Model Based Approach for Content Based Image Retrievals Based on Fusion and Relevancy Methodology

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Abstract: *This paper proposes a methodology for Content Based Image Retrievals (CBIR) using the concept of fusion and relevancy mechanism based on KL divergence associated with generalized gamma distribution to integrate the features corresponding to multiple modalities, feature level fusion technique is considered. The relevancy approach considered bridges the link to both high level and low level features. The target in the CBIR is to retrieve the images of relevancy based on the query and retrieving the most relevant images optimizing the time complexity. A generalized gamma distribution is considered in this paper to model the parameters of the query image and basing on the maximum likelihood estimation the generalized gamma distribution, the most relevant images are retrieved. The parameters of the generalized gamma distribution are updated using the EM algorithm. The developed model is tested on the brain images considered from brain web data of UCI database. The performance of the model is evaluated using precision and recall.*

Keywords: *CBIR, generalized gamma distribution, relevance image, query image, EM algorithm, precision, recall.*

Received May 23, 2013; accepted October 12, 2013; published online December 3, 2014

1. Introduction

Content Based Image Retrievals (CBIR) are generally focused on the description of the low level features of an image. These low level features help to describe the image, compare the image and retrieve the relevant images based on the query posed by the user. In practical situation, since the usage of internet has drastically improved, retrieving the most appropriate information becomes tedious. In the huge dataset of images retrieved the main challenge is to identify the identical images by separating the similar images and discarding irrelevant images [14]. CBIR have many applications ranging from security, telecommunication, Business Process Outsourcing (BPO) [6, 10]. The main objective of considering CBIR in this paper is subjected to the application of its usage in medical domain [3]. With this objective the methodology is to apply in remote areas for assisting the rural area people and to the doctors with minimum facilities to draw conclusions from the available data by the means of ECG, scanning and the other preliminary medical aids. These dataset of the scanned images or the reports available are searched for the relevancy among the available sources to decide the minimum necessary first aids to be adopted to the patient or to literate the patients regarding the disease.

Many images can be retrieved based on the search and some may be relevant and some irrelevant. The relevant images retrieved may not be accurate enough [1, 4, 11, 13]. Hence, to retrieve the images more exactly with relevantly, a methodology to find the relevant images is proposed by using KL divergence algorithm in section 2. The relevant images obtained are used as the base for the radiologist user to process the query image and obtain information of relevance [7, 8, 15]. This query based technique is presented in section 3. The output images retrieved may not be legible and hence to have more final details, the feature level fusion technique proposed in section 4 is utilized. The processed image is sent for the generalized gamma distribution and Probability Density Function (PDF) of each of the images are obtained. Based on the maximum likelihood estimates most relevant images are retrieved. The methodology is presented in section 5 and the results derived thereof are evaluated using performance metrics like precision and recall and are presented in section 6.

2. Relevant Images Identification using KL Divergent Method

Majority of the similar images based on the criteria will be retrieved of which some may be relevant, similar and identical. The ideology is to extract the most relevant images for which the PDF [9, 16] of each of the retrieved image is calculated and for the query image also the PDF's are calculated. In order to find the relevancy KL Divergence algorithm [5] is used which is given by:

$$KL(p_1, p_2) = \int p_1(x) \log \left(\frac{p_1(x)}{p_2(x)} \right) dx \qquad (1)$$

Where p_1, p_2 are the two PDF computed on different brain images, formulated using generalized gamma distribution.

The set of images retrieved and the images retrieved based on relevancy are exhibited in Figures 1, 2-a and b.

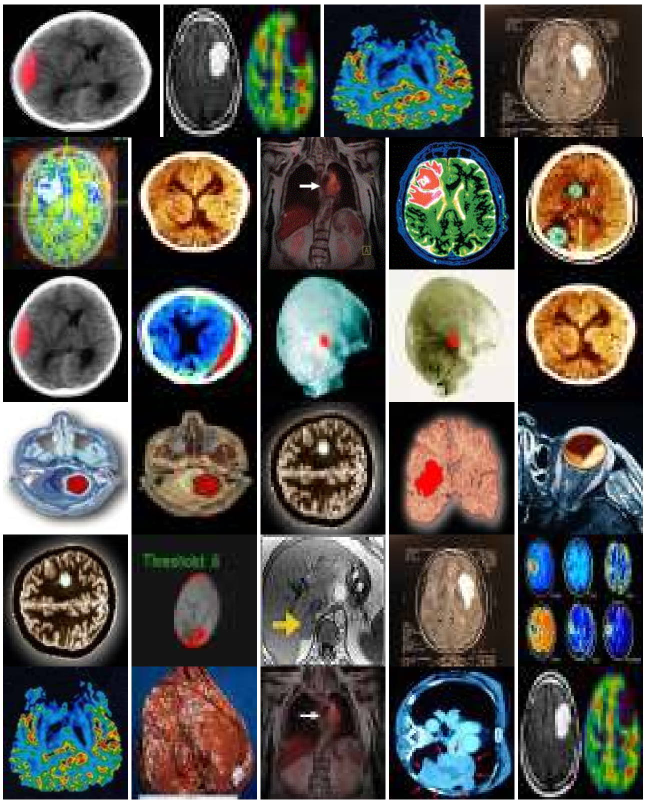
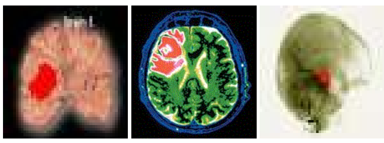
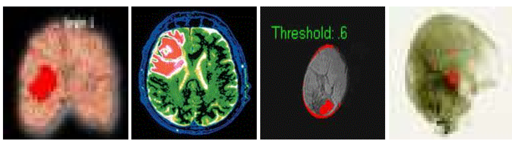


Figure 1. Image dataset.



a) Relevant Images.



b) Retrieved images

Figure 2. Showing relevant and retrieved images

3. Query Image

Using the query given in Equation 2 one can retrieve an image of interest from the identical set of images [12].

$$Q = \alpha Q + \beta \left[\frac{1}{N_R} \Sigma_{i=1}^{N} N_R \right] - \gamma \left[\frac{1}{N_N} \Sigma_{i=1}^{N} N_N \right] \qquad (2)$$

Where α, β, γ are randomly chosen values with criteria that $\alpha+\beta+\gamma=1$ and N_N is the set of non-relevant images.

The images retrieved by processing the query are shown in Figure 3.

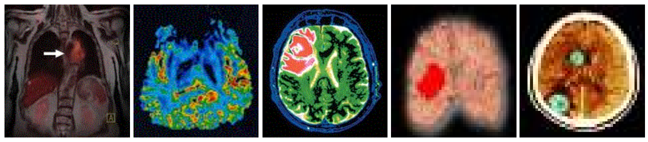
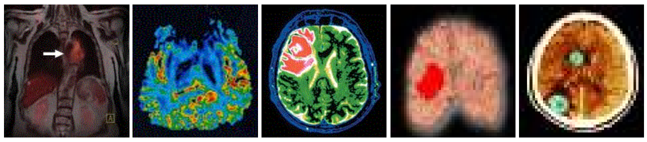


Figure 3. Query images.

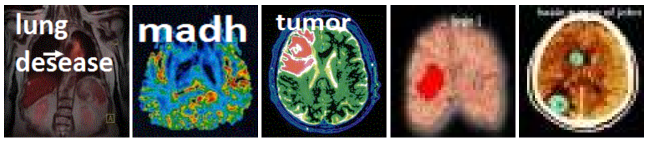
4. Fusion

Fusion addresses the process of combining the relevant images from the set of images to get a clarity image. Many CBIR techniques are available in literature [2, 12, 14] and we have considered feature level fusion where the most relevant features considered in the query image are fused into a single image. The only restriction considered for fusion is that the images to be fused should be of same dimension.

The output of the fusion image is shown in Figures 4-a, b and 5.



a) Images without fusion.



b) Images with fusion.

Figure 4. Showing Images without and with fusion.

Figure 5. Output after applying fusion.

5. Generalized Gamma Distribution

The generalized gamma distribution is utilized for the purpose of identifying the most similar images based on maximizing the likelihood estimate. Generalized gamma distribution is considered because of its asymmetry and in general the shapes of the body organs are asymmetric in nature [4]. The parameters of the generalized gamma distribution are updated using EM algorithm and are presented below.

The PDF of the generalized gamma distribution is of the form:

$$f\left(x,k,c,a,b\right)=\frac{c(x-a)^{ck-1}e^{-\left(\frac{x-a}{b}\right)^{c}}}{b^{ck}\Gamma(k)} \tag{3}$$

Where *a*, *b* and *x* are called gamma variants and *c* and *k* are called shape parameters. By varying the value of the shape parameters, the particular cases of gamma distribution can be modeled.

The updated Equations 4, 5 and 6 of the generalized gamma distribution using EM algorithm are:

$$c^{(l+1)}=\frac{1}{\frac{1}{f^{l}}\frac{\partial f}{\partial c}-klog\left(\frac{x-a}{b}\right)+\frac{(x-a)^{c}}{b^{c}\log\left(\frac{x-a}{b}\right)}} \tag{4}$$

$$k^{(l+1)}=1+\frac{\left[\int_0^{\infty}e^{-t}(log_e t)t^{k-1}dt\right]}{\Gamma(k-1)\left[clog\left(\frac{x-a}{b}\right)-\frac{1}{f}\frac{\partial f}{\partial k}\right]} \tag{5}$$

$$b^{(l+1)}=\frac{ck}{\frac{c}{b^{c+1}}(x-a)^{c}-\frac{1}{f}\frac{\partial f}{\partial b}} \tag{6}$$

6. Methodology

The proposed methodology is for the usage of experts decisions for ratifying decease and to suggest the minimum necessary steps to the doctors available in small hospitals at remote areas of rural villages. So, that the patient can be supported with life saving drugs till he is shifted to nearest specialized hospitals. This methodology proposed helps to plan for effective treatment to the patient.

In order to demonstrate the methodology, brain images obtained from UCI medical database is considered. The main intension is to identify the type of brain disorders which include Parkinson's disease, Alzheimer's, femur etc., In order to retrieve the relevant information, the query image (Brain Scanned MRI Image) of a patient available at the primary health center is considered as the query image. In order to retrieve the relevant images, KL Divergence algorithm proposed in section 3 is utilized. To have a better quality image or to identify the features inside the Brain images more appropriately the fusion technique proposed in section 4 is utilized. The processed image is given as input to the PDF of the generalized gamma distribution and basing on the MLE the most relevant images are retrieved. The outputs of the derived models are evaluated using the bench mark metrics *Precision* and *Recall* are given in Equations 7, 8 and 9 respectively.

$$Precision=\left(\frac{A}{(A+C)}\times 100\right) \tag{7}$$

Where A: No. of relevant images retrieved, C: No. of irrelevant images retrieved and $A+C$: Total number of irrelevant+relevant images retrieved.

Whereas, Recall is the ratio of the number of relevant images retrieved to the total number of relevant images in the database. It is usually expressed as a percentage.

$$Recall=\left(\frac{A}{(A+B)}\times 100\right) \tag{8}$$

Where A: No. of relevant images retrieved, B: No. of relevant images not retrieved and $A+B$: The total number of relevant images.

The *Precision* and *Recall* values are tabulated by varying the relevant images and fixing the non-relevant images are presented below in Table 1. The *Precision* and *Recall* values are calculated by applying fusion techniques, proposed in section 4 and the values are tabulated by varying relevant images and the results are shown below in Table 2. The corresponding graphical values of *Precision* and *Recall* for the values of Tables 1 and 2 are presented in Figures 6, 7, 8 and 9.

Table 1. Without fusion technique.

No. of Relevant Images in the Database	No. of Non-Relevant Images in the Database	Ratio of Relevance to Non-Relevance	Precision	Recall
8	50	0.16	80	6
7	50	0.14	74	26
6	50	0.12	62	35
5	50	0.1	53	42
4	50	0.08	42	53
3	50	0.06	35	62
2	50	0.04	26	74
1	50	0.02	6	80

Table 2. With fusion technique.

No. of Relevant Images in the Database	No. of Non-Relevant Images in the Database	Ratio of Relevance to Non-Relevance	Precision	Recall
8	50	0.16	82	10
7	50	0.14	78	28
6	50	0.12	64	37
5	50	0.1	58	45
4	50	0.08	45	58
3	50	0.06	37	64
2	50	0.04	28	78
1	50	0.02	10	82

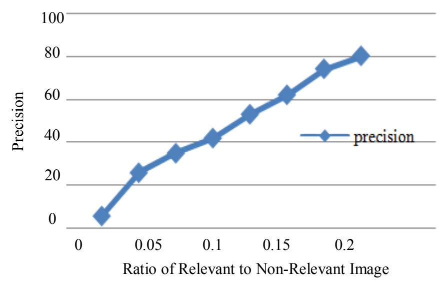


Figure 6. Variation of precision value with R/NR ratio.

The number of relative images retrieved is calculated using the *Precision* and the values obtained are represented in the form of a graph shown in Figure 6.

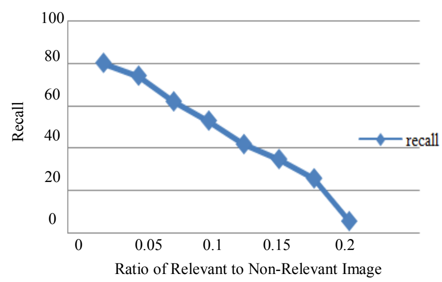


Figure 7. Variation of recall value with R/NR ratio.

Figure 7 represents the graph showing the *Recall* accuracy of relative and non-relative images.

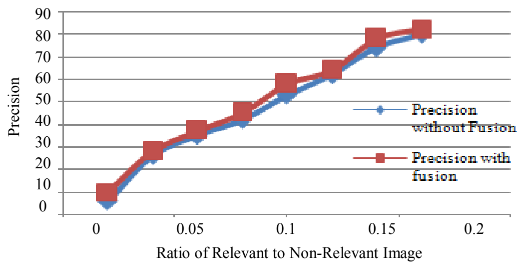


Figure 8. Variation of precision value with R/NR ratio considering fusion and without fusion.

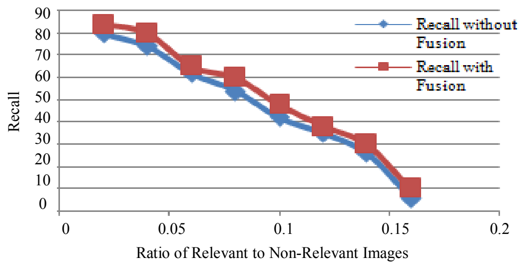


Figure 9. Variation of recall value with R/ NR ratio considering fusion and without fusion.

Figures 8 and 9 exhibits the ratio of relative and non-relative images against the *Precision* and *Recall* accuracy by using the concept of fusion and without fusion respectively.

7. Conclusions

This paper highlights a novel methodology for content based image retrieval that can be very much useful to retrieve the images based on the query and relevance together with fusion. This methodology is presented with the application on patients at primary health center. The outputs of the results derived are evaluated using metrics *Precision* and *Recall* and are presented which show good accuracy.

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