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Counting crowd flow based on feature points

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A B S T R A C T

A counting approach for crowd flow based on feature points is proposed. The objective is to obtain the characteristics of the crowd flow in a scene, including the crowd orientation and numeric count. For the feature point detection, a three-frame difference algorithm is used to obtain a foreground containing only the moving objects. Therefore, after the SURF feature point detection, only the feature points of the foreground are retained for further processing. This greatly reduces the time complexity of the SURF algorithm. For feature point clustering, we present an improved DBSCAN clustering algorithm in which the non-motion feature points are further eliminated and only the remaining feature points are clustered. For the calculation of the crowd flow orientation, the feature points are tracked based on a local Lucas–Kanade optical flow with Hessian matrix algorithm. In the crowd flow number counting, the crowd eigenvectors are constructed based on the SURF feature points and are trained using a support vector regression machine. The experimental results show that the proposed crowd orientation and counting method are more robust and provide crowd flow statistics with higher accuracy than previous approaches.

1. Introduction

Counting crowd flow is a video-frame analyzing process, which uses computer vision techniques to estimate the crowd information. It has been widely applied in fields such as public security, urban public transport, resource allocation, and optimization. Crowd-flow statistics are, therefore, of great value and significance.

There are primarily two types of crowd flow analyzing techniques: one is based on target detection and the other is based on features. Various target detection techniques can be used to detect crowds, such as face detector [1], pedestrian detector [2], and especially head–shoulder detector [3,4]. The human head and shoulders can convey a great deal of information such as gender and clothing habits. This can facilitate the prediction of a person's occupation [5]. Once individuals are identified using these detectors, the crowd number can be counted and the crowd orientation can be obtained using target tracking techniques [6]. However, in the presence of object occlusions and perspective phenomena, these methods are not sufficiently robust and hence yield crowd flow statistics with low accuracy. Feature-based techniques normally consist of feature detection, including interest points, segmented areas, and edge orientations [7–9], and modeling, including clustering [10], constructing neighborhood similarity [11,21], neural network [12], sparse geometric features [13], and Gaussian Process Regression [8]. Feature-based techniques can produce a complete estimation of the crowd number and are more suitable for working in a dense scene. Furthermore, feature-based techniques are more robust since they are based on features that are easier to detect and thus are more widely used for high-density crowds.

Besides feature detection and modeling, crowd movement trend and orientation calculation techniques are also challenging. Methods have been proposed for target-movement trend detection such as background subtraction, optical flow [15], and neural network [11]. The background subtraction method requires accurate binarization, well-established background models, and an effective shadow removal algorithm to avoid occlusion and broken blobs. These are difficult to achieve. And a slow learning process and high training failure rate discourage the widespread usage of the neural network algorithm. Conversely, optical flow provides both information about moving objects and a three-dimensional structure of the current scene. Therefore, the detection of moving objects and their moving direction using an optical flow method is preferred.

In this paper, a crowd-flow statistics method based on feature points is proposed. We utilize the SURF (Speeded Up Robust Feature) algorithm to detect feature points of the crowd flow and exploit the moving foreground as a mask image to reduce the time complexity of the SURF algorithm. Then an improved DBSCAN (Density Based Spatial Clustering of Application with Noise) clustering method of the feature points is proposed to enhance the overall performance. Finally, a Lucas–Kanade local optical flow with Hessian matrix method and a

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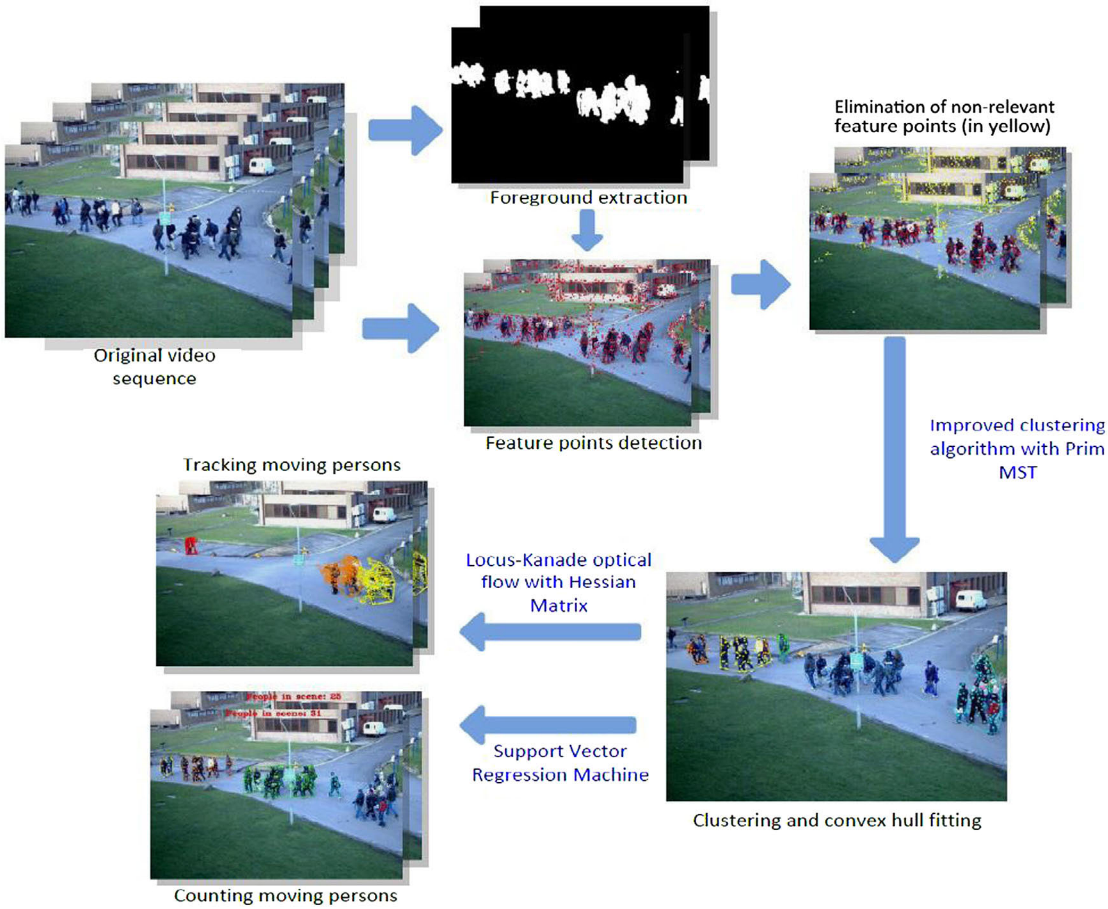

Fig. 1. Overview of the proposed algorithm.

support vector regression machine are used to track and count the crowds.

2. Algorithm description

The proposed algorithm is depicted in Fig. 1. In this paper, the crowd will be regarded as a whole for the initial investigation. The number of individuals in the crowd and the orientation will be calculated later by utilizing a support vector regression machine with the extracted SURF feature points and a local optical flow with Hessian matrix method.

2.1. Moving SURF point detection

The Harris detector, SIFT algorithm, and SURF algorithm [17] are the most frequently used feature point extraction algorithms in image processing. A Harris detector is suitable for conditions that have a high demand of interest points and a complex light source. It is sensitive, however, to the scale size of the target objects that can lead to the non-repeatability of the extracted features. Conversely, the feature points detected by the SURF algorithm are more stable since they are invariant to translation, rotation, and scaling, and have high resistance to brightness variation, occlusion, and noise. The SURF algorithm also improves on the multi-scale space construction method included in SIFT algorithm. Therefore, the SURF algorithm is used in this paper for feature point extraction. For simplicity, we assume that the camera is still and the difference between any two adjacent frames is small, that is, the environmental factors in the scene rarely change. We also accept that the main moving objects are pedestrians.

Because the objects from which we wish to extract feature points are moving between frames, the SURF algorithm in this paper is improved by employing a three-frame difference algorithm. As its name suggests, the three-frame difference algorithm extracts moving objects with at least three frames. It is sensitive to the movement of the objects and possesses a self-adaptive ability to noise. This results in excellent robustness.

Unlike previous approaches such as Ref. [16], we obtain a moving foreground of the crowd that is represented by a binary image. Then we utilize the binary image as a mask to detect SURF feature points using the SURF algorithm. That is, there is no need to detect SURF feature points in the areas that do not belong to the moving crowd. This method greatly reduces the time complexity and enhances the overall performance of the algorithm. In Fig. 2, the comparison results of SURF feature point detection are demonstrated.

2.2. SURF point clustering

Using defined similarity constraints, clustering groups a set of objects in such a way that objects in the same group (called a cluster) are more similar to each other than those in other groups. Clustering algorithms such as the K-MEANS, CLARNS, DBSCAN, OPTICS and CURE algorithms are well recognized and commonly used. The DBSCAN (Density-based Spatial Clustering of Application with Noise) algorithm is a density-based clustering algorithm that can not only find arbitrary-shaped clusters but also identify noise points or outliers effectively. DBSCAN is insensitive