"SPARSE COLOR INTEREST POINTS FOR IMAGE RETRIEVAL"

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Abstract- The main aim of this project is to detect color interest points which is used for image matching. This project 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 invariance,color interest point, local features, image retrieval .**

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. THE SYSTEM STRUCTURE

A. Overall block diagram

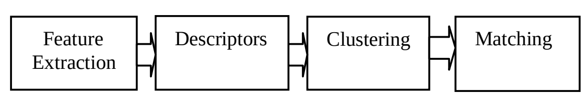

Fig. 1. Basic block diagram

Fig.1 shows system architecture of whole project. The whole system can 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 cluttering (e.g,, [13] and [14]) 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) [15]. 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. There are hierarchical and partitional approaches to clustering. Due to the excessive memory and runtime requirements of hierarchical clustering [16], partitional clustering, such as the k-means, is the method of choice in creating feature signatures.the last part concerned with **Matching** summarizes the classification of images. Image descriptors are compared with previously learnt and stored models. This is computed by a similarity search or by building a model based on supervised or unsupervised learning techniques.

III. THE RELATED WORK

A. Interest Points

The Harris–Laplacian is taken as the basis of our color interest point as the Hessian–Laplacian gives similar but additional locations resulting in better results due to the number (better probability of matching) and the quality of locations (better distinctiveness).

*1)Light-Invariant Points:*To extract invariant points from an arbitrary color image, the input image is transformed to the illumination-invariant image . The fully illuminated variant part of the image in HIS is discarded. For the stable photometric invariants are estimated. The structure tensor is built under increasing scales and with a constant factor. Scale selection is carried out on all three color components [R,G,B], from which the saliency image is built.

2) *Color Boosted Points*: Color boosted points are extracted in the OCS color space . The saliency boosting function is estimated based on the whole set of training images. For experiments without training images, the results on the Corel data set are used The saliency boosting function is estimated for every location, providing an image where rare colors provide higher gradient magnitudes compared with more common colors. The subsequent operations are equal to the extraction of light-invariant points.

B.SURF (Speeded- Up Robust Features) algorithm

It is composed of three consecutive steps: 1.Interest point detection, 2.Interest point description, 3.Feature matching.

1) 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.

2) 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) Finally, the third step matches the descriptors of both images. Exhaustive comparisons are performed here by computing vector distance between all potential matching pairs. Best matching interest points are shown by horizontal line.

C. Proposed Algorithm

The proposed work concentrates on following points:

1) Detect color interest points from the image.

2) Matching of corresponding points between two images.

This can be done using following steps:

Step 1**.**Convert image in to double precision.

Step2**.**Obtain color interest points using Basic SURF Algorithm.

Step 3**.**Put landmark descriptor into matrix.

Step 4**.** Find best matches.

Step 5**.**Sort these matches on vector distance [sorting in ascending & descending manner].

Step 6**.** Make vectors with co-ordinate of best matches.

Step 7**.**Show matching interest points between two images**.**

IV. RESULTS

Fig 1 Original image

Fig 2 Color interest points in the image

Fig 3 Matching of color interest points between two images

V. CONCLUSION

In Image retrieval system, first interest points are detected from which local image descriptors are computed for image matching. . However, 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. In this way, color interest points are used for sparse image representation. To reduce the sensitivity to varying imaging conditions,color boosed Points are introduced. Color statistics based on occurrence probability lead to color boosted points, which are obtained through saliency-based feature selection.

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. His 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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