CT Image Texture analysis of Intracerebral Hemorrhage

S.A.Kabara[1], M.Gabbouj[1], P.Dastidar [2]
F. A. Cheikh[1], P. Ryymin[2],E. Laasonen[2].
kabara@cs.tut.fi
1. Signal Processing Institute , Tampere University of Technology ,
P.O. Box 553,FIN-33101,
2. Departement of Diagnostic Radiology, Tampere University Hospital,
Tampere, Finland

***Abstract*— :** The development of new modalities, such as computed tomography (CT) and magnetic resonance imaging (MRI), have substantially increased the number and complexity of images presented to radiologists and physicians. In this paper image analysis for the classification of healthy tissue and intracerebral hemorrhage (ICH) is reported. In the investigation computerized tomography (CT) images were taken from human brain, 151 healthy regions in brain and 80 disease regions for 12 patients. In the texture analysis, similarity between the variance, correlation and sum average features was measured, based on the Euclidian distance and tree classification in order to classify healthy regions and ICH regions.

Index Terms*:* computerized tomography (CT) image, intracerebral hemorrhage (ICH), gray level co-occurrence (GLCM), texture analysis.

1. INTRODUCTION

Clinical images, such as CT images, are still assessed manually. This is to ensure that as few mistakes as possible are made, because any mistake could have serious consequences for the patient, if the image is taken as an aid to treatment or therapy. Automation of this analysis would be of great help to radiologists and medical doctors, as they have very many images to assess each day. However, results of automated analysis are not yet adequate for clinical use. Relatively little effort has been expended in image analysis of medical images. Some initial studies on a small number of images has been carried out. This work has been preceded by some other research using texture analysis to classify sets of medical images into either healthy or abnormal regions. They have achieved a correct classification percentage of more than 90%. They studied Medical image by investigating the expression of features, and found that by a linear combination of features they were able to discriminate between healthy and disease regions [6,7,9]

2. METHODS

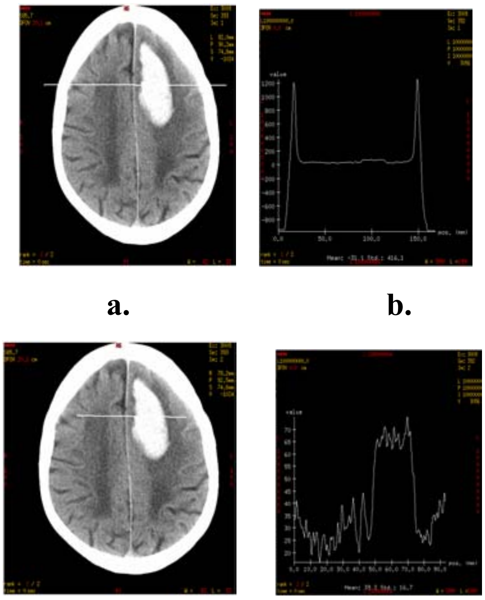
2.1 Image Analysis

Image analysis techniques play an important role in several medical applications. This application involves automatic extraction of features from the images, The goal is to extract features that can distinguish normal from abnormal tissues. In this case, CT image of ICH are selected. Computed tomography (CT) of the brain is an established imaging technique that combines x-rays with computer technology. X-ray beams from a variety of angles are used to create a series of detailed cross-sectional images of the brain.

Hypertension, aneurysm and vascular malformations account for 80% of intracerebral hemorrhages. All cerebral hematomas, whatever the cause, have a similar resolution pattern on CT. The rate of resolution depends on the size of the hematoma, usually within one to six weeks, and resorbs from outside towards the center. Perihematoma low density (edema) appears in 24-48 hours [3,10] (Figure1).

CT images of intracerebral hemorrhage (ICH) were obtained from the radiology department of Tampere University Hospital. The 151 image slices of computerized tomography (CT) images were taken from human brain, 151 healthy areas in brain and 80 disease areas for 12 patients.

Any texture measure that provides a value, or a vector of values at each pixel, describing the texture in a neighbourhood of that pixel can be used to segment an image into regions of similar textures. There are two major categories: region-based techniques which attempt to group or cluster pixels with similar texture properties and boundary-based that tries to find "texture-edges" between pixels from different texture distributions [12].



a. b. c. d.

Figure 1. CT image and CT number measured: a. and c. CT image of Intracerebral Hemorrhage (ICH), b. curve of CT number across the brain (soft tissue and bone), d. CT number across soft tissue of healthy and ICH area in the brain .

2.2 Texture Analysis

Texture refers to the visual patterns that have properties of homogeneity that do not result from presence of only a single color or intensity. It is an innate property of virtually all surfaces, including clouds, trees, bricks, hair, fabric, human tissue, etc. It contains important information about the structural arrangement of surfaces and their relationship to the surrounding environment.

In the early 70's, Haralick et al. proposed the co-occurence matrix representation of texture features [8]. The approach explored the gray level spatial dependence of texture. First a co-occurence matrix is constructed based on orientations and distances between image pixels and then some statistics are extracted from the matrix as texture features. Many other researchers followed a similar approach and further proposed enhanced versions of these features. For example, Baraldi and Parmiggiani studied the statistics originally proposed in [8] and experimentally found out that contrast, inverse deference moment and entropy home the greatest discriminatory power [2].

2.3 Co-occurence Matrix

Gray level co-occurrence matrix is a second order statistical tool useful to characterize texture features. It considers the contemporary occurrences of gray levels in corresponding displaced positions of the original image. Suitable statistics are computed from these co-occurrences (usually denoted as P(i,j)), whose meaning is the probability to find (for a given displacement in a given direction) the j-th gray value if the starting point assumes the i-th one. These statistics in turn may be used to compute various measures, related to the spatial distribution of the gray levels. If these measures are computed not for the whole image, but only for a *NxN* window around each pixel, they provide spatial features that may be very useful for a successive classification step [5, 12].

The following texture features proposed by Haralick et al [8] are applied to different disciplines of CT images to extract useful texture information from co-occurrence matrices with different displacements. The selected features are based on [8]. The following describe the normalized co-occurrence matrix.

In this study we derived 13 texture measures from each co-occurrence matrix. We denote the co-occurrence matrix P(i; j), and the number of distinct gray levels in the quantized image as N. We also define:

P value in specific matrix pixel

I integer pixel number along a row

J integer pixel number up a column

μx mean of row sums

μy mean of column sums

(with square matrix $\mu x = \mu y$)

σx s. d. of rows sums

σy s. d. of column sums

$$Px(i) = \sum_{J=1}^{N} P(i,j)$$

$$Py(i) = \sum_{i=1}^{N} P(i,j)$$

$$Px+y(k) = \sum_{\substack{i=1 \\ i+j=k}}^{N} \sum_{J=1}^{N} P(i,j), \quad k= 2,3,\ldots 2N$$

$$Px-y(k) = \sum_{\substack{i=1 \\ i-j=k}}^{N} \sum_{J=1}^{N} P(i,j), \quad k= 2,3,\ldots N-1$$

and μ, μx, μy, σx and σy as the means and standard deviations of P(i,j), Px and Py, respectively.

Here we consider only the following features: variance, correlation and sum average, defined as.

$$\text{Variance} = \sum_{i=1}^{N} \sum_{J=1}^{N} (i - \mu)^2 P(i,j).$$

$$\text{Correlation} = \left(\sum_{i=1}^{N} \sum_{J=1}^{N} i*jP(i,j) - \mu x \mu y \right) / \sigma x \sigma y .$$

$$\text{Sum average} = \sum_{i=2}^{2N} iP_{x+y}(i).$$

Images in dataset of medical image are normalized with respect to mean and standard deviation. The idea is to overcome the effects of transformations of the real image gray levels caused by exposition to X-ray radiation and absorption of human tissues.

2.4 Feature Extraction

In a CT image processing and analysis system, effective feature extraction and similarity measure between feature vectors are most important. In our system (fig 2), region of interest is segmentated manually as mask (healthy and ICH regions). In order to extract features of textures efficiently, we compute co-occurence matrix of every segmented region, then compute the features [8]. The features with high separation between regions are selected (variance, correlation and sum average) as feature vector with respecting normalization. The classification step is implemented using tree classification [2]. It is a competition-based tree node classification, which categorizes the features into two classes. The other reason of using the tree classification is to reduce the sensitivity of texture analysis to the delineation of abnormal regions.

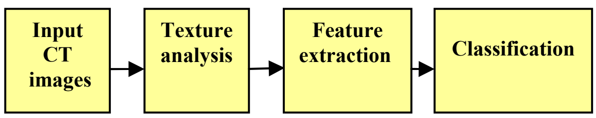


Figure2. ICH CT image processing and analysis system

2.5 Classification and Similarity Measure

In order to determine the discriminating effectiveness of texture features extracted from co-occurrence matrices, a classification was initially performed using each normalized feature vector and linear discriminant analysis. The feature vector giving the best threshold was selected for subsequent classification using simple tree classification. This classification is a simple, fast, and efficient type of a hierarchical classifier. Figure 9. shows a simple tree classification with 3 features and 2 classes where circular nodes are decision nodes. When an unknown feature vector is submitted for classification, it will first go to the root node, which is always a decision node, and then take one of the two branches based on the outcome of testing one of its features against the threshold at that decision node. This process continues until the feature vector reaches one of the terminal nodes where it is assigned a class. This tree structured classification approach has several advantages [4]: Firstly, tree classification does automatic stepwise feature selection and complexity reduction; secondly, tree classification is robust with respect to outliers and misclassified points in the training set; thirdly, the final classifier can be compactly stored; fourthly, classification tree efficiently classifies new data; and finally, classification tree provides easily understood and interpreted information regarding the predictive structure of the data.

Similarity between images is measured by computing distances between feature vectors. The Euclidean distance has been the most popular similarity measure in features extracted, representative features for each region healthy and ICH are determined from CT image.

Textural features that were described in detail in [1, 8, 11] are used for image representation in this paper. The set of features are the variance, correlation and sum average of gray level spatial dependencies that use second-order (co-occurrence) statistics of gray levels of pixels in particular spatial relationships. After normalization of features extracted, we compute the Euclidean distance between all features mean that similarity between region of healthy part then ICH regions (fig 7,fig 8).

3. RESULTS AND DISCUSSION

In this work we have investigated the texture analysis method of gray level co-occurence matrix applied to CT images of intracerebral hemorrhage. The set of images contained 151 CT image slices from 12 patients. (In the image slices a high resolution CT scan represents a thin~1mm "slice" of the target structure. The scan is acquired over an interval of approximately 1 second, so movement artefacts may be present around the head. Scan data is stored as a 512x512, 16 bit grey level image, with pixel intensity being proportional to tissue density.)

Texture is a feature used to partion images into regions of interest and classify those regions. There are two primary issues in texture analysis: texture segmentation is concerned with automatically determining the boundaries between various texture regions in an image (in this case we have done manual segmentation with assistant of a neuroradiologist because of the difficulty of those images), while texture classification is concerned with identifying a given textured region from a given set of texture classes [4].

Each of these regions has unique texture characteristics. Statistical methods are extensively used (GLCM, contrast, entropy, homogeneity etc.). Using the gray level co-occurrence approach, representative texture features can be measured to characterize the property of each image. The adopted gray level co-occurrence matrix method consists of two main steps. The first step computes the co-occurence matrices, and second uses those matrices to deduce the second order statistical features. Of the 13 exracted features [4] we selected three features: variance, correlation and sum average.

Those features were normalized and combined. The results are represented by curve of figure3 (variance-correlation), which shows that thresholding appears between healthy and ICH regions. The same shows in figure4 (variance-sum average) and figure5 (sum average-correlation). In 3 dimension curve fig 5 (variance-correlation - sum average) ensures that thresholding appears clearly between regions. Tree classification was based on previous curves and implemented to classify the two classes: healthy and ICH regions. Figure9. shows a simple classification scheme with 3 features and 2 classes.

Finally, the computation of the Euclidean distance between all the features achieves a good separation of the healthy areas and the areas affected by ICH (see figures 7 and 8). This serves as a second method to perform this separation. If the separation is not good enough, then it means that we still need more information to train the system (e.g., more pathological samples) (see figure 9)

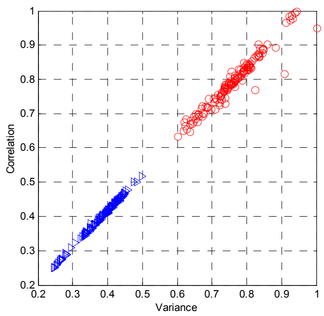


Figure3. Variance-Correlation
(Δ: healthy regions, O: ICH regions)

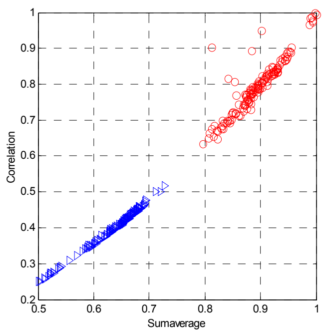


Figure4. Variance-Sum average

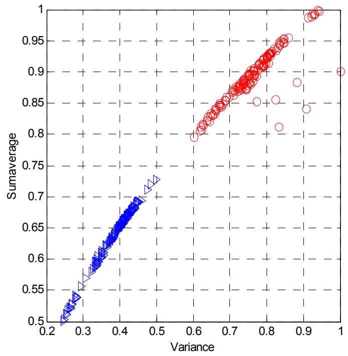


Figure5. Sum average-Correlation

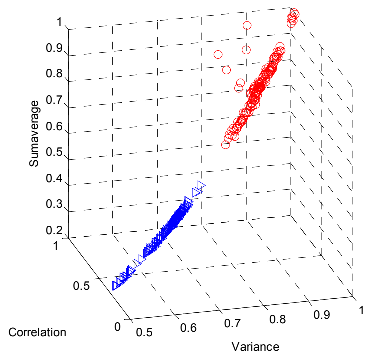


Figure6. Correlation-Variance-Sum average
(Δ: healthy regions, O: ICH regions)

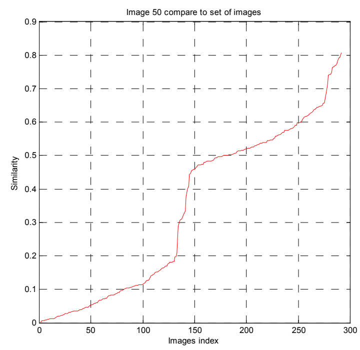


Figure7. Plot of normalized similarity (Euclidean distances) from ICH area to all sets of healthy and ICH regions.

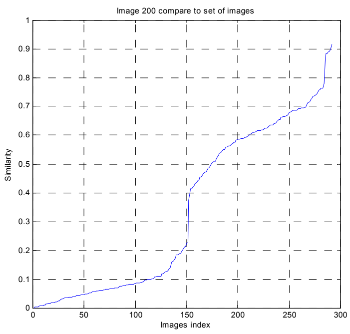


Figure8. Plot of similarity scores (Euclidean distances) from healthy area to all sets of healthy and ICH regions.

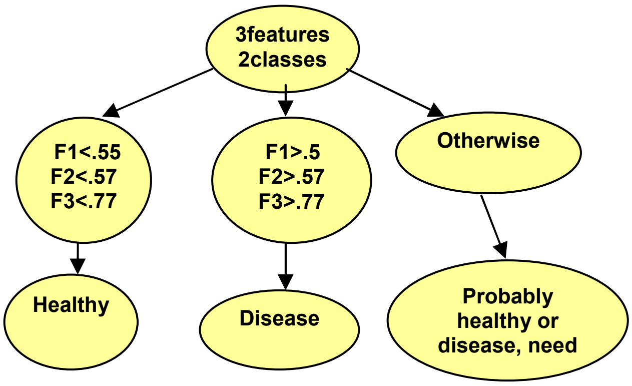


Figure9. A simple classification scheme with 3 features and 2 classes.

5. CONCLUSION

The accuracy of detection of ICH region is particularly important for any diagnosis or automated system. This study demonstrates that features extracted from region images can result in highly significant classification and discrimination of healthy and ICH regions. Therefore, the results of this study show that co-occurrence matrix approach is also an effective method in similarity evaluation of CT image. As can be seen from figure 3 till figure 8, the differences between two classes of regions are distinct.The perspectives for further work are the following: a) to increase the dataset of patients; b) to associate texture information with other data, for example histopathology and clinical data; c) to compare co-occurrence method with other methods.

6. REFERENCES

[1] S. Aksoy, and R. M. Haralick. "Textural features for image database retrieval" In *Proceedings of IEEE Workshop on Content-Based Access of Image and Video Libraries, CVPR'9*8, pages 45–49, Santa Barbara, CA, June 1998.

[2] A. Baraldi, F. Parmiggiani, "An Investigation of the Textural Characteristics Associated with Gray Level Cooccurence Matrix Statistical Parameters", IEEE Transaction On Geoscience and Remote Sensing, vol.33, No 2, pp.293-304, 1995.

[3] L Bozzao, S Bastianello et al," Early angiographic and CT findings in patients with hemorrhagic infarction: the distribution of middle cerebral artery" *AJNR* 12:1115-1121, 1991.

[4] L. Breiman, J. H. Friedman, R. A. Olshen, and C. J. Stone, "Classification and Regression Trees" Wadsworth, Inc., 1984.

[5] G.E. Carlson, W.J. Ebel."Co-occurence matrix modification for small region texture measurment and comparison". In IGARSS' 88-Remote Sensing:Moving Towards the 21st Century, pp.519-520,IEEE, Edinburgh,Scotland.1988.

[6] A. N. Esgiar, B. S. Sharif, R. N. G. Naguib, M. K. Bennett, and A. Murray, "Texture descriptions and classification for pathological analysis of cancerous colonic mucosa," in Proc. Inst. Elect. Eng. Image Processing Applicat., Conf. Publication 465, 1999, pp. 335-338.

[7] A. P. Freeborough, N.C. Fox, "MR Image Texture Analysis Applied to the Diagnosis and Tracking of Alzheimer´s Disease" IEEE, Transactions on Medical Imaging, Vol. 17, No 3.1998.

[8] R. M. Haralick, K. Shanmugan, and I. Dinstein, "Textural features for image classification," IEEE Trans. Systems, Manufact, Cybernet, vol.SMC-3,no. 6, pp. 610-621, 1973.

[9] S. Herlidou, I. Idy-Peretti, R. Grebe, F. Grados, N. Lecuyer, P. Fardellone, "Quantitave evaluation of trabecular bone structure by calcaneus MR images texture analysis of healthy volunteers and osteoporotic subjects," Proceedings of EMBS International Conference, 2001.

[10] Y-Y Lee, R Moser, JM Bruner, P Van Tassel,"Organized intracerebral hematoma with acute hemorrhage:CT patterns and pathologic correlations" *AJNR* 7:409-416, 1986.

[11] M. Partio, B. Cramariuc, M. Gabbouj, and A. Visa, "Rock Texture Retrieval using Gray Level Co-occurrence Matrix", *NORSIG-2002, 5th Nordic Signal Processing Symposium*, On Board Hurtigruten M/S Trollfjord, October 4-7,2002, Norway.

[12] T.R. Reed and J.M.H. Dubuf, CVGIP: Image Understanding, 57:pp.359-372. 1993.