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Fabric Image Retrieval Using Combined Feature Set and SVM

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Abstract— Content-Based Image Retrieval (CBIR) retrieves similar images from a large database based on a given input query image. A conventional keyword - based search was inefficient in retrieving data because of large scale digitization of images, diagrams and paintings. A CBIR system gets inputs and responds to image queries relying on image content through use of techniques from computer vision and image processing to interpret it. It uses techniques from information retrieval and databases to locate and retrieve images suiting the query. CBIR is used in medicine as it increases doctor's confidence when they make informed decisions. This work presents a CBIR system that extracts features such as LBP and gabor filter. All these features are grouped and Curvelet is applied over the image. In the testing phase, the user retrieves the relevant image by passing the query image. The query image undergoes the same feature extraction process, Curvelet application, application of the SVM classifier. This approach considers texture and color features. The experimental results prove the efficacy of the work.

Keywords— CBIR, feature extraction, curvelet, LBP, Gabor filter

I. INTRODUCTION

Today's world revolves around data and the data growth is observed to be exponential. The term 'data' may refer to audio, video, image or textual data. Among all kinds of data, image data is popular and voluminous. The stored data in remote or local server must be effectively accessible. The importance of image data is increasing day-by-day, as a picture worth thousand words. All the technologies or domains incorporate images for better understanding purposes. Thus, it becomes necessary to introduce a Content Based Image Retrieval (CBIR) system which boosts up the accuracy of retrieval rate.

A standard CBIR system works in two different phases and they are training and testing. A CBIR system works by extracting features such as colour, shape and texture from each and every image of the training dataset. The extracted features are stored in the feature database. The features are the abstraction of the image, which can discriminate images.

In the testing phase, the CBIR system deals with the query image, which extracts the features of the query image. The feature vector of the query image is compared with the feature vector of the train dataset. The result is returned based on the relevance score of the feature vector. The result can be presented in two ways, which are exact image retrieval and retrieval of related images. The second option is more popular than the first one, as the related images are also retrieved.

Basically, a CBIR system works in four major stages. Initially, the training dataset is formed with a set of images. Then, the features of the train images are extracted and stored. In the third step, a query image is passed into the system for checking the capability of the system in retrieving relevant images. The features are extracted from the query image and compared with the stored feature set of the trained image set. The computed results are returned in sorted order with respect to the relevance score.

In the generic CBIR process, the process involves three stages. The first stage involves extraction of features from the images in the database. The extracted features are further indexed and compiled into the database. In the second stage, the query image in input is extracted for features. The final stage involves the comparison of the extracted feature from query with the feature database, and the image is retrieved. The block diagram of the CBIR process is shown in Figure 1.

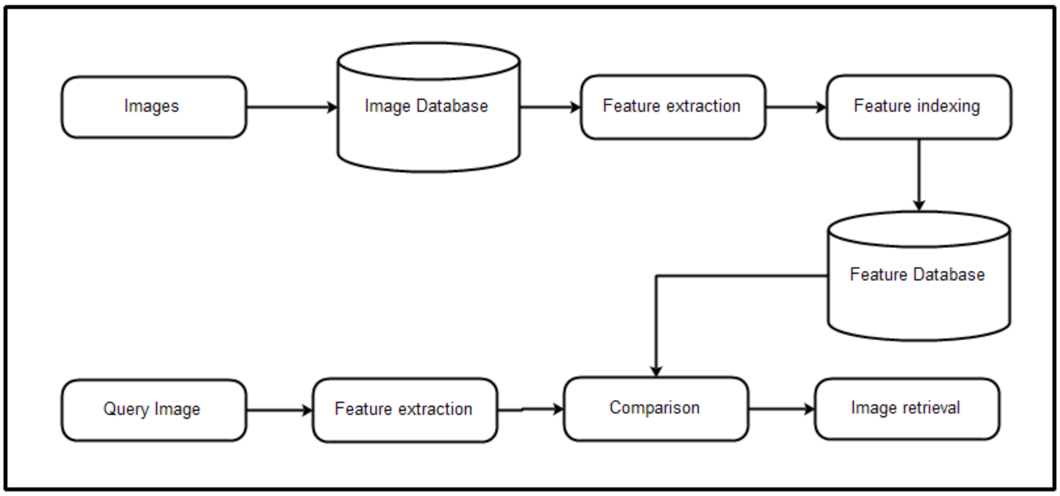

Fig 1: Process of CBIR

- Image database - The images are uploaded into database from which the relevant images are to be retrieved.
- Feature extraction - All the images in the database are processed to extract features. Generally low level features like color, shape and texture are used as features.
- Feature indexing - The features extracted are further indexed for easy comparison.
- Feature database - The indexed features are stored in a feature database. Any new image included in the database is processed and its feature is indexed in the feature database.
- Query image - When images are to be retrieved from the image database based on the content of image, a query image for which similar images are required is given as input.
- Comparison - The features extracted from the query image are compared with the features indexed in the feature database. The similarity is compared using distance metrics, decision tree and Neural Networks.
- Image retrieval - The images whose features are most similar to the query image features are retrieved from the image database.

The objective of this work is to present an efficient CBIR with system that is faster and accurate. Accuracy of the CBIR system relies on the set of features being extracted. Thus, this work combines three different feature extraction techniques, in order to arrive at a standard feature set. Accurate and effective image retrieval is made possible with these extracted set of features.

II. Review of Literature

Several image retrieval systems, which extract the rotation-invariant texture features of images, have been developed recently in the works of [1-4]. The feature extractions of several proposed methods have been devised in frequency domain for extracting rotation-invariant features by [1,2,4].

The work proposed in [2] combines a dual-tree rotated complex wavelet filter (DT-RCWF) and a dual-tree complex wavelet trans-form (DT-CWT) to obtain the texture features for rotation-invariant from 12 different angles. However, the similarity measurement formula is not optimized. Thus, the method cannot get better discrimination between two different images.

In [6], kullback-leibler-divergence (KLD) method which employs the Gaussianized steerable pyramids to extract the texture features of images, is proposed. Nevertheless, it is insufficient to search for the optimal number of outputted images. The rotation-invariant Gabor (RIG) method is proposed which combines the Gabor filters with same scales and different angles to extract the rotation-invariant texture features of images.

In [4], wavelet-based hidden Markovtrees (WBHMT) which combines the wavelet transformation and the hidden Markov tree to extract the rotation-invariant texture features of images, is presented. Unfortunately, the feature extraction algorithm of the method requires high computational complexity.

The work presented in [7] proposes the modified Zernike moments (MZM) which combine the discrete Fourier transformation and the Zernike moments to construct the rotation-invariant texture features of images. Nevertheless, the similarity measurement formula is not optimized. Hence, the method cannot get nearly optimal solutions in the number of outputted images, various feature weights etc.

III. PROPOSED APPROACH

This chapter aims at presenting the overview of the proposed methodology. The proposed work focuses on texture rich features, which is available on fabric images. The textile industry lacks CBIR systems, as the fabric images are difficult to deal with. CBIR is at its limelight because of its vast requirement of efficient image retrieval. Every CBIR system comprises four different phases namely data collection, feature database extraction, searching the database and process and ordering the results. The proposed system focuses on two features namely colour and texture.

Curvelet is employed because of its degree of directionality, near shift invariance and minimal redundancy. Local Binary Pattern (LBP) and gabor filter are employed for extracting texture features. The LBP, gabor filter are applied over the approximation band of the image. Finally, SVM classifier is employed as the classifier to differentiate between the images. This work retrieves similar images from the database with the accuracy and sensitivity rate of cent percent.

The proposed work relies on image acquisition, training and testing phases. Image acquisition aims at acquiring images to perform information retrieval. The images can be acquired from the real time photography or from the existing dataset. There are several datasets available for images.

The training phase trains the system by taking the extracted features into account. The training phase aims at extracting the LBP, Gabor and Zernike moment features from the images. This is followed by the application of DWT. The feature set is used for learning process.

The testing phase passes a query image and the images from databases are retrieved and ranked with respect to the relevance score. SVM is employed as the classifier for distinguishing between images. Finally, the proposed work is tested for its performance with respect to sensitivity, specificity and accuracy rate. The proposed work is compared with several wavelets and the comparative analysis is performed.

The detailed flow of the proposed work is presented in fig 3.1. The major components are LBP, Gabor filter and Curvelet. This feature set is distinguishable by the classifier. This work employs SVM as its classifier.

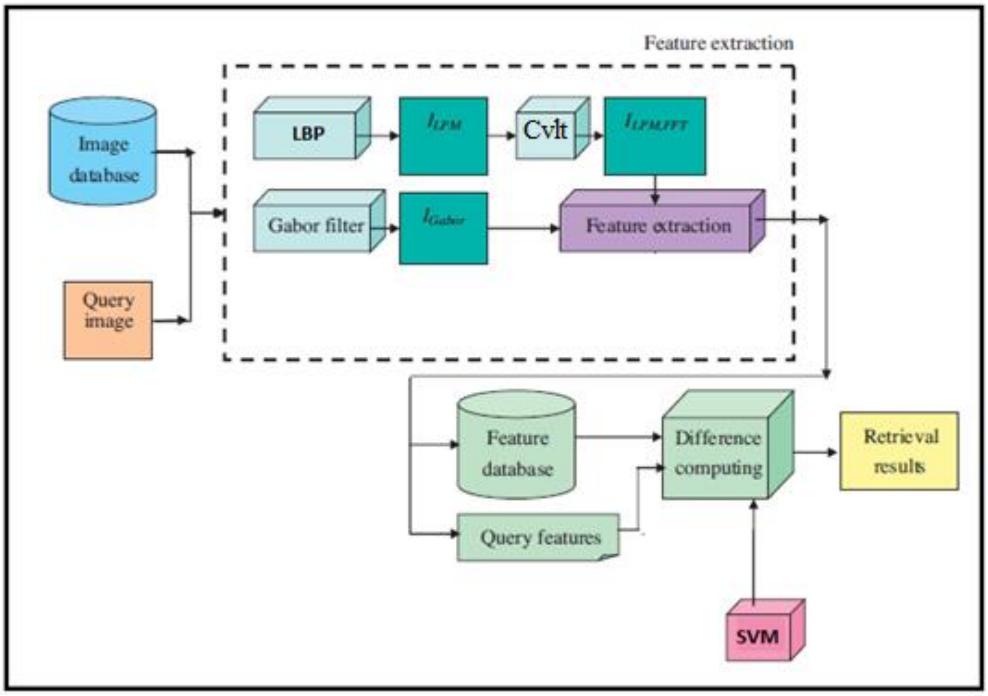

Fig 2: Architectural diagram

A. Proposed Algorithm

The proposed algorithm is presented below.
Step 1: Obtain an image dataset.
Step 2: Apply Gabor filter and LBP in order to extract texture features.
Step 3: Apply curvelet transform over the image.
Step 5: Combine all the features and save them for classification purpose.

Step 6: Pass the query image.
Step 7: Repeat steps from 1 to 5.
Step 8: Pass the train and test features to the SVM classifier, in order to retrieve the images by taking the degree of relevancy into account. This is done by the below given equation.

$$d(q, x_i) = \sum_{f \in F} \omega_f \delta(q_f , x_{if} \quad (1)$$

where

$$(q_f, \ x_{if}) = \begin{cases} 0 \\ 1 \\ |q_f - x_{if}| \end{cases} \quad \textbf{(2)}$$

This system is compared with different systems which employs Gabor filter, curvelet + Gabor and curvelet. The performance of the proposed work is analysed in terms of accuracy. The proposed system proves better results when compared to other techniques.

IV. PERFORMANCE EVALUATION

The performance of the proposed work is evaluated against different approaches, which utilizes only Gabor and Curvelet. The experimental results show that the combination of Gabor and curvelet works better than the approaches which employ any one of them. The accuracy of the system is measured by the following equation.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

Where TP – True Positive, TN – True Negative, FP – False Positive, FN – False Negative and these are given by the following equations.

$$TP = \frac{Number\ of\ Correctly\ retrieved\ images}{Total\ number\ of\ images} \times 100 \quad (4)$$

$$TN = \frac{Number\ of\ correctly\ rejected\ images}{Total\ number\ of\ images} \times 100 \quad (5)$$

$$FP = \frac{Number\ of\ wrongly\ retrieved\ images}{Total\ number\ of\ images} \times 100 \quad (6)$$

$$FN = \frac{Number\ of\ wrongly\ rejected\ images}{Total\ number\ of\ images} \times 100 \quad (7)$$

The graphical results are presented below in figure 3.

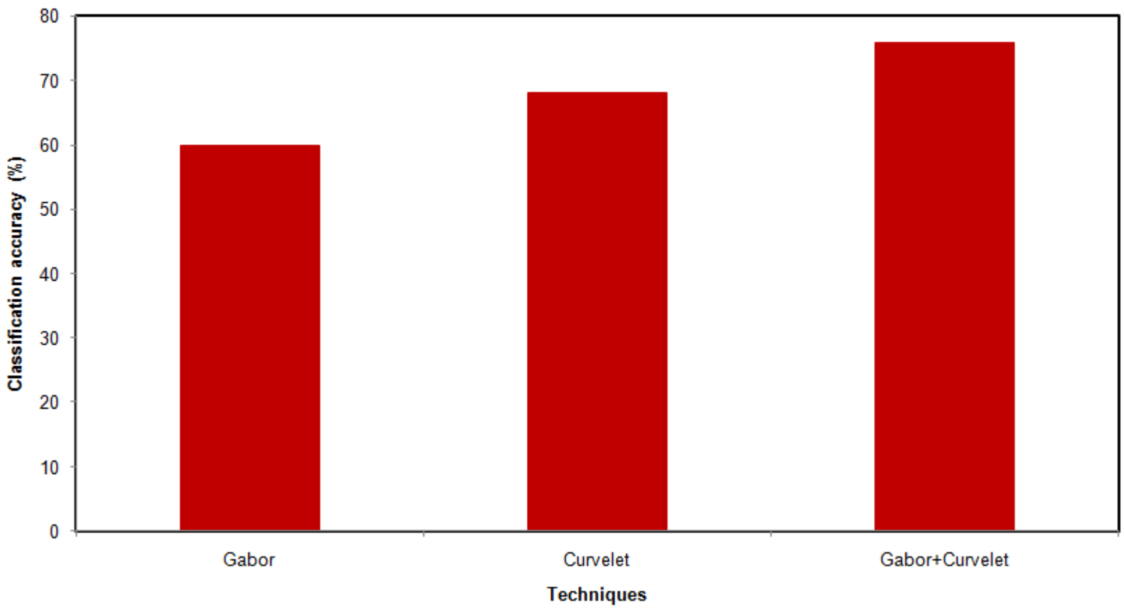

Figure 3: Accuracy analysis

From the experimental analysis, it is evident that the Gabor shows 62% accuracy and the curvelet exhibits 69.8% accuracy. On the other hand, the combination of curvelet and Gabor filter proves 78.2% accuracy.

V. Conclusions

In this work, an image retrieval system is proposed which stems on color and texture features. The aforementioned features are collected by exploiting Local Binary Pattern (LBP) and gabor filter and curvelt. LBP and gabor filter are responsible for extracting texture and color features. This is followed by the application of curvelet to every resultant image. The approximation band of the image is then extracted. Curvelet is employed because of its degree of directionality, near shift invariance and minimal redundancy. The LBP and gabor filter are applied over the approximation band of the image. Thus, the objective of the work is attained.

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