IMAGE RETRIEVAL AND OBJECT CATEGORIZATION USING COLOR INTEREST POINT

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ABSTRACT

The main aim of this paper is to detect color interest points which is used for image matching. This paper deals with interest point detection from which local image descriptors are computed for image matching. In general, interest points are based on luminance & the use of color increases the distinctiveness of interest points. The use of color may therefore provide selective search reducing the total number of interest points used for image matching. This paper proposes color interest points for sparse image representation. Color statistics based on occurrence probability lead to color boosted points. For color boosted points, the aim is to exploit color statistics derived from the occurrence probability of colors. This way, color boosted points are obtained through saliency-based feature selection.

Keywords* : *Color Interest Point ,Color Invariance, Image Retrieval, Local Features, Object Categorization.

I. INTRODUCTION

Interest point detection is an important research area in the field of image processing and computer vision. In particular, image retrieval and object categorization heavily rely on interest point detection from which local image descriptors are computed for image and object matching [1]. The majority of interest point extraction algorithms are purely intensity based [2]-[4]. However, it was shown that the distinctiveness of color-based interest points is larger and therefore, color is important when matching images [5]. Furthermore, color plays an important role in the preattentive stage in which features are detected [6].

Salient points, also referred to as *interest points*, are important in current solutions to computer vision challenges. In general, the current trend is toward increasing the number of points [7], applying several detectors or combining them [8,9], or making the salient point distribution as dense as possible [10,11]. Therefore, computational methods are proposed to compute salient points, designed to allow a reduction in the number of salient points while maintaining state of the art performance in image retrieval . The ability to choose the most discriminative points in an image is gained through including color information in the salient point determination process.

Our aim is to exploit state-of-the-art object classification and to focus on the extraction of distinctive and robust interest points. In fact, the goal is to reduce the number of interest points extracted while still obtaining state-of-the-art image retrieval or object recognition results. Recent work has aimed to find distinctive features, i.e., by performing an evaluation of all features within the data set or per image [12]. Therefore, in this paper, we propose color interest points to obtain a sparse image representation. To reduce the sensitivity to imaging conditions, color boosted points are proposed. For color boosted points, the aim is to exploit color statistics derived from the occurrence probability of colors. This way, color boosted points are obtained through saliency-based feature selection.

II. SYSTEM STRUCTURE

2.1 Overall block diagram

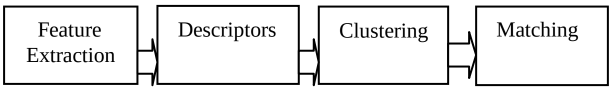

Fig. 1. Basic block diagram

Fig.1 shows system architecture. The whole systean be divided into four parts. The first part concerned with extraction of local features. **Feature extraction** is carried out with either global or local features. In general, global features lack robustness against occlusions and provide a fast and efficient way of image representation. Local features are either intensity- or color-based interest points. The second part represents **descriptors** which gives the local image information around the interest points. They can be categorized into three classes: They describe the distribution of certain local properties of the image [e.g., scale-invariant feature transform (SIFT)], spatial frequency (e.g., wavelets), or other differentials (e.g., local jets)[13]. For every feature extracted, a local descriptor is computed.

The third part is **Clustering** for signature generation, feature generalization or vocabulary estimation assigns the descriptors into a subset of categories. The result of image segmentation(clustering) is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Groups of pixels in each region are similar with respect to some characteristic or computed property, such as color, intensity or texture. Adjacent regions are significantly different with respect to the same characteristic(s).

The last part concerned with **Matching** summarizes the classification of images. Image descriptors are compared with previously learnt and stored models. Classification approaches need feature selection to discard irrelevant and redundant information [14]–[15]. The search for images similar to a query image'q' results in finding the 'k' nearestneighbors of 'q'. In the case of threshold-based matching, two regions are matched if the distance between their descriptors is below a threshold.

III. REATED WORK

First, 'interest points' are selected at distinctive locations in the image, such as corners, blobs, and T-junctions. The most valuable property of an interest point detector is its repeatability, i.e. whether it reliably finds the same interest points under different viewing conditions. Next, the neighbourhood of every interest point is represented by a feature vector. This descriptor has to be distinctive and, at the same time, robust to noise, detection errors, and geometric and photometric deformations. Finally, the descriptor vectors are matched between different images. The matching is often based on a distance between the vectors i.e SURF Algorithm

3.1 SURF (Speeded Up Robust Features) Algorithm:

It is composed of three consecutive steps

3.1.1Interest point detection

In the detection step, the *local maxima* of the *Hessian determinant* operator applied to the scale-space are computed to select interest point candidates. These candidates are then validated if the response is above a given threshold. Both scale and location of these candidates are then refined using an iterated procedure to fit a quadratic function. Typically, a few hundred interest points are detected in a digital image of 1 Mega-pixels.

3.1. 2 Interest point description

The purpose of the second step is to build a descriptor that is invariant to view-point changes of the local neighborhood of the point of interest. Recall that the location of this point in the scale-space provides invariance to scale and translation changes. To achieve rotation invariance, a dominant orientation is defined by considering the local gradient orientation distribution, estimated with Haar wavelets. Making use of a spatial localization grid, a 64-dimensional descriptor is then built, corresponding to a local histogram of the Haar wavelet responses.

3.1.3 Image matching

Finally, the third step matches the descriptors of both images. Exhaustive comparisons are performed here by computing vector distance between all potential matching pairs. Using the similarity metrics defined for color,the similarity distances between the query image and every image in the database are calculated and then are sorted in ascending order. The first *N* similar target images (with smallest distance value to the query) are retrieved and shown to the user, where *N* is the number of the retrieved images required by the user.

3.2 Object Categarization

We evaluate the color salient points on the dataset. This dataset contains many images of different object categories, e.g. rose, ball,bulb, car, chair, hibiscus and scooty. The data set is divided into a predefined train set and test set.

Over this data set, repeatable experiments have been defined. The experiments decompose automatic category recognition into a number of components, for which they provide a standard implementation. This provides an environment to analyze which components affect the performance most.

The average precision is taken as the performance metric for determining the accuracy of ranked category recognition results. The average precision is a single-valued measure that is proportional to the area under a precision-recall curve. This value is the average of the precision over all images judged to be relevant. Hence, it combines both precision and recall into a single performance value.

When performing experiments over multiple object and scene categories, the average precisions of the individual categories are aggregated. This aggregation, mean average precision, is calculated by taking the mean of the average precisions. As average precision depends on the number of correct object and scene categories present in the test set, the mean average precision depends on the data set used.

IV. RESULTS

Fig 1. Query Image

a) Image 1 **b) Image 2** **c) Image 3**

Fig2. Images in data set

4.1 Color interest points between two images

Fig 3. Color interest points between Query Image & Image 1.

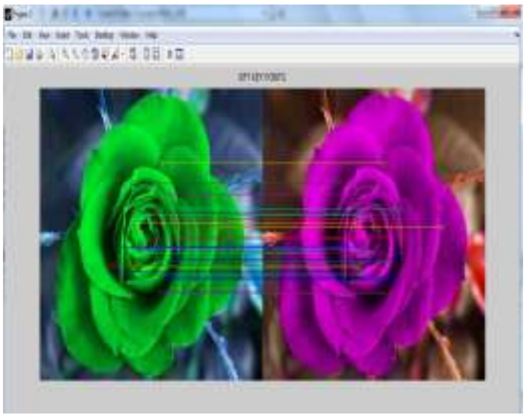

Fig 4. Color interest points between Query Image & Image 2.

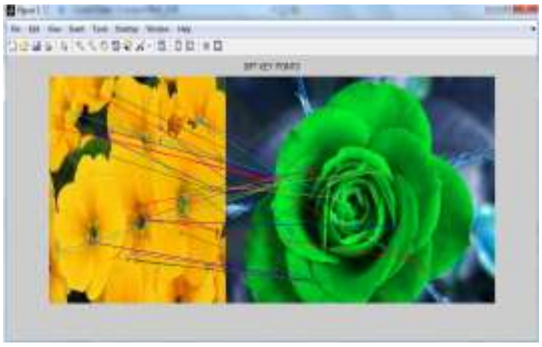

Fig 5. Color interest points between Query Image & Image 3.

4.2 Image Retrieval & Object Categarization

Fig 6 Matching Image & Object Categarization of Query Image & Image1

Fig 7 Matching Image & Object Categarization of Query Image & Image2

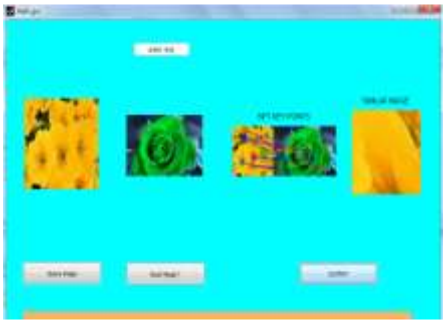

Fig 8 Matching Image & Object Categarization of Query Image & Image3

V. CONCLUSION

Computational methods have been introduced to allow the usage of fewer but more distinctive salient points for Image retrieval and Object categorization. These distinctive points are obtained by making use of color information. Extensive experimental results show that a sparser but equally informative representation, obtained by making use of color information, can be directly passed to current and successful image retrieval and object categorization frameworks, which then obtain state of the art results while processing significantly less data.

It has been shown that the proposed color interest point detector has higher repeatability than luminance-based one. Furthermore, a reduced number of color features increase the performance in image retrieval.Whereas object categorization using only a subset of the features used for matching, reducing the computing time considerably.

VI. ACKNOWLEDGEMENT

I must mention several individuals and organizations that were of enormous help in the development of this work. **Mrs. Shinde S.S. & Mrs.Tamboli S.S.** my supervisor encouraged me to carry this work. Her continuous invaluable knowledgably guidance throughout the course of this study helped me to complete the work up to this stage and hope will continue in further research.

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