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Utilising Fuzzy Rough Set based on Mutual Information Decreasing Method for Feature Reduction in an Image Retrieval System

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Abstract

Content-Based Image Retrieval (CBIR) system has become a focus of research in the area of image processing and machine vision. General CBIR system automatically index and retrieve images with visual features such as colour, texture and shape. However, current research found that there is a significant gap between visual features and semantic features used by humans to describe images. In order to bridge the semantic gap, some researchers have proposed methods for managing and decreasing image features, and extract useful features from a feature vector. This paper presents an image retrieval system utilising fuzzy rough set based on mutual information decreasing method and the Support Vector Machine (SVM) classifier. The system has training and testing phases. In order to reduce the semantic gap, the propose retrieval system used relevance feedback to improve the retrieval performance. This paper also compared the proposed method with other traditional retrieval systems that use PCA, kernel PCA, Isomap and MVU for their feature reduction method. Experiments are carried out using a standard Corel dataset to test the accuracy and robustness of the proposed system. The experiment results show the propose method can retrieve images more efficiently than the traditional methods. The use of fuzzy rough set based on mutual information decreasing method, SVM and relevance feedback ensures that the propose image retrieval system produces results which are highly relevant to the content of an image query.

Keywords: CBIR system, fuzzy rough set, mutual information, relevance feedback.

1. Introduction

In recent years, Content-Based Image Retrieval (CBIR) system has become a focus of research in the area of image processing and machine vision. General CBIR system automatically index and retrieve images with visual features such as colour, texture and shape [1]. However, current research found that there is a significant gap between visual features and semantic features used by humans to describe images. In order to bridge the semantic gap, some researchers have proposed methods for managing and decreasing image features, and extract useful features from a feature vector [2].

Each image in an image retrieval system is represented by its features such as colour features, texture features and shape features. These three groups of features are stored in the feature vector. Therefore each image managed by the CBIR system is associated with one or more feature vectors [3]. As a result, the storage space required for feature vectors is proportional to the amount of images in the database. In addition, when comparing these feature vectors, the CBIR system understand which images in the database are similar to another [1]. Nonetheless, researchers are still facing problems when working with huge image database since so much time is spent to compare huge feature vectors that require large amount of memory to run the CBIR system. Due to this problem, feature reduction methods are employed in order to alleviate the storage and time requirements of large feature vectors. There are many feature reduction methods, including the linear projection methods such as the Principal Component Analysis (PCA) and the Linear Discriminate Analysis (LDA), and the metric embedding techniques (both linear and non-linear) [4]. However, these methods could not improve the image retrieval performance and efficiently reduce the semantic gap. Therefore, an efficient feature decreasing method that can deal with image features is required.

Even though research on CBIR systems has been carried out for quite some time now, some of the issues such as handling the semantic gap, processing large amount of image features and, dealing with incomplete and vagueness in image feature vector are still unresolved. From literature, researchers have proposed various methods to overcome these problems [1, 5].

In this research, the authors propose a pre-processing stage to overcome these problems and improve the CBIR system. Using fuzzy rough set based on mutual information method in the pre-processing stage of the system, can select important features from a massive image feature vectors, and omitting features which are not important. These redundant features could influence further analysis in the wrong direction. Consequently, from these significant features, semantic rules are then extracted that can classify the images more accurately and show more relevance images to the user hence improving the retrieval performance [4]. In addition, in this system relevance feedback is used to bridge the semantic gap. Relevance feedback is an iterative supervised learning process which consists of two steps: (i) the user labels a set of ''relevant'' and ''irrelevant'' images as training samples and (ii) the parameters of the system are updated and a set of better retrieval results is returned [3]. The learning process terminates when the user retrieves a set of satisfactory results. In order to improve the performance of CBIR systems, the relevance feedback is a powerful method.

Section 2 of this paper presents a brief literature review. Then, in section 3, the authors briefly describe the stages of the work. The experimental results on the COREL image database are presented in section 4, and finally in section 5, the authors conclude the study.

2. Related Work

In this section, a number of related papers are discussed. Current research related to image retrieval can be divided into two strands; one focusing on text query e.g. Google's image retrieval system, and the other on image query e.g. the IBM QBIC system. Since this research is more concerned with the Content Based Image Retrieval (CBIR) system, the second strand is therefore more relevant.

In [6], the research scope focuses on the development of a CBIR system for non-texture image databases. Using this approach, the authors combined a well-known clustering algorithm k-means with B^+-tree data structure. Although they can reduce the size of the search space considerably, their work has some limitations. They have not used image segmentation. Finding the segments of the images and developing a similarity criteria based on the similarity of objects in the images would enhance the accuracy of their system for images which contain multiple objects. In this similarity criterion, they can give the background a smaller weight and a higher weight to objects in the centre. Such a similarity measure would reflect better of the human perception.

Research conducted by [1] introduces the Fast Compression Distance (FCD); a similarity measure based on compression with dictionaries directly extracted from the data. The FCD uses offline extraction of a dictionary for each object which has previously been encoded into a string. In the string encoding step, some textural information is embedded within each pixel value to preserve as much information as possible. Subsequently, similarities between two objects are computed through an effective binary search on the intersection set between the relative dictionaries. The FCD has a reduced computational complexity with respect to the most popular compression-based similarity measure i.e. the Normalized Compression Distance (NCD). The NCD processes iteratively the full data in order to discover similarities between the objects. One disadvantage of the FCD is that it is less suitable for the detection of objects within a scene.

In [7], a simple and yet efficient CBIR based on orthogonal polynomials model is presented. This model is built with a set of carefully selected orthogonal polynomials and is used to extract the low level texture features present in the image under analysis. The orthogonal polynomials model coefficients are reordered into a multi resolution sub band like structure. Simple statistical and perceptual properties are derived from the sub band coefficients to represent the texture features and these features form a feature vector. Authors concluded that the field is expanding rapidly, but many major research challenges remain, including the difficultly of expressing semantic information in terms of primitive image features, and the need to significantly improve the user interfaces.

In [8], they proposed a method to automatically annotate image through the rules generated by the support vector machines and decision trees. In order to obtain the rules, they collect a set of training regions by image segmentation, feature extraction and discretisation. They first employ a support vector machine as a pre-processing technique to refine the input training data and then use it to improve the rules generated by decision tree learning. This method requires some parameters to be specified in order to find the appropriate clusters. In addition Searching images with a similarity threshold range gave researchers the opportunity to overcome the limitations of clustering in small sized clusters.

In summary and based on the abovementioned related works, the semantic gap continues to be a big challenge for image descriptors, especially in the context of information retrieval (in opposition to image classification with large learning sets). Users' assignment of answer relevance based on a single image is subtle, because obviously, a single image may represent many different concepts. The necessity to represent a main object capturing the concept of interest over variable complex backgrounds is also a challenge.

Although there are some improvement methods of traditional CBIR as shown in [1] or as suggested new methods in [2] and [9], most of the methods have problem with huge image features.

3. Stages of the Proposed Image Retrieval System

In this paper, Figure 1 shows the stages of the proposed image retrieval system used in the experimental study. In Figure 1, the system has training and testing phases. Firstly, in the training phase, the shape, colour and texture features of the image database are extracted. The features are then decreased by using fuzzy rough set based on mutual information method. Semantic rules are then generated with these features. After that, the SVM classifier is built using these semantic rules.

Still referring to Figure 1, in the testing phase, user feed the query image to the system. The system extracted the queried image features and gave these features to the SVM classifier which is built in the training phase. This classifier represents the relevant images with query image to the user. After that, the user can give his/her feedback to the system. If the user is not satisfied with the results, the user will give feedback to the system and the system will apply it to the classifier before showing new retrieval results. This relevance feedback between the user and the system will happen continuously until the user satisfies with the results.

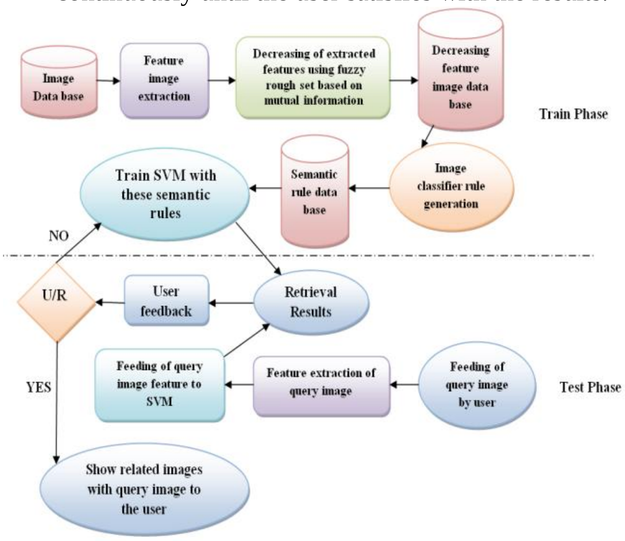

Figure1. Stages of proposed image retrieval system

The fuzzy rough set based on mutual information decreasing method is described here. This decreasing method is based on the work from [10]. The fuzzy rough set based on mutual information method starts with an empty set and it seeks the relative reduction from bottom up. The process of this algorithm is: selecting the most significant attribute for adding to the relative potential reduces one by one, according to the significance of condition attribute, until the ending condition is satisfied. The algorithm of this decreasing method is as follows:

Step-1. Compute the mutual information $\mathrm{I}(\mathrm{C};\mathrm{D})$ between condition attribute set C and decision attribute set D in the fuzzy decision table.

$$I(C;D) = H(D) - H(D|C)$$

$H(D)$ is information entropy and $H(D|C)$ is conditional entropy.

Step-2. Let $R = 0$, do{

1. For every attribute $A^j \in C - R$, compute the significance of fuzzy condition attribute A^j i.e. $SGF(A^j, R, D)$; (R is a subset of fuzzy condition attributes. $SGF(A^j, R, D) = \mathrm{I}(\mathrm{R} \cup \{\mathrm{A}^j\}; \mathrm{D}) - \mathrm{I}(\mathrm{R}; \mathrm{D})$)
2. Select the attribute which brings the maximum of significance $SGF(A^j, R, D)$, then record it as A^j (if it exists as multi attributes achieving the maximum at the same time, choose one that has the least number of equivalence classes as A^j); then $R \Leftarrow R \cup \{A^j\}$;

} Until $I(C;D) = I(R;D)$;

Step-3. Condition attribute set R is the relative reduction required. It is worth highlighting the following aspects of the proposed method.

- Image query removes the difficulty of describing the feature of an image into words when similar images are searched.
- The fuzzy rough set based mutual information method as a pre processing stage makes the proposed approach more robust than conventional approaches.
- This proposed system can effectively and efficiently handle large image databases, and can be smoothly embedded into different image retrieval systems.
- This retrieval system refines decision rules of image retrieval by fuzzy rough set based mutual information.
- Rough sets provide reasonable structures for the overlap boundary, given domain knowledge.
- The proposed method can work efficiently in vague and uncertain area.

The SVM is used as a classifier in the proposed method. In an image annotation and retrieval, SVM is a widely used machine learning method. SVM can generate a hyper plane to separate two data sets of features and provide good generalisation. SVM is used as the learning tool to handle image retrieval problems [8]. SVM is known to perform well with noisier data compared with other machine learning methods [8]. As for the SVM classifier, it is important to select the right kernel function.

The authors use the nonlinear SVM along with the Gaussian radial basis function kernel in the system. This is because it achieves better results compared with linear and polynomial kernels [8].

In the Experiment results section, other retrieval systems with different decreasing methods (PCA, Kernel PCA, Isomap, and MVU) are compared with the proposed system. Using the same condition, in the four abovementioned retrieval systems, the authors use SVM as a classifier along with the train and test phase being the same as the proposed system.

4. Experiment Results

In this section, other decreasing methods are briefly described and the results that compare the four retrieval systems with the proposed retrieval system are presented.

To investigate the function of the image retrieval system based on the above mentioned methods, the authors use the COREL image database containing one thousand images. In this database, images are classified into ten semantic groups. The groups are Africans, beach, bus, flower, mountains, elephant, horse, food, dinosaur, and building. The authors express the results of each group with a number. For example, number 1 represents Africans, 5 represents mountains, and etc.

a. Decreasing Methods

The four decreasing methods used in this paper are as follows:

Principal Components Analysis (PCA): is a linear method for dimensionality reduction, which means that it performs dimensionality reduction by embedding the data into a linear subspace of lower dimensionality [11]. PCA constructs a low-dimensional representation of the data that describes as much of the variance in the data as possible. This is done by finding a linear basis of reduced dimensionality for the data, in which the amount of variance in the data is maximal.

Isomap: Classical scaling has proven to be successful in many applications, but it suffers from the fact that it mainly aims to retain pair wise Euclidean distances, and does not take into account the distribution of the neighbouring data points [12]. If the high-dimensional data lies on or near a curved manifold, classical scaling might consider two data points as near points, whereas their distance over the manifold is much larger than the typical inter point distance. Isomap is a technique that resolves this problem by attempting to preserve pair wise geodesic (or curvilinear) distances between data points. Geodesic distance is the distance between two points measured over the manifold.

Kernel PCA (KPCA): is the reformulation of traditional linear PCA in a high-dimensional space that is constructed using a kernel function [13]. Kernel PCA computes the principal eigenvectors of the kernel matrix, rather than those of the covariance matrix. The reformulation of PCA in kernel space is straightforward, since a kernel matrix is similar to the in-product of the data points in the high-dimensional space that is constructed using the kernel function. The application of PCA in the kernel space provides KPCA the property of constructing nonlinear mappings.

Maximum Variance Unfolding (MVU): As previously described, KPCA allows for performing PCA in the feature space that is defined by the kernel function. Unfortunately, it is unclear how the kernel function should be selected. Maximum Variance Unfolding (MVU is formerly known as Semi definite Embedding) is a method that attempts to resolve this problem by learning the kernel matrix [14]. MVU learns the kernel matrix by defining a neighbourhood graph on the data (as in Isomap) and retaining pair wise distances in the resulting graph. MVU is different from Isomap in that it explicitly attempts to 'unfold' the data manifold. It does so by maximizing the Euclidean distances between the data points, under the constraint that the distances in the neighbourhood graph are left unchanged i.e. under the constraint that the local geometry of the data manifold is not distorted. The resulting optimisation problem can be solved using a semi definite programming.

b. Precision-Recall Graph

Recall equals to the number of the related retrieval images to the number of the related images available in images database. The precision equals to the number of the related retrieval images to all the retrieval images [1]. Figure 2 shows the precision-recall graph for ten semantic groups that is used for measuring the efficiency of the proposed retrieval system. In the experiment results the proposed retrieval system is shown as FRMI. From the graph, the authors observe that the proposed retrieval system achieved better results than the other four systems. The reason for this is better algorithm has been applied in the training phase to save appropriate and eliminate useless image features (see Figure 1). With useful features the system can train the SVM classifier with more accurate rules.

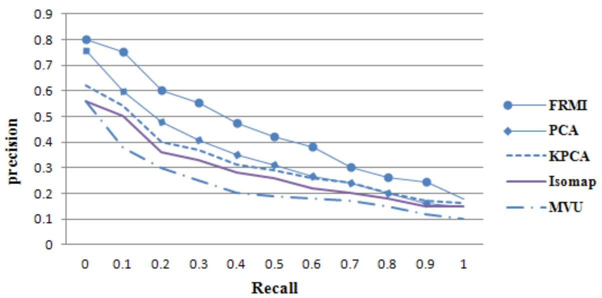

Figure2. Precision- recall graph

c. Investigation of the Retrieval Precision

To investigate the total precision of the above mentioned retrieval systems, 1000 images are fed into the system as queried images. The average of the retrieval precision is calculated for each class with relevance feedback and without relevance feedback. Figure 3 shows the results with relevance feedback, and Figure 4 shows the results without relevance feedback. As expected, the results are better using the proposed system. The average of the retrieval precision with relevance feedback is 75.80%, 70.43% and 67.60% for PCA, KPCA and Isomap respectively, and 63.30% for MVU. It increases to 80.40% for FRMI.

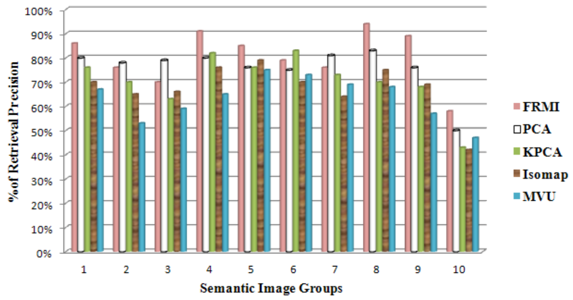

Figure3. Precision of retrieval with relevance feedback

The results of retrieval precision without relevance feedback are as follows: 68.20%, 59.50%, 56.00% and 51.80% for PCA, KPCA, Isomap and MVU respectively. The results jump to 75.50% for FRMI.

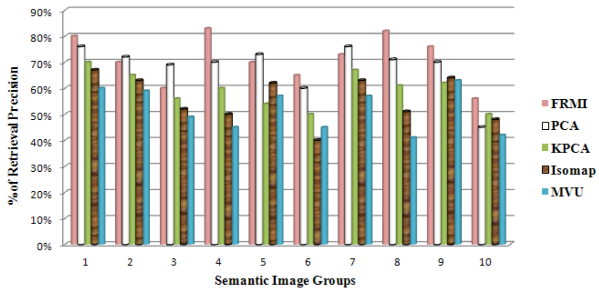

Figure4. Precision of retrieval without relevance feedback

The reasons behind superiority of FRMI because:

1) Rough set theory is a useful method for describing and modelling vagueness in ill-defined environments
2) The use of membership function of a fuzzy set has many advantages in the definition, analysis, and operation with fuzzy concepts.
3) One of the main advantages of using mutual information is it can be used to align images of different groups. It also requires no decomposition of the data into modes, so there is no need to assume additively of the original variables. It also consumes less computational resources and its parameters are easier to tune.
4) The SVM can perform well with noisier data.

The results achieved with relevance feedback are better than those without relevance feedback. This is because with relevance feedback, user can cooperate with retrieval system and gives his/her opinion directly. This in turn, can help the system to improve the retrieval performance.

d. Image Comparison of the Retrieval Systems.

In the last test, the authors show the retrieval results for the queried bus image (Figure 5). The first, second, and up to the fifth row in Figure 6 is related to fuzzy rough set based on mutual information, PCA, Kernel PCA, Isomap and MVU respectively. Referring to Figure 6, the retrieval system with the fuzzy rough set based on mutual information method more related output images to the user. The first left image in Figure 6 matched closely to the queried image.

Figure5. Queried image

The reason why the proposed method has better results than those in other retrieval systems is that the rules extracted from features that decreased with fuzzy rough set based on mutual information, are semantic and can better train the SVM classifier. Consequently, the SVM classifier can show more relevant images to user. If the user is not satisfied with the results, with the proposed method, a user does not need to send his/her feedback in long iterations. Users are only required to provide minimum feedback (2 to 3 times) to the system, and the system will then be able to achieve and provide the relevant results to the users.

5. Conclusion

In this paper, an image retrieval system is proposed. This system used the fuzzy rough set based on mutual information method for feature decreasing and the SVM as a classifier. The system is compared with other retrieval systems that used different methods for decreasing image features. The feature decreasing methods used include the PCA, Kernel PCA, Isomap and MVU. From the experiments results, it can be seen that the proposed image retrieval system has better performance compared to the other four retrieval systems. The drawbacks of these four decreasing methods described in this paper are as follows: (1) In PCA, the computation of the eigenvectors might be infeasible for very high dimensional data, (2) The Isomap algorithm is topologically unstable, (3) The Kernel PCA's kernel matrix size is proportional to the square of the number of instances in the dataset, and (4) MVU has a weakness similar to Isomap. Based on these drawbacks, the four retrieval systems cannot achieve better results than the proposed retrieval system.

By utilising fuzzy rough set theory, the proposed system has the advantage and deal efficiently in image feature environment that is vague and uncertain. In addition, rules extracted from the decreasing features with fuzzy rough based on mutual information are semantic and can train the classifier presciently. An important advantage of this work is training the SVM with semantic rules that can separate the relevant images from irrelevant ones more accurately. Furthermore, by using the relevance feedback, the semantic gap is reduced. The relevance feedback process in the proposed system is not a tedious and time consuming task for the users. Users are only required to provide minimum feedback (2 to 3 times) to the system, and the system will then be able to achieve and provide the relevant results to the users. In conclusion, this proposed system that utilises fuzzy rough set based on mutual information decreasing method, SVM and relevance feedback can achieve better results comparing with other image retrieval systems.

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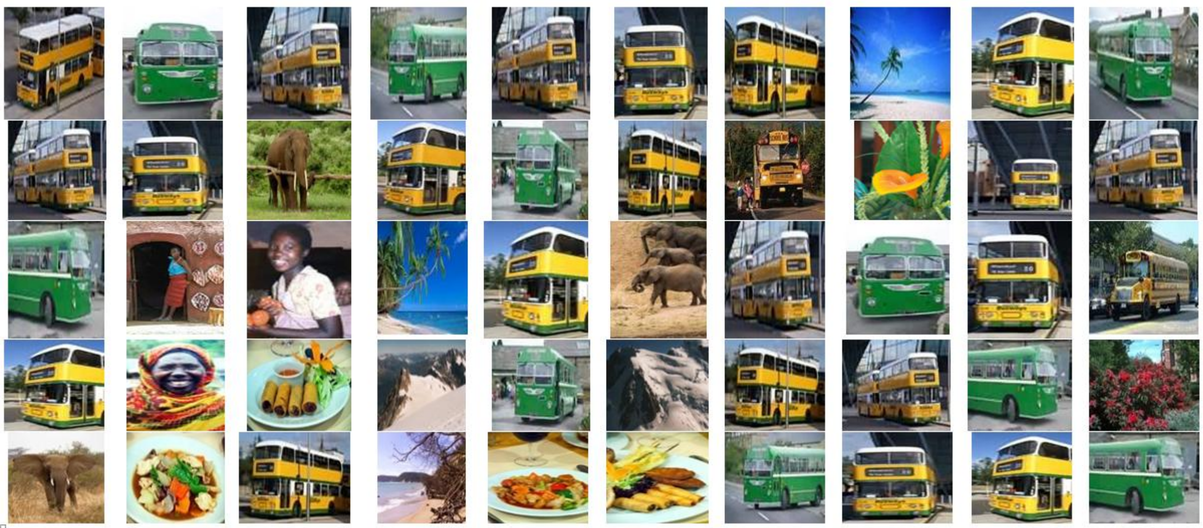

Figure6. Retrieved images according to: first raw- fuzzy rough based on mutual information, second raw- PCA, third raw- Kernel PCA, fourth raw- Isomap, fifth raw- MVU.