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Content-Based Image Retrieval using SURF and Colour Moments

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Abstract- Content-Based Image Retrieval (CBIR) is a challenging task which retrieves the similar images from the large database. Most of the CBIR system uses the low-level features such as colour, texture and shape to extract the features from the images. In Recent years the Interest points are used to extract the most similar images with different view point and different transformations. In this paper the SURF is combined with the colour feature to improve the retrieval accuracy. SURF is fast and robust interest points detector/descriptor which is used in many computer vision applications. To improve the performance of the system the SURF is combined with Colour Moments since SURF works only on gray scale images. The KD-tree with the Best Bin First (BBF) search algorithm is to index and match the similarity between the features of the images. Finally, Voting Scheme algorithm is used to rank and retrieve the matched images from the database.

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I. Introduction

Content-based image retrieval (CBIR) is a system, in which retrieves visual-similar images from large image database based on automatically-derived image features, which has been a very active research area recently. In most of the existing CBIR systems[1], the image content is represented by their low-level features such as colour, texture and shape[2][3]. The drawback of low-level features is losing much detail information of the images, in case of looking for images that contain the same object or same scene with different viewpoints. In recent years, the interest point detectors and descriptors [4] are employed in many CBIR systems to overcome the above drawback.

SURF (Speed Up Robust Feature) is one of the most and popular interest point detector and descriptor which has been published by Bay et al.[5]. It is widely used in most of the computer vision applications. The SURF has been proven to achieve high repeatability and distinctiveness. It uses a Hessian matrix-based measure for the detection of interest points and a distribution of Haar wavelet responses within the interest point neighborhood as descriptor. An image is analyzed at several scales, so interest points can be extracted from both global and local image details. In addition to that, the dominant orientation of each of the interest points is determined to support rotation-invariant matching. SURF is one of the best interest point detectors and descriptors currently available.

The Proposed System

The proposed CBIR system is shown in Figure 1. The feature vectors are extracted from the images in the database and described by multidimensional feature vectors, which form a feature database. To retrieve images, the feature vectors are extracted from the given query image. The similarities between the feature vectors of the query image and the feature vectors of the database images are then calculated. And the retrieval is performed with the aid of an indexing scheme and matching strategy, which provide an efficient way to search the image database. In this work, SURF algorithm is used to extract the features and the first order and second order colour moments is calculated for the SURF key points to provide the maximum distinctiveness for the key points. The KD-tree with the Best Bin First (BBF)[6] algorithm is used to index and match the similarity of the features of the images. In section II, the feature extraction algorithm is proposed; indexing and matching is discussed in section III; the experiments based on COIL-100 object database are discussed in section IV; the paper is concluded in section V.

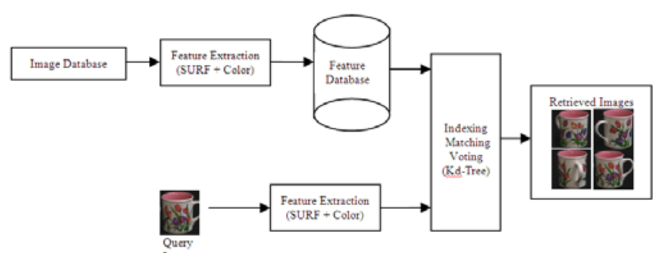

Fig.1. The Proposed CBIR system

II. Feature Extraction

a) *SURF Algorithm*

The Speeded up robust features algorithm is a scale and rotation-invariant interest point detector and descriptor which is computationally very fast. It uses Integral images to improve the speed. The key points are detected by using a Fast-Hessian matrix. The descriptor describes a distribution of Haar-wavelet

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responses within the interest point neighborhood. The performance of SURF increased by using an intermediate image representation known as the *Integral Image*. The integral image is computed rapidly from an input image and is used to speed up the calculation of any upright rectangular area. The major computational steps of SURF algorithm is as follows:

Step 1 : Fast Interest Point Detection.

The SURF feature detector is based on the Hessian matrix. The determinant of the Hessian matrix is used to determine the location and scale of the descriptor. The Hessian matrix is defined as H(x, σ) for a given point $\boldsymbol{x} = (x, y)$ in an image as follows:

$$H(x,\sigma) = \begin{bmatrix} L_{xx}(x,\sigma) L_{xy}(x,\sigma) \\ L_{xy}(x,\sigma) L_{yy}(x,\sigma) \end{bmatrix} \quad (1)$$

where $L_{xx}(x,\sigma)$ is the convolution of the Gaussian second order derivative $\frac{\partial^2}{\partial x^2} g(\sigma)$ with the image I in point x and similarly for $L_{xy}(x,\sigma)$ and $L_{yy}(x,\sigma)$. The SURF approximates second order derivatives of the Gaussian with box filters. Image convolutions with these box filters can be computed rapidly by using integral images.
The determinant of the Hessian matrix is written as:

$$Det(H_{approx}) = D_{xx} D_{yy} - (0.9D_{xy})^2 \quad (2)$$

In order to localize interest points in the image and over scales, a non maximum suppression in a 3 × 3 × 3 neighborhood is applied. Finally, the found maxima of the determinant of the Hessian matrix are then interpolated in scale and image space.

Step 2 : Interest Point Descriptor

The SURF descriptor is extracted from an image in two steps : the first step is assigning an orientation based on the information of a circular region around the detected interest points. The orientation is computed using Haar-wavelet responses in both x and y direction. Once the Haar-wavelet responses are computed and they are weighted with a Gaussian with σ = 2.5s centered at the interest points. In a next step the dominant orientation is estimated by summing the horizontal and vertical wavelet responses within a rotating wedge which covering an angle of π/3 in the wavelet response space. The resulting maximum is then chosen to describe the orientation of the interest point descriptor.

In a second step, the region is split up regularly into smaller square sub-regions and a few simple features at regularly spaced sample points are computed for each sub-region. The horizontal and vertical wavelet responses are summed up over each sub-region to form a first set of entries to the feature vector. The responses of the Haar-wavelets are weighted with a Gaussian centered at the interest point in order to increase robustness to geometric deformations and the wavelet responses in horizontal d_x and vertical Directions d_y are summed up over each sub-region. Furthermore, the absolute values $|d_y|$ and $|d_y|$ are summed in order to obtain information about the polarity of the image intensity changes. Therefore each sub-region has a four-dimensional descriptor vector

$$V = (\sum d_x, \sum |d_x|, \sum |d_y|) \quad (3)$$

where dx denotes the horizontal wavelet response and dy the vertical response. The resulting descriptor vector for all 4 by 4 sub-regions is of length 64.

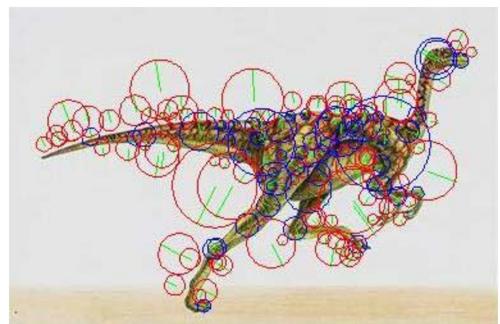

Fig.2. SURF Interest points of a dinosaur

b) *Colour Feature*

Surf works only on gray scale images to extract the colour features around the region of each interest points the Colour Moments [7] are used. Colour moments are calculated for a 5x5 region around the SURF interest point for the RGB channel. Since most of the information is concentrated on the low order moments, only the first moment (mean) and the second moments (variance) will be used as the colour features. The value of the i-th colour channel at the j-th image pixel is p_{ij}. The index entries related to this colour channel are calculated by:

$$E_i = \frac{1}{N} \sum_{j=1}^{N} P_{ij} \quad (4)$$

$$\sigma_i = \left[\frac{1}{N} \sum_{j=1}^{N} (P_{ij} - E_i)^2\right]^{\frac{1}{2}} \quad (5)$$

where N is the number of pixels in the image patch. The first order and second order colour information are concatenated to obtain the descriptor vector length as 70.

III. Indexing and Matching

In our CBIR system the KD-tree [8] algorithm is used to match the features of the query image with those of the database images. The KD-tree with the BEST bin First(BBF) search algorithm is used for indexing and matching the SURF features. The KD-tree is a kind of binary tree in which each node chooses a dimension from the space of the features being classified: all features with values less or equal to the node in that particular dimension will be put in the left sub-tree; the other nodes will be put in the right sub-tree and thus recursively. The BBF algorithm uses a priority search order to traverse the KD-tree so that bins in feature space are searched in the order of their closest distance from the query. The k-approximate and reasonable nearest matches can be returned with low cost by cutting off further search after a specific number of the nearest bins have been explored. The Voting scheme algorithm is used to rank and retrieved the matched images.

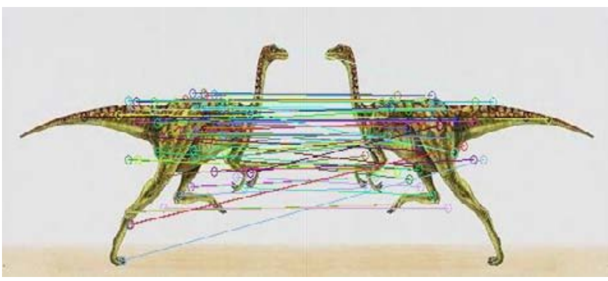

Fig.3. Matching SURF Interest points

IV. Experiment and Results

The image retrieval system based on SURF with colour feature tested on COIL-100 object database[9]. COIL-100 is a popular image database for benchmark which contains 72 views for 100 objects acquired by rotating the object under study about the vertical axis. In figure 4, shows sample views for the each of the objects in the database. Our database consists of total 1080 images of size 128x128. There are 15 different categories consisting of 72 images in each category. To test this system, a single query image is selected from each category. The SURF feature and colour moments are extracted for all images in the database. The feature database consist the features of the database images. The size of the feature vector is 70(64-d SURF + 3 X 2 First order and second order colour moments of RGB channel). The fast and multidimensional KD-tree data structure is used to compare the features of the query image with the data base images. To check the performance of proposed technique the precision and recall is used. The standard definitions of these two measures are given by following equations.

$$Precision = \frac{Number\ \ of\ relevant\ \ images\ \ retrieved}{Total\ \ number\ \ of\ \ image\ s\ retrieved} \qquad (6)$$

$$Recall = \frac{Number\ \ of\ relevant\ \ images\ \ retrieved}{Total\ number\ \ of\ relevant\ \ images\ \ in\ the\ database} \qquad (7)$$

Figure 4 shows a sample database of 15 images by randomly selecting one image from each category. The database has 15 categories, for a total of 1080 images. Figure 5 Shows Results of Paper-Box query image. Note that the database contains total 72 Paper-Box's images. Table 1. Shows the Results of retrieved images by using SURF feature alone. The percentage of Precision/Recall vs Number of Retrieved images for all categories are given in Table 1. The Average Precision obtained is 65.47%. Table-2 Shows the Results of retrieved images using SURF and Colour feature for all 15 categories of images. The Average Precision obtained using the proposed method is 88%.

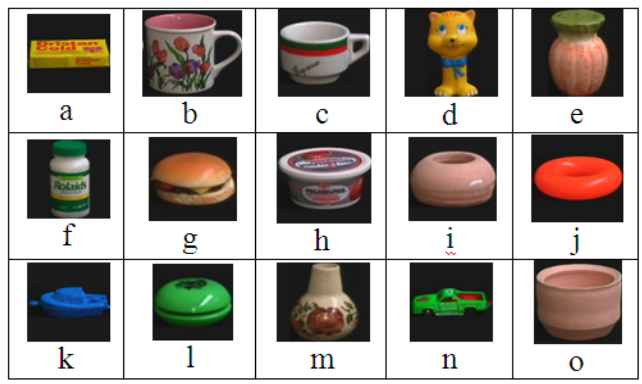

Fig.4. shows a sample database of 15 images by randomly selecting one image from each category. The database has 15 categories, for a total of 1080 images. [Image categories are named as from a to o]

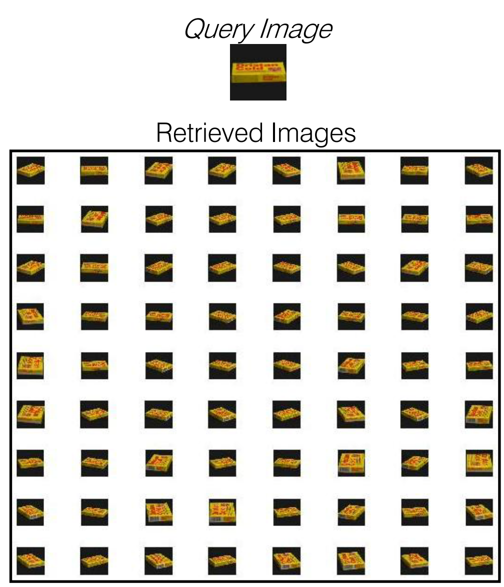

Fig.5. Shows Results of Paper-Box query image. Note that the database contains total 72 Paper-Box's images. For the query image as shown in figure for 72 retrieved images the total relevant images obtained are all 72.

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Table 1. Retrieved images using SURF Features

Object Category	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	Average Precision / Recall
No. of relevant images retrieved	18	26	70	10	46	71	36	70	59	71	12	72	55	11	71	
Precision/Recall (%)	**25**	**36**	**97**	**13**	**63**	**98**	**50**	**100**	**97**	**98**	**16**	**100**	**76**	**15**	**98**	**65.47**

*Table-1 gives number of total relevant images in the set of first 72 retrieved images for all 15 categories. The percentage of Precision/Recall for all categories of the resultant images are shown in Table-1.The Average Precision for all 15 categories is **65.47%***

Table 2. Retrieved images using SURF and Colour Moments

Object Category	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	Average Precision / Recall
No. of relevant images retrieved	72	61	50	56	72	69	64	72	66	60	52	72	71	50	66	
Precision/Recall (%)	**100**	**84**	**70**	**78**	**100**	**96**	**89**	**100**	**92**	**83**	**72**	**100**	**99**	**70**	**92**	**88**

*Table-2 gives number of total relevant images in the set of first 72 retrieved images for all 15 categories. The percentage of Precision/Recall for all categories of the resultant images are shown in Table-2.The Average Precision for all 15 categories is 88**%**.*

V. Conclusion

The explosive growth of image data leads to the need of research and development of Image Retrieval. Content-based image retrieval is currently a very important area of research in the area of multimedia databases. Plenty of research works had been undertaken in the past decade to design efficient image retrieval techniques from the image or multimedia databases. More précised retrieval techniques are needed to access the large image archives being generated, for finding relatively similar images. In this work the SURF is combined with colour Moments to improve the retrieval accuracy of the system which improves 23% of Average Precision. The proposed method gets 88% of Average Precision, for 15 categories of 1080 images which outperforms than SURF alone which gives only 65.47% of Average Precision.

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