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On shadow elimination after moving region segmentation based on different threshold selection strategies

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Abstract

A popular approach for detecting moving object regions in video sequences is the application of the background subtraction technique. According to this technique the background (reference) image is subtracted from the current image frame and the moving parts are detected by the selection of a suitable threshold. In this paper we present our work to discriminate the moving pixels of the generated difference images from the relatively stationary pixels through the use of three different threshold selection strategies, namely, (i) '3σ edit rule', (ii) rule utilizing the Hampel identifier, and (iii) rule based on an *ad hoc* selection of threshold. Further, after segmentation a method of classification, based on a moving shadow search technique, previously developed by the authors, has been applied to segregate the moving shadow region from the actual moving object. The speed-up achieved through the use of the three aforementioned techniques on the core moving shadow search process, compared to that where no such process has been applied, has been documented. The final outcomes of applying the shadow detection technique after segmenting using each of the threshold selection strategies, one at a time, on some indoor video sequences have been demonstrated and comparison of the methods made.

Keywords: Outliers detection strategy; '3σ edit rule'; Hampel identifier; Moving shadow detection method

1. Introduction

An outlier can be defined as 'an observation which deviates so much from other observations as to arouse suspicions that it was generated by a different mechanism' [1]. In other words, outliers are data points, $\lambda_k s$, in a data set, ζ, that deviate from our expectations based on the majority of the data [2]. Presence of such aberrant data points, if not properly handled, can seriously disrupt a critical process-control mechanism [2,3]. A thorough literature survey thus reveals that a lot of research has been done on outlier detection mechanisms [2–6] and also on data preprocessing and filtering [2,3]. However, apart from some studies such as [7], not much work has been done on the use of the outlier detection process to detect moving pixels from video sequences. In this work, we have deployed some of the popular outlier detection techniques to segment the moving region of the current image frames from the relatively stationary parts. We have then applied a shadow detection technique to discriminate the moving shaded region from the actual moving object.

A shadow is formed when light from a source is intercepted by an opaque body in such a way that the other side of the body not facing the source is in darkness. Projection of this dark region on a surface behind the object is known as a shadow region. Shadows, in general, can be categorized as static shadows or moving shadows depending upon whether the causal object is relatively static or moving [8]. Elimination of static shadows that usually form a part of the background has never been judged as a crucial pre-processing step as such shadows usually do not jeopardize the actual foreground object recognition process of surveillance systems [9]. On the other hand, shadows cast by dynamic objects or by objects suddenly brought into a background scene are often misclassified as the actual foreground objects leading to poor object segmentation and tracking [8]. Hence, a foreground shadow region elimination process has become an unavoidable pre-processing step for the development

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and implementation of a robust and reliable real-time video surveillance system.

In this context, it should be mentioned that the use of relaxed thresholds to mark or eliminate as much as possible both the strong and soft portion of the moving shadow region for real-time applications calls for a prior segmentation method, based on a threshold, to mark the locations of the moving pixels of the current frame. This requirement, together with the idea that background pixels can be considered as inliers and moving pixels as outliers, served as the basic motivation behind our work.

In this paper, a preliminary idea about outliers and some of the popular outlier detection strategies are described in the next section. The following section describes how such detection strategies have been utilized to generate the binary mask from the difference image, and how further classification is made. Finally results obtained through the use of a prior segmentation method have been demonstrated and compared with the results where no such method has been applied.

2. Outliers and outlier-detection strategies

Outliers are data points, $\lambda_k s$, in a data set, ζ, that do not comply with our expectations based on the bulk of the data [2]. Various detection strategies have been thought of to detect such aberrant data points for data preprocessing or filtering. Such strategies include visual inspection of data values of the set, fitting of models of desired form to the data and then examining the residuals or using deletion diagnostic approaches, etc. [2]. However, efforts made towards the detection of outliers using the above-mentioned strategies may prove to be futile due to the reasons described in [2] and, even if possible, are not applicable to meet our objective, as not only is the data set we are dealing with typically large but also due to the fact that the overall process has severe time constraints. In this respect, it should be mentioned that the visual inspection method of outlier detection cannot even be considered, as the overall process of moving region detection and classification has to be inherently automatic.

Fortunately, there are some other popular approaches for outlier detection. These well known and frequently used strategies depend on two estimates: (1) an estimate of a nominal reference value for the data set, and (2) a scatter estimate of the data. Based on these estimators, outliers can be detected based on the following criterion:

$$|\lambda_k - \lambda_{kr}| > \alpha\gamma \Rightarrow \lambda_k = \lambda_{ko}, \quad \forall \lambda_k \in \zeta, \tag{1}$$

where in (1), λ_{kr} is the nominal reference value of the data set, α is the threshold parameter, γ the scatter estimate, and λ_{ko} an outlier.

2.1. The '3σ edit rule'

The '3σ edit rule' considers the mean of the data values of the data set as the nominal reference value and the corresponding standard deviation as an estimate of the scatter:

$$\lambda_{kr} = \lambda_{\text{mean}} = \frac{1}{N}\sum_{k=1}^{N} \lambda_k, \tag{2}$$

where in (2), N is the total number of observations in the data set.

$$\gamma = \left[\frac{1}{N-1}\sum_{k=1}^{N}(\lambda_k - \lambda_{\text{mean}})^2\right]^{1/2}. \tag{3}$$

It should be noted that if the distribution is assumed to be approximately normal, then the probability of getting a data value greater than three times the standard deviation of the data ($\alpha = 3$), added to the mean, is around 0.3% [2]. However, the technique suffers from the fact that both the mean and the standard deviation of the data are very much outlier sensitive [2]. Moreover, the strategy heavily depends on the assumption that the underlying distribution is approximately Gaussian.

2.2. Strategy based on Hampel identifier

This strategy capitalizes on the fact that the outlier sensitive mean and standard deviation estimates are replaced by the outlier resistant median (breakpoint value of 50%) and median absolute deviation from the median (MAD) scale estimates, respectively. The median of a data sequence is obtained as follows [10]:

(1) The observations are ranked according to their magnitude.
(2) If N is odd, the median is taken as the value of the $[(N+1)/2]^{\text{th}}$ ranked observation; otherwise if N is even, the median is taken as the mean of the $(N/2)^{\text{th}}$ and $[(N/2)+1]^{\text{th}}$ ranked observations.

The MAD scale estimate is defined as

$$\gamma = \text{MAD}_{\text{se}} = 1.4826 \times \text{median}\,\{|\lambda_k - \lambda_{\text{median}}|\}, \tag{4}$$

where in (4), 'the factor 1.4826 was chosen so that the expected value of γ is equal to the standard deviation for normally distributed data' [2].

The strategy, although quite often very effective in practice [2], is stymied by the fact that if more than 50% of the observations are of the same value, then the scale estimate is equal to 0, i.e. every data value greater than the median would then be considered as an outlier.

In this context, it should be noted that the mean could also be replaced by the median and the standard deviation by the interquartile deviation, giving rise to the so called standard box plot outlier detection strategy [11].

3. The computational model

The colour model utilized [9] is based on a statistical approach [12], and is analogous to the one developed by