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질감 기반 이미지 검색을 위한 질감 서술자 및 컴퓨터 조력 진단 시스템의 적용

(Texture Descriptor for Texture-Based Image Retrieval and Its Application in Computer-Aided Diagnosis System)

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요 약

질감 정보는 객체 인식과 분류에서 중요한 역할을 하고 있다. 정확한 질환 판별을 위해 분류에서 사용되는 질감 특징은 식별성이 높아야 한다. 본 논문에서는 질감-기반 영상 검색 및 폐기종 진단을 위해 컴퓨터 조력진단(Computer-Aided Diagnosis) 시스템을 위한 새로운 질감 기술자를 제안한다. 제안한 질감 기술자는 이웃화소간의 차이값과 중심화소와 이웃화소간의 차이값의 결합에 기반을 두고 있어 결합된 주변화소 차이(Combined Neighborhood Difference; CND)라고 한다. 화소들간의 CND는 비교후 이진 코드워드로 변환된다. 그다음에, 식별성이 높은 값을 생성하기 위하여 이진 계수가 코드워드에 할당된다. 이와 같은 값들의 분포가 계산되어 질감 특징 벡터를 구성한다. Outex와 Brodatz 데이터집합을 이용한 질감 특징 분류에 관련하여 CND는 92.5%의 정확성을 보이는 데 비해, LBP, LND와 Gabor 픽터는 89.3%, 90.7%와 83.6%의 정확성을 각각 보여준다. 본 논문에서는 CND를 이용한 폐기종의 진단 기능을 CAD 시스템에서 구현하였다.

Abstract

Texture information plays an important role in object recognition and classification. To perform an accurate classification, the texture feature used in the classification must be highly discriminative. This paper presents a novel texture descriptor for texture-based image retrieval and its application in Computer-Aided Diagnosis (CAD) system for Emphysema classification. The texture descriptor is based on the combination of local surrounding neighborhood difference and centralized neighborhood difference and is named as Combined Neighborhood Difference (CND). The local differences of surrounding neighborhood difference and centralized neighborhood difference between pixels are compared and converted into binary codewords. Then binomial factor is assigned to the codewords in order to convert them into high discriminative unique values. The distribution of these unique values is computed and used as the texture feature vectors. The texture classification accuracies using Outex and Brodatz dataset show that CND achieves an average of 92.5%, whereas LBP, LND and Gabor filter achieve 89.3%, 90.7% and 83.6%, respectively. The implementations of CND in the computer-aided diagnosis of Emphysema is also presented in this paper.

Keywords: Texture descriptor, Texture-based image retrieval, CAD system, Texture classification

I. Introduction

Texture analysis plays an important part in computer vision, pattern recognition and many image processing applications such as document analysis, target detection, industrial surface detection, remote

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sensing and texture-based image retrieval. The most important things in texture analysis are the texture itself that represented by the coarseness and statistical characteristics of the local variation of brightness between neighboring pixels. Texture can be modeled by basic texture primitives that form texture elements, called *textons*[1] or *texels*[2]. An effective texture feature must be able to describe the textons in texture images. This can be done by extracting the texture feature locally because textons are determined by the spatial relations between neighboring pixels.

Over the years, there were a lot of studies regarding texture feature extraction and texture descriptor. Among the most popular texture descriptors are the Gabor wavelet[3] and local binary pattern (LBP)[4]. The Gabor representation has been shown to be optimal in the sense of minimizing the joint two-dimensional uncertainty in space and frequency. The Gabor filters can be considered as orientation and scale tunable edge and line (bar) detectors, and the statistics of these microfeatures in a given region are often used to characterize the underlying texture information. The Gabor wavelet has been widely used in image analysis applications, including texture classification and segmentation, image registration, motion tracking and face recognition. Zhou et al.[5] proposed a texture descriptor by using the magnitude of the 1D local Fourier transform with a 3x3 local window named Local Fourier Histogram (LFH). K. Muzzammil et al.[6] utilize the phase of the differences between the neighboring pixels and the center pixel to extract texture feature which is invariant to image blurring, scale changes and illumination changes. Another important texture descriptor is LBP, which has gained increasing attention due to its simplicity and excellent performance in various texture and face image analysis tasks. Many variants of LBP have been recently proposed and have achieved considerable success in various applications.

However, LBP ignores the differences between each of the neighboring pixels and only considers the centralized neighborhood differences between the neighboring pixels and the center pixel of a local neighborhood. The differences between each of the neighboring pixels produces more discriminative information compared to the differences between the neighboring pixels and the center pixel of a local neighborhood because of the originality of the textons. K. Muzzammil et al.[7] proposed Local Neighbors Difference (LND) based on those differences between each of the neighboring pixels and completely removed the centralized neighborhood differences.

In this paper, we propose a texture descriptor based on the combination of two neighborhood differences explained above which are the centralized and surrounding neighborhood differences and named as Combined Neighborhood Differences (CND). The local differences of surrounding neighborhood difference and centralized neighborhood difference pixels are compared and converted into binary codewords. Then binomial factor is assigned to the codewords in order to convert them into high discriminative unique values. The 256 dimensional histogram of these unique values is constructed and used as the texture feature vectors.

The remainder of this paper is organized as follows: in Section Ⅱ, related work of the current research is presented; in Section Ⅲ, detailed construction of the CND method is presented; experimental studies and evaluations are described in Section Ⅳ and finally conclusions and future works are given in Section Ⅴ.

Ⅱ. Related Works

1. Local Binary Patterns

Ojala et al.[4] proposed a robust way for describing pure local binary patterns (LBP) of texture in an image. In the original version, there are only $2^8 = 256$ possible texture units. The original 3x3 neighborhood (see Fig. 1a) is thresholded by the

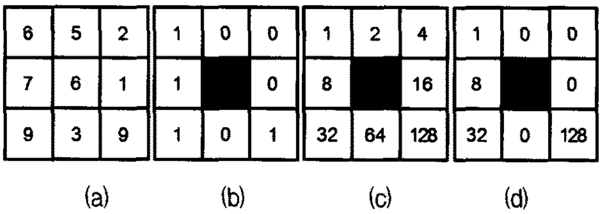

그림 1. 기본적인 LBP 알고리즘
Fig. 1. Basic LBP algorithm.

value of the center pixel. If the neighboring pixel values are larger than or equal to the center pixel, the values are set to 1, otherwise they are set to 0. The values of the pixels in the thresholded neighborhood (see Fig. 1b) are then multiplied by the weights given to the corresponding pixels (Fig. 1c). The results for this example are shown in Fig. 1d. Finally, the values of the eight pixels are summed to obtain the texture unit value of center pixel.

The LBP method is invariant to gray scales and the enhanced version of LBP[8] implements circular neighborhoods instead of square neighborhoods. An image can be converted to its texture spectrum image by replacing the pixels' gray level values with the values of the corresponding texture units. It is shown that the texture spectrum image takes on the visual character of the original image, and the image texture can be represented by the 256-bin LBP histogram for the frequency of the value of the texture unit.

2. Local Neighbors Difference

The detail explanation about LND method using 3x3 neighborhoods is shown in Fig. 2. First, the neighboring pixels of the 3x3 neighborhood are extracted. Then differences between those pixels are computed and thresholded into 8-bit binary code. A binomial factor of 2 is assigned for each binary code to transform the codewords into a unique LND number that represents the texture unit of the 3x3 neighborhood. This LND value is a decimal value between 0 and 255 resulting from the 8-bit binary code. Next, a histogram is constructed with 256 dimensions using the LND codes and the histogram

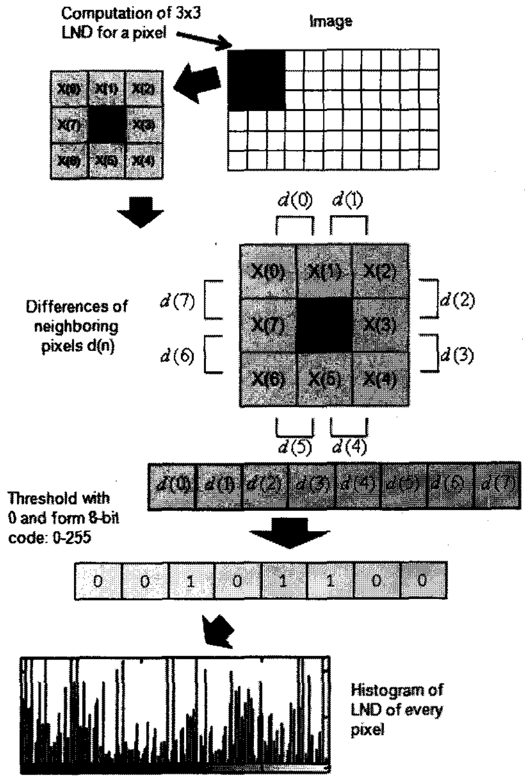

그림 2. LND 기법의 구성
Fig. 2. The construction of LND method.

denotes the distribution of the LND values. Finally, the texture descriptor is obtained from the histogram.

3. CAD System for Emphysema Classification

Computed tomography (CT) scans are applied to examine the pathological change of the tissues inside the body. However, for examining the pathological change of the tissues, CT scans generate a large number of images. Thus, radiologists are exhausted to diagnose pathological changes using a lot of CT images. Recently, a number of computer-aided diagnosis (CAD) systems have been developed to help the radiologists to diagnose diseases[9~10]. Using CAD systems to detect lung diseases such as emphysema, lung cancer, etc., is one of the important fields in the medical image processing in nowadays[11].

Previous work of the authors[12] has developed a CAD system for classifying abnormal regions of lung CT images as shown in Fig. 1. To locate the lung region from the CT image of lung, the contrast of the

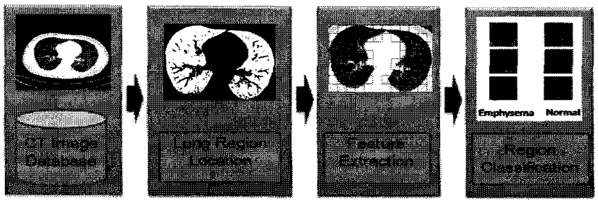

그림 3. 폐기종 분류를 위한 CAD 시스템
Fig. 3. The CAD System for Emphysema Classification.

input image is enhanced using gamma correction. Then the binary image is obtained using the Otsu method. Using morphology and region growing method, the noise in the image and lung vessels themselves are excluded to obtain the lung region without the vessels[13]. For the feature extraction, the texture feature of the subregion separated from the lung image is extracted using texture descriptors. Lastly the resulting features are used to determine whether it contains emphysema or not in the region classification step.

Ⅲ. Proposed Method

The proposed texture descriptor CND is based on the combination of difference values used in LBP and LND, namely the centralized neighborhood differences and the surrounding neighborhood differences. Two types of combinations have been tested. The first one is by using the phase between the difference values of LND and LBP as implemented in [14]. The second one is to threshold differences values of LND against the differences values of LBP. By comparing the entropy and the feature vectors, the thresholding of LND and LBP difference values generated more discriminative information compared to that of the phase. Because of that, we are using the thresholding of the difference values to combine the difference values of LND and LBP.

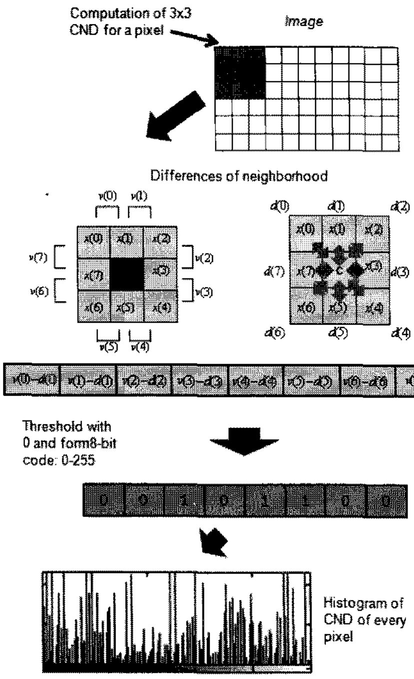

그림 4. CND 기법의 구성
Fig. 4. The construction of CND method.

The detail explanation of CND method is shown in Fig. 4. For each 3x3 window of an image, two neighborhood differences which are the centralized $v(n)$ and surrounding neighborhood $d(n)$ differences are calculated. $v(n)$ and $d(n)$ can be calculated using the following formula:

$$v(n) = x(n) - x\{(n+9)\mathrm{mod}N\}, \quad n = 0,1,\ldots,N-1 \tag{1}$$

$$d(n) = c - x(n), n = 0,1,\ldots,N-1 \tag{2}$$

where N is the number of neighbors which is eight for 3x3 neighborhood and c is the center pixel of the window. Then the differences between $v(n)$and $d(n)$ are thresholded against zero in order to converted the difference values into binary codewords, given by

$$p(n) = \begin{cases} 1, \text{if } \{v(n) - d(n)\} > 0 \\ 0, \quad otherwise \end{cases} \tag{3}$$

The next step is to create a unique value from the binary codewords by assigning binomial factor of 2 for each $p(n)$ and it can be calculated using the following formula:

$$CND = \sum_{k=0}^{N-1} p(k)2^k \tag{4}$$

Based on (4), this CND is a decimal value between 0 and 255 resulting from the 8-bit binary code. Next, a histogram is constructed with 256 dimensions using the CND codes and the histogram denotes the distribution. Finally, the texture descriptor is obtained from the histogram. A statistical approach using the distribution of the feature values is known to work well for micro-textures[2, 4].

The starting point of $d(n)$ and pixel gap of $v(n)$ play an important role in generating informative texture feature of CND. It is because, the wrong location of starting point and pixel gap will result in the same information retrieved by LBP or LND. The reason we chose $x(0)$ for the starting point of $d(n)$ and 1 as the pixel gap of $v(n)$ is because they generated highest histogram entropy based on the evaluation on Brodatz texture database[15]. The entropy of a histogram can be calculated using the following formula:

$$Entropy = -\sum_{i=0}^{D-1} p_i \log(p_i) \tag{5}$$

where D is the histogram dimension and p_i is the probability for each bin of the histogram.

Ⅳ. Experimental Results

1. Experiment Setup

In the experimental studies, the classification accuracy of the CND is measured in terms of various conditions, such as normal and gray value shifted cases. We also conducted experiment in order to compare the amount of information containing in CND descriptor. And lastly we implement CND in the CAD system for classification of Emphysema region. Two other local-based texture descriptors, LBP and LND, and the famous Gabor filter have been compared with the proposed CND method.

Two texture datasets are implemented in the experiment. The first one gives 32 different texture classes from Brodatz texture[15] as implemented in some literatures[4, 16]. For each texture, 64 sample images of size 64x64 are extracted. There are now a total of 2048 texture images and a sample of these images can be viewed in Fig. 5. Each texture class is divided into 2 groups for the testing and the training.

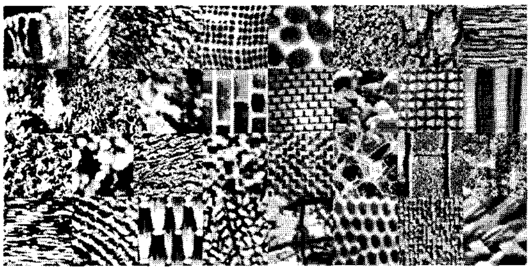

그림 5. Brodatz 질감 데이터베이스에 있는 영상들의 표본

Fig. 5. Sample of images from Brodatz texture database.

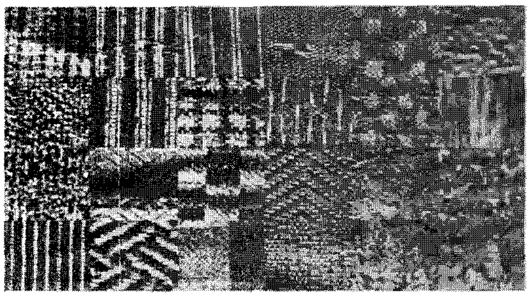

그림 6. Outex_TC_0001 질감 데이터베이스에 있는 영상들의 표본

Fig. 6. Sample of images from Outex_TC_0001 texture database.

Each group contains 32 images.

The second texture database used for the experiment is the Outex_TC_0001 test suite[17]. Outex_TC_0001 test suite contains 24 classes, 44 images (64×64) per texture class and has a total of 2,112 images. The samples of the images are shown in Fig. 6. Half of the images in each class are used for training and the remaining images are used for testing. A standard 3 Nearest Neighbor classifier is used in the texture classification where the distances between feature vectors are measured using Manhattan distance that can be calculated using the following formula:

$$d = \sum_{i=1}^{256} |H_1(i) - H_2(i)| \tag{6}$$

where $H(i)$ denotes the value of the feature vector for each method. In the case of CND, LBP and LND, the feature vectors are the histogram bins. Herein, the classification accuracy can be calculated using the following formula:

$$accuracy(\%) = \frac{\text{no. of correct classifications}}{\text{no. of total images}} \quad (7)$$

2. Experiment Results

The first experiment is to compare the histogram entropy of CND, LBP and LND using formula (5) on the Brodatz texture images. The texture image and the histograms of CND, LBP and LND are shown in Fig. 7. The entropy of those histograms are calculated and shown in Table 1. As you can see CND produces the highest entropy. This means that CND contains more information compared to those of LBP and LND. The high entropy of CND is caused by the small number of zero bin in its histogram. From formula (5), one can see that the entropy is depending on the value on each bin. If the histogram is less distributed, the information contains in the histogram will decrease.

The next experiment is the classification of Brodatz and Outex_TC_0001 texture images. Using

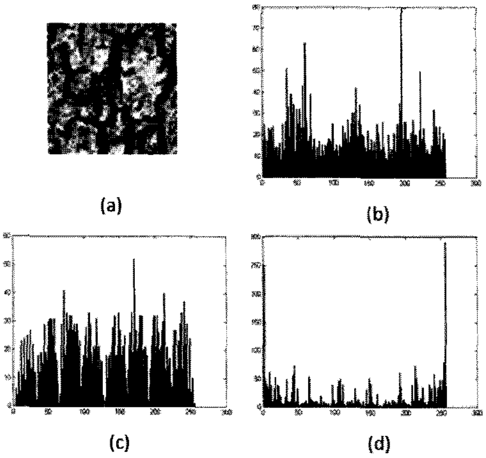

그림 7. (a) Brodatz 질감 데이터베이스의 표본영상. (b) (a)의 CND 히스토그램, (c) (a)의 LND 히스토그램, (d) (a)의 LBP 히스토그램

Fig. 7. (a) Sample image of Brodatz texture database, (b) CND histogram of (a), (c) LND histogram of (a), and (d) LBP histogram of (a).

표 1. CND, LBP 그리고 CND에 대한 히스토그램 엔트로피

Table 1. The histogram entropy for CND, LBP and LND.

Method	CND	LBP	LND
Entropy	5.4	4.77	5.28

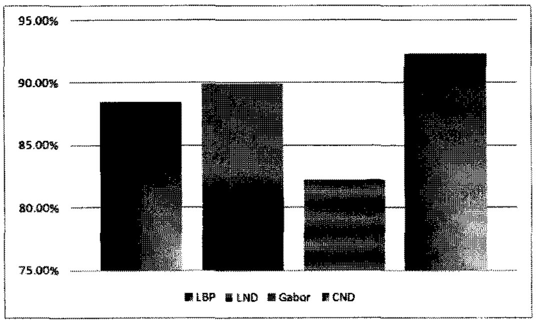

그림 8. Brodatz 데이터베이스에 평균 분류 정확도

Fig. 8. Average classification accuracy on Brodatz database.

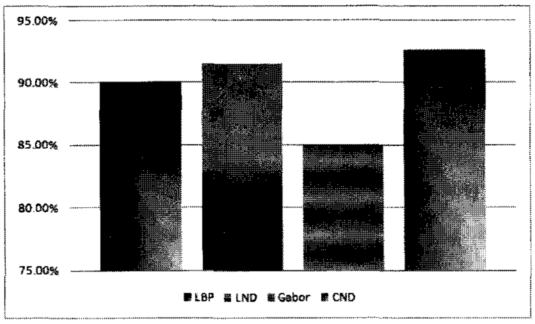

그림 9. Outex_TC_0001 데이터베이스에 평균 분류 정확도

Fig. 9. Average classification accuracy on Outex_TC_0001 database.

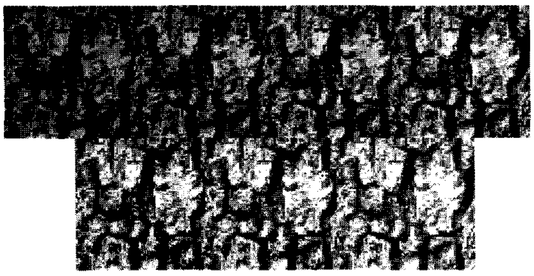

그림 10. -50, -30, -10, 0, 10, 30 그리고 50 그레이 값들을 더한 Brodatz의 샘플 영상들

Fig. 10. Sample images of Brodatz added with -50, -30, -10, 0, 10, 30 and 50 gray values.

the experiment setup discussed earlier, the average classification accuracy for each method on Brodatz and Outex_TC_0001 database are calculated and shown in Fig. 8 and Fig. 9, respectively. From the results we can see that CND performs the best with average accuracy of 92.5% from both texture databases. This is because the texture information described by CND is more discriminative compared to those of LBP, LND and Gabor filter. Because CND

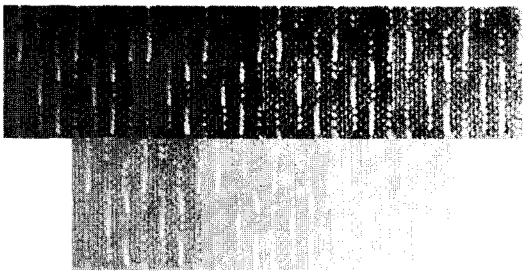

그림 11. -50, -30, -10, 0, 10, 30 그리고 50 그레이 값들을 더한 Outex_TC_0001의 샘플 영상들
Fig. 11. Sample images of Outex_TC_0001 added with -50, -30, -10, 0, 10, 30 and 50 gray values.

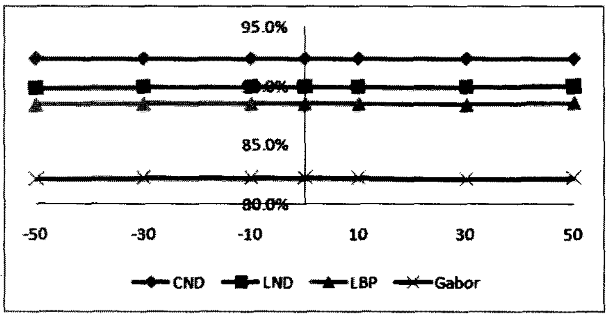

그림 12. Brodatz 데이터베이스에서 조도가 변화된 영상들의 평균 분류 정확도
Fig. 12. Average classification accuracy with illumination changed images in Brodatz dataset.

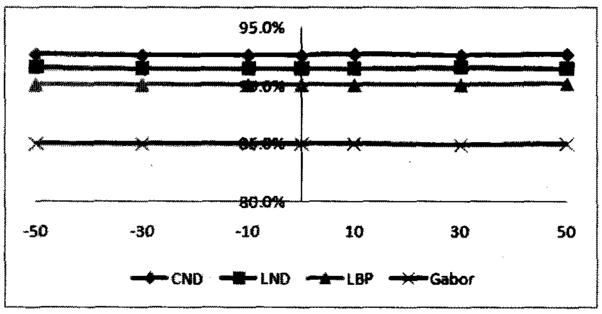

그림 13. Outex_TC_0001 테스트 모음에서 조도가 변화된 영상들의 평균 분류 정확도
Fig. 13. Average classification accuracy with illumination changed images in OUTEX_TC_0001 test suite.

extracts more information, the performance of texture image retrieval using CND texture descriptor can be improved.

We also perform the texture classification on illumination changed textures. In this experiment, the gray value of each testing images are added and subtracted by 10, 30 and 50, respectively. The illumination changed images are shown in Fig. 10 and Fig. 11. As we can see, after shifting the gray value, the contrast of the images is also changed. Because the contrast becomes lower than the original image, human eyes are hard to classify these texture images. However, all the methods are still able to classify these illumination and contrast changed images with very small accuracy differences in different level of illuminations.

The average classification accuracies for the illumination changed images are shown in Fig. 12 and Fig. 13. From what we can see, the accuracies of all the methods only altered a little bit in different level of illuminations. It is because all of the methods are invariant to illumination changes. We also can see that the accuracy never decreases when the illumination is changed. This is great property of CND, LND and LBP. Even using low contrast images, all of the methods still manage to achieve classification accuracy similar to classification accuracy using original images. Nonetheless, CND achieves higher classification accuracy with 92.5% compared to those of LBP, LND and Gabor filter with average classification accuracies of 89.3%, 90.7% and 83.6%, respectively.

3. Implementation of CND in CAD system for Emphysema analysis

The feature extraction is one of the most important steps for recognizing the abnormal regions from the medical image. In the past decades, texture features such as the gray level difference method (GLDM)[18], the gray level run-length method (GLRLM)[19], the special gray level dependent method (SGLDM)[20], and the LBP have been widely used for medical image analysis. The combination of LBP and gray level generates a powerful texture descriptor in classifying three types of Emphysema and lung regions[21~22].

LBP and gray level are combined by joining them to form a co-occurrence matrix. A co-occurrence matrix based on gray level local binary pattern can then be formed as follows:

$$\begin{bmatrix} P(0,0) & P(0,1) & \cdots & P(0,L-1) \\ P(1,0) & P(1,0) & \cdots & P(0,L-1) \\ \vdots & \vdots & \ddots & \vdots \\ P(2^N-1,0) & P(2^N-1,0) & \cdots & P(2^N-1,L-1) \end{bmatrix} \quad (8)$$

where L is the gray level of the image which is 256 for 8-bit image, and $P(x, y)$ denotes the probability of pixels whose LBP value equal to $x(0 \le x \le 2^N - 1)$ and gray value equal to $y(0 \le y \le L-1)$. Texture features can then be derived from the co-occurrence matrix by calculating the 2D variance, sum variance, different variance, contrast, sum am am a, sum entropy, different entropy, angular second moment, and entropy. In the case of CND, we replace LBP value with CND value in co-occurrence matrix.

To evaluate the feature extraction efficiency and the classification performance of the proposed method, we took 288 CT images from Inha University Hospital, including 108 normal images and 180 emphysema ones. The size of the images is 1024x1024 and gray value depth is 8-bit.

Fig. 14 shows some image samples of the normal CT image and emphysema CT images. On the next step, lung region without vessels are firstly located and subregions are obtained as mentioned in Section 2.2. Texture features are then extracted from the sub-regions covering more than 70% of the lung. 1500 sub-regions, which are separated into two classes－1000 normal sub-regions and 500 emphysema sub-regions, are randomly selected for the following experiments. Fig.15 shows some normal and emphysema sub-regions.

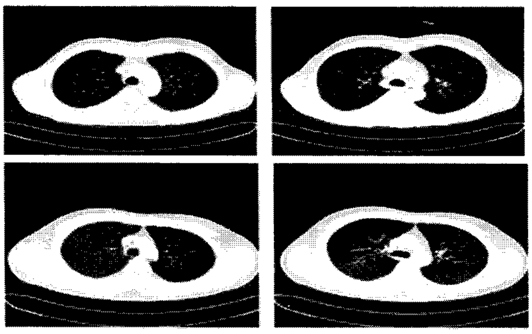

그림 14. 첫 줄, 폐기종 CT 연상들, 두 번째 줄, 정상 CT 연상들

Fig. 14. First row, Emphysema CT images, second row, normal CT images.

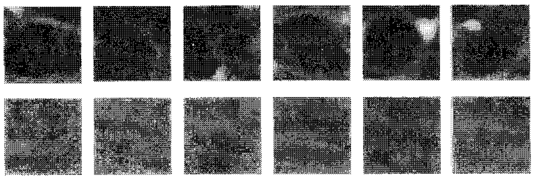

그림 15. 첫 줄, 폐기종 소구역의 샘플, 두 번째 줄, 정상 소구역의 샘플

Fig. 15. First row, samples of Emphysema subregions and second row, samples of normal subregions.

To evaluate the performance of CND, we performs the classification between the Emphysema and normal subregions. We compared the classification performance of CND with LBP and SGLDM. Linear Discriminant Analysis (LDA) is used to classify the Emphysema and normal subregions. Standard 3x3 window is applied for CND and LBP while three directions of 0, 45 and 90 degrees are applied to SGLDM. The nine features explained earlier of the CND, SGLDM and LBP co-occurrence matrices are extracted to classify the emphysema regions and normal regions. 100 normal sub-regions and 100 emphysema sub-regions are used to train the LDA. The remainder subregions (900 normal ones and 400 emphysema ones) are used for testing. Table 2 shows the true positive (TP), true negative (TN), false positive (FP), false negative (FN), sensitivity and specificity of the CND, SGLDM and LBP, respectively and can be calculated as follows:

$$\text{TP} = \text{no. of Emphysema regions correctly classified} \quad (9)$$

$$\text{TN} = \text{no. of normal regions correctly classified} \quad (10)$$

$$\text{FP} = \text{no. of Emphysema regions wrongly classified} \quad (11)$$

$$\text{FN} = \text{no. of normal regions wrongly classified} \quad (12)$$

$$Sensitivity = \frac{TP}{(TP+FN) \times 100} \quad (13)$$

$$Specificity = \frac{TN}{(FP+TN) \times 100} \quad (14)$$

표 2. 분류 성능
Table 2. The classification performance.

Methods	CND	LBP	SGLDM		
Direction			0	45	90
TP	397	393	363	359	357
FP	0	0	0	0	0
FN	3	7	37	41	43
TN	900	900	900	900	900
Sensitivity(%)	99.3%	98.3%	90.8%	89.8%	89.3%
Specificity(%)	100%	100%	100%	100%	100%

As we can see, the performance of correctly classifying the emphysema regions of SGLDM depends on the feature extraction directions. The texture features extracted by LBP includes multiple directions. Hence, its performance is the best comparing with SGLDM from any direction. Since CND extracts more information than LBP, it achieves the best sensitivity and specificity performances compared to LBP and SGLDM. This shows that CND demonstrates the technical viability for implementation of the proposed method in texture analysis applications, especially for computer aided diagnosis.

V. Conclusions

In this paper, we propose a texture descriptor based on the combination of two neighborhood differences called the Combined Neighborhood Differences (CND). Those local difference values are thresholded into binary codewords and assigned with binomial factor of 2 to convert them into unique values. The 256 dimensional histogram of these unique values is constructed and used as the texture feature vectors.

CND applies simple computation and demonstrates technical viability for implementation in texture analysis applications, especially for medical image analysis. By applying CND, the time consumption of medical image texture analysis can be reduced significantly. Moreover, the result of the CAD system also shows that CND can generate high sensitivity and specificity, which are compulsory in medical image analysis. Texture classification results show that CND can extracts useful texture feature that generates highly discriminative feature. This property is very useful in obtaining high accuracy in image retrieval and classification.

Real-world textures may take place at random spatial rotations. The CND method is still variant to rotation and future work on the CND intends to extend it to be a rotation invariant texture descriptor.

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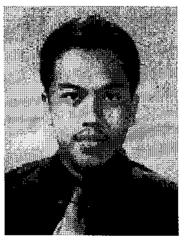
저 자 소 개



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