BACKGROUND SUBTRACTION BASED AFA FOR MOVING OBJECT SEGMENTATION

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***Abstract*- The new algorithm for moving object detection in the presence of challenging dynamic background conditions is proposed in this paper. Moving object detection from video sequence is a fundamental step in many visual surveillance applications like optical tracking, human action recognition, high level behavior understanding etc. The algorithm use a set of fuzzy aggregated multi feature similarity measures applied on multiple models corresponding to multimodal backgrounds. The algorithm enrich with a neighborhood-supported model initialization strategy for fast convergence. A model level fuzzy aggregation measure driven background model maintenance ensures more robustness. Similarity functions evaluate between the corresponding elements of the current feature vector and the model feature vectors. Concept from Sugeno and Choquet integrals are incorporated in our algorithm to compute fuzzy similarities from the ordered similarity function values for each model. Model updating use to the foreground/background classification decision is based on the set of fuzzy integrals. The propose algorithm is shown to outperform other multi-model background subtraction algorithms. The propose approach completely avoids explicit offline training to initialize background model and can be initialized with moving objects. The feature space use a combination of intensity and statistical texture features for better object localization and robustness. The qualitative and quantitative studies illustrate the mitigation of varieties of challenging situations by the approach.**

***Index Terms*—Moving object detection, statistical local texture features, model feature vectors, model level fuzzy similarity, neighborhood supported model initialization, model level fuzzy aggregation.**

I. INTRODUCTION

Background subtraction is a widely used approach for detecting moving objects in videos from static cameras. The rationale in the approach is that of detecting the moving objects from the difference between the current frame and a reference frame, often called the ―background image‖, or ―background model‖. As a baric, the background image 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.

More complex models have extended the concept of ―background subtracticn‖ beyond its literal meaning.Several methods for performing background subtraction have been proposed in the recent literature. All of these methods try to effectively estimate the background model from the temporal sequence of the frames. However, there is a wide variety of techniques and both the expert and the newcomer to this area can be confused about the benefits and limitations of each method.

All these methods have the following steps: Background Modeling, Background Initialization, Background Maintenance and Foreground Detection. Developing a background subtraction method, researchers must design each step and choose the features size (pixel, a block or a cluster) and type (color, edge, stereo, motion and texture) in relation to the critical situations they want to handle. In this article, we focus on the foreground detection and the background maintenance using color features.

In this paper, we propose a novel background model that consists of a fuzzy rule-based system which adaptively adjusts the weights of the texture and color features based on the pixel's local properties. The method is leveraging on the complementary nature of texture and color features and it does not require parameter learning from the clean background scene. Experimental results on nine challenging videos show that our method can provide more robust background subtraction under dynamic conditions.

The rest of the paper is organized as follows: Section 2 describes some the related work of background image subtraction techniques reviewed. Section 3 presents detailed explanation of our proposed model of background subtraction Section 4 presents experimental and results of proposed model.

II. RELATED WORK

The approaches reviewed in this paper range from simple approaches, aiming to maximise speed and limiting the memory requirements, to more sophisticated approaches, aiming to achieve the highest possible accuracy under any possible circumstances. All approaches aim, however, at real-time performance, hence a lower bound on speed always exists. The methods reviewed in the following are

A. GMM Background Subtraction

Over time, different background objects are likely to appear at a same (i,j) pixel location. when this is due to a permanent change in the scene's geometry, all the models reviewed so far will, more or less promptly, adapt so as to reflect the value of the current background object. However, sometimes the changes in the background object are not permanent and appear at a rate faster than that of the background update. A typical example is that of an outdoor scene with trees partially covering a building: a same (i,j) pixel location will show values from tree leaves, tree branches, and the building itself. Other examples can be easily drawn from snowing, raining, or watching sea waves from a beach. In these cases, a single valued background is not an adequate model.

Gaussian Mixture Model (GMM) has been a popular approach to background modeling. Each pixel is modeled by a mixture of Gaussian distributions where each Gaussian represents the pixel's intensity distribution over time.

However, the Gaussian assumption for the distribution does not always hold. The estimation of the model parameters (especially variance) can become unreliable for noisy images.

B. Feature based Background Subtraction

It is proposed to use both color and texture information, they modeled each pixel with LBP and photometric invariant RGB color features. The invariance is achieved by measuring the relative angle between foreground and background pixels in RGB space with respect to origin and extreme values for the background pixels which are obtained in the background learning process. However, the learning process requires background frames containing no foregroundobject. As a result, the learned background parameters are inaccurate if the background is noisy or the background ischanging.

C. Fuzzy Rule Dynamic Background Subtraction

In this paper, we propose a novel background model that consists of a fuzzy rule-based system which adaptively adjusts the weights of the texture and color features based on the pixel's local properties. The method is leveraging on the complementary nature of texture and color features and it does not require parameter learning from the clean background scene. Experimental results on nine challenging videos show that our method can provide more robust background subtraction under dynamic conditions.conventional LBP approaches fail to detect uniform foreground objects in large uniform areas. This is because the texture information in these regions is very low. As such, color information should be more reliable in identifying the foreground objects. Conversely, hue values are unstable when saturation values are approaching zero (achromatic axis) [13]. Thus, texture information should be emphasized instead. The decision should also factor in whether the current pixel is more likely to be classified as foreground or background. For example, if both texture and color similarity scores are high, then it is quite confident that the pixel belongs to the background and the importance of both features should be on par. In view of this, we propose a fuzzy rule-based system that adaptively adjusts the weight of the texture and color features based on the pixel's local properties, namely the current pixel texture similarity score, the uniformity of the binary pattern, the color similarity score and the saturation value. This is in contrast to the trial and error method which is a common practice in the literature.

In this subsection, present the definitions of the fuzzy measures and the fuzzy integrals, which would be necessary for a proper understanding of the algorithm. Let X= {x_1, x_2, . .

.Definition-1 Fuzzy measure: A fuzzy measure μ on a set X (the universe of discourse with the subsets E, F,…) is a set function μ: μ(X)→ [0, 1], satisfying the following two conditions:

(a) μ(φ) = 0,μ(X) = 1 (boundary conditions).

(monotonicity condition).

The boundary and the monotonicity conditions permit us to interpret the measure of a set as the measure of its importance. As more information sources (in the context, more features) are added, the importance increases, and attains maximum value, which is one, when all the sources are considered. now consider a set of r model feature vectors $\{X^{m_k}\}$(k = 1, . . . , r) at the pixel (p, q) and let $X_{p,q}$be the current feature vector.

Definition-2 Similarity function: The similarity function $h(x_i^k)$ for the i^{th} component of the k^{th} model feature vector is given by

$$h(x_i^k) = \frac{\min(x_i^{m_k}, x_i)}{\max(x_i^{m_k}, x_i)} \qquad (1)$$

where, $x_i^{m_k}$ indicates the i^{th} component of the k^{th} model feature vector and xi indicates the ith component of the current feature vector. Let $x_1^{\prime k}, x_2^{\prime k}, \ldots\ldots\ldots . x_n^{\prime k}$ be a permutation of $x_1^k, x_2^k, \ldots\ldots\ldots . x_n^k$ that produces a non-decreasing order of similarity functions, i.e., $h(x_1^{\prime k}) \le h(x_2^{\prime k}) \le, \ldots\ldots\ldots . \le h(x_n^{\prime k})$.

III. PROPOSED WORK

Background subtraction is commonly used in the field of video surveillance [3], optical motion capture [4], and multimedia application [2] where it needs in the first step to detect the moving objects in the scene. The basic idea is to classified pixel as background or foreground by thresholding the difference between the background image Bt(x; y; t) and the current image It+1(x; y; t). Due of the presence of critical ituations, false positive or negative detection appear

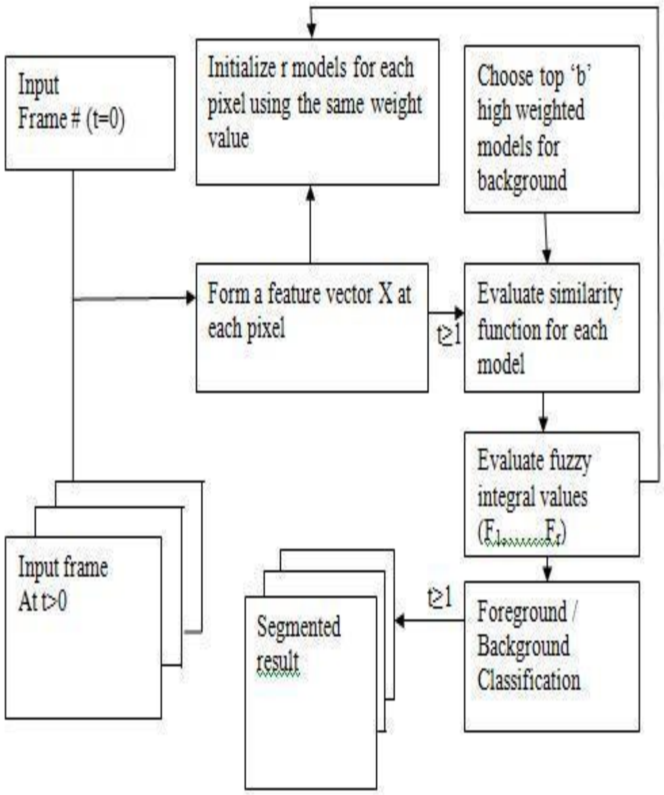

Fig 3.1 Schematic Diagram for Proposed Approach

corresponding to false classification of pixels. To decrease these effects, the different background subtraction methods have been developed and can be classified following the model used in the background representation step:

A. Choquet integral

In the litterature, many features are used for the detection of moving objects. In the case of color features, some authors make the foreground detection in each dimension independently and then aggregate the corresponding foreground mask using the binary operator (OR). The disadvantage is that a false positive in one dimension generate false positive in the final result. We propose thus to use a fuzzy operator i.e. the Choquet integral to aggregate the results obtained in each dimension to avoid crisp decision. In the following subsections, we first present the color similarity measure. Then, we summarize briefly concepts around fuzzy integrals and finally apply the Choquet integral to aggregate the similarity measure computed in different dimensions.

Definition-3 Choquet Integral: The Choquet integral FC of the similarity function with respect to the fuzzy measure μ is defined by

$$F^C = \sum_{i=1}^{n} \left(h(x_i') - h(x_{i-1}')\right)\mu(x_1', x_2', \ldots . x_n') \qquad (2)$$

$h(x_0')$= 0 and n is the number of features.

The superscript k on the i^{th} feature $x_i$is omitted as the integral is to be computed for every model for k = 1, . . . , r . Choquet integral not only generalizes arithmetic mean and weighted mean but also generalizes ordered weighted average.

Definition-4 Sugeno Integral: The Sugeno integral FS of the similarity function with respect to the fuzzy measure μ is defined by

$$F^S = \mathrm{Max}_{i=1}^{n}\left(\mathrm{Min}\left(h(x_i'), \mu(x_1', x_2', \ldots . x_n')\right)\right) \qquad (3)$$

Sugeno integral generalizes weighted maximum, weighted minimum, and weighted median operators. require the use of Sugenoλ-measure to compute the fuzzy measure μ on a subset of X, $\mu(x_1', x_2', \ldots . x_n')$.

B. *Advanced Fuzzy Aggregation Based Background Subtraction (AFABS)*

In AFABS, each pixel is modeled with a feature vector, composed of intensity and ST features, a combination of pixel and region-based features, to inherit the advantages of both types of features. By giving an importance value to each feature and fusing those by a fuzzy integral, correlations or interactions between the features can be considered. In this approach, multiple models are constructed for each pixel, where the models are initialized with neighborhood support, thereby achieving faster convergence of the background model to the background variations.

Model level fuzzy similarity, calculated between each model and the current by the fuzzy integral, represents the amount of matching between those, and the model is updated accordingly. The schematic diagram of the proposed approach is shown in Fig. 1. The algorithm consists of five steps — model initialization, background models selection, fuzzy integral calculation for all the models, background model updating, and the foreground detection. The last subsection deals with the optimization of the parameter values used in the proposed algorithm.

C. Local Binary Pattern

LBP is a robust gray-scale invariant texture feature. The LBP operator consists of labeling a pixel with a binary number obtained by thresholding the gray-scale difference between the gray-scale value of each neighbor of the pixel and the pixel's gray-scale value, and considering the multiple 0,1 output as a binary number. More formally, the LBP of the pixel **x** in an image **I** can be represented as follows:

$$LBP = \left\{LBP_{P,R}^{(p)}(X)\right\}_{p=1,\ldots,P}$$

$$LBP_{P,R}^{(P)}(X) = S(I^g(V_p) - I^g(X) - n), s(x) = \begin{cases} 1 & x \geq 0, \\ 0 & x < 0, \end{cases}$$

where$\mathbf{I}g(\mathbf{x})$ denotes the gray value of the pixel **x** in the image **I** and $\{\mathbf{v}p\}p=1,\ldots,P$ as a set of P equally spaced pixels located on a circle of radius R and center **x**. The parameter n is a noise parameter which should make the LBP signature more stable against noise (e.g. like compression) in uniform areas.

It is the minumum amount of positive grayscale variation that is considered as a significant change. Note that the LBP can be extended to color images with the LBP computed on each separated color channel. Also, multi-scale LBP can be defined with different radiuses at different levels.

LBP has several properties that are beneficial to its usage in background modeling. As a (binary) differential operator, LBP is robust to monotonic gray-scale changes, whether global or local illumination. In the latter case, cast shadow can be coped with when the shadow areas are not too small and the chosen circle radius for the LBP features is small.

Finally, LBP features are very fast to compute, which is an important property from the practical implementation point of view. The main limitation is that both memories and computation costs increase exponentially with the increasing of P. In this paper, we prefer to represent the LBP feature by a set of P binary numbers, with memory and computation cost linearly proportional to P.

IV. EXPERIMENT & RESULTS

We collected video sequences from internet The video datasets named Perception Test Images Sequences from web site[10] is used as testing our background model. For testing, we have used has four different video and each contains approximately 20 frames and its ground truth. The frame has size of 128x160 pixels.

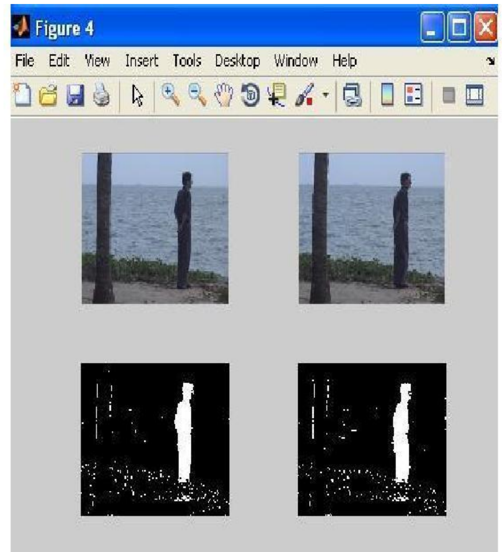

Figure-1 Background subtraction Water Surface video

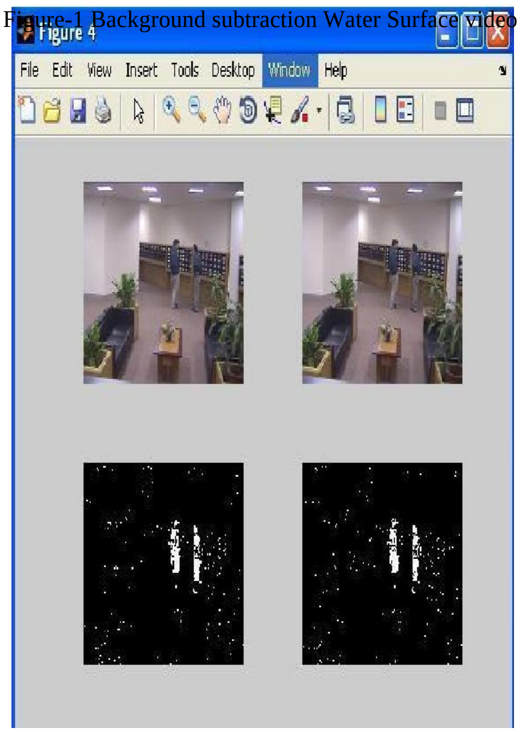

Figure-2 Background subtraction result lobby video

Metrics

We use several metrics in our evaluation to try to best characterize the performance. The most direct measure we use is the precision and recall of each pixel, following the methodology of Sheikh's work [11]. They are defined as follows:

$$precision = \frac{\#True\ Positives}{\#True\ Positives + \#\ True\ Negatives}$$

$$Recall = \frac{\#True\ Positives}{\#True\ Positives + \#FalseNegatives}$$

$$F = \frac{2.Recall.Precision}{Recall + Precision}$$

This measures the accuracy of the approach at the pixel level, but does not capture precisely its ability to give reasonable detections of birds for higher level classification.

Table 1 Performance of proposed model metrics

Video	Precision	Recall	Accuracy	F-Measure
Curtain	0.59	0.51	0.91	0.55
Fountain	0.59	0.40	0.95	0.45
Water Surfcae	0.80	0.81	0.97	0.80
Lobby	0.61	0.55	0.92	0.51

V. CONCLUSION

A model level fuzzy aggregation based background subtraction algorithm using intensity and ST features is presented and its superiority over other features' pixel level fusion is shown visually and numerically for both Sugeno and Choquet integrals. The models at a pixel are initialized with neighbors' feature vectors for faster convergence of the model by adapting the background variations occurring spatially. Qualitative and quantitative experiments are carried out to show the effectiveness of AFABS in handling various challenging situations by comparing with the state-of-the-art. AFABS (C)'s performance is superior as compared to AFABS (S). Being a hybrid approach, AFABS inherits the advantages of both types of approaches, using pixel and region-based features, by extracting moving objects with accurate shape and with minimum error in dynamic backgrounds. The resource analyzes consumption and performance in Spartan3 Xilinx FPGAs and compared to others works available on the literature, show that the current architecture is a good trade-off in terms of accuracy, performance and resource utilization. With less than a 65% of the resources utilization of a XC3SD3400 Spartan-3A low-cost family FPGA, the system achieve a frequency of 66.5 MHz reach 32.8 fps with resolution 1,024 × 1,024 pixels, and an estimated 5.76 W power consumption.

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