A New Relevance Feedback Approach Based On Similarity Refinement in Context Based Image Retrieval (CBIR)

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Abstract—In this research, a new approach is suggested in Relevance feedback, in which similarity function, will correct by using of information which are relate to, relevant and irrelevant image. In suggested method, for correcting the weight of each feature component, is using form the information which are relate to mean and standard deviation of that component on relevant and irrelevant image. And the weight of each feature, adjusted according to the rank of relevant images in retrieval on the basis of that kind of feature. The suggested method will be testing on an image base which include 1000 image from 10 different meaning group. The result of experiments shows the superior of suggested method to existing method.

Keywords—Relevance feedback, image retrieval, similarity refinement, queries refinement.

I. INTRODUCTION

In recent years, growing of computer technology, remarkable importance of multimedia information and existing of large digital archive, attracted the effort of most researchers for making appropriate equipment of picture recovery. In early of 1990, picture recovery on the basis of content in declared a dynamic field for investigation [1].

There are two different approaches in image retrieval. First: Text based image retrieval and second: context based image retrieval. In the first approach an image features extract handy but in second approach these features extract automatically. Context based image retrieval approach use low-level features and visual (e.g., color, texture, shape, etc.) for indexing and retrieval. In general condition there is no direct relationship between high-level features and low-level features. For decreasing this gap we use Relevance feedback. Relevance feedback which is used in content-based image retrieval (CBIR) has been considered as the efficient technique to improve the retrieval performances. Picture recovery systems are acted in 2 steps. In first step, the visual features of base picture have derived automatically and in second step, after receiving user’s inquiry picture, it’s low level features in extracted and the base of visual features, is investigated for finding he closet pictures to inquiry picture.

In picture recovery systems on the basis of content, the user in following the meaningful search of picture while the system is searching the data base on the basis of low level features and the picture. Which is deliver to the user have. Low level features that are close to user’s inquiry picture but may be they don’t have user’s desirable meaning. This subject demonstrates that low level features are not enough for presentation of meaningful features. On the other hand, the taste of different people is different from each other. And it may various people perceived different meaning from one picture [2] for removal these limitations, it need to recovery work associate with user’s collaborate. In this collaboration will try to modeled the user’s desirable inquiry. And user reach to desirable picture with adjusting the features indicates. The structure of a picture recovery system is illustrated in figure 1. In this system the image base is include the images that user search them for finding desirable image suitable visual features form extracted image and image are index with them [3] [4] [5]. Extracted features of image are keeping in visual features base or low level features. This system in include a graphical connector or inquiry interface. Which by using of it, communicate [connect] with user. Subsystem of inquiry processing, extract the suitable features. From inquiry image. Subsystem of similarity measurement, computed, the similarity between vectors of images feature. Then, system find the closet image, to inquiry image. These image represent to user through the graphical connector, and communicating c connections will be connecting. Will be continuing, until the user reach to desirable image. This process which is known to connector feed back is used for short – term learning.

II. SURVEY ON SHORT – TIME LEARNING METHODS

These methods are divided into two general group, the algorithms which are basis on machine learning and the algorithms that are basis on inquiry vector and similarity function. The methods that are basis on machine learning are divided in two supervised and unsupervised
learning. Supervised learning methods, like support vector machine (sum) [7] [8] [9], fuzzy support vector machine [10] Bayesian classifier [11], artificial neural network [12] [13], decision tree [14] usually are used for learning the high _level conception from low _level features. It is used from support vector machine [sum] as a data distinctive in one group and two groups [short- time learning]. In support vector machine with supportability of 2 groups. The system divided the data base image in two relevant and un relevant groups[15]. In support vector machine of one group, the system separate the images that are just relevant to database. It used from super screen for separation the data. Research [15] compare the support vector machine of one group with two groups. In relevance feed back process in retrieval system of image collaboration. The results demonstrate in stages numbers of low retrievals the support vector machine with one group is suitable, while with increasing the number of retrievals, the support vector machine. (sum) with two group works better.

In reference [16] is used from genetic programming in connection feedback. In another research [17] connection feedback is consider as a Bayesian classifier problem basis on user's feedback. Which divided the images to 2 relevant and un relevant groups?
The results show that this method works better than multimedia Analysis and Retrieval system (MARS).

The methods of unsupervised learning are clustering image base automatically and without user’s intervention. Image clustering is an unsupervised method and it aim is images clustering in the manner that the similarity of inside the cluster is high and the similarity between the cluster is low. The methods of mean (k) cluster sings maximum-A-posterior(MAP), clustering maximum–likelihood (ML), clustering maximization(EM), discriminate EM (D-EM) learning vector quantization (LVQ), self- organizing map tree- structured (TS-som) Normalized cut (ncut) locality preserving clustering (LPC) optimum – path forest(OPF) clustered – based Erieval (CLUE) are a part of unsupervised learning methods. Research [19] is shown that locality preserving clustering have more efficiency in retrieval image than normalized cut and k’s mean.

Algorithms which are basis on inquiry vector and similarity functions divided in two group improvement of similarity function and improvement of inquiry vector. The goal of improvement of inquiry vector is moving the inquiry vector in search space in some way that irrelevant images become far and relevant images become close. This method for the first time is suggested in multimedia Analysis and Retrieval systems 1997. [20] in this method the features mean of all relevant images are calculated and they consider as a new inquiry vector. In research [21] it is used from relevant and irrelevant images for improvement of inquiry vector. In this manner that in every stage.

Inquiry vector become closer to relevant images and far from irrelevant images. This method is known to Rochio method and it is shown in Relation [1].

\[ F_{q}^{\text{new}} = F_{q} + \frac{1}{Q_{p}} \sum_{F_{p} \in Q_{p}^{+}} F_{p} + \frac{1}{Q_{p}^{-}} \sum_{F_{p} \in Q_{p}^{-}} F_{p} \] (1)

\[ F_{q}^{\text{new}} \] and \[ F_{q} \] in order are the new inquiry vector and inquiry vector in last stage. \( Q_{p}^{+} \) and \( Q_{p}^{-} \) in order are shown the relevant and irrelevant collecting images. \( F_{p}^{+} \) and \( F_{p}^{-} \) in order are in dilative feature vector of relevant and irrelevant selected images by users.

In improvement of similarity function , the weight of low level features of inquiry image in order to reach to user’s goal will change during the connection feed back. In [21] research according to relation 2, the weight of each feature component in similarity function will estimate (calculate) according to distance of features vector of inquiry image with feature vectors of relevant images.

\[ h_{i} = 1 / \sum_{j=1}^{m} (F_{q,i} - F_{j,i}^{+})^2 \] (2)

\[ h_{i} \] is the weight of \( i(s) \) component \( F_{q,i} \) and \( F_{j,i}^{+} \) in order are showing \( i(s) \) component from inquiry feature vector and \( i(s) \) relevant image and \( m \) is showing the number of feed back relevant images from the user in reference of [23] and [24] , for determining the weight of each features component the standard deviation of that component is calculated on the collection of relevant image and it consider the weight of mentioned component – proportional with it’s reverse(Relation3)

\[ h_{i} = 1/\sigma_{i}^{+} \] (3)

Features \( \sigma_{i}^{+} \) in this relation vectors of images which are related with inquiry image For determining the weight of every feature components, calculate the standard deviation of that component ratio to collection of relevant images and proportional consider the weight of mentioned component with it reverse. Reference[25] had used from the information of irrelevant images and it had considered the weight of each feature component equals with ratio of standard deviation of that component on irrelevant images to standard deduction of that component on relevant images

\[ h_{i} = \frac{1 + \sigma_{i}^{-}}{1 + \sigma_{i}^{+}} \] (4)

in this relation \( \sigma_{i}^{+} \) and \( \sigma_{i}^{-} \) in order are indicative the standard deviation of \( i[s] \) component from feature vectors of relevant images and feature vectors of irrelevant images with inquiry.

In [24] reference, retrieval starts with using the stable and equal weights, the system has renewal and represent N number image on the basis of features structure, in answer to user’s demand.

After, the user declared his opinion toward the images.

For adjusting the function of every kind of features, the retrieval image is done on the basis of that kind of feature and it put N image in the listed of that feature then, with comparing the retrieval images which are on the basis of feature compound, with retrieval images which are on the basis of that kind of feature and determining the common images on two lists, the weight which is relate to the effect of feature kind is assigned according to relevant or irrelevant of common image.

In improvement of similarity function, the weight of low level features of inquiry image in order to reach to user’s goal will change during the connection feed back. In [21] research according to relation 2, the weight of each feature component in similarity function will estimate [calculate] according to distance of features vector of inquiry image with feature vectors of relevant images.

\[ h_{i} = 1 / \sum_{j=1}^{m} (F_{q,i} - F_{j,i}^{+})^2 \]
component is calculated on the collection of relevant image and it consider the weight of mentioned component – proportional with it’s reverse[Relation3]

\[ H_{i} = L_{i}/\delta_{i}^{l} \]

In this relation \( \delta_{i}^{l} \) indicative the standard deviation of \( i[s] \) component from features vectors of images which are related with inquiry image.

For determining the weight of every feature components, calculate the standard deviation of that component ratio to collection of relevant images and proportional consider the weight of mentioned component with it reverse.

In reference [26], for every one of feature component, the distances mean of that component is calculated from images which are related to inquiry image, on the other hand the distance mean of that component is calculated for relevant and irrelevant images. If a feature component was effective in retrieval the distance mean of that component should less than that mean in collection of relevant and irrelevant images. With considering the mentioned suppose, the weight which is relate to each one of features component will increase or decrease.

In reference [27], the distance mean between relevant images are calculated on the basis of each feature and related coefficient to the effect of proportional, feature kind is consider to converse of this amount.

In reference [23], for determining the related weight to effect of every features in similarity function has used from relevant image retrieval of image has began by using the pro-determined weight and on this basis present images to the user.

After dealer the user’s opinion, for adjusting. The weight of each feature, retrials are done on the basis of individually of features. The common season of images. Which are determining by the users as irrelevant images? With retrial superior images on the basis of every one of these features will determine with this job, the more effective feature. Will clear in retrieval the weight of this feature will increase in retrieval of next stage in reference [28], for adjusting the related coefficient to every features is used from relevant and irrelevant images. in the manner that, the weight of every feature will change, with comparing the variance of that feature on relevant and irrelevant image.

In reference [29], the weight of every one of feature components will adjust by using the collected information from user and retrieval images on the basis of that feature component. In short – term learning, system consider the user’s information. about the relation of presented image to inquiry and on the basis of them by using of machine learning tools or collection of observational rules, it correct the inquiry vector and improvement of similarity function in a way that make the user, get close step by Step to desirable image.

The algorithms, which are basis on inquiry vector and similarity function are using from feed backing image by user, while the machine learning method. Are applied in the image. Of whole base. And they are more expensive from the time view. In improvement of similarity function method, the aim is using of relevant and irrelevant image. in order to adjust component weight of features vector, for this reason, in different research are used from different information such as mean and variance of every component on relevant and irrelevant image.

III. SUGGESTED METHOD FOR IMPROVEMENT OF SIMILARITY FUNCTION.

This research represent a method in order to improve the similarity function by using the relevant and irrelevant information. At first it needs to mention that in suggested system, the low level general features, are discovered from image base. For this reason suppose that \([N] \) number of image exist. in image base \( X = \{x_1, x_2, ..., x_N\} \)

In corresponding with \([x_1]\) image, there is a feature vector of \([f_1]\) which is including relevant low level features. Therefore, features base that is include \([N]\) vector feature is like

\[ F = \{F_1, F_2, ..., F_N\} \]

Feature vector of \([I]\), is a mixed of some heterogeneous features vector.

For example, suppose from an image discovered \((s)\) different kind of feature \([k]\) kind includes \(L_k \) feature component and \(k = \{1, 2, ..., k\} \) and discovered features are attach in the shape [format] of feature vector it means that \( F_i = [f_{i1}, f_{i2}, ..., f_{iK}] + FK \) demonstrate the feature of \((k)\) kind And \(k = \{1, 2, ..., k\}\) [30] [31] – in improvement of similarity function methods similarity function represents in model of relation.

\[
d(F_i, F_j) = w_n \sum_{l} h^l \left( f_{il} - f_{jl} \right)^2 + ... + w_n \sum_{l} h^l \left( f_{il} - f_{jl} \right)^2 \]

In this relation \( F_i \) and \( F_j \) and, \( d \) in order are indicative feature vectors of two image \(i\) and \(j\) and they are criterion for unsimilarity. Between these two feature vectors, \(f_{ik}\), \(L_k\) component which is derived from feature of \(k\), kind, is from \(i\), image, \(L_k\) demonstrate the vector length of \(k(s)\) kind feature \(, W^k_n\) is normalized weight which is relate to \(k(s)\) kind feature and \(h^k_l\) is related weight to \(L\) component from \(k(s)\) kind feature. for improvement of similarity function. It only use from the collection of relevant image but in some other it use from the both collection of relevant and irrelevant images. In suggested system, similarity functions. Will be corrected by using the information of relevant and irrelevant image in first stage of retrieval, after discovering the features of inquiry image, the related weight to effect of each kind of features \((w)\) and \((h)\) feature components. will equal to one Or distance of each component from the feed backing image with different ration

IV. SUGGESTED METHOD FOR CORRECTING THE WEIGHT OF (W), KIND FEATURE.

After start the retrieval, in next stages, the weight which is relate to different features of \((w)\), will adjust according to relevant images. In this method for adjust the weights, the image retrieval is done on the basis of individually of features and without considering the other feature. Then the rank of images which are determine as relevant images. Will calculate on retrieval with every one of features. After that, the weight of every feature. will consider primordial with converse of total of relevant images ranks. For that feature. We use from math language for more explanation. Suppose in one stage of

Retrieval, image collection \( \mathcal{Q}^+ = \{ X^+_1, X^+_2, ..., X^+_m \} \)
Are selected as relevant image, for determining the weight of each one of these feature in next stage. The base images are arranged on the basis of individually features toward the inquiry, hence forth, the rank of each one of images of Q+ collection, will determine in retrieval on the basis of each features. Then, the weight of every kind of features will determine according to relation 6.

\[
w^k = \frac{1}{\sum_{i=1}^{m} \text{rank}^k(X_i^+)}, \quad w^k = \frac{w^k}{\sum_{k=[1,2...,K]} w^k}
\]  

which on that the rank^k(X_i^+) demonstrate the rank of relevant image of X_i^+ in retrieval list on the basis of k, kind and w^k is related normalized weight to that features.

Suggested methods for correcting the weight of features component.

As it mentioned at first, the weight of all component are considered equal to one, in next stage, the weights which are relate to each one of feature component, will adjust according to suggested method to relevant and irrelevant images. In this method, for adjusting the weight of feature component. Which is a base principle methods it used from the variance. And the mean of every component on relevant and un relevant images [32] For represent these principles, put the related weights to different feature components, next to each other, and feature component vector is defined for all the image features.

In on other words we have  \( h = [h_1^1, h_2^1, ..., h_K^1, h_1^2, h_2^2, ..., h_K^2, ..., h_1^K, h_2^K, ..., h_K^K] \) or more accurate

\[ h = [h_1^1, h_2^1, ..., h_l^1, h_1^2, h_2^2, ..., h_l^2, ..., h_l^K, h_{l+1}^2, ..., h_K^K] \]

Suggested principles will represent in 7 to 12 relations, in these principle, if the variance of \([l]s\) component from feature vector, on relevant image \(\sigma_{l-}^1\), the weight of that component will decrease (8,7 relation) There wise, it will increase (9,10 relations) in both state if the mean of mentioned component on relevant images \(\mu_{l+}^1\) is less than the mean on irrelevant images \(\mu_{l-}^1\), the weight of that component will decrease (8 relation to ward 7 and 10 relation toward 9)

If \((\sigma_{l-}^1 > \sigma_{l-}^1)\) and \((\mu_{l+}^1 > \mu_{l+}^1)\) and \((\sigma_{l-}^1, \sigma_{l-}^1 \neq 0)\)

Then \(h_l(\text{new}) = h_l(\text{old}) - 0.4 \times \frac{l}{\sigma_{l-}^1} \times h_l(\text{old})\) (7)

If \((\sigma_{l-}^1 > \sigma_{l-}^1)\) and \((\mu_{l+}^1 < \mu_{l+}^1)\) and \((\sigma_{l-}^1, \sigma_{l-}^1 \neq 0)\)

Then \(h_l(\text{new}) = h_l(\text{old}) - 0.8 \times \frac{l}{\sigma_{l-}^1} \times h_l(\text{old})\) (8)

If \((\sigma_{l-}^1 < \sigma_{l-}^1)\) and \((\mu_{l+}^1 > \mu_{l+}^1)\) and \((\sigma_{l-}^1, \sigma_{l-}^1 \neq 0)\)

Then \(h_l(\text{new}) = h_l(\text{old}) + 0.8 \times \frac{l}{\sigma_{l+}^1} \times h_l(\text{old})\) (9)

If \((\sigma_{l-}^1 < \sigma_{l-}^1)\) and \((\mu_{l+}^1 < \mu_{l+}^1)\) and \((\sigma_{l-}^1, \sigma_{l-}^1 \neq 0)\)

Then \(h_l(\text{new}) = h_l(\text{old}) + 0.4 \times \frac{l}{\sigma_{l+}^1} \times h_l(\text{old})\) (10)

If \((\sigma_{l-}^1 = 0)\) Then \(h_l(\text{new}) = h_l(\text{old}) - 0.8 \times h_l(\text{old})\) (11)

If \((\sigma_{l-}^1 = 0)\) Then \(h_l(\text{new}) = h_l(\text{old}) + 0.8 \times h_l(\text{old})\) (12)

\(l = 1,2,...,L_F\), \(L_F = L_1 + L_2 + ... + L_K\) this in LF the length of feature vector of every image. The variance of \([l]s\) component on relevant and irrelevant image will show in order with \(\mu_{l+}^1\) and \(\mu_{l+}^1\), \(\sigma_{l+}^1\) and \(\sigma_{l+}^1\) in order are indicative the mean of \([l]s\) component on relevant and irrelevant images. \(h_l(\text{new})\) is the corrected weight a \(h_l(\text{old})\) is the weight of \([l]s\) component impervious stage.

V. EXPERIMENTS, RESULTS AND COMPARISON

In this research, use Database (Implicitly), whit 1000 images that these are in 10 categories (African, Beach, Building, Bus, Dinosaur, Elephant, Flower, Horse, Mountain and Food). as we can observe in table1 and fig.4. In suggested system for categorizing Africa, busses, flowers and food is stronger than Implicitly system.

<table>
<thead>
<tr>
<th>Implicitly system</th>
<th>Our system</th>
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<td><strong>variance</strong></td>
<td><strong>score</strong></td>
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<td>180.0</td>
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<td>205.8</td>
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</table>

VI. CONCLUSION

In image retrieval system on the basis of content is using from Relevance feedback tool such as improvement of inquiry vector and improvement of similarity function for elevating the system efficiency in improvement of inquiry vector usually use from relevant and irrelevant image for correction the inquiry vector, in improvement of similarity function for elevating the system impervious stage.
features is using from information collection of relevant images and for correcting the weight of features component is used from the both relevant and irrelevant image collection. the result show that the accuracy of suggested method in 4 category more than implicitly system.

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