Information Sciences 299 (2015) 283–295

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

Probabilistic neural networks based moving vehicles extraction algorithm for intelligent traffic surveillance systems

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A R T I C L E   I N F O

Article history:
Received 3 December 2013
Received in revised form 4 December 2014
Accepted 11 December 2014
Available online 17 December 2014

Keywords:
Moving vehicle detection
Traffic video surveillance
Variable bit-rate
Neural network

A B S T R A C T

Automated vehicle detection plays an essential role in the traffic video surveillance system. Video communication of these traffic cameras over real-world limited bandwidth networks can frequently suffer network congestion or unstable bandwidth, especially in regard to wireless systems. This often hinders the detection of moving vehicles in variable bit-rate video streams. This paper presents a novel approach for vehicle detection based on probabilistic neural networks through artificial neural networks, which can accurately detect moving vehicles not only in high bit-rate video streams but also in low bit-rate video streams. The overall results of detection accuracy analyses demonstrate that the proposed approach has a substantially higher degree of both qualitative and quantitative efficacy than other state-of-the-art methods. For instance, the proposed method achieved *Similarity* and F_1 accuracy rates that were up to 61.75% and 69.38% higher than the other compared methods, respectively.

1. Introduction

In recent years, the intelligent transportation system has been prevailing in traffic management, especially in regard to the optimization of traffic flow. It involves the application of advanced technologies including intelligent computing, network communications, visual-based analysis, and sensor electronics [24,19,26,8,3]. The enhanced transportation system management approach is primarily intended to improve the safety, efficiency, and reliability of subsystems within the transportation system. These include traffic flow measurement systems, regional multimodal traveler information systems, coordinated traffic control systems, freeway and road management systems, and electronic tagging systems [14,11].

Currently, wireless traffic video surveillance is a key technology in the management of intelligent transportation systems. The tasks associated with designing efficient traffic video surveillance systems include vehicle detection, vehicle classification, vehicle recognition, vehicle tracking, and collision avoidance [18,2,27]. Developing automated vehicle detection is the first essential process in the design of a traffic video surveillance systems. This is accomplished in order to extract information regarding moving vehicles and obtain effects of stabilization within a given area such as vehicle recognition and vehicle tracking.

However, video communication from these traffic cameras over real-world limited bandwidth networks can frequently suffer network congestion or unstable bandwidth. This is especially true in regard to wireless video communication systems. To allocate the available amount of network bandwidth and produce variable bit-rate video streams, a rate control scheme was adopted by using H.264/AVC as an effective video-coding tool. Suitable bit-rate video streams are thus produced for transmission over real-world limited bandwidths [21,23].

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http://dx.doi.org/10.1016/j.ins.2014.12.033
0020-0255/

There are three conventional approaches by which to detect moving vehicles: optical flow, temporal difference, and background subtraction [9]. The optical flow technique is based on the projected motion on the image plane [25]. Unfortunately, optical flow is both very sensitive to noise and very inefficient for traffic applications. In order to adjust for environmental changes when detecting moving vehicles, the temporal differencing technique calculates the difference between consecutive frames [13]. However, this method incompletely extracts the shapes of moving vehicles, a problem which is especially prevalent when vehicles are motionless or exhibit limited mobility. Background subtraction is a particularly popular method for the detection of moving vehicles in video sequences [1,22,4,15,16,28,17,5,12]. It accomplishes detection by comparing the pixel feature differences between the current image and the reference background model of the previous image. The technique of background subtraction is currently the most satisfactory method for solving vehicle detection problems.

Many background subtraction methods have been proposed and used in previous studies to detect moving vehicles within video sequences in ideal bandwidth network environments. Candes et al., Xu et al., and Guan et al. built their motion detection methods [1,22,4] via Robust Principal Components Analysis (RPCA) on a robust subspace model in which the foreground and the background are separated based on sparse representation and rank minimization, respectively. In particular, Candes et al. [1] proposed a Principal Component Pursuit (PCP) method for motion detection based on RPCA, which recovers the low-rank and sparse matrices via convex optimization. Xu et al. [22] employed a Stable Outlier Pursuit (SOP) method for detection of moving objects by which to robustly achieve decomposition while the outliers corrupt entire columns. The Manhattan Non-negative Matrix Factorization (MahNMF) method proposed by Guan et al. [4] is able to more robustly estimate the low-rank and sparse portions of a non-negative matrix by minimizing the Manhattan distance in terms of the PCP and SOP methods. By doing so, the MahNMF method is capable of not only approximating a low-rank background, but also restoring the foreground when noise is present. However, these methods [1,22,4] are not suitable for vehicle detection in real-world scenarios because they usually require stacking a batch of video frames in their input observation matrix before detection of moving vehicles can occur.

Moreover, an Σ–Δ filter technique is employed by the Sigma Difference Estimation (SDE) approach so as to estimate two orders of temporal statistics for each pixel of the sequence in accordance with a pixel-based decision framework [15]. Unfortunately, using a single Σ–Δ filter for each incoming pixel may be insufficient for complete vehicle detection when the SDE approach operates in certain complex environments. The Multiple SDE (MSDE) approach, which combines multiple Σ–Δ estimators to calculate a hybrid background model, was developed in order to solve the problem [16]. In addition to the Σ–Δ filter technique, each pixel value is modeled independently in one particular distribution by using the Gaussian Mixtures Models (GMM) approach [28]. The subsequent distribution of each pixel is determined based on whether or not it belongs to the background. In contrast, a background model derived by the Simple Statistical Difference (SSD) uses the temporal average as the main criteria to accomplish the detection of moving vehicles [17]. The Multiple Temporal Difference (MTD) approach retains several previous reference images with which to calculate the differences between each frame [5]. This, in turn, shrinks gaps within the moving objects. In addition, Kim et al. proposed a Codebook Background Subtraction (CBS) method in [12] for detecting moving objects via a highly compressed background model, which is composed of codewords from a training sequence over a long period of time.

However, it is often a difficult endeavor to detect moving vehicles within the variable bit-rate video streams from most traffic camera systems operating over real-world limited bandwidth networks [6,7]. Under current conditions, the traditional state-of-the-art background subtraction methods [15,16,28,17,5,12] cannot easily be applied to these networks.

Recently, many researchers [6,7] have proposed various techniques to detect moving vehicles in variable bit-rate video streaming. In [7], a motion detection approach was proposed to alleviate this situation by using the Fisher's linear discriminant-based radial basis function neural network. An additional artificial neural networks-based scheme called cerebellar-model-articulation-controller network was employed for motion detection in [6], in which a weight memory space are maintained by manipulating the information from several previous frames in order to facilitate the efficacy of motion detection for variable bit-rate video streaming.

In response, this paper proposes a novel approach based on the Probabilistic Neural Networks (PNN) through artificial neural networks that exploits the advantages of the proposed reliable background generation module and the proposed moving vehicle detection module, and combines them in order to effectively detect moving vehicles from variable bit-rate video streams. In contrast to these techniques [6,7], the proposed technique is built on a probabilistic neural networks strategy. Based on this strategy, the proposed method can detect moving vehicles more precisely and more completely than can state-of-the-art background subtraction methods on account of its ability to successfully adapt to bit-rate variations in video streams. Our proposed method operates as follows:

(1) The neurons of the pattern layer and the summation layer are activated by the proposed reliable background generation module for the generation of a precise background model. The neurons are then separated into different categories for construction of the summation layer in order to adjust to the differing properties of variable bit-rate video streams.
(2) Afterward, the precise background model is mapped to each incoming pixel by the proposed moving vehicle detection module, whereupon accurate and complete detection of moving vehicles is accomplished. This can be done in either low bit-rate or high bit-rate video streams via a block estimation procedure, a vehicle detection procedure, and a background updating procedure.