Robust hybrid technique for moving object detection and tracking using cartoon features and fast PCP

S.H. Jeevith [1], S. Lakshmikanth [2]
[1] Sri Siddhartha Institute of Technology, Tumakuru-572105, India;
[2] Acharya Institute of Technology, Bengaluru-560107, India

Abstract

In various computer vision applications, the moving object detection is an essential step. Principal Component Analysis (PCA) techniques are often used for this purpose. However, the performance of this method is degraded by camera shake, hidden moving objects, dynamic background scenes, and / or fluctuating exposure. Robust Principal Component Analysis (RPCA) is a useful approach for reducing stationary background noise as it can recover low rank matrices. That is, moving object is formed by the low power models and the static background of RPCA. This paper proposes a simple alternative minimization algorithm to fix minor discrepancies in the original Principal Component Pursuit (PCP) or RPCA function. A novel hybrid method of cartoon texture features used as a data matrix for RPCA taking into account low-ranking and rare matrix is presented. A new non-convex function is proposed to better control the low-range properties of the video background. Simulation results demonstrate that the proposed algorithm is capable of giving consistent random estimates and can indeed improve the accuracy of object recognition in comparison with existing methods.

Keywords: principal component pursuit, robust principal component analysis, cartoon features, local binary patterns.

Citation: Jeevith SH, Lakshmikanth S. Robust hybrid technique for moving object detection and tracking using cartoon features and fast PCP. Computer Optics 2022; 46(5): 783-789. DOI: 10.18287/2412-6179-CO-1056.

Introduction

Motion detection is the primary step in computer vision, focusing at grouping moving objects into video images. It has originated many applications for human observation, image capture, motion behavior analysis and vision-based interaction of computer and humans. Several articles on motion detection have been published over the past 20 years. However, there are still significant difficulties in detecting fast moving objects, for example, against a complex background. For example, rapidly changing the frequency of bright objects in the background (such as branches and leaves), camera shake, side effects, stationary foreground, efficiency, etc. It is important to note that detecting static images and background is a trade-off as anyone expects to remove as many backgrounds as favorable while maintaining the forefront. Though, it is challenging to achieve the desired outcome because they have many similar functions. Existing methods rarely solve this problem [1]. Conventional motion detection techniques are established on noise reduction, which usually involves three phases. First, the background image is mathematically defined. Second, new observations of the background or foreground are ranked allowing to the resemblance between the background and observations. At final phase, updating the background model for new observations using an adaptive strategy.

Liu and Zhang [2] utilized the difference in histogram resemblance between the imaginary field and the real field of a moving object to complete the performance. However, this does not apply to the alignment of cover and moving objects.

Varcheie et al. [3] proposed a region based BGS method on color histograms and texture information with the GMM to model the background and detection motion. This method improved performance than classical BGS methods, but the intricacy was extremely high. Varadarajan et al. [4] developed a general structure of GMM by region that considered the pixel dependencies. The frame-level method models the entire image as a vector, rather than simulating changes in individual pixels or regions. The most popular types of approaches are electronic space decomposition and PCA [5 – 8]. In particular, a background model (matrix) is created on behalf of input frames with vector representations in an image frame, so that the correlation matrix is split into eigenvalues. Deep neural networks have become quite popular in recent years. CNN [9 – 12] examined the detailed structure of a large number of benchmark datasets, which significantly improved the performance of the project. However, real-time performance on embedded systems is not possible without a dedicated GPU or processor.

In the process of background subtraction, due to the internal time-domain coupling of the background image, the remodeled matrix has a low order. And the L-1 norm was used to characterize the scarcity in the foreground. But the model works for background subtraction tasks, assuming approximate dynamic and static components analogous to the foreground and background of the video, respectively. Therefore, it is necessary to take into ac-