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Efficient adaptive non-maximal suppression algorithms for homogeneous spatial keypoint distribution

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ABSTRACT

Keypoint detection usually results in a large number of keypoints which are mostly clustered, redundant, and noisy. These keypoints often require special processing like Adaptive Non-Maximal Suppression (ANMS) to retain the most relevant ones. In this paper, we present three new efficient ANMS approaches which ensure a fast and homogeneous repartition of the keypoints in the image. For this purpose, a square approximation of the search range to suppress irrelevant points is proposed to reduce the computational complexity of the ANMS. To further speed up the proposed approaches, we also introduce a novel strategy to initialize the search range based on image dimension which leads to a faster convergence. An exhaustive survey and comparisons with already existing methods are provided to highlight the effectiveness and scalability of our methods and the initialization strategy.

1. Introduction

Keypoint detection is often the first step for various tasks such as SLAM [14], panorama stitching [4], camera calibration [3], and visual tracking [5,12]. Therefore, this stage potentially affects the robustness, stability, and accuracy of the aforementioned applications. In the past decade, we have witnessed significant advances in keypoint detectors leading to major improvements in terms of accuracy, speed, and repeatability. But while the detection of keypoints has been intensively studied, ensuring their homogeneous spatial distribution has attracted a rather low level of attention. It is well known that spatial point distribution is crucial to avoiding problematic cases like degenerated configurations (for structure from motion or SLAM) or redundant information (i.e. cluster of points) as depicted in Fig. 1. Moreover, a homogeneous and unclustered point distribution might speed up most computer vision pipelines since a lower number of keypoints is needed to cover the whole image. One of the most effective solutions to ensure well-distributed keypoint detection is to apply an Adaptive Non-Maximal Suppression (ANMS) algorithm on the keypoints extracted by a detector. However, despite all the advantages offered by such approaches, these methods have been rarely used in practice due to their high computational complexity. To overcome this limitation we propose three novel approaches called Range Tree ANMS (RT ANMS), K-d tree ANMS (K-dT ANMS), and Suppression via Square Covering (SSC). The developed algorithms aim to efficiently select the strongest and well-distributed keypoints across the image. We achieve such performance using a square search range approximation which is initialized in an optimal and intuitive manner (see Fig. 2).

An abundant number of experiments are used to demonstrate the relevance of our ANMS algorithms in terms of speed, spatial distribution, and memory efficiency. Furthermore, we experimentally highlight that ANMS is a beneficial step for SLAM, which drastically improves the accuracy of the motion estimation while using a restricted number of keypoints. To sum up, the contributions of this paper are the following:

- Three novel and efficient ANMS algorithms
- A new and optimal initialization of the search range
- An extensive series of experiments against state-of-the-art
- Efficient and optimized ANMS codes are made available at https://github.com/BAILOOL/ANMS-Codes.

This paper is organized as follows. In Section 2, we provide an extensive literature review of existing approaches. The notations as well as proposed methods are introduced in Section 3. Finally, a large number of experiments is provided in Section 4 followed by a brief conclusion (Section 5).

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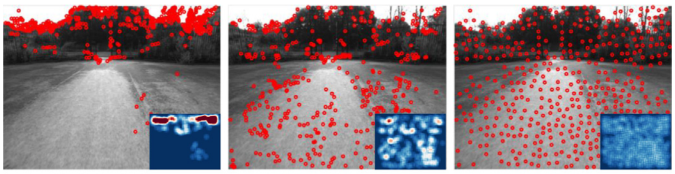

(a) (b) (c)

Fig. 1. Keypoint detection: (a) TopM NMS, (b) bucketing, (c) proposed ANMS. The bottom right subimage represents the coverage and clusteredness of keypoints computed using a Gaussian kernel. The red color in the subimage stands for a dense cluster of points, while the blue color represents an uncovered area. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2. Related work

In this section, we report existing methods that have been developed to improve the spatial distribution of keypoints. These approaches can be divided into three categories: bucketing approaches, Non-Maximal Suppression (NMS), and ANMS.

2.1. Bucketing approach

Currently, the bucketing-based point detection approach [10] is the most common technique used to ensure good repartition of the keypoints. This approach is relatively simple: the source image is partitioned into a grid and keypoints are detected in each grid cell. The bucketing-based approach is efficient for detecting keypoints all over the image, however, it is unable to avoid the presence of redundant information (i.e. clusters of keypoints).

2.2. Non-maximal suppression

NMS (also referred to as TopM) is often used to remove a large number of keypoints which are mostly redundant or noisy responses of the keypoint detectors. The most common approach for NMS [15] consists of suppressing the weakest keypoints using an empirically determined threshold. Thereafter, the clusteredness is often reduced by suppressing the keypoints which do not belong to a local maximum in a particular radius. NMS is a straightforward and fast way to reject unnecessary corners, but, in many real case situations, this approach leads to a very limited spatial dissemination of the keypoints (see Fig. 1(b)).

It should be noted that certain works have recently attempted to improve the NMS stage by introducing a novel adaptive cornerness score calculation taking into consideration the local contrast around the keypoints [16]. Thus, these approaches tend to improve the spatial distribution as well as the robustness against illumination variations. However, they suffer from the point clustering effect inherent to NMS approaches.

2.3. Adaptive non-maximal suppression

ANMS methods have been developed to tackle the aforementioned drawbacks. These techniques enforce better keypoint spatial distribution by jointly taking into account the cornerness strength and the spatial localization of the keypoints. The very first ANMS approach was proposed by Brown et al. [4]. The authors initially introduced this concept to robustify the image matching for panorama stitching. In that work, the keypoints are suppressed based on their corner strength and the location of the closest strong keypoint. Unfortunately, the original implementation of this ANMS has a quadratic complexity which is not suitable for real-time applications such as SLAM.

To overcome this problem, multiple attempts to reduce the computational time of ANMS have been investigated. For instance, Cheng et al. [7] proposed an algorithm using a 2-dimensional k-d Tree for space-partitioning of high-dimensional data. Using this data structure, the keypoints are separated into rectangular image regions. Then, from each cell, the strongest features are selected as the output sample set. This algorithm was extended by Behrens et al. [1] using a general tree data structure. While these methods perform faster than the traditional ANMS [4], they do not necessarily output homogeneously distributed points.

More recently, Gauglitz et al. [8] have proposed two complementary approaches that reportedly perform in a subquadratic run time. In the first approach, the authors have chosen to use an approximate nearest neighbor algorithm [6] which relies on a randomized search tree [17]. The second algorithm named Suppression via Disk Covering (SDC) aims to further boost the performance of the ANMS. The algorithm simulates an approximate radius-nearest neighbor query by superimposing a grid onto the keypoints and approximating the Euclidean distance between keypoints by the distance between the centers of the cells into which they fall.

Our proposed approaches tackle the limitations of previous works while maintaining favorable efficiency and scalability.

3. Methodology

In this section, we describe a problem statement and propose several efficient algorithms which ensure a homogeneous repartition of keypoints in the image. Specifically, we cover ANMS based on Tree Data Structure (TDS) (includes K-dT and RT ANMSs) followed by Suppression via Square Covering (SSC). Lastly, we

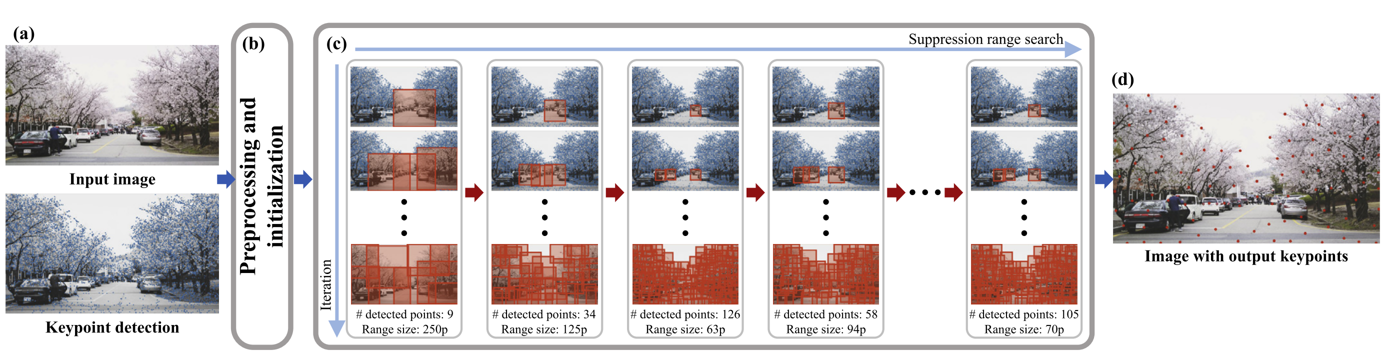

Fig. 2. Algorithm's workflow: (a) keypoint detection in the original image (depicted in blue), (b) sorting keypoints by strength and initialization of the search range, (c) conceptual representation of our ANMS algorithm where: every column represents the search range guess (orange boxes) through a binary search process iterated until queried number of points is reached (100 in this example); while every row depicts the iterations through input points, (d) final result where the red dots represent the selected keypoints. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)