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A NOVEL KEYPOINT DETECTOR BASED ON SPARSE CODING

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Abstract- Most popular hand-crafted key-point detectors such as Harris corner, MSER, SIFT, SURF rely on some specific pre-designed structures for detection of corners, blobs, or junctions in an image. The very nature of pre-designed structures can be considered a source of inflexibility for these detectors in different contexts. Additionally, the performance of these detectors is also highly affected by non-uniform change in illumination. To the best of our knowledge, while there are some previous works addressing one of the two aforementioned problems, there currently lacks an efficient method to solve both simultaneously. In this paper, we propose a novel Sparse Coding based Key-point detector (SCK) which is fully invariant to affine intensity change and independent of any particular structure. The proposed detector locates a key-point in an image, based on a complexity measure calculated from the block surrounding its position.

Keywords: Sparse Coding, SCK, Preprocessing, Normalization

I. Introduction

Detection of key-points has been researched for decades, and a large number of successful key-point detectors such as Forstner corner , Harris corner , SIFT , SURF , MSER , SFOP [6]. have been proposed, which provide a strong foundation for a vast number of applications in computer vision such as image matching, image registration and object recognition.Although hand-crafted detectors are widely used in many computer vision applications, they are known not to be flexible to different contexts . In fact, hand-crafted detectors are often developed based-on a human designed structure such as a corner, blob, or junction, with some specially predefined characteristics, such that the structures can be easily and stably localized in different images under various transformations.

Although a human designed structure may help increase performance metrics such as repeatability in specific situations, at the same time, it restricts the effectiveness of the detectors tothese situations only. In other words, when being used in a different context in which there is a lack of high quality key-points satisfying the pre-defined structures, the performance of these detectors will degrade.Another undesirable characteristic of the aforementioned popular detectors is that they are sensitive to non-uniform changes in illumination of the scenes. Take Harris corner detector as an example. Derivatives of intensity are used in the calculation of its corner-ness, and since derivatives are proportional to the multiplicative effect of illumination, it follows that the corner-ness also varies with illumination.

Therefore, with the same threshold for corner-ness, a corner selected in one image may not be selected in another image of the same scene because of changes in illumination. As a direct result, the repeatability of Harris corners decreases with light change. Similar phenomena happen with SIFT, SURF, MSER, SFOP…Although there are some works which have been proposed to address one of the two challenges highlighted above, to the best of our knowledge, currently there does not exist an effective method to solve both problems simultaneously. For example, to detect key-points without relying on any particular pre-defined structures, there are works such as [9]-[11].change.

II. Literature review

A Sparse Coding Based Key-Point Detector (2018): All current popular hand-crafted key-point detectors such as Harris corner, MSER, SIFT, SURF… rely on some specific pre-designed structures for the detection of corners, blobs, or junctions in an image. In this paper, a novel sparse coding based key-point detector which requires no particular predesigned structures is presented. The key-point detector is based on measuring the complexity level of each block in an image to decide where a key-point should be. The complexity level of a block is defined as the total number of non-zero components of a sparse representation of that block. Generally, a block constructed with more components is more complex and has greater potential to be a good key point. Experimental results on Webcam and EF datasets show that the proposed detector achieves significantly high repeatability compared to hand-crafted features, and even outperforms the matching scores of the state-of-the-art learning-based detector.

Detection of key-points has been researched for decades, and a large number of successful key-point detectors have been proposed, which provide a foundation for a vast number of applications in computer vision such as image matching, image registration and object tracking. Currently, there are two main categories of key-point detectors: hand-crafted detectors and learning based detectors. Hand-crafted detectors have attracted much attention since the introduction of corner detection works by Forstner et al., and Harris et al. in the 1980s [3, 4]. Several other outstanding hand-crafted detectors are SIFT [5], SURF [6], MSER [7], and SFOP [8].

Although hand-crafted detectors generally produce good results, they often rely on specific pre-designed structures. In fact, hand-crafted features are known not to be very flexible in different contexts [1, 9] probably due to the nature of pre-designed structures. In practice, there are situations in which a large number of high-quality key-points are expected, but cannot be easily located by one specific detector. A common solution is a careful re-selection of an alternative detector or combination of multiple. However, in such cases, if multiple structure types could be detected with a single detector, it would be a simple but very effective solution.

III. System Model

A. Input Image

The process starts with an input image from which key points need to be detected.

B. Pre-processing

Normalization: Adjust the brightness and contrast of the image to ensure uniformly.

- Filtering: Apply Gaussian or other filters to reduce noise.
- Scaling: Create image pyramids to handle different scales of key points.

C. Sparse Coding

- Patch Extraction: Divide the image into overlapping or non overlapping patches.
- Dictionary Learning : Train dictionary on a set ofrepresentative image patches
- Sparse Representation: For each image patch, find a sparse representation using the dictionary.

D. Key point Detection

•Saliency Map Construction: Use the sparse codes to construct a saliency map. Patches with higher sparse representation errors or high sparse coefficients can indicate potential key points.

•Non-Maximum Suppression:Apply non-maximum suppression on the saliency map to localize key point precisely.

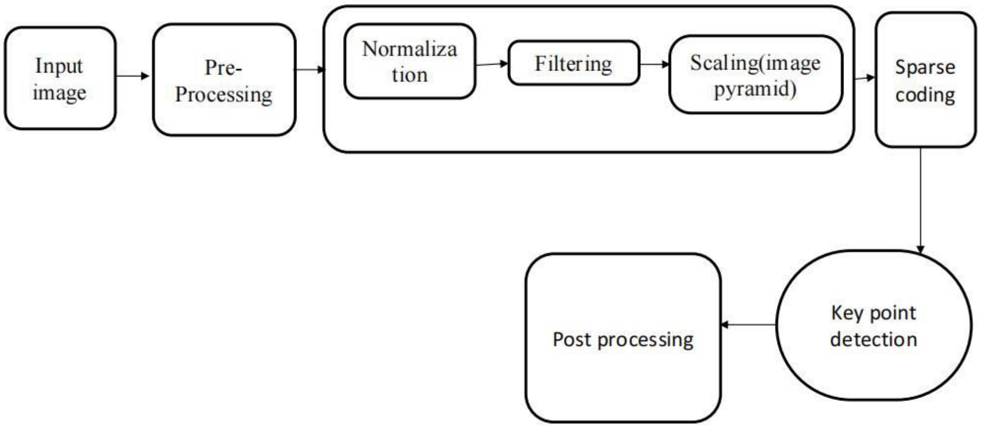

Fig 1: Block diagram of Novel key point detector based on sparse coding.

E. Post-Processing

•Refinement: Refine the key points using techniques like sub-pixel accuracy enhancement.

•Descriptor Generation: Generate descriptors for each detected key point for further use in task matching recogonisation.

IV.Result

Fig 2: An example of matching image with SCK detector and SIFT descriptor
(Matched images have drastic changes in illumination)

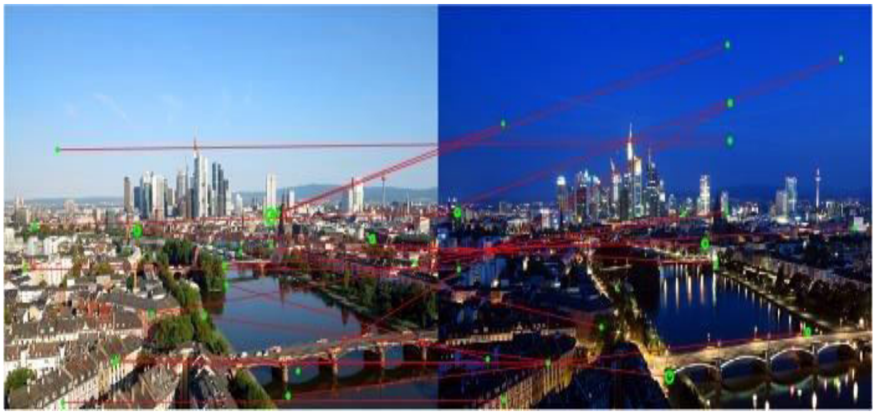

Fig 3: An example of matching image with SIFT detector and SIFT descriptor
(Matched images have drastic changes in illumination).

In this section, we demonstrate qualitative results of the proposed detector. Fig. 4 shows a pair of images from Webcam dataset with drastic changes in illumination. Top 20 matched key-points and their correspondences are plotted on top of these images. In this experiment, SCK key-points are first located with the Cosine dictionary, block size 11, and $\lambda = 0.25$ for the sparse coding algorithm. The detected points are then matched by SIFT descriptor based on Euclidean distance. Thematching

code is provided by [32]. In this matching scheme, two key-points a, b in two different images are deemed matched ifFig 2the distances between two corresponding descriptors $\boldsymbol{D}a$ and $\boldsymbol{D}b$ multiplied by a threshold (1.5) is lessthan the distance of $\boldsymbol{D}a$ to all other descriptors. We can see from Fig. 4 that although there are several spurious matches, generally the matching results are extremely encouraging.

V.Conclusion

A novel key-point detector based on sparse coding which requires no particular human designed structures to detect distinctive points in images has been proposed. The key-point detector is proved to be fully invariant to affine intensity change and can detect all types of structures. Experimental results have shown that the proposed detector demonstrates excellent performances on three benchmark datasets. The current work can be applied in numerous vision-based applications. An interesting future extension of this work could be an algorithm which incorporates scale-invariant key-point detection.

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