FAST CORNER POINT DETECTION THROUGH MACHINE LEARNING

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Abstract: Traditionally, corner point detection is performed through evaluation of some corner amplifying function and thresholding its results. Recently, an alternative machine learning-based approach was introduced. This contribution focuses on corner point detection through machine learning and proposes an approach that has good performance, low resource requirements, and is well implementable in parallel environments and programmable hardware. The paper also introduces the achieved results and discusses them.

Keywords: Corner point detection, Machine learning, Comparison of corner point detection methods

1 INTRODUCTION

Corners play an important role in image processing and computer vision algorithms, because they are very distinctive features.

For some of the approaches, the CRF (Corner-Response-Function) can be shown to be invariant in scale, rotation or even affine transformations. In general, the computational costs increase with the number of invariant corner features. Therefore, many traditional approaches focus either on the computation speed, or the distinctiveness of the detections.

State of the art methods of detection are introduced in section 2. Following chapter describes the basic idea of training the WaldBoost classifier in the task of corner point detection. Chapter 3 shows the comparison between the Harris-Laplace corner detector and the WaldBoost detector. In the end the summarized results and improvements are highlighted.

2 RELATED WORK

In 1988, based on the Moravec Operator [1], C. Harris and M. Stephens [2] presented an improved corner detector which is nowadays known as Harris detector. The Harris corner detector is based on the local auto-correlation function. The local auto-correlation function measures the local changes of the signal with patches shifted by a small amount in different directions. The Harris detector is rotation-invariant, but not scale-invariant. Keeping the size of the sliding window constant while zooming into an detected corner, the corner will get more and more the characteristics of an edge.

To get rid of the above mentioned disadvantage, newer approaches like Harris-Laplace [3] was introduced. It takes also the characteristic corner-scale into account. Multi-scale point detection is evaluated. The decision of which scale to use is then made. It uses the Harris detector in multi-scale image for scale invariance. The auto-correlation matrix is adapted to scale changes to make it independent of image resolution.

In 2006 Edward Rosten, Reid Porter and Tom Drummond presented a group of detectors [7], which are based on binary decision processes, at which their decision-paths are determined by the kind of detector and the intensity of the chosen pixel. The suggested optimization in terms of computation speed minimized the average time to decision, respectively the average path-length of the binary decision process.

In 2007 Jiří Matas and Jan Sochman introduced a framework [10], where detectors can be emulated in order to speed up the decision process and being suitable for real-time applications. To demonstrate the superiority the emulation is compared in [7] with two traditional blob detectors, the Hessian-Laplace [3] and the Kadir Brady saliency detector [4].

3 DESCRIPTION OF THE APPROACH

WaldBoost is a speeded up modification of AdaBoost, which is a well known supervised machine learning algorithm. It belongs to the statistical classification algorithms and the learning process is based on finding a quasioptimal sequential strategy for a given binary-valued decision problem using a greedy learning algorithm.

An arbitrary traditional corner detector gets images from an image pool and generates the training samples. Each training sample contains an annotation about the image-name, the location within the image, the characteristic scale and the label ”corner point“ or “not corner point”. During the WaldBoost training the subimages can be retrieved from the annotations and the corresponded images. After the training WaldBoost has learned a strong classifier, clearly defining a sequential strategy for the corner detector based on WaldBoost classifier.

3.1 DATASET

Corner detector based on WaldBoost classifier should emulate nearly every traditional corner detector. This statement is supported by results of this article.

To show the emulation works fine with almost any traditional corner detector the training set is generated by an new corner detector, which is in the following text called “HCC - High Contrast Corner detector”.

Samples which were used for classifier training were obtain by a new simple corner detector which is based on measuring the distance between predefined corner masks and the region in the image. The mask with the lowest distance denotes the corner type. The distance is also used to measure the cornerness. Each mask is defined as HCC mask (high contrast corner mask). Figure 1 shows two typical HCC masks of maximum and minimum intensities.

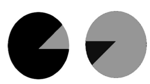


Figure 1: HCC masks

The distance can be measured with the sum of squared differences. In that case, a low CRF value marks a corner point. For generating the training set 16 different HCC masks were used, covering 8 corners with an angle of 45°.

About 5000 natural images were used to cover the main aspects of corners and non-corners in the training set. The corners and non-corners were calculated by an arbitrary traditional corner detector, at which a low CRF value was marking a non-corner point. To improve the accuracy of the detections Non Maximum Suppression was used.

Figure 2 illustrate detections of the HCC detector.

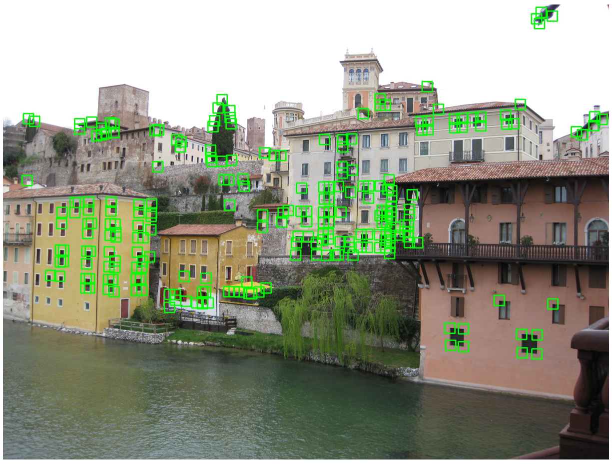


Figure 2: Corner detections of the HCC detector

4 RESULTS

Since the Harris-Laplace detector is the state of the art within the class of scale-invariant corner detectors, it is most likely being compared with the WaldBoost detector. For comparison Mikolajczyk's data set [5] is used[1]. The weak classifiers are unnormalized haar-like features [6] combined with centre-surround features [11], which can be computed in a fast way due to the calculation of integral images.

The repeatability rate is defined as the percentage of points presented in two images and their relation can be described by the homography. To measure the repeatability rate of a detector only regions located at the key-points respectively the corners are used for the comparison. Each region can be bounded by an ellipse and the repeatability rate can be calculated by measuring the overlap of corresponded regions. In contrast to the Blur Test, in the Viewpoint Change Test the images differ pairwise from the homography. In the Blur Test the images differ pairwise from the change of the camera focus. Because both Harris-Laplace and WaldBoost use circular regions instead of elliptic, the overlap error increases with increasing viewpoint changes.

The results (Figure 3) show nearly the same repeatability rates for the Viewpoint Change Test. Only for the Zoom and Rotation Test the performance of WaldBoost is worse than Harris-Laplace but this fact is compensated by the better results in the Decreasing Light Test and the Blur Test.

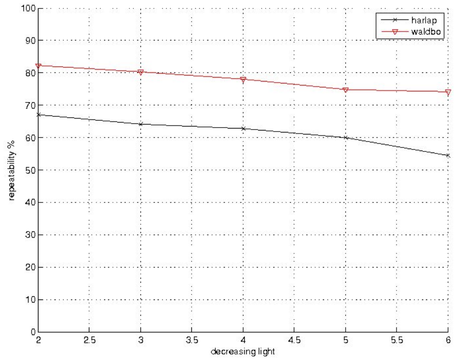
Finally the repeatability rates for Harris-Laplace and WaldBoost seems to be similar. The average time to decision speed shows (Figure 4), which could be used as a metric of speed for

There is no comparison of SIFT or SURF descriptors in this article proposed, because corner detector via WaldBoost classification unlike SIFT or SURF does not use any kind of description of key point area. However this could be the topic of another work.

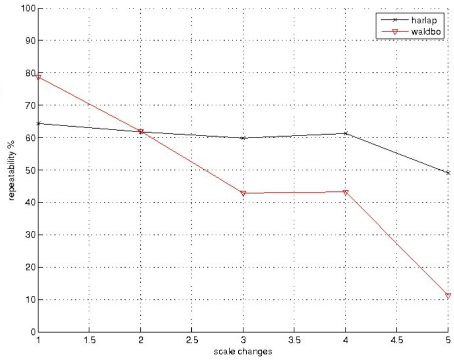
5 CONCLUSION

This paper focused on the corner point detection using the sliding window classification. It has been demonstrated that the approach is feasible, that it can have better or same performance as the traditional approaches. As a next topic could be the measurement the time of corner detection, which was not done in this paper. The speed of detection is promising but another experiments should be done to approve it.

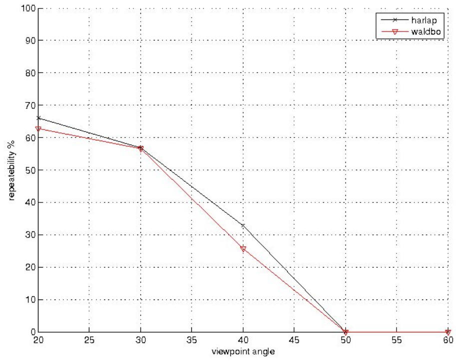
[1] The data set is available at http://www.robots.ox.ac.uk/ vgg/ research/affine



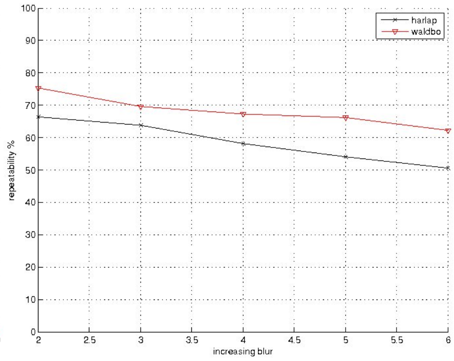
(a) Decreasing Light



(b) Zoom and Rotation

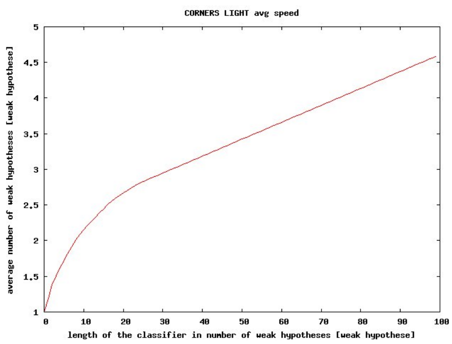


(c) Viewpoint Change

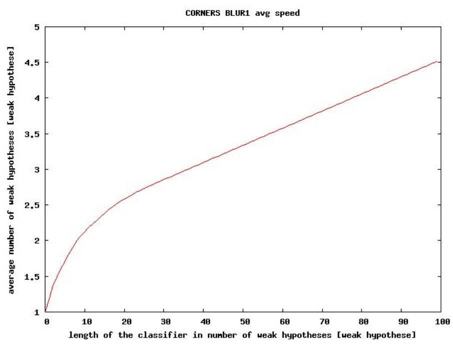


(d) Increasing Blur

Figure 3: Comparison of Harris-Laplace corner point detector and Corner point detector emulated by WaldBoost classifier



(a) Decreasing Light



(b) Increasing Blur

Figure 4: Speed of detection according to number of evaluated classifiers.

Some methods of detection, tracking and localization depend on the accuracy and speed of key point detection. From this point of view it is important to try achieve better results than today's state of the art methods offer. The profit of this improvement could be used in R3COP project, which is focused on robotic tasks.

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