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Using Resources Competition and Memory Cell Development to Select the Best GMM for Background Subtraction

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ABSTRACT

Background subtraction is an essential step in the process of monitoring videos. Several works have proposed models to differentiate the background pixels from the foreground pixels. Mixtures of Gaussian (GMM) are among the most popular models for a such problem. However, the use of a fixed number of Gaussians influence on their results quality. This article proposes an improvement of the GMM based on the use of the artificial immune recognition system (AIRS) to generate and introduce new Gaussians instead of using a fixed number of Gaussians. The proposed approach exploits the robustness of the mutation function in the generation phase of the new ARBs to create new Gaussians. These Gaussians are then filtered into the resource competition phase in order to keep only ones that best represent the background. The system tested on Wallflower and UCSD datasets has proven its effectiveness against other state-of-art methods.

KEYWORDS

Background Pixel, Background Subtraction, Foreground Pixel, Gaussian Model, Moving Objects, Pixels Classification, Static Objects, Video Surveillance

INTRODUCTION

Moving objects segmentation from scenes that are captured with a stationary/non-stationary camera is one of the most difficult and interesting activities in computer vision (Brutzer et al., 2011; Lim and Keles, 2018b). Subtracting the background requires a powerful method that ensures a good separation between the background and the foreground.

In the literature, there are several methods for detecting moving objects without knowing any prior information about them (Toyama et al., 1999). Generally, all these methods share the following steps (Bouwmans, 2012):

Background Initialization

In this step, a primary background model is constructed and learned by a set of frames that have no moving objects. There are many ways which can be designed this model like (statistical, fuzzy, neuro-inspired, etc.).

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Foreground Detection

After initializing the background model, each frame is compared with the background model to define the foreground.

Background Maintenance

During this step, all settings of the background model are updated to pick up any novel changes in the background within a video.

GMM is one of the most popular methods that has achieved considerable success in detecting changes in videos. However, this method has failed in problems related to: lighting changes and hidden areas. Several studies showed that the number of Gaussians in GMM influence on the results quality. The contribution of this work is to manage dynamically the number of Gaussians based on the AIRS algorithm instead of fixing them a priori by the user. This paper proposes to generate a set of new Gaussians using two different strategies: the first one (Random generation) uses the AIRS to improve the system decision while the second one (Directed generation) uses the AIRS to improve the GMM learning phase.

Random Generation

Firstly, the system stars with a learning phase using the GMM algorithm. During the classification stage, the AIRS generates several Gaussian models using Memory cell identification and ARB generation process for all pixels regardless their nature. These models are filtered according to the resource competition and memory cell development process of the AIRS algorithm to select only the best models. Once the AIRS algorithm is finished, the GMM method is used to decide the pixels nature.

Directed Generation

It begins with the same first step as a random generation method and consists to apply Memory cell identification and ARB generation process only for pixels representing the background. Indeed, the system used the GMM algorithm to filter background from foreground pixels before the mutation process to reduce the time consumed to generate new models and to improve accuracy since the mutation process is based only on pixels representing the background.

To cover all sections, the paper is organized as follows: Section 2 provides an overview of literature works related to background subtraction in which we proposed a taxonomy. Section 3 and 4 present a definition of methods used (GMM, AIRS). Section 5 is dedicated to our contribution in which we present two propositions. Some experiments on Wallflower and UCSD datasets are discussed in section 6. Section 7 concludes the paper.

RELATED WORKS

Subtracting the background from videos remains a crucial problem due to the background variations. Several studies have been proposed to improve the quality of background subtraction results. These studies can be divided into two groups: the first group is focused on selecting a good feature (color, texture, edge), while the other try to choose the best algorithm for video changes detection. Among the approaches that are interested in selecting the right features:

St-Charles et al. (2015b) proposed a new universal pixel-level segmentation method based on the selection of spatiotemporal binary features and colors to detect video changes. Authors in (Wang et al., 2018) exposed a type of multi-view learning based on the use of heterogeneous features such as: brightness variation, chromaticity and texture variation to define background and foreground pixels. In (Allebosch et al., 2015), authors proposed a model that combines RGB color space and edge descriptors to classify the pixels.