Improved Kernel Density Background Estimation with Diversity Sampling and Neighbor Information for Traffic Monitoring

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Abstract. Dynamic background extraction is one of the key tasks in moving object detection in static camera surveillance for traffic monitoring. The kernel density estimation is for nonparametric multi-mode background modeling with the advantage of dealing with waving tree leaves, high frequency and repeated motion etc. To its computation expensive with repeated similar samples, an improved nonparametric background model using novel diversity-sampling mechanism is proposed to extract the important and diverse samples. In the learning phase, several samples having more popular and various intensity values are extracted from the original sample set. Different weights are given to the distinct samples according to the related intensities. In the evaluation phase, the underlying probability density function is estimated using the weighted diversity samples in kernel density estimation. The diverse sample-set makes the evaluation computation inexpensive and efficient. The effectiveness of the proposed method is demonstrated in the traffic monitoring application.

Keywords: nonparametric background modeling, kernel density estimation, diversity sampling, traffic monitoring.

1 Introduction

Moving objects detection is an important task in computer vision and the first significant step for high-level understanding in traffic monitoring. As a simplified and efficient method, background subtraction (BGS) is the most popular approach for detecting moving objects in video sequence from static cameras. BGS compares the current frame with the estimated reference model of the stationary scenes, and then get the moving foreground mask with applying a threshold to the absolute difference (Fig.1). The background model must be a representation of the scene with no moving objects and must be kept regularly updated so as to adapt to the varying luminance conditions and geometry settings [1] [2], as such, background modeling is at the heart of any BGS algorithm [3]. A reliable and robust BGS algorithm should deal with sudden and gradual illumination changes, high frequency and repetitive motion in the scenes, e.g. tree leaves along the monitoring road and long-term scene changes, e.g. a car is parked for a certain long time, etc. Maintenance and updating of the scene...
representation which is called the background modeling is the main difficulty of BGS technique. In the literature numerous works have been published on background modeling. They can be divided into two classifications: non-recursive and recursive. The advantage and disadvantage are described in [1] [4].

Nonparametric approaches estimate the density function directly from the data without any assumptions about the underlying distribution. This avoids choosing a model and estimating its distribution parameters. However, nonparametric approaches are lazy learning methods in the machine learning techniques [5]. That is, they involve almost no computation in the learning phase while are computationally intensive in the evaluation phase.

2 BGS with Improved Kernel Density Estimation

2.1 Kernel Density Background Estimation

The values of a particular pixel over time can be considered as a pixel process, i.e. a time series of scalars for gray-value or vectors for color pixel values. Kernel density estimation is a particular nonparametric technique that estimates the underlying density as a weighted average of local functions centered at each sample point. It can asymptotically converge to any density function [7].

The density estimate \( \hat{p}(x_k) \) of at time \( t = k \cdot \Delta t \) can be calculated using

\[
\hat{p}(x_k) = \frac{1}{h} \sum_{i=1}^{N} \alpha_i K \left( \frac{x_k - x_i}{h} \right)
\]

where \( \{x_1, x_2, \ldots, x_N\} \) is a sample set of intensity values for a pixel, \( N \) is the number of samples, \( K(\cdot) \) is a kernel estimator with bandwidth \( h \) which is chosen to be Gaussian, \( \alpha_i \) are weighting coefficients that sum up to one. Usually, \( \alpha_i \) are set to \( \frac{1}{N} \) and every sample is treated as having the same contribution to the density estimation. However, there are several identical or similar samples, and different samples have different contributions to estimation. Therefore, a diversity-sampling mechanism is introduced and different weights are set to distinct samples.