Asian Journal of Engineering and Applied Technology
ISSN: 2249-068X (P) Vol. 7 No. 2, 2018, pp.37-41

DOI: https://doi.org/10.51983/ajeat-2018.7.2.1014

A Novel Hybrid Framework for Medical Image Retrieval

A. Saravanan[1], M. Natarajan[*2] and S. Sathiamoorthy[3]
Assistant Professor, Division of Computer and Information Science, Annamalai University, Annamalai Nagar, India
*Corresponding Author
(Received 2 June 2018; Revised 25 June 2018; Accepted 14 July 2018; Available online 21 July 2018)

***Abstract* - A new hybrid framework for Content-Based Medical Image Retrieval (MCBIR) is proposed in this paper to deals with the accuracy issues related with the existing MCBIR. The proposed hybrid framework initially divides the images into number of non-overlapping rectangular regions. Subsequently, statistical based color autocorrelogram (CA) and texture autocorrelogram (TA) is extracted for each region respectively. Then the geometric based chordiogram descriptor (CD) is extracted for each region. Both the statistical based and geometric based descriptors are combined to create a feature vector. The corresponding image regionsor patches in the query and target medical images are compared using the Canberra distance measure. The proposed hybrid framework is evaluated using the benchmark database and it is confirmed that it significantly outperforms the state-of-the-art system in terms precision, recall and G-measure.**
***Keywords:* Color autocorrelogram, texture autocorrelogram, chordiogram descriptor**

1. INTRODUCTION

Today incredible quantity of medical images has been produced by the hospitals using various modalities such as CT, MRI, X-ray, mammogram, microscopy, endoscopy, etc. Since the disease diagnosis is drastically based on medical images, effective use of massive medical image collection is extremely important for precise disease analysis, research and education in the domain of medicine. Content based image retrieval (CBIR) systems has been proposed by number of researchers in the medical domain [1] to search and retrieve the medical images based on low-level visual contents of an image like color, texture, shape, spatial information, etc and these information are either captured in global or local level. The global level feature characterizes the full image as whole. While the local level features exemplify the information about the regions or patches or objects of interest. The discriminative power of features extracted from the images will play a central role in the accuracy, less storage and computational cost of medical image retrieval system. Thus, the feature to be extracted must characterize the image extremely well.

In specific, medical images are extremely complicated and very vast in variety because of various organs captured using various modalities for various disease analysis. Moreover, medical images of specific organ captured using specific modality for different disease condition is differing very minutely in details [2] and it will be used to distinguish the images as well as diseases.

In erstwhile, lot of attempt has been spent for enhancing the accuracy of medical image retrieval and different low-level visual features are used. For instance, an open source system for medical image retrieval is suggested in [1] and is named as MedGIFT [1] which employed low-level visual features namely Gabor blocks, response of histogram of Gabor filter, global color histogram and color blocks. It also employed text based keywords additionally for medical image retrieval. Afterward, Lehmann et al., [3] introduced a retrieval system named as image retrieval for medical applications (IRMA). Rahman *et al.*, [4] reported a retrieval system for medical images using the “Bag of words” and low-level visual features namely CLD, EHD, color moments, GLCM, edge frequency, primitive length, Gabor moments, Tamura moments, SIFT, LBP, LBP-I, CEDD, FCTH, autocorrelation coefficient. The image related text based keywords like title, organ, modality, region of interest, disease examination details, etc are conserved in the “Bag of words”.

In [5], edge co-operative map is computed by doing phase congruency process in L*a*b* color space then the key points are derived from the edge co-operative map by using the SIFT. Later on, spherical SOM with geodesic data structure is employed to construct a codebook for the derived key points. Murala and Wu [6] proposed local mesh peak valley edge pattern for medical image retrieval in which for a specified center pixel the relationships among the neighbors are captured using the first order derivative and are peak or valley edges.

Local ternary co-occurrence patterns (LTCoP) is presented in [7] by Murala and Wu for biomedical image retrieval and is formed by the co-occurrence of similar ternary edges which is computed based on the gray values of center pixel and its neighboring pixels. Banerjee et al.,[8] introduced a novel texture descriptor called local neighborhood intensity pattern (LNIP) in which the relative intensity difference between a particular pixel and the center pixel is computed by means of considering its adjacent neighbors and produces a sign and magnitude pattern and are combined together to form LNIP. It is reported that the LNIP is more resistant to illumination changes.

In [9], novel graph structure is described and it retrieves similar medical images based on tumor location by constraining tumors to its related anatomical structures and is achieved by using a graph in which the edges are connected to tumour vertices based on the spatial proximity of tumours and organs. Seetharaman and Sathiamoorthy [10] introduced a new version of EOAC with the consideration of color and fine edges using a framework based on FRAR model which will preserve the loss of very minute edges due to chromatic changes and spectral variations [11], and less sensitive to noise then they combined a new version of EOAC with color autocorrelogram and textures [10, 12] to form a feature vector for medical image retrieval. Later, an effective descriptor for describing the textures and its spatial information is suggested in [13] and is called as Texture autocorrelogram. It is reported that texture autocorrelogram significantly outperforms the micro-textures [14] and Gray level spatial dependence matrix of [15]. Subsequently, Qayyum et al., [16] suggested a image retrieval technique for 24 classes and 5 modalities using deep convolutional neural network. Wavelet based centre symmetric-local binary pattern is used for retrieval of mammogram images in [17].

Recently Wang et al., [18] presented a novel shape based descriptor called local chordiogram descriptor which is extracted from the local edges and instead of image intensities it captures local geometric features and it is used with the partial sum of the order statistics of the patch-wise distances to handle the noise and lighting variations in the scenes, and it significantly outperforms SURF, GIST, SIFT AND MROG descriptors for place recognition especially when the illumination variations are severe.

Being inspired by the aforementioned fact, in this paper, a medical image retrieval system is proposed using the combination of chordiogram descriptor, color autocorrelogram and textures autocorrelogram and is compared with framework proposed in [11].

This paper is designed as follows: Introduction about the medical image retrieval system and related works in medical image retrieval system are précised in Section 1. The proposed work of the manuscript is highlighted in Section 2. Experimental results and conclusion is revealed in Sections 3 and 4 respectively.

II. PROPOSED METHOD

In this paper, the image I of size M x N is divided into number of non-overlapping rectangular patches/regions say

$$I = \{I_1, I_2, \ldots I_n\} \tag{1}$$

The number of regions is determined empirically and in our case the number of regions are 12. For each patch, we compute the color and texture autocorrelogram and chordiogram descriptor as described follow.

A. Color Autocorrelogram

The color autocorrelogram calculates the spatial information of color and shape respectively. It is also reported that color autocorrelogram is more robust to color, appearance, contrast and brightness changes and also invariant to translation and scaling [11, 19]. Hence, in this paper, the color autocorrelogram is selected as a color descriptor.

Let I is an image of size N X N. Assume that the colors in I is quantized into m colors say $c_1, c_2, \ldots, c_m$. Let us consider the pixels p1 and p2 where p1=(x1, y1) and p2=(x2, y2). Let a distance between p1 and p2 is *d* and $d \in N$. The correlogram for image I is defined in equation (2) as in [19].

$$\varphi^{d}_{c_i c_j}(I) \overset{\Delta}{=} \Pr_{p_1 \in i_{c_i}, p_2 \in i_{c_j}} [p_2 \in I_{c_i} \mid |p_1 - p_2| = k] \tag{2}$$

Where $k \in d$ and $i, j \in m$. For any pixel of color c_i in the image, $\varphi^{d}_{c_i c_j}(I)$ gives the probability that a pixel at distance k away from the given pixel is of color c_j. The autocorrelogram of I captures spatial correlation between identical colors only and is defined in equation (3) as in [19]

$$\Phi^{k}_{c}(I) \overset{\Delta}{=} \varphi^{d}_{c_i c_j}(I) \tag{3}$$

Since smallest correlation distance offers in depth local properties of an image, the color autocorrelogram extracts the spatial correlation between the identical colors at distance *d*= 1 [19].

B. Texture Autocorrelogram

Texture plays significant role in image classification and retrieval because it characterizes the surfaces in an image like fineness, coarseness, etc and also captures the association between the surfaces.

In this paper, while the spatial information of the pixels is so important in image analysis [20,21], the texture autocorrelogram proposed in [13] based on full range of Autoregressive model is incorporated which extracts the spatial correlation between the identified micro-textures and examine the change of its correlation with respect to distance. The identified micro-textures are represented in a table whose 1st column belongs to texnums and 2nd column belongs to distance. Each value in the table designate the probability of finding a micro-texture of texnum *i* at a correlation distance *d* from a micro-texture of texnum *i*. i.e. In [13], the correlation distance *d* is set to 1 since smallest correlation distance offers in depth local properties of an image.

C. Chordiogram Descriptor

A shape-based global image descriptor called chordiogram descriptor is described in [18], which is insensitive to illumination changes and robust to small rotation and scaling. It captures the local geometric features instead of image intensities. The chordiogram is a four-dimensional histogram feature and each dimension in chordiogram corresponds to histogram bins of

1. Length of the line segment between all the pair edge

pixels in the region. For example, say p1 and p2 are a pair of pixel in a region then the length of line segment ranges from 0 to the diameter of the each region,

2. Angle between line segment and the horizontal axis of the image and it lies between 0 and 2Π,
3. The angular differences between the normal directions of the pixels p1 with the line segment and it lies between 0 and 2Π.
4. The angular differences between the normal directions of the pixels p2 with the line segment and it lies between 0 and 2Π.

In order to compute the chord feature, a small subset S of outstanding edge pixels is detected from the regions as described in [18] then a histogram encoding geometric features of pixel pairs in G is calculated as in [18].

D. Min-Max Normalization

The values of computed features are arbitrarily differing from each other in a boundless way. Hence, normalization is essential to bind the large and small difference in the feature value to the range of [0, 1]. Hence, Min-Max normalization is incorporated in the proposed work for normalizing the computed features and is computed as follows in equation (4).

$$Y = \frac{(X - MIN)}{(MAX - MIN)} \tag{4}$$

E. Distance measure

The objective of retrieval system is finding the best *n* number of images that are akin to query image. Finding the similarity between the images is evaluated using the similarity measure. Thus, the effective similarity measure play a central role in determining the accuracy and time complexity of a retrieval system [11] and it measures the distance between the similarity of two images. Thus, various aspects of prominent similarity measures like manhattan, Euclidean, Canberra, Jeffrey, etc have been analyzed and it is revealed in the literature that Canberra distance significantly provides the overall best performance [22] and is a weighted version of L1 distance. Hence, Canberra is incorporated in the proposed work to measure the similarity between the images and is computed as follows in equation (5).

$$S(Q,T) = \sum_{i=1}^{n} \frac{|Q_i - T_i|}{|Q_i| + |T_i|} \tag{5}$$

Where Q and T represent the query and target image feature vectors respectively and n is the number of features in each feature vector. The features are placed in increasing order that the value in the top most gives high similarity. The algorithm for the proposed method is as follows.

Algorithm:

Input: Q_I stands for query image and N_{DB} stands for number of images in the benchmark database.

Output: T_I stands for number of retrieved images akin with query image Q_I.

1. Image Q_I is divided into number of non-overlapping rectangular regions say N_p and is determined empirically.
2. for p=1 to N_p

For a Region Q_p in query image

a. Compute Color autocorrelogam.
b. Compute texture autocorrelogram using FRAR model.
c. Compute chordiogram descriptor.
d. Combine the extracted feature vectors into a single one.
e. Normalize the combined feature vector using Min-Max normalization and is stored in F_p.

end

3. [Assume that the feature vector is computed as mentioned in step 2 for all the images in the benchmark database]
4. int D[N_{DB}];
5. For i=1 to N_{DB}

for p=1 to N_p

i. Measure the similarity between the Q_p and T_p and is assigned to D_p.
ii. D[i] = D[i] + D_P;

End

D[i] =D[i]/N_p

end

6. Quick sort is performed on D[N_{DB}].
7. Return the N_P number of similar images in ascending order of similarity.i.e. the highest similar image is first in the list.

III. EXPERIMENTS AND RESULTS

A. Experimental setup

The proposed medical image retrieval system is implemented using the benchmark database [11], which consists of images collected with the ground truth from the Rajah Muthiah Medical college Hospital, Annamalai University, Annamalai Nagar, India. The database contains 6400 images of 83 classes produced by different modalities like CT, X-ray, MRI, Mammogram, Ultrasound, Microscopy, and Endoscopy modalities. The total number of medical images in the category of CT, X-ray, MRI, Mammogram, Microscopy, Ultrasound, and Endoscopy modalities are 592, 1510, 580, 858, 1708, 663 and 489 respectively. In this paper, we limited our discussion to grey scale images only. Hence, we are not considered microscopy and endoscopy images for our experimental setup. The images are stored in TIFF and JPEG format. The size of the medical images is differing in size. Some of the images from the benchmark database are presented in Figure 1.

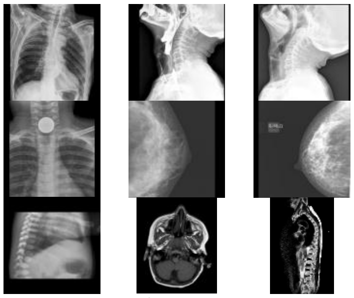
Fig.1 Sample images from the benchmark database

The CA, TA and CD are extracted for each region in the image and the extracted features are combined into a single vector for each region in the image and are normalized as aforementioned in section 2.4. The similarity measure is computed for the feature vector of corresponding regions of both query and target images then the average result of the similarity measure of all the regions of an image is considered for final result.

Different sub-sets of query images from the entire benchmark database is selected to assess the performance of the proposed system and number of images in each sub set is differing depends on the number of images in each modality category. The experiments are executed in the dual core processor, 2 GB memory and 64 bit windows operating system and are carried out using the MATLAB.

B. Performance assessment

To assess the performance of the proposed system, we used average retrieval precision (MAP) [23]. Let I_N be the first N number of images retrieved akin to the query image, M be the number of images in the benchmark database akin to query image, then precision and recall calculation is done as follows in equations (6) and (7) respectively.

$$\text{Precision (P)} = \frac{I_N}{N} \tag{6}$$

$$\text{Recall (R)} = \frac{I_N}{M} \tag{7}$$

For instance the values of I_N, N and M are 60, 100 and 592 respectively then precision P(100) is 60/100=60% and recall R(100)=60/592 =0.10%. The average precision versus recall for CT, MRI, Mammogram, Ultrasound, X-ray images in the proposed and existing system [11] is shown in Fig.2. We also incorporated G-measure which combined the results of precision and recall into single result and provides better results [23] and is computed as follows in equation (8). In Table 2, the G-measure for CT, MRI, Mammogram, Ultrasound and x-ray images are reported.

$$GM = \sqrt{\text{Precision} \times \text{Recall}} \tag{8}$$

It is observed in the results that the proposed combination CA, TA and CD features significantly outperforms the method in [11] and it is because of capturing of local spatial correlation of identified texture elements; capturing the geometric features of prominent edges. The average precision Vs recall of the proposed work and existing work for different modalities

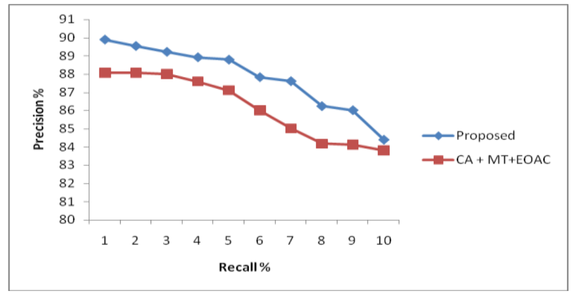

Fig. 2 CT

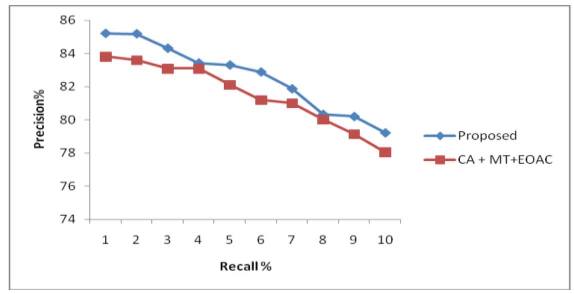

Fig. 3 MRI

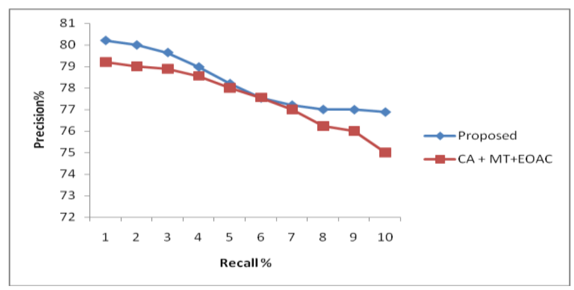

Fig. 4 Mammogram

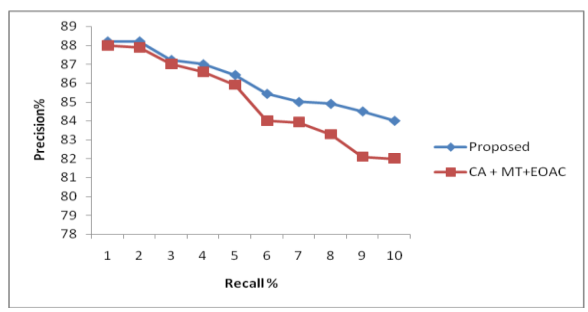

Fig. 5 Ultrasound

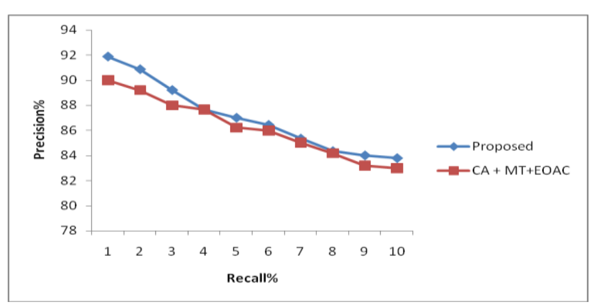

Fig. 6 X-ray

TABLE I GM FOR THE PROPOSED AND EXISTING SYSTEMS FOR THE IMAGES OF VARIOUS MODALITIES IN THE BENCHMARK DATABASE

Method	CT	MRI	Mammogram	Ultrasound	X-Ray
Proposed	87.85	82.61	78.27	86.09	87.05
Existing	86.20	81.56	77.54	85.07	86.25

Fig. 7 Example query image

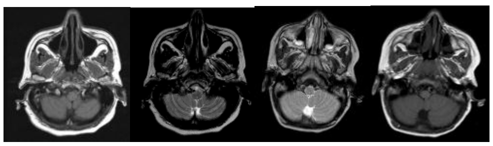

Fig. 8 Top 4 retrieval results obtained with the proposed system corresponding to the query image

IV. CONCLUSION

In this paper, we have proposed a hybrid framework for fast and efficient medical image retrieval system using color autocorrelogrm, texture autocorreloram and chordiogram features. The proposed combination of features is very effective in representing color, texture and shape features. Moreover, features are extracted for each non-overlapping rectangular regions of the image and .the similarity measure is computed for the corresponding regions of both query and target images then the average result of the similarity measure of all the regions in the image is considered for final result which also leads to significant increase in the accuracy. The accuracy of the proposed system is significantly better than that of the existing system and it will be very useful for people working in the medicine domain.

REFERENCES

[1] H. Müller, A. Rosset, A. Garcia, J. P. Vallée, and A. Geissbuhler,"Benefits of Content-based Visual Data Access in Radiology", *Radio Graphics,* Vol. 25, No. 3, pp. 849-858, 2005.

[2] H. L. Tang,Rudolf Hanka and Horace Ho-Shing Ip, "Histological image retrieval based on semantic content analysis", *IEEE Transactions on Information Technology in Biomedicine,* Vol. 7, No. 1, pp. 26-36, 67, 2003.

[3] T. M. Lehmann,M.O. Gu¨ld,T. Deselaers,D. Keysers,H. Schubert,K. Spitzer,H. Ney and B. B. Wein, "Automatic categorization of medical images for content-based retrieval and data mining", *Computerized Medical Imaging and Graphics*, Vol. 29, pp. 143-155, 2005.

[4] Mahmudur Rahman, Md., Daekeun You, Matthew S. Simpson, Dina Demner-Fushman, Sameer K. Antani, and George R. Thoma, "Multimodal biomedical image retrieval using hierarchical classification and modality fusion", *Int J Multimed Info Retr.*, Vol. 2, pp. 159-173, 2013.

[5] M. S. Sudhakar and Bhoopathy K. Bagan, "An effective biomedical image retrieval framework in a fuzzy feature space employing Phase Congruency and GeoSOM", *Applied Soft Computing*, Article in press, 2014.

[6] Subrahmanyam Murala and Q. M. Jonathan Wu, "MRI and CT image indexing and retrieval using local mesh peak valley edge patterns", *Signal Processing*, Vol. 29, No. 93, pp. 400-409, 2014.

[7] Subrahmanyam Murala and Q. M. Jonathan Wu, "Local ternary co-occurrence patterns: A new feature descriptor for MRI and CT image retrieval", *Neurocomputing*, Vol. 119, pp. 399-412, 2013.

[8] Prithaj Banerjeea, Ayan Kumar, Bhuniab Avirup Bhattacharyyac, Partha Pratim Royd and Subrahmanyam Muralad, "Local Neighborhood Intensity Pattern–A new texture feature descriptor for image retrieval", *Expert Systems with Applications*, Vol. 113, pp. 100-115, 2018.

[9] Ashnil Kumar, Jinman Kim, Lingfeng Wen, Michael Fulham and Dagan Feng, "A graph-based approach for the retrieval of multi-modality medical images, *Medical Image Analysis,* Vol. 18, No. 2, pp. 330-342, 2014.

[10] K. Seetharaman and S. Sathiamoorthy, "A unified learning framework for content based medical image retrieval using a statistical model", *Journal of King Saud University-Computer and Information Sciences*, Vol. 28, No. 1, pp. 110-124, 2016.

[11] G. H. Liu, Z. Y. Li,L. Zhang and Y. Xu, "Image retrieval based on micro-structure descriptor. *Pattern Recognition.* Vol. 44, No. 9, pp. 2123-2133, 2011.

[12] K. Seetharaman and S. Sathiamoorthy, "An Improved Edge Direction Histogram and Edge Orientation AutoCorrlogram for an Efficient Color*", Proceedings of International Conference on Advanced Computing and Communication Systems (ICACCS -2013),* Coimbatore, India, Dec. 19- 21, 2013.

[13] K. Seetharaman and S. Sathiamoorthy, "A Novel scheme for texture feature characterization using a statistical approach", *Proceedings of International Conference on Advanced Computing and Communication Systems (ICACCS -2017),* Coimbatore, India, 6-7 Jan. 2017.

[14] K. Seetharaman, "Texture analysis based on a family of stochastic models", Signal and Image Processing Applications (ICSIPA), *IEEE International Conference*, pp. 518-523, 2009.

[15] K. Seetharaman and M. Kamarasan, "Statistical framework for image retrieval based on multiresolution features and similarity method", *Mul. Tools App.,* Vol. 3, No. 1, pp. 53-66, 2014.

[16] Adnan Qayyum Syed Muhammad Anwar Muhammad Awais Muhammad Majid, "Medical image retrieval using deep convolutional neural network", *Neurocomputing,* Vol. 266, pp. 8-20, 2017.

[17] Vibhav Prakash Singh and Rajeev Srivastava, "Automated and effective content-based mammogram retrieval using wavelet based CS-LBP feature and self-organizing map", *Bio cybernetics and biomedical engineering*, Vol. 38, No. 1, pp. 90-105, 2018.

[18] Xiaolong Wang, Hong Zhang and Guohua Peng, "A chordiogram image descriptor using local edgels", *J. Vis. Commun. Image R.*, Vol. 49, pp. 129–140, 2017.

[19] Y. D. Chun,N. C. Kim, and I. H. Jang, Content-Based Image Retrieval using Multiresolution Color and Texture Features, *IEEE Transactions on Multimedia*, Vol. 10, No. 6, pp. 1073-1084, 2008.

[20] G. Qiu and K. M. Lam, Frequency layered color indexing for content-based image retrieval. *IEEE Trans. Image Process*. Vol. 12, No. 1, pp. 102–113, 2003.

[21] Iqbal, Kashif, Odetayo, O. Michael, James and Anne, "Content-based image retrieval approach for biometric security using color, texture and shape features controlled by fuzzy heuristics", *Journal Comput. Syst. Sci*. Vol. 78, pp. 1258-1277, 2012.

[22] G. H. Liu and J. Y. Yang, "Content-based image retrieval using color difference histogram", *Pattern Recognition*, Vol. 46, pp. 188-198, 2013.

[23] Yesu bai Rubavathi Charles and Ravi Ramra, *International Journal of Electronics and Communications (AEÜ),* Vol. 70, No. 3, pp. 225-233, 2016.