High Definition Video Segmentation Techniques-A Review

R. S. Sabeenian and S. Lavanya

Abstract—Real time segmentation of moving regions in image sequences is a fundamental step in many vision systems including automated visual surveillance human-machine interface and very low bandwidth telecommunications. Background identification is a common feature in many video processing systems. One of the most important back ground identification algorithm is the Gaussian Mixture Model algorithm (GMM). On implementation of the Gaussian mixture model on FPGA results in Reduction of the processing capability of the overall system. Trainable Segmentation is adapted to improve the processing capability. After analyzing and evaluating the performance we conclude with several promising directions for future research.

Index terms—Video segmentation, background identification.

I. INTRODUCTION

Background modeling [1], is often used in different applications to model the background and then detect the moving objects in the scene like in video surveillance [2], [3], optical motion capture [4]-[6] and multimedia [7]-[10]. The simplest way to model the background is to acquire a background image which doesn't include any moving object. In some environments, the background isn't available and can always be changed under critical situations like illumination changes, objects being introduced or removed from the scene. To take into account these problems of robustness and adaptation, many background modeling methods have been developed and the most recent surveys can be found in [11], [12]. These background modeling methods can be classified in the following categories: Basic Background modeling [13], [14], Statistical Background Modeling [15], Fuzzy Background Modeling [16] and Background Estimation [17]. Other classifications can be found in term of prediction, recursion, adaptation, or modality [18]. All these Modeling approaches are used in background subtraction context which presents the following steps and issues: background modeling, background initialization, background maintenance, foreground detection, choice of the feature size (pixel, a block or a cluster), choice of the feature type (color features, edge features, stereo features, motion features and texture features). Developing a background subtraction method, all these choices determine the robustness of the method to the critical situations met in video sequence [3] Noise image due to a poor quality image source (NI), Camera Jitter (CJ), Camera automatic adjustments (CA), Time of the day (TD), Light Switch (LS), Bootstrapping (B), Camouflage (C), Foreground Aperture (FA), Moving background objects (MO), Inserted Background Objects (IBO), Multimodal Background (MB), Waking Foreground Object (WFO), Sleeping Foreground Object (SFO) and Shadows (S). Different datasets benchmarks are available to evaluate the robustness of the background subtraction methods against these critical situations which have different spatial and temporal characteristics which must be take into account to obtain a good segmentation. We explain the video segmentation algorithms in section ii and back Ground modeling in section iii and proposed solution to the drawback is given in section IV.

II. VIDEO SEGMENTATION ALGORITHMS

Chien et al developed an adaptive background model using so called background registration approach. In their paper, they assume that the longer a pixel remains stationary, the more probable that it belongs to the background. By counting whether a pixel stays approximately in the same value for a predefined period, a new background pixel is registered to the background memories where the old value is discarded. In this way, background plane is updated progressively and the moving object is detected by thresholding the difference between the current frame and the registered background plane. A number of other adaptive background models have also been reported. Although these algorithms produce better modeling towards real world scenarios by background learning process, most of them fail to deal with multi-modal background distribution. A multimodal background distribution is caused by repetitive background object motion, for example, swaying trees, reflections of the lake surface, flickering of the monitor etc. As the pixel, lying in the region where repetitive motion occurs, will generally consists of two or more background colors, the RGB value of that specific pixel changes over time. This would result in false foreground object detection by most adaptive background estimation approach mentioned above. In [19], a background model based on multi-modal pixel distribution is proposed to address the issue. By representing each pixel process using a mixture of Gaussian distributions, repetitive background motions are merged into one of the several background distributions for each pixel. However, as the

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algorithm processes video stream pixel wise by updating several Gaussian distributions for each pixel, the calculation burden in parameter updating is unbearable for computers in real time applications. In [19], only a frame rate of 11-13 frames/s is obtained even for small frame size of 160×120 on an SGI O2 workstation. For real time video applications with larger frame size, dedicated hardware architecture seems to be a must. However, as far as the authors’ knowledge, no such hardware implementation has been reported before. Furthermore, issues emerge with regard to memory bandwidth and storage when it comes to implementation, which is quite common to most video/image processing task. Since the update of background distribution is slow most of the time in a slowly changing scene, the word length of each parameter tends to grow to fulfill the increasing dynamic range. With a reasonable frame size of 352×288 that is used throughout this paper, and under the assumption that 3 Gaussian are used for each pixel process, approximately 6 MB data have to be updated for each frame. This imposes a huge demand for calculation as well as memory bandwidth and size. In paper, dedicated hardware architecture is developed aiming to address all the issues mentioned. With an FPGA platform, simulations can be accomplished in real-time to observe long term effects resulting from fixed point quantization as well as parameter settings. In addition, a controller synthesis tool is developed to reduce the design effort for controller design.

### III. BACKGROUND MODELING USING MIXTURE OF GAUSSIANS

In the context of a traffic surveillance system, Friedman and Russell proposed to model each background pixel using a mixture of three Gaussians corresponding to road, vehicle and shadows. This model is initialized using an EM algorithm. Then, the Gaussians are manually labeled in a neural network or a set of neural networks. After such a classification, each pixel is compared with each Gaussian and is classified according to it corresponding Gaussian. The maintenance is made using an incremental EM algorithm for real time consideration. Stauffer and Grimson [19] generalized this idea by modeling the recent history of the color features of each pixel \(X_t, \ldots, X_{t+j}\) by a mixture of \(K\) Gaussians. We remind below the algorithm.

**Principle**

First, each pixel is characterized by its intensity in the RGB color space. Then, the probability of observing the current pixel value is considered given by the following formula in the multidimensional case:

\[
P(X_t) = \sum \omega_{i,t} \eta(X_t; \mu_{i,t}, \sum_{i,t})
\]

where the parameters are \(K\) is the number of distributions, \(\omega_{i,t}\) is a weight associated to the \(i^{th}\) Gaussian at time \(t\) with mean \(\mu_{i,t}\) and standard deviation \(\sum_{i,t}\) \(\eta\) is a Gaussian probability density function:

\[
\eta(X_t; \mu_{i,t}, \sum_{i,t}) = \frac{1}{(2\pi)^{n/2}} \left| \sum_{i,t} \right|^{-1/2} e^{-\frac{1}{2} (X_t - \mu_{i,t})^T \sum_{i,t}^{-1} (X_t - \mu_{i,t})}
\]

For computational reasons, Stauffer and Grimson [19] assumed that the RGB color components are independent and have the same variances. So, the covariance matrix is of the form:

\[
\sum_{i,t} = \sigma_{i,t} I
\]

So, each pixel is characterized by a mixture of \(K\) Gaussians. Once the background model is defined, the different parameters of the mixture of Gaussians must be initialized. The parameters of the MOG’s model are the number of Gaussians \(K\), the weight \(\omega_{i,t}\), associated to the \(i^{th}\) Gaussian at time \(t\), the mean \(\mu_{i,t}\) and the covariance matrix \(\sum_{i,t}\). \(K\) determined the multimodality of the background and by the available memory and computational power. Stauffer and Grimson [19] proposed to set \(K\) from 3 to 5. The initialization of the weight, the mean and the covariance matrix is made using an EM algorithm. Stauffer and Grimson [19] used the \(K\)-mean algorithm for real time consideration. Once the parameters initialization is made, a first foreground detection can be made and then the parameters are updated. Firstly, Stauffer and Grimson [19] used as criterion the ratio \(r_{i,t} / \sigma_{i,t}\) and ordered the \(K\) Gaussians following this ratio. This ordering supposes that a background pixel corresponds to a high weight with a weak variance due to the fact that the background is more present than moving objects and that its value is practically constant. The first \(B\) Gaussian distributions which exceed certain threshold \(T\) are retained for a background distribution:

\[
B = \arg \min_b (\sum \omega_{i,t} \sum_{i,t})
\]

### IV. TRAINABLE SEGMENTATION

Most segmentation methods are based only on color information of pixels in the image. Humans use much more knowledge than this when doing image segmentation, but implementing this knowledge would cost considerable computation time and would require a huge domain-knowledge database, which is currently not available. In addition to traditional segmentation methods, there are trainable segmentation methods which can model some of this knowledge. Neural Network segmentation relies on processing small areas of an image using an artificial neural network or a set of neural networks. After such processing the decision-making mechanism marks the areas of an image accordingly to the category recognized by the neural network. A type of network designed especially for this is the Kohonen map.

Pulse-Coupled Neural Networks (PCNNs) are neural models proposed by modeling a cat’s visual cortex and developed for high-performance biomimetic image processing. In 1989, Eckhorn introduced a neural model to emulate the mechanism of a cat’s visual cortex. The Eckhorn model provided a simple and effective tool for studying the visual cortex of small mammals, and was soon recognized as having significant application potential in image processing. In 1994, the Elkhorn model was adapted to be an image
Open-source Implementations of trainable segmentation:
1) Trainable Segmentation Plug-in
2) IMMI Segmentation benchmarking.
   Several segmentation benchmarks are available for comparing the performance of segmentation methods with the state-of-the-art segmentation methods on standardized sets. 1. Prague On-line Texture Segmentation Benchmark
3) The Berkeley Segmentation Dataset and Benchmark

V. PERFORMANCE EVALUATION

For the performance evaluation, we have chosen some typical algorithms that specifically ones which the authors used the Wallflower dataset to evaluate them. This dataset is the most used and consists in a set of image sequences where each sequence presents a different type of difficulty that a practical task may meet. The performance is evaluated against hand-segmented ground truth. The three terms used in evaluation: False Positive (FP) is the number of background pixels that are wrongly marked as foreground; False Negative (FN) is the number of foreground pixels that are wrongly marked as background; Total Error (TE) is the sum of FP and FN. A brief description of the Wallflower image sequences can be made as follows:
1) Moved Object (MO) - A person enters into a room, makes a phone call, and leaves. The phone and the chair are left in a different position.
2) Time of Day (TOD) - The light in a room gradually changes from dark to bright. Then, a person enters the room and sits down.
3) Light Switch (LS) - A room scene begins with the lights on. Then a person enters the room and turns off the lights for a long period. Later, a person walks in the room, switches on the light, and moves the chair, while the door is closed.

4) Waving Trees (WT) - A tree is swaying and a person walks in front of the tree.
5) Camouflage (C) - A person walks in front of a monitor, which has rolling interference bars on the screen. The bars include similar color to the person’s clothing.
6) Boosting (B) - The image sequence shows a busy cafeteria and each frame contains people.
7) Foreground Aperture (FA) - A person with uniformly colored shirt wakes up and begins to move slowly.

In Fig. 1, we have represented the overall performance for the five first algorithms and in Fig. 2 for the seven algorithms but without the image sequences Moved Object, Time of Day and Light Switch. Fig. 1 and Fig. 2 are not intended to be a definitive ranking of these algorithms. Such a ranking is necessarily task-, sequence-, and application dependent.

VI. CONCLUSION

The various video segmentation algorithms are reviewed and the drawbacks of implementing the Gaussian mixture model on FPGA can be overcome by adapting the trainable segmentation to improve the processing capability of the overall system. Due to the real time processing reduces the analysis of long term effects due to changes in algorithms and parametric changes. The main bottleneck of image processing algorithms is the high memory requirements.

REFERENCES


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