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Image Retrieval Using Color Interest Point

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Abstract **- In image retrieval scenarios, many methods use interest point detection at an early stage to find regions in which descriptors are calculated The main aim of this paper is to detect color interest points which are 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.**

Index Terms **- Color Interest Point, Color Invariance, Image Retrieval, Local Features.**

I. INTRODUCTION

Interest point detection is an important research area in the field of image processing and computer vision. **Interest point detection** is a recent terminology in computer vision that refers to the detection of interest points for subsequent processing. 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.

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, applying several detectors or combining them, or making the salient point distribution as dense as possible. The salient point methods for retrieval assign features to a salient point based on the image features of all the pixels in a window around the salient point. Salient features are generally determined from the local differential structure of images. They focus on the shape saliency of the local neighbourhood. Most of these detectors are luminance based which have the disadvantage that the distinctiveness of the local color information is completely ignored in determining salient image features. The salient point methods for retrieval assign features to a salient point based on the image features of all the pixels in a window around the salient point.

II. RELATED WORK

The majority of interest point extraction algorithms are purely intensity based. However, it was shown that the distinctiveness of color-based interest points is larger and therefore, color is important when matching images. Furthermore, color plays an important role in the retentive stage in which features are detected.

Feature detection is a low-level image processing operation. That is, it is usually performed as the first operation on an image, and examines every pixel to see if there is a feature present at that pixel. 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. Once features have been detected, a local image patch around the feature can be extracted. This extraction may involve quite considerable amounts of image processing. The result is known as a feature descriptor or feature vector.

III. SYSTEM STRUCTURE

A. *Overall block diagram:*

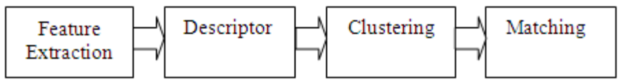

Fig. 1. Basic block diagram

Fig.1 shows system architecture. The whole system is 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

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.

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. The search for images similar to a query image ‘q’ results in finding the k nearest neighbours of ‘q’. In the case of threshold-base matching, two regions are matched if the distance between their descriptors is below a threshold.

B. SURF (Speeded Up Robust Features) Algorithm:

It is composed of three consecutive steps-

1. Interest 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

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 neighbourhood 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. 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.

III. RESULTS

Fig 2. Query Image

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

Fig 3. Images in data

Fig 4. Matching Image Of Query Image & Image 1

Fig 5. Matching Image Of Query Image & Image 2

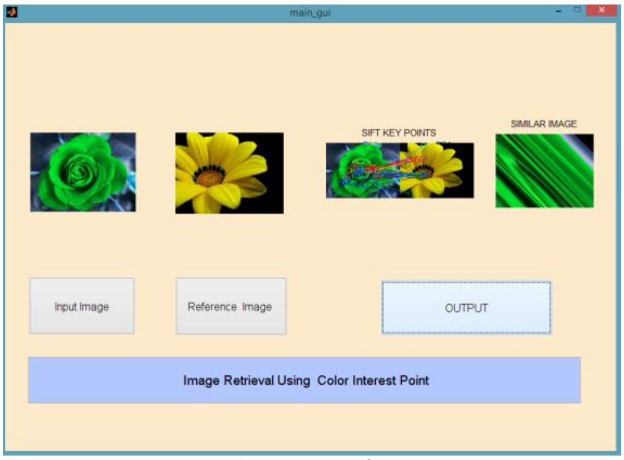

Fig 6. Matching Image Of Query Image & Image 3

IV. Conclusion

Computational methods have been introduced to allow the usage of fewer but more distinctive salient points for Image retrieval. 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 which then obtains state of the art results while processing significantly less data.

It has been shown that a reduced number of color features increase the performance in image retrieval.

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