

# Adaptive Background subtraction in Dynamic Environments Using Fuzzy Logic

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**Abstract**— Extracting a background from an image is the enabling step for many high-level vision processing tasks, such as object tracking and activity analysis. Although there are a number of object extraction algorithms proposed in the literature, most approaches work efficiently only in constrained environments where the background is relatively simple and static. We extracted features from image regions, accumulated the feature information over time, fused high-level knowledge with low-level features, and built a time-varying background model. A problem with our system is that by adapting the background model, objects moved are difficult to handle. In order to reinsert them into the background, we run the risk of cutting off part of the object. In this paper, we develop a fuzzy logic inference system to detach the moving object from the background. Our experimental results demonstrate that the fuzzy inference system is very efficient and robust.

**Keywords**— Median filter, Background subtraction, Fuzzy.

## I. INTRODUCTION

Background subtraction is commonly used in the field of video surveillance, optical motion capture, and multimedia application where it needs in the first step to detect the moving objects in the scene. The basic idea is to classify 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 to the presence of critical situations, the detection and segmentation of moving objects in natural video sequences is an important requirement for multimedia indexing and retrieval, but also for adaptation. With the advent of broadly available mobile video players, it has become desirable to adapt video contents to small screens by choosing a suitable compromise between scaling and cropping [1]. This however requires the detection of video-objects that might be of interest. Approaches like Kopf's automatic scaling and cropping rely on pre-trained detectors for fixed kinds of objects like faces or superimposed text [2]. In contrast, background subtraction only relies on the assumption that an object moves. In our generalized approach, it

is only necessary that objects move different from global motion. In surveillance applications, background subtraction has become a standard method for video object segmentation. Even recent publications like [2] still use the scheme that originates from the publication by Stauffer and Grimson [7] who proposed to model the background image pixel-wise by Gaussian Mixture Models (GMM). This exploits the fact that background pixels in subsequent frames of a video should be highly correlated and therefore can be described by average color and variance. See [1] for an introductory overview. For a non-static camera however, the correspondences between background pixels are not given by their fixed coordinates but have to be estimated with a global motion model. The estimation of global motion as well as choosing a suitable model representation are still unsolved problems. For background subtraction however, pixel exact mosaics are required and it has been stated in literature that it is "impractical or even impossible to use a single background image" for a whole shot.

Our approach is to extract the object from the background and fill the corresponding image region with white pixels so as to block the identifying features. Our approach is to extract feature information from the object and develop statistical models, such as Hidden Markov Models, to model and track. In this paper, we address those problems through the use of fuzzy logic.

The rest of this paper is organized as follows. In section II, overview of Background subtraction is illustrated. In section III show the proposed scheme and fuzzy logic are presented in detail. Section IV shows the experimental results. Finally the conclusion is given in section V.

## II. OVERVIEW OF BACKGROUND SUBTRACTION

We assume that the camera is fixed. We formulate object extraction as an adaptive classification problem. The input video frame is partitioned into small blocks, for example, 4x4 blocks. For each block, a classification decision is made: the block belongs to the changes or not. To this end, we extract invariant features from the image blocks, as illustrated in Fig. 1.

Based on these features, we build a statistical model for the background and classify the image blocks into two categories: foreground and background. Because the background is time-varying, the background model and the classifier should be adaptive. However, background adaptive is also risky. For example, if a person sits still or sleeps in the couch for a long time, say hours, the adaptive background model will consider the person part of the background. This is not acceptable because of unprotected privacy. To solve this problem, we fuse the high-level knowledge obtained from object tracking with the low-level feature-based classification so as to guide the background update. At this stage, the foreground may still contain objects. To address this issue, we develop a decision process based on a fuzzy logic inference system to detach these objects from the background. In the following sections, we explain the proposed background subtraction scheme in detail.

### III. PROPOSED METHOD

We extract features in the RGB color space. Two feature variables: chromaticity and brightness distortions are used to classify the foreground and background [6]. The color model used here separates the brightness from the chromaticity components. The foreground and background classification is based on the following observation: image blocks in the background should have little change in their color distortion. The brightness distortion is very helpful in detecting shadows. In the proposed adaptive background modeling and classification scheme, we use the image data in the past  $\Delta$  frames to compute the joint distribution of these to build a background model. Based on these two features and background model, we classify the image block into foreground or background. Fig. 1 shows the basic block diagram of background subtraction.

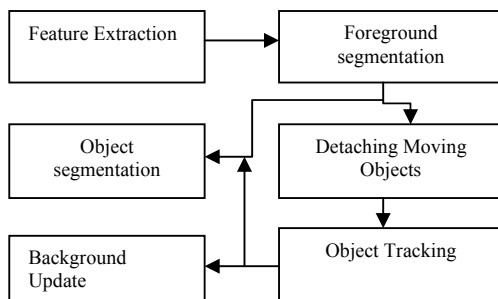


Figure 1. Basic block diagram

It should be noted that the value of the size of the shifting window should be appropriately chosen. If it is too small, the background is updated very fast. This

implies that the time duration of the shifting window should be quite large. However, if the time duration is too large, the background is updated very slowly. If a new object is introduced into the background or a background object is moved, before the background is updated, this object will be classified into the foreground and hence become part of the silhouette. To solve this problem, we utilize high-level knowledge about object motion to guide the adaptive update of the background model. Our basic idea is to track the object and predict its region in the scene. The image blocks which contain the object should be updated very slowly such that the object would not be updated as background.

The main contribution of this paper is a methodology to detach objects being moved. Detaching objects from the adaptive background is a challenging task because of the lack of automated reasoning about what is, and is not, a target object, as evidenced in a video sequence.

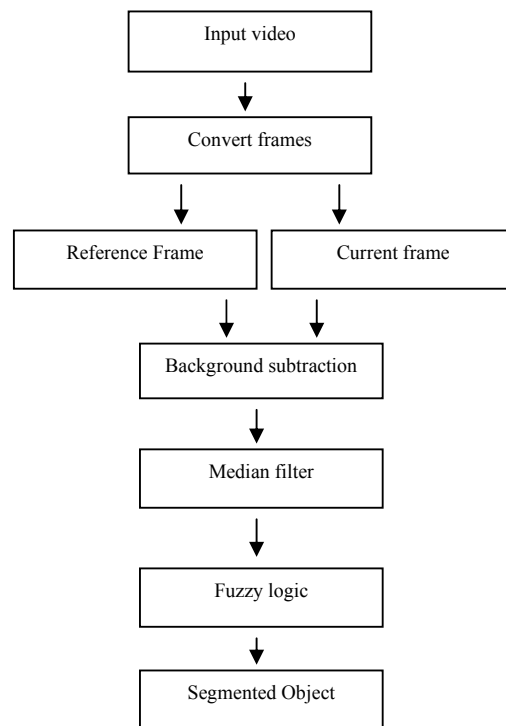


Figure 2. Proposed method

Certainly, sophisticated object recognition and identification algorithms could be used. However, these algorithms are often computationally intensive and not robust in a dynamic environment. Therefore, in this work, we propose a simple yet efficient algorithm for a object segmentation. Our scheme is based on a fuzzy logic inference system, which fuses multiple sources of information together for decision making. Suppose we are working on frame  $n$  and the object in frame  $n-1$  has been correctly extracted, denoted by  $O_{n-1}$ . Let the foreground image region in

frame  $n$  be  $O_n$ , which might contain the human body and moving objects. Our fuzzy logic inference system is based on the following observations.

- (1) If an image block in  $O_n$ , belongs to the object, it should have a high possibility of finding a good match in  $O_{n-1}$ . We use the SAD (sum of absolute difference) to measure the “goodness” of matching.
- (2) If a lot of blocks in its neighborhood have good matches in  $O_{n-1}$ , it is a high possibility that this block also belongs to the object.
- (3) If this block is far from the predicted position of the object centroid, as described in Section 4, it is a low possibility that this block belongs to the object. Based on these observations, we extract the following feature variables from each block in  $O_n$ 
  - ✓ SAD (Sum of Absolute Difference) in motion matching. For each block in  $O_n$ , we find its best match in frame  $n-1$ . The SAD between this block and its best match form the first feature variable.
  - The number of neighboring blocks having a good match in the object.
  - ✓ The distance between the new block and the predicted object centroid.

To determine the membership functions of these feature variables. A set of membership functions were defined from these distributions. The following 3 rules are used in our fuzzy logic inference system, and is illustrated in Fig 3 and Fig 4 in a MATLAB implementation [8].

1. If Difference is medium AND Neighborhood is small, THEN Object is low.
2. If SAD is high AND Neighborhood is small AND, THEN Object is high.
3. If SAD is high AND Neighborhood is high AND, THEN Object is high.

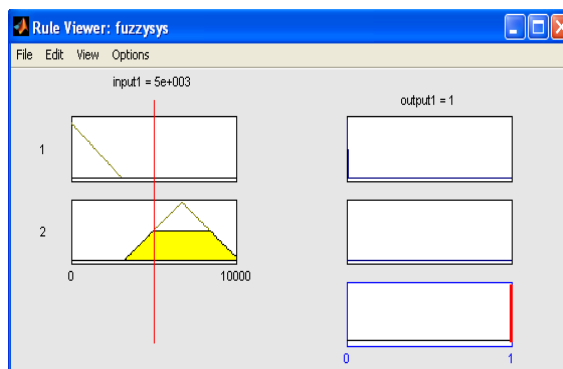


Figure 3. Ruleviewer of our fuzzy system

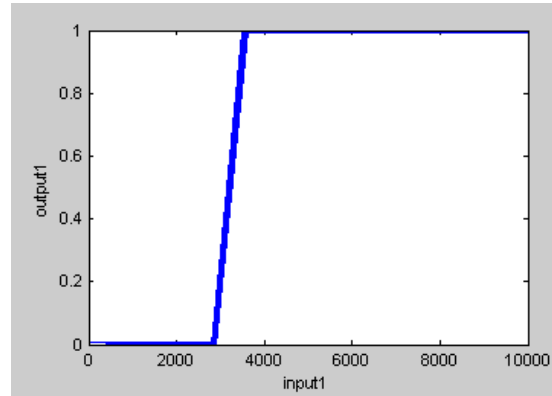


Figure 4. surface viewer of our fuzzy systems

We observe that using the fuzzy inference system to detach

moving objects will erode the object due to Misclassification. We use morphological operations and neighborhood information to repair these missing parts.

#### IV. EXPERIMENTAL RESULT

The following experimental results on several sequences show that the proposed fuzzy inference system for moving object detachment not only preserves the advantage of the low-level feature-based object extraction algorithm. As illustrated in Figs. 5 contains the original images, fig 6 shows the results of feature based object extraction, i.e., with no fuzzy logic processing, and fig 7 displays the results after moving object detachment using the fuzzy logic inference system. These results also verify the robustness of the proposed detaching algorithm. The fuzzy system even has the added benefit of removing some of the dark shadows that our color-based algorithm fails to detach. However, some of the hardened silhouettes appear slightly eroded. Since the goal is to perform activity analysis, the eroded object should not cause serious problems, although we are investigating better algorithms to fill out the fuzzy shape. Fig. 8 contains the results on one frame of the sequence “Moving car”. While the fuzzy logic system performs better than the corresponding crisp one, a good portion of the adaptive background is lost. As the sequence progresses, this error is compounded. Hence, we need more research on techniques to “rebuild” the displayed crisp silhouette from the fuzzy silhouette and methods to reacquire a good silhouette occasionally during the sequence. Since we will process long sequences of activity, a reasoning module should be able to detect when the object is stationary for a short time. Then, we believe that we can “reset” the golden standard silhouette.



Figure 5. Reference frame and current frame



Figure 6. Background subtraction for the adaptive video without fuzzy interference



Figure 7. Background subtraction for the adaptive video with fuzzy interference

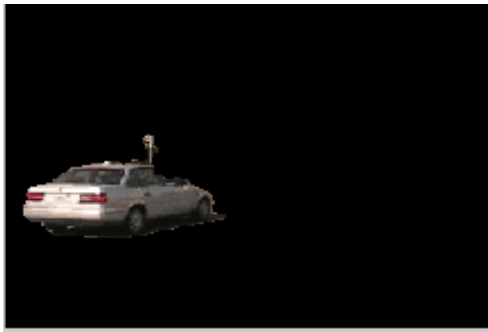


Figure 8. Segmented object

## V. Conclusions

In this paper, we proposed an accurate and robust object extraction scheme for a dynamic environment. We built a background model and extract classification features in RGB color space. To deal with the challenges of object extraction in dynamic environment, we fused high-level knowledge and low-level features and developed a fuzzy logic inference system. The results on several sequences show that this algorithm is efficient and robust for the dynamic environment with new objects in it. We are currently working on making the prediction more accurate and

creating a scheme to recover missing moving parts using known results from feature-based classification. Also, we intend to study the impact of the accuracy of results on the performance of future activity modeling and analysis

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