.

This research proposes a study to extract the nodule thyroid features which recorded in the USG images by using texture analysis with statistical methods, to distinguish between cystic and solid nodules. GLCM, GLRLM, and histogram are compared and combined to get the best accuracy of classification by using MLP.

This paper is organizing as follows: Section II represents the proposed approach for preprocessing, segmentation, feature extraction and classification. Experimental results, discussion and a comparison study are described in section III, and finally section IV is the conclusions.

II. Approach

A. Preprocessing

1) Median Filter: median filter is used to remove noise in the image. This filter uses the median value of the pixels in the window as the output *f,* can be written by the following equation:

$$f(x,y) = median_{\,(p,q)\in S_{yx}}\big(g(p,q)\big) \tag{1}$$

Median filter is one of low pass filters that work by changing the values of a pixel in the original image with the median value of the pixel and its neighbor environment, by using the zero padding that is by providing the auxiliary pad around the image with a value of zero (0). Figure 1 illustrates the concept of median filter [11].

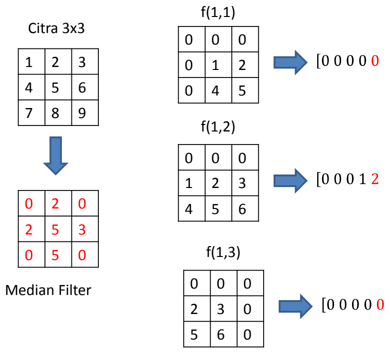


Fig. 1. Illustration of median filter

2) Morphological Methods: morphological method is a common operation to change the structure of the object contained in the binary image. Morphology, apart as spatial filter, is also used to obtain object skeleton, determine the location of object in image, and obtain object structures. The core of the morphological methods involves two arrays of pixels. The first array is images that will be subject to morphological operations, while the second array is called as a kernel or element structure. Morphology can also be subjected to grayscale images [12].

3) Histogram Equalization: histogram equalization is a technique to obtain a histogram that has uniformly distributed intensity in the image. The approach taken is to get broader levels of gray in the area that has many pixels and narrow levels of gray in the area that has few pixels. It can be used to improve overall contrast. histogram equalization including in the non linear mapping [13] .

B. Active Contour Without Edge (ACWE)

The basic idea of active contour models or snake is to evolve a curve, subject to constraints from a given image, in other to detect objects in that image. Starting with a curve around the object to be detected, the curve moves toward its normal interior under some constraints from the image, and will stop on the boundary of the object.

Active contours without edges (ACWE) is the minimization of energy based-segmentation and the active contour models to detect objects in a given image, based on techniques of curve evolution, Mumford-Shah functional for image segmentation and level are set. ACWE can detect objects which the boundaries are not necessarily defined by the gradient [14].

C. Feature Extraction

A method that can be used for feature extraction based on the texture, consist of three groups: statistical methods, structural methods, and spectral methods. The method used in this research is the statistical method, the first order based on histogram and the second order based on Gray Level Co-occurrence Matrix (GLCM) and Gray Level Run Length Matrix (GLRLM).

1) Histogram-texture: a simple method to get the texture. The frequency of occurrence of each level in an image represented by the histogram. To obtain a histogram-based on statistical characteristics, texture of an image can be calculated through the following features [15].

a) Mean: a feature to generate the average brightness of possessed objects in the image. Components of these features are calculated based on equation (2).

$$m = \sum_{i=0}^{L-1} i\, p(i) \tag{2}$$

With *i* denoted the level of gray in the image, *p(i)* denoted as the probability of *i*, and *L* denote the highest gray level of the image.

b) Standard deviation: a feature that provides the size of the image contrast can be calculated with equation (3).

$$\sigma = \sqrt{\sum_{i=1}^{L-1} (i-m)^2 p(i)} \tag{3}$$

c) Skweness: a feature that expressed asymmetry of the average intensity which expressed by the equation (4).

$$skweness = \sum_{i=1}^{L-1} (i-m)^3 p(i) \tag{4}$$

d) Energy: is a measure the distribution of pixel intensities toward the reach gray level. The equation is as follows.

$$energy = \sum_{i=1}^{L-1} [p(i)]^2 \tag{5}$$

e) Entropy: indicates the complexity of the image. The higher entropy, the more image complexity, which calculated as equation (6):

$$entropy = \sum_{i=1}^{L-1} p(i) log_2\big(p(i)\big) \qquad (6)$$

f) Smoothness: used to measure the fineness or roughness intensity in the image which defined by equation (7):

$$smoothness = 1 - \frac{1}{1-\sigma^2} \qquad (7)$$

2) GLCM: first proposed by Haralick with 28 features. GLCM using textures on second-order, by considering the relationship of the neighboring pixels. Newsman and Kammath used only 5 GLCM features, which are Angular Second Moment (ASM), contrast, Inverse Different Moment (IDM), entropy, and correlation [16].

a) Angular Second Moment (ASM): homogeneity relationship of an image, calculated in the equation (8).

$$ASM = \sum_{i=1}^{L}\sum_{j=1}^{L}\big(GLCM(i,j)\big)^2 \qquad (8)$$

b) Contrast: is a measure of the presence of variations of gray level image pixel, is defined by equation (9):

$$contrast = \sum_{n=1}^{L} n^2 \left\{ \sum_{|i-j|=n} GLCM(i,j) \right\} \qquad (9)$$

c) Inverse Different Moment (IDM): used to measure homogeneity. IDM is calculated by equation (10).

$$IDM = \sum_{i=1}^{L}\sum_{j=1}^{L}\frac{\big(GLCM(i,j)\big)^2}{1+(i-j)^2} \qquad (10)$$

d) Entropy: declare the irregularity of gray levels in the image, represent as equation (11).

$$Entropy = -\sum_{i=1}^{L}\sum_{j=1}^{L}\big(GLCM(i,j)\big)log(GLCM(i,j) \qquad (11)$$

e) Correlation: is a measure of linear dependence among the gray level values in the image, which explains by equation (12).

$$Correlation = \frac{\sum_{i=1}^{L}\sum_{j=1}^{L}(ij)\big(GLCM(i,j) - \mu_i'\mu_j'\big)}{\sigma_i'\sigma_j'} \qquad (12)$$

3) GLRLM: GLRLM superior in mapping patterns textures that have similar long-pixels. Gray level is a value level image intensity which consecutively equal either vertically, diagonally or horizontally, while the run length is the number of pixels which occupied by the intended value of the intensity level. There are seven features of GLRLM which used in this research. Five features which proposed by Galloway are Short Run Emphasis (SRE), Long Run Emphasis (LRE), Gray Level Nonuniformity (GLN), Run Length Nonuniformity (RLN), and Run Percentage (RP). Two features proposed by Chu *et al.* are Low Gray Level Run Emphasis (LGRE) and High Gray Level Run Emphasis (HGRE) [17].

D. Classification

Multilayer perceptron (MLP) is a further development of perceptron neural network. ANNs are used widely in the artificial intelligence for pattern recognition and classification. MLP consists of neurons (nodes) and multiple hidden layers which at each branches contained weighted value which will always change as the process of learning and training. Input contains quantitative values that became the unique character of the object classification. The quantitative values are the texture value of an excavation, while the hidden layer and neuron value can be tailored according to the complexity of the problem. Each value entered in neuron (node) will produce output values via an activation function.

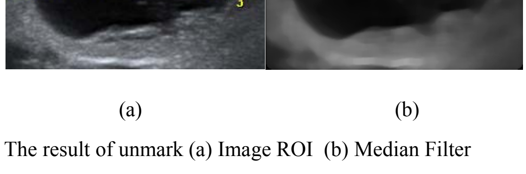
In this research, the MLP uses three layers which consist of one input layer, one hidden layer and one output layer. The input layer, the hidden layer and the output layer consists of seven nodes, three neurons, and two neurons respectively. Weka is used to calculate the parameters automatically. K-fold cross validation is chosen to evaluate the training process performance and to examine the dataset feature prior to classification process.

III. RESULT AND DISCUSSION

In this research, thyroid USG images are obtained with the permission from Sardjito Hospital Yogyakarta database with bitmap format (bmp.). It consists of 25 cystic and 14 solid thyroid USG images. The block diagram of this approach is shown in Fig. 3.

A. Preprocessing

In the preprocessing stage, the first step is to determine the region of interest (ROI), ROI process is still done manually based on data obtained from the radiologist. The image based on ROI process still has a marker and label. Therefore, it required filtering process to reduce the marker and label. In this study, the median filter is effective to reduce the marker and label, but the image result tends to be blurry. Figure 2 shows the image of the ROI and the image of the median filter.



(a) (b)

Fig. 2. The result of unmark (a) Image ROI (b) Median Filter

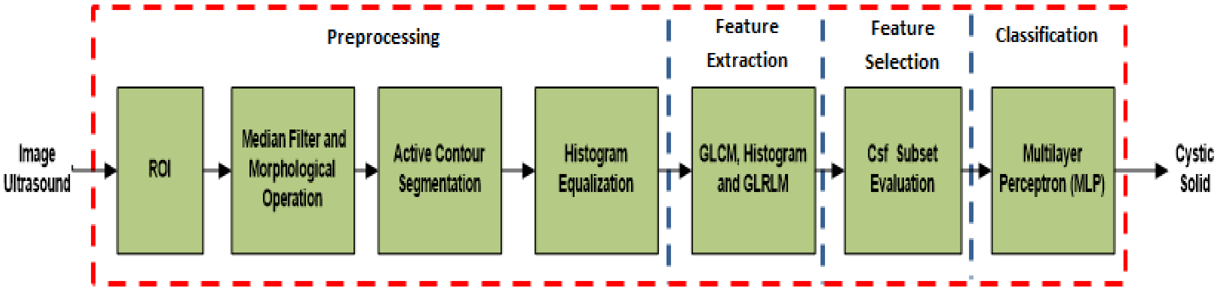


Fig. 3. Block diagram system

Morphological operations is performed to reduce speckle noise and softens of the unmark image. The result image then segmented to separate the objects (nodule) from the background. The segmentation process required an initial masking and iterations. It greatly affects the segmentation results. The final stage of preprocessing uses histogram equalization that generates more uniform histogram. The results of preprocessing images are presented in Fig. 4.

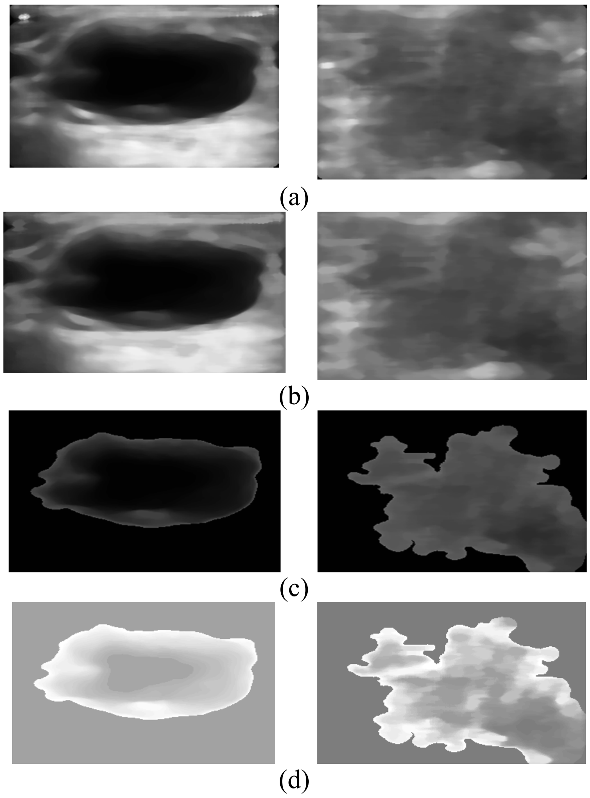


Fig. 4. Left: Cystic , Right: Solid (a) The result of median filter (b) The result of morphological operation (c) The result of segmentation (d) The result of histogram equalization.

B. *Feature Extraction and Feature Selection*

In this stage, feature extraction is conducted based on the texture analysis. In this study, statistical methods first order and second order are used the feature summarize is shows in Table I.

TABLE I. TEXTURE FEATURES

Method	Approach	Number of Feature
Statistical	GLCM	20
	Histogram	6
	GLRLM	7
Total		33

Feature selection is used to get a dominant feature. It aims to improve learning performance, minimise complex computation time, simplifying the model and reduce the space needed. Cfs Subset Evaluation based on Weka [18] brings in 8 dominant features selected of 33 features. These 8 features are shown in Table II.

TABLE II. FEATURE SELECTION BY CFS SUBSET EVALUATION

No	Features
1	Contrast at 0^0
2	Contrast at 45^0
3	Contrast at 90^0
4	Contrast at 135^0
5	Entropy at 135^0
6	Mean
7	Standard deviation
8	Short Run Emphasis

C. *Classification*

Selection feature is used to classify the nodules on thyroid ultrasound images whether it's cystic or solid. Multilayer Perceptron (MLP) is used to classify the data set of the sample. MLP is used to train and test the features in the dataset, because the number of data is limited. The cross validation method uses three folds, with two folds as training data and one fold as a testing data. To evaluate the performance of the proposed method, GLCM, GLRLM, and histogram are compared and combined to get the classification by using MLP algorithm. Table III shows the comparison of the classification results of some features.

TABLE III. COMPARISON OF CLASSIFICATION RESULT

Performance	Features (The number of feature)							
	GLCM (20)	Hist. (6)	GLRLM (7)	GLCM + Hist. (26)	GLCM+ GLRLM (27)	Hist.+GLRLM (13)	GLCM+Hist.+ GLRLM (33)	Proposed Method (8)
Accuracy	87.18%	82.05%	79.49%	84.62%	89.74%	82.05%	89.74%	89.74%
Sensitivity	88.46%	87.50%	81.48%	88.00%	88.89%	82.14%	88.89%	88.89%
Specificity	84.62%	73.33%	75.00%	78.57%	91.67%	81.82%	91.67%	91.67%
PPV	92.00%	84.00%	88.00%	88.00%	96.00%	92.00%	96.00%	96.00%
NPV	78.57%	78.57%	64.29%	78.57%	78.57%	64.29%	78.57%	78.57%

The comparison and combination of the classification results in Table III shows that the proposed methods (8 features) has the same accuracy as the combination of GLCM, Histogram and GLRLM (33 features), and combination of GLCM and GLRLM (27 features), that is 89.74%. The training result of MLP could recognize 25 cases, 24 are classified as cystic and one of the rest is wrongly recognized. Solid has total 14 cases, 11 are correctly recognized as solid while the other three were wrongly recognized. It means the proposed methods are classified the selected features successfully.

IV. CONCLUSION

This research proposes a method of thyroid cancer nodules classification based on texture analysis. The proposed method consists of preprocessing, segmentation, feature extraction, feature selection and classification. It successfully classifies the thyroid nodules in USG images with two categories of cystic and solid. The result shows that performance of the proposed method achieves the accuracy of 89.74%, sensitivity of 88.89%, specificity of 91.67%, PPV of 96.00%, and NPV of 78.57% with only 8 features of classification. These findings are useful to aid the radiologists in classifying nodules of thyroid cancer on ultrasound images and expected to be a second opinion in decision making. In the next work, it is suggested to propose other preprocessing technique and feature extraction for nodule texture analysis.

ACKNOWLEDGMENT

The authors would like to thank Department of Radiology, RSUP Sardjito Yogyakarta for providing the database for this research and the radiologist for helpful discussion and also thank to the colleagues Intelligent System research group at the Department of Electrical Engineering and Information Technology, Universitas Gadjah Mada.

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