International Journal on
"Technical and Physical Problems of Engineering"
(IJTPE)
Published by International Organization of IOTPE

ISSN 2077-3528
IJTPE Journal
www.iotpe.com
ijtpe@iotpe.com

June 2013 | Issue 15 | Volume 5 | Number 2 | Pages 148-153

A REVIEW ON CONTENT BASED IMAGE RETRIEVAL IN MEDICAL DIAGNOSIS

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Abstract- This article gives an overview of the currently available literature on content based image retrieval in the medical domain, especially in cancer diagnosis. Content Based Image Retrieval in Medical (CBIRM) a technique for retrieving image on the basis of automatically derived features such as color, texture and shape to index images with minimal human intervention. The need to find a brain cancer tumor image from a body image collection is shared by many professional groups, including skin images, backbone images, face images and etc. CBIRM consists of retrieving the most visually similar images to a given query image from a database of medical images.

Keywords: Content Based Image Retrieval in Mediacal (CBIRM), Imaging Informatics, Information Storage and Retrieval, Image Segmentation, Feature Extraction.

I. INTRODUCTION

Some years ago, medical information systems only provided textual information about patients in treatment; later, this data is stored in large databases where queries could be made by searching for the text information [1]. Today, this type of information has become the main subsidy for medical diagnosis, even, there is area called, medical imaging diagnose. Content Based Image Retrieval (CBIR), also known as query by image content (QBIC) and content-based visual information retrieval (CBVIR) [2, 3] . Image retrieval has been an extremely active research area over the last 10 years, but first review articles on access methods in image databases appeared already in the early 80s [4].

CBIR systems retrieve images from that database which are similar to the query image. Primarily research in Content Based Image Retrieval has always focused on systems utilizing color and texture features [5]. There has also been some work done using some local color and texture features. These account for Region Based Image Retrieval (RBIR) [6]. There are three important feature components for content based image retrieval [7]. The most common are color [3, 8], texture [9, 10]and shape [11, 12] or combinations of these. These features are combined to achieve higher retrieval efficiency [8]. The proposed content based medical image retrieval scheme is outlined in Figure 1.

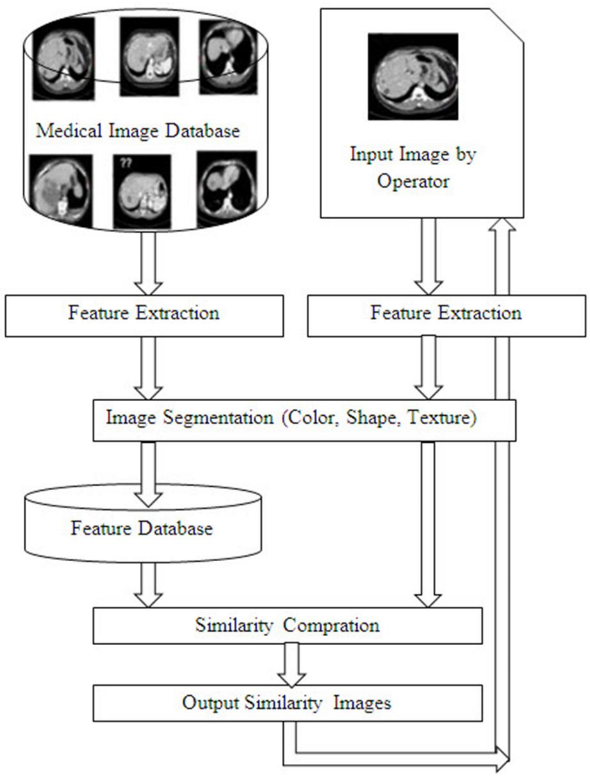

Figure 1. Outline of the proposed content based image retrieval in medical methodology

The image retrieval process consists of two main phases: pre-processing phase and retrieval phase. Both phases are described as follows [13].

II. PRE-PROCESSING PHASE

Image segmentation is the process of separating or grouping an image into different parts. The goal of image segmentation is to cluster pixels into salient image regions, where the regions corresponding to individual surfaces, objects, or natural parts of objects Image segmentation methods can be divided into three types: Boundary based techniques, Region based techniques, and Pixel based direct classification methods [14]. Pre-processing method is depicted in Figure 2.

Input image Output image

Figure 2. Sample pre-processed Image

The pre-processing phase is composed of two main components:

- The Feature Extraction model
- Classification model

The idea behind feature extraction is to use the lowest level pixel values to extract slightly higher level features, such as gray-levels, texture or shape and combine them into an ideally high level representation of the image content. The feature extraction model operates on the image database to produce three kind of features:

A. Shape Feature

Shape is one of the important features and contains the most attractive visual information for human perception [15]. We use the term shape to refer to the information that can be deduced directly from images and that cannot be represented by color or texture; as such, shape defines a complementary space to color and texture [16]. Shape representations techniques used in similarity retrieval are generally characterized as being region based and boundary based [17]. Boundary based shape representation only uses the outer boundary of the shape as shown in Figure 3.

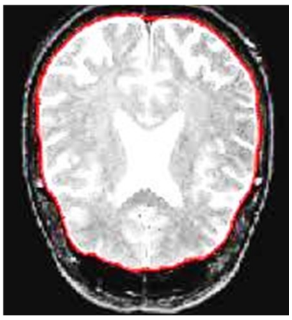

Figure 3. Boundary based shape representation

Methods that extract region based features take into account all the pixels within the shape. They map each shape into a fixed sized grid or circle to achieve scale, rotation and translation invariance. This normalized shape is viewed as a probability density of a two-dimensional variable, from which orthogonal moments that describe some global properties of the shape can be computed [15, 18]. Low level visual features are used for representation and retrieval of images.

B. Color Feature

The color feature has widely been used in CBIR systems, because of its easy and fast computation [19]. Color is one of the visual attributes that can provide more information about the visual content of an image and the most widely used feature in CBIR [20, 21].

This is a compact representation of the color feature to characterize a color image [22-24]. The purpose of a color space is to facilitate the specification of colors. In fact, most existing image retrieval systems such as QBIC [25], Netra [26], and VisualSEEK [27] are most efficient in color retrieval. The color feature three-dimensional values make its discrimination potentiality superior to the single dimensional gray values of images. These values are:

- **Color Space**

Each color in the color space is a single point represented in a coordinate system. several color spaces, such as RGB, HSV, CIE $L*a*b$, and CIE $L*u*v$, [28] have been developed for different purposes. The RGB space is a widely used color space for image display. It is composed of three color components red, green, and blue. The CIE $L*a*b^*$ and CIE $L*u*v*$ spaces are device independent and considered to be perceptually uniform. They consist of a luminance or lightness component (L) and two chromatic components a and b or u and v. In HSV (or HSL, or HSB) space is widely used in computer graphics and is a more intuitive way of describing color. The three color components are hue, saturation (lightness) and value (brightness). In contrast, CMY space is a color space primarily used for printing. The three color components are cyan, magenta, and yellow.

- **Color Moments**

Color moments have been successfully used in many retrieval systems (like QBIC CBIR system [29, 30]). It has been shown that most of the color distribution information is captured by the three low order moments. The first order moment (μ) captures the mean color, the second order moment (σ) captures the standard deviation, and the third-order moment captures the skewness (θ) of color. These three low order moments $(\mu_c, \sigma_c, \theta_c)$ are extracted for each of the three color planes, using the following mathematical formulation.

$$\mu_c = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} P_{ij}^{c} \quad (1)$$

$$\sigma_c = \left[\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(P_{ij}^{c} - \mu_c)^2\right]^{\frac{1}{2}} \quad (2)$$

$$\theta_c = \left[\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(P_{ij}^{c} - \mu_c)^3\right]^{\frac{1}{3}} \quad (3)$$

Weighted Euclidean distance between the color moments of two images has been found to be effective to calculate color similarity [31].

- **Color Histogram**

The color histogram is the most traditional and the most widely used way to represent color patterns in an image [32, 33]. many applications require methods for comparing images based on their overall appearance Color histograms are frequently used to compare images [34]. The color histogram serves as an effective representation of the color content of an image if the color pattern is unique compared with the rest of data set.

The color histogram is easy to compute and effective in characterizing both the global and local distribution of colors in an image. In addition, it is robust to translation and rotation about the view axis and changes only slowly with the scale, occlusion and viewing angle. Color histogram distances should include some measure of how similar two different colors are, for example, QBIC system defines its color histogram distance as [32]:

$$d_{hist}(I,Q) = (h(I) - h(Q))^T . A . (h(I) - h(Q)) \quad (4)$$

To solve this problem, the joint histogram technique is introduced [71]. The color histogram does not take the spatial information of pixels into consideration, thus very different images can have similar color distributions. A simple approach is to divide an image into sub-areas and calculate a histogram for each of the sub-areas (Figure 4).

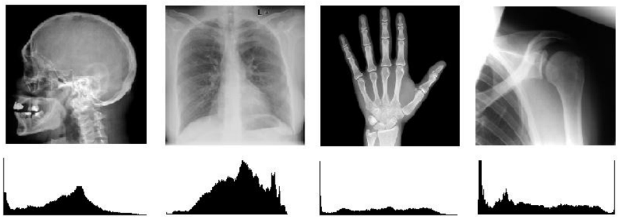

Figure 4. The gray level histograms of several medical images

C. Texture Feature

Texture is one of the most important defining features of an image [32]. In image classification texture provides important information as in many images of real world [35, 36]. Texture provides important information as in many images of real world. Texture determination is ideally suited for medical image retrievals Systems [37]. The autocorrelation function of an image is used to quantify the regularity and the coarseness of a texture. This function is defined for an image I as:

$$p(x,y) = \frac{\sum_{u=0}^{N}\sum_{v=0}^{N} I(u,v) I((u+x),(v+y))}{\sum_{u=0}^{N}\sum_{v=0}^{N} I^2(u,v)} \quad (5)$$

A texture is characterized by a set of values [38]:

1) energy
2) entropy
3) contrast
4) homogeneity

$$\begin{aligned} &\text{Energy} = \sum_i \sum_j P_d^2(i,j) \\ &\text{Entropy} = -\sum_i \sum_j P_d(i,j) \log P_d(i,j) \\ &\text{Contrast} = \sum_i \sum_j (i-j)^2 P_d(i,j) \\ &\text{Homogeneity} = \sum_i \sum_j \frac{P_d(i,j)}{1+|i-j|} \end{aligned} \quad (6)$$

The comprises spectral features achieved by using Gabor filtering, wavelet transform texture features commonly used by system of retrieving images [36]. Some common measures for capturing the texture of images are wavelets and Gabor filters.

The Gabor filter has been widely used to extract image features, especially texture features [39, 40]. We can extract features from those filtered images using some techniques, such as applying spatial smoothing or to pass them through a sigmoidal nonlinearity [14, 41]. The basic idea of using Gabor filters to extract texture features is as follows.

A two dimensional Gabor function $g(x, y)$ is defined:

$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2} \right) + 2\pi j w_x \right] \quad (7)$$

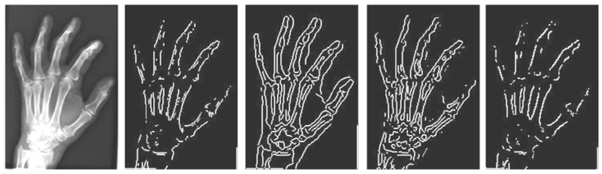

Figure 5. Edge operators: (a) Original image, (b) Prewitt, (c) Canny, (d) Laplacian of Gaussian, (e) Roberts

The texture measures try to capture the characteristics of images or image parts with respect to changes in certain directions and scale of changes [42]. There are different types of texture feature extraction methods like statistical, geometrical, and model based and signal processing reported in the Literature. Purpose of texture analysis [14]:

1. To identify different textured and nontexture regions in an image.
2. To classify different texture regions in an image.
3. To extract boundaries between major texture regions.
4. To describe the Texel unit.

Basically, texture representation methods can be classified into two categories: structural and statistical. Structural methods, including morphological operator (Figure 5) and adjacency graph, describe texture by identifying structural primitives and their placement rules. They tend to be most effective when applied to textures that are very regular. Statistical methods, including Fourier power spectra, co-occurrence matrices, shift invariant principal

The component analysis (SPCA), Tamura feature [43], Wold decomposition, Markov random field, fractal model, and multi-resolution filtering techniques such as Gabor and wavelet transform, characterize texture by the statistical distribution of the image intensity. Textural features usually play only a secondary role in most CBIR systems that deal with colored images. However, in medicine, textural features gain an extra importance, because (a) gray-level features alone may not have enough discriminatory power [13] and (b) some diseases can affect the organs in such a manner that x-ray images of those organs show texture changes [14].

Medical image interpretation consists of three key tasks: (1) perception of image findings, (2) interpretation of those findings to render a diagnosis or differential diagnosis, and (3) recommendations for clinical management (biopsy, follow up, etc.) or further imaging if a firm diagnosis has not been established [16].

D. Similarity Measure

The Similarity functions seek calculates the content difference between two images based on their features. One of the images is given as search parameter and another is stored in the database and had their features previously extracted [44]. There are different ways to show results for users, the most common is use the ranking method and present images thumbnails according to the similarity degree in relation to a query [45]. The judgment of how similar a database image is to a query is dependent on which image distance measure or measures are used to judge similarity. Calculate Euclidean Distance then get Euclidean (D) [46]:

$$Deucld(r,s) = \sqrt{\sum_{i=1}^{N}(r_i - s_i)^2} \tag{8}$$

While ($T_i \equiv O_i$), where T_i is the test (query) Image and O_i is the object images. Repeat above procedure for N object images. Now we have 'N' object image and its Euclidean distance matrices.

There are four major classes of similarity measures:
1. color similarity,
2. texture similarity,
3. shape similarity,
4. object and relationship similarity.

III. CONTENT BASED IMAGE RETRIEVAL SYSTEMS

Content based image retrieval has frequently been proposed for various applications. Some of applications are described as follows:

A. TeleMed-VS [47]

TeleMed-VS is one medical image visualization and segmentation tool. It is like an eye to aid doctors in medical image analysis and in diagnosis, who use medical images in neurology, radiology, surgery, or any other field. For image visualization, it renders 3D image data both in slice mode and volume mode. For medical image processing system, finding out the area that interested by physicians Image segmentation is primary work for anatomical analysis and pathological diagnosis. However, it is still challenge and unsolved problem (Figure 6).

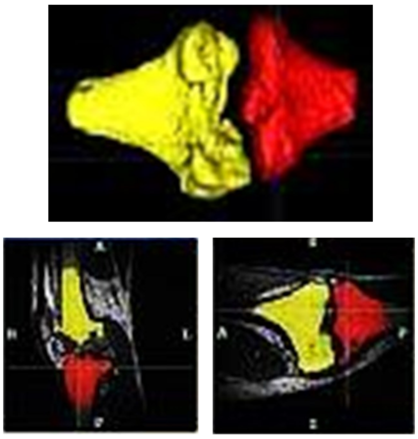

Figure 6. The TeleMed-VS system radiology image retrieval system

B. ASSERT [48]

ASSERT (Automated Search and Selection Engine with Retrieval Tools) is a CBIR system for the domain of HRCT (High Resolution Computed Tomography) images of the lung with emphysema-type diseases. It uses the computer's computational efficiency to determine and display to the user the most similar cases to the query case.

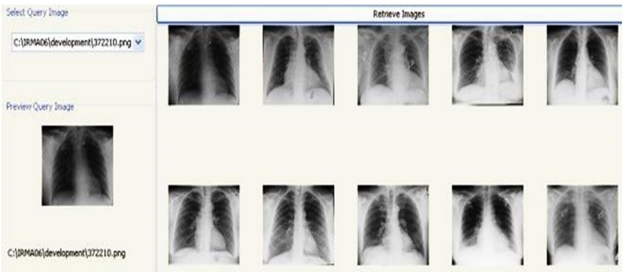

Figure 7. The ASSERT system radiology image retrieval system

C. PACS/ Health Database Management [49]

Picture Archive and Communication Systems (PACS) are comprehensive management systems for diagnostic imaging studies that are increasingly used in hospitals and health care systems [49]. The idea of PACS is to integrate imaging modalities and interfaces with hospital and departmental information systems in order to manage the storage and distribution of images to radiologists, physicians, specialists, clinics, and imaging centers.

1.

2.

D. IRMA (Image Retrieval in Medical Applications) [50, 51]

The IRMA system splits the image retrieval process into seven consecutive steps, including categorization, registration, feature extraction, feature selection, indexing, identification, and retrieval [52] (Figure 8).

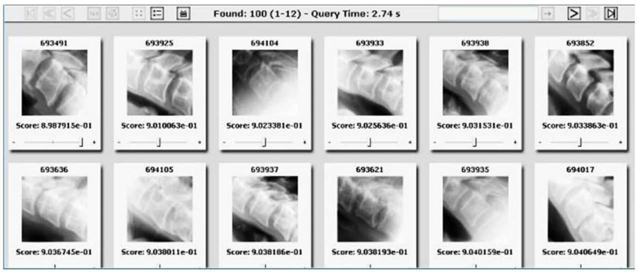

Figure 8. The SPIRS-IRMA system radiology image retrieval system

IV. CONCLUSIONS

This paper has focused on the CBIR applications in medical domain, the majority of the medical CBIR systems have emerged as adaptations of the multimedia CBIR systems. The goal of medical image databases is to provide an effective means for organizing, searching, and indexing large collections of medical images. Content based retrieval is a promising approach to achieve these tasks and has developed a number of techniques used in medical images. CBIR approach provides semantic retrieval, but effective and precise techniques still remains elusive.

REFERENCES

[1] H. Chuctaya, et al., "M-CBIR: A Medical Content Based Image Retrieval System Using Metric Data Structures", Computer Science Society (SCCC), 30th IEEE International Conference of the Chilean, 2011.

[2] A.W.M. Smeulders, M. Worring, S. Santini, A. Gupta, R. Jain, "Content Based Image Retrieval at the End of the Early Years", IEEE Trans. on Pattern Anal. Mach. Intell., Vol. 22, No. 12, pp. 1349-1380, 2000.

[3] Y. Rui, T.S. Huang, S.F. Chang SF, "Image Retrieval: Current Techniques, Promising Directions and Open Issues", J. Vis. Commun. Image Rep., Vol. 10, No. 4, pp. 39-62, 1999.

[4] S.K. Chang, T. Kunii, "Pictorial Database Applications", IEEE Computer, Vol. 14, No. 11, 1981.

[5] P.S. Hiremath, J. Pujari, "Content Based Image Retrieval Using Color Texture and Shape Features", 15th International Conference on Advanced Computing and Communications, pp. 780-784, 2007.

[6] J. Li, J.Z. Wang, G. Widerhold, "IRM: Integrated Region Matching for Image Retrieval", 8th ACM International Conference on Multimedia, pp. 147-156, October 2000.

[7] H.J. Lin, et al. "A Study of Shape Based Image Retrieval", 24th IEEE International Conference on Distributed Computing Systems Workshops, 2004.

[8] P. Hiremath, J. Pujari, "Content Based Image Retrieval Using Color, Texture and Shape Features", IEEE International Conference on Advanced Computing and Communications, ADCOM, 2007.

[9] M.M. Islam, D. Zhang, G. Lu, "Automatic Categorization of Image Regions Using Dominant Colour Based Vector Quantization", Digital Image Computing: Techniques and Applications, Canberra, Australia, pp. 191-198, December 1-3, 2008.

[10] N. Rasiwasia, N. Vasconcelos, P.J. Moreno, "Query by Semantic Example", 15th International Conference on Image and Video Retrieval, Lecture Notesin Computer Science, Vol. 4071, Springer, Berlin, pp. 51-60, 2006.

[11] V.A. Tanase, "Content Based Image Retrieval Systems: A Survey", Dept. of Computing Science, Utrecht University, Technical Report, 2000.

[12] W. Zhang, et al., "Shape Based Indexing in a Medical Image Database", IEEE Workshop on Biomedical Image Analysis, 1998.

[13] J.C. Caicedo, F.A. Gonzalez, E. Romero, "Content Based Medical Image Retrieval Using Low Level Visual Features and Modality Identification", Advances in Multilingual and Multimodal Information Retrieval, Springer, pp. 615-622, 2008.

[14] B.C. Ramamurthy, K.R. Chandran, S. Aishwarya, P. Janaranjani, "CBMIR: Content Based Image Retrieval using Invariant Moments, GLCM and Grayscale Resolution for Medical Images", European Journal of Scientific Research, Vol. 59, Issue 4, p. 460, 2011.

[15] D. Zhang, G. Lu, "Shape Retrieval Using Fourier Descriptors", 2nd IEEE Pacific Rim Conference on Multimedia, Citeseer, 2001.

[16] C.B. Akgul, et al., "Content Based Image Retrieval in Radiology: Current Status and Future Directions", Journal of Digital Imaging, Vol. 24, No. 2, pp. 208-222, 2011.

[17] A.A.A. Youssif, A.A. Darwish, R.A. Mohamed, "Content Based Medical Image Retrieval Based on Pyramid Structure Wavelet", International Journal of Computer Science and Network Security, Vol. 10, No. 3, 2010.

[18] D. Zhang, G. Lu. "Content Based Shape Retrieval Using Different Shape Descriptors: A Comparative Study", IEEE International Conference on Multimedia and Expo, 2001.

[19] Y.K. Chan, C.Y. Chen, "Image Retrieval System Based on Color Complexity and Color Spatial Features", Journal of Systems and Software, Vol. 71, No. 1, pp. 65-70, 2004.

[20] D. Shi, L. Xu, L. Han, "Image Retrieval Using Both Color and Texture Features", Journal of China Universities of Posts and Telecommunications, 2007.

[21] H. Muller, et al., "A Review of Content Based Image Retrieval Systems in Medical Applications Clinical Benefits and Future Directions", International Journal of Medical Informatics, Vol. 73, No. 1, pp. 1-24, 2004.

[22] M.A. Stricker, M. Orengo, "Similarity of Color Images", IS&T/SPIE's Symposium on Electronic Imaging: Science and Technology, International Society for Optics and Photonics, pp. 381-392, 1995.

[23] J. Huang, et al. "Image Indexing Using Color Correlograms", IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 1997.

[24] H. Zhang, et al. "Image Retrieval Based on Color Features: An Evaluation Study", Photonics East'95, International Society for Optics and Photonics, 1995.

[25] C. Faloutsos, et al., "Efficient and Effective Querying by Image Content", Journal of Intelligent Information Systems, Vol. 3, No. 3-4, pp. 231-262, 1994.

[26] W.Y. Ma, B. Manjunath, "Netra: A Toolbox for Navigating Large Image Databases", IEEE International Conference on Image Processing, 1997.

[27] J.R. Smith, S.F. Chang, "Local Color and Texture Extraction and Spatial Query", IEEE International Conference on Image Processing, 1996.

[28] T. Gevers, A.W. Smeulders, "Pictoseek: Combining Color and Shape Invariant Features for Image Retrieval", IEEE Transactions on Image Processing, Vol. 9, No. 1, pp. 102-119, 2000.

[29] J. Jasiewicz, T.F. Stepinski, "Example Based Retrieval of Alike Land Cover Scenes", NLCD2006 Database, 2013.

[30] A.J. Afifi, W.M. Ashour, "Image Retrieval Based on Content Using Color Feature", ISRN Computer Graphics, 2012.

[31] H. Zhang, D. Zhong, "Scheme for Visual Feature Based Image Indexing", IS&T/SPIE's Symposium on Electronic Imaging: Science and Technology, International Society for Optics and Photonics, 1995.

[32] P. Suhasini, K.S.R. Krishna, I.M. Krishna, "CBIR Using Color Histogram Processing", Journal of Theoretical and Applied Information Technology, Vol. 6, No. 1, pp. 116-122, 2009.

[33] S. Nandagopalan, D.B.S. Adiga, N. Deepak, "A Universal Model for Content Based Image Retrieval", World Academy of Science, Engineering and Technology, Vol. 46, 2008.
[34] G. Pass, R. Zabih, "Histogram Refinement for Content Based Image Retrieval", 3rd IEEE Workshop on Applications of Computer Vision, WACV'96, 1996.
[35] J.R. Smith, C.S. Li, "Image Classification and Querying Using Composite Region Templates", Computer Vision and Image Understanding, Vol. 75, No. 1, pp. 165-174, 1999.
[36] M. Rehman, et al., "Content Based Image Retrieval: Survey", World Applied Sciences Journal, Vol. 19, No. 3, pp. 404-412, 2012.
[37] T.M. Lehmann, et al., "Automatic Categorization of Medical Images for Content Based Retrieval and Data Mining", Computerized Medical Imaging and Graphics, Vol. 29, No. 2-3, pp. 143-155, 2005.
[38] Y.F. Fathabad, M. Balafar, "Application of Content Based Image Retrieval in Diagnosis Brain Disease", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 13, Vol. 4, No. 4, pp. 122-128, December 2012.
[39] J.G. Daugman, "Complete Discrete 2D Gabor Transforms by Neural Networks for Image Analysis and Compression", IEEE Trans. on ASSP, Vol. 36, pp. 1169-1179, July 1998.
[40] A.K. Jain, F. Farrokhinia, "Unsupervised Texture Segmentation Using Gabor Filters", Pattern Recognition, Vol. 24, No.12, pp. 1167-1186, 1991.
[41] K.H. Jernigan, et al., "Texture Segmentation Using Gabor Filters", Biotechnology and Health Engineering Centre, 2000.
[42] K. Wanjale, T. Borawake, S. Chaudhari, "Content Based Image Retrieval for Medical Images Techniques and Storage Methods", Review Paper, IJCA Journal, Vol. 1, p. 19, 2010.
[43] H. Tamura, S. Mori, T. Yamawaki, "Textural Features Corresponding to Visual Perception", IEEE Transactions on Systems, Man and Cybernetics, Vol. 8, No. 6, pp. 460-473, 1978.
[44] L.C.C. Bergamasco, F.L.S. Nunes, "Content Based Retrieval for 3D Medical Models: A Study Case Using Magnetic Resonance Imaging", Data Inicio, 2012.
[45] R. Da Silva Torres, A.X. Falcao, "Content Based Image Retrieval: Theory and Applications", Journal of Theoretical and Applied Informatics (RITA), Vol. 13, No. 2, pp. 161-185, 2006.
[46] R.S. Dubey , R. Choubey, J. Bhattacharjee, "Multi Feature Content Based Image Retrieval", International Journal on Computer Science and Engineering (IJCSE), Vol. 2, No. 6, pp. 2145-2149, 2010.
[47] R. Currell, et al., "Telemedicine Versus Face to Face Patient Care: Effects on Professional Practice and Health Care Outcomes", Cochrane Database Syst. Rev., Vol. 2, No. 2, 2000.
[48] C.R. Shyu, et al., "ASSERT: A Physician in the Loop Content Based Retrieval System for HRCT Image Databases", Computer Vision and Image Understanding, Vol. 75, No. 1, pp. 111-132, 1999.
[49] C.H. Wei, C.T. Li, Y. Li, "Content Based Retrieval for Mammograms", Proc. IEEE Image Retrieval on Artificial Intelligence for Maximizing, 2008.
[50] P. Ghosh, et al. "Review of Medical Image Retrieval Systems and Future Directions", 24th IEEE International Symposium on Computer Based Medical Systems (CBMS), 2011.
[51] T.M. Lehmann, et al., "IRMA Content Based Image Retrieval in Medical Applications", Medinfo, pp. 842-848, 2004.
[52] Y. Fanid Fathabad, M.A. Balafar, "Content Based Image Retrieval for Medical Images", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 12, Vol. 4, No. 3, pp. 177-182, September 2012.

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