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Foreground-Background Segmentation Based on Codebook and Edge Detector

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Abstract—Background modeling techniques are used for moving object detection in video. Many algorithms exist in the field of object detection with different purposes. In this paper, we propose an improvement of moving object detection based on codebook segmentation. We associate the original codebook algorithm with an edge detection algorithm. Our goal is to prove the efficiency of using an edge detection algorithm with a background modeling algorithm.

Throughout our study, we compared the quality of the moving object detection when codebook segmentation algorithm is associated with some standard edge detectors. In each case, we use frame-based metrics for the evaluation of the detection. The different results are presented and analyzed.

Keywords-codebook; edge detector; video segmentation; mixture of gaussian;

I. INTRODUCTION

The detection of moving objects in video sequence is the first step in video surveillance system. The performance of the visual surveillance depends on the quality of the object detection. Many segmentation algorithms extract moving objects from image/video sequences. The goal of segmentation is to isolate moving objects from stationary and dynamic background. The variation of local or global light intensity, the object shadow, the regular or irregular background and foreground have an impact on the results of object detection.

The object detection techniques are subdivided in three categories which are without background modeling, with background modeling and combined approach. The techniques based on background modeling are recommended in case of dynamic background observed by a static camera. These techniques generally model the background with respect to relevant image features. So Foreground pixels can be determined if the corresponding features from the input image significantly differ from those of the background model. Three methods are used: background modeling, background estimation, background subtraction. Many research works have already been done [1], [2], [3], [4]. Generally, background modeling techniques improve the foreground-background segmentation performance significantly in almost every challenging envi-

ronment. They have better performance in both outdoor and indoor environments. The objects are integrated in background if they remain static over a specific delay. Sudden variation of light intensity make background model unstable.

The method proposed in [1] has better performance in these situations. Kim et al. [1] propose a real time foreground background segmentation using codebook model. This algorithm works in two steps which are learning phase and update phase. The learning consists to determine a background model which is compared to the input image. The model is updated with new image.

In this work, we are interested to combine the algorithm proposed in [1] with an edge detection algorithm. The main idea is to highlight the boundaries of objects in a scene. The using of an edge detector will verify if foreground pixels detected by the codebook algorithm belong to an object or not. In this paper we have explored three edge detectors : Sobel operator, Laplace of Gaussian operator and Canny edge detector.

The paper consists of five sections. In Section II we made a review on moving object detection using codebook. In section III we presented the proposed algorithm for foreground-background segmentation. In Section IV we presented the experimental results and we used some measures to evaluate the performance of the system. Finally in Section V we ended this work with further directions.

II. OBJECT DETECTION BASED ON CODEBOOK

The basic codebook background model is proposed in [1]. This method is widely used for moving object detection in case of stationary and dynamic background.

In this method, each pixel is represented by a codebook $\mathcal{C} = \{c_1, c_2, \dots, c_L\}$. The length of codebook is different from one pixel to another. Each codeword c_i , $i = 1, \dots, L$ is represented by a RGB vector $v_i = (R_i, G_i, B_i)$ and a 6-tuples $aux_i = \{\hat{I}_i, \hat{I}_i, f_i, p_i, \lambda_i, q_i\}$ where \hat{I} and \hat{I} are the minimum and maximum brightness of all pixels assigned to this codeword c_i , f_i is the frequency at which the codeword has occurred, λ_i is

the maximum negative run length defined as the longest interval during the training period that the codeword has not recurred, p_i and q_i are the first and last access times, respectively, that the codeword has occurred.

The codebook is created or updated using two criteria. The first criteria is based on color distortion δ whereas the second is based on brightness distortion. We calculate the color distortion δ using equation (1).

$$\delta = \sqrt{\|p_t\|^2 - C_p^2} \quad (1)$$

In this equation, C_p^2 is the autocorrelation of R, G and B colors of input pixel p_t and the codeword c_i , normalized by brightness. The autocorrelation value is given by equation (2).

$$C_p^2 = \frac{(R_i R + G_i G + B_i B)^2}{R_i^2 + G_i^2 + B_i^2} \quad (2)$$

According to [1], the brightness I has delimited by two bounds. The lower bound is $I_{low} = \alpha \hat{I}_i$ and the upper limit is $I_{hi} = \min\{\beta \hat{I}_i, \frac{\hat{I}_i}{\alpha}\}$. For an input pixel which have R, G and B colors, the formula of the brightness is given by equation (3).

$$I = \sqrt{R^2 + G^2 + B^2} \quad (3)$$

For each input pixel, if we find a codeword c_i which respect these two criteria (distorsion criteria and brightness criteria) then we update this codeword by setting v_i to $(\frac{f_i R_i + R}{f_i + 1}, \frac{f_i G_i + G}{f_i + 1}, \frac{f_i B_i + B}{f_i + 1})$ and aux_L to $\{\min(I, \hat{I}_i), \max(I, \hat{I}_i), f_i + 1, \max(\lambda_i, t - q_i), p_i, t\}$. If we don't find a matched codeword, we create a new codeword c_K . In this case, v_K is equal to (R, G, B) and aux_K is equal to $\{I, I, 1, t - 1, t, t\}$.

After the training period, if an incoming pixel matches to a codeword in the codebook, then this codeword is updated. If the pixel doesn't match, his information is put in cache word and this pixel is treated as a foreground pixel. If a cache word is matched more frequently so this cache word is put into codebook.

Although the original codebook is a robust background modeling technique, there are some failure situations. Firstly, for example, in winter, people commonly use black coats. If foreground-background segmentation is done using the codebook method, it may adopt black colour as background for many pixels. That is why a lot of pixels are incorrectly segmented. Secondly, if an object in the scene stops its motion, then it is absorbed in the background. Kim et al. [1] indicate tuning parameter to overcome this problem, but these modifications reduce the global performance of the algorithm in another situation. Due to the performance of the proposed method by [1], several researchers continue by digging further. These improvements can be classified into four points.

The first point is the improvement of the algorithm suggested by Kim et al. [1] by changing algorithm's parameters. In this category, Ilyas et al. [5] proposed to use maximum negative run length λ and frequency f_i to decide whether to delete codewords or not. They

also proposed to move cache codeword into the codebook when access frequency f_i is large. In [6], Cheng et al. suggested to convert pixels from RGB to YUV space. After this conversion they use the V component to build single gaussian model, making the whole codebook. Shah et al [7] used a statistical parameter estimation method to control adaptation procedure. Pal et al. [8] spreaded codewords along boundaries of the neighboring layers. According to this paper, pixels in dynamic region will have more than one codeword.

The second point is about the improvement of the codebook algorithm by changing algorithm's model. Some papers such as [9], [10] are proposed in this category. Doshi et al. [9] proposed to use the V component in HSV representation of pixels to represent the brightness of these pixels. They suggested a hybrid cone-cylinder model to build the background model. Donghai et al. [10] proposed codebook background modeling algorithm based on principal component analysis (PCA). The model overcomes the mistake of gaussian mixture model sphere model and codebook cylinder model.

The third point concerns the improvement of codebook algorithm by extension on pixels. Doshi et al. [9] proposed to convert pixel from RGB to HSV color space and Wu et al. [11] suggested to extend codebook in both temporal and spatial dimensions. Then the proposed algorithm in [11] is based on the context information. Fang et al. [12] proposed to convert pixels from RGB to HSL color space, and use L component as brightness value to reduce amount of calculation.

The fourth point concerns the improvement of the algorithm proposed in [1] by combining it with other methods. In this category, some papers are proposed such as [13], [14], [15]. Li et al. [13] suggested to combine gaussian mixture model and codebook whereas Wu et al. [14] proposed to combine local binary pattern (LBP) with codebook to detect object. LBP texture information is used to establish the first layer of background. Li et al [15] proposed to use single gaussian to model codewords. It builds a texture-wise background model by LBP. This work proposes moving object detection based on the combination of codebook with edge detector. We use the gradient information of the pixel to improve the detection.

III. PROPOSED ALGORITHM

Our proposed algorithm consists to combine the codebook with an edge detector algorithm. The goal of this combination is to improve the moving object detection in video.

After running the codebook algorithm for foreground-background segmentation we proposed to find the convex hull of each contour which have been detected in the result. We computed an edge detection algorithm and applied it on the original frame which have been converted from color image to grayscale. We perform a two-level thresholding. We thresholded image by using the edge detector response and pixels are displayed only if the gradient is greater than a value φ . The value of φ is given

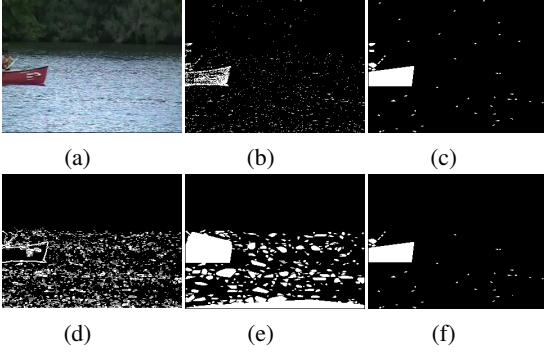


Figure 1. (a) image F_t , (b) image Ψ , (c) image t_1 , (d) image ϖ (using Sobel operator), (e) image t_2 , (f) image r .

by formula (4).

$$\varphi = G(1 - \theta) \quad (4)$$

In equation (4), G is the maximum gradient of input image and θ is a variable which value belongs to $[0, 1]$. The value of θ depends on the characteristics of the input sequence. This double thresholding allows us to select only the major edges. After that we also find the convex hull of contours which have been detected in thresholded image. At this step the potential objects which are on the frame are detected. Finally a comparison between the pixels detected by codebook and the pixel detected once thresholding is done. The role of this comparison is to identify effective foreground pixels. An effective foreground pixel is a pixel which has been classified to foreground pixels by codebook and has been detected to be an object's pixel by the edge detector.

The detailed algorithm is given by Algorithm 1. In this algorithm, we assume that :

- for each image of the sequence, the result of the segmentation is given by r ;
- the input pixel p_t has R, G and B colors;
- N is the number of images that we use for the training;
- L is the length of codebook;
- the size of the input image F_t is $m \times n$;
- Ψ , t_1 , t_2 , r , ϖ are the grayscale images which have same size with initial image F_t .
- $Threshold(x)$ is a procedure which thresholds the image x . The detailed procedure is given in Algorithm 2;
- $BGS(F_t)$ is a procedure which subtracts the current image F_t from the background model. It's described in [1]. For all pixels of the frame F_t , this procedure searches a matched codeword in the codebook. If a pixel doesn't match to any codeword, this pixel is treated as a foreground pixel.

Algorithm 1: Foreground-background segmentation

Input: video sequence S

Output: moving object

```

1  $l \leftarrow 0, t \leftarrow 1$ 
2 for each frame  $F_t$  of input sequence  $S$  do
3   for each pixel  $p_t$  of frame  $F_t$  do
4      $p_t = (R, G, B)$ 
5      $I \leftarrow \sqrt{R^2 + G^2 + B^2}$ 
6     for  $i = 1$  to  $l$  do
7       if ( $colordist(p_t, v_i)$ ) and ( $brightness(I, \{\hat{I}_i, \hat{I}_i\})$ ) then
8         Select a matched codeword  $c_i$ 
9         Break
10      if there is no match then
11         $l \leftarrow l + 1$ 
12        create codeword  $c_L$  by setting parameter
13         $v_L \leftarrow (R, G, B)$  and  $aux_L \leftarrow \{I, I, 1, t - 1, t, t\}$ 
14      else
15        update codeword  $c_i$  by setting
16         $v_i \leftarrow (\frac{f_i R_i + R}{f_i + 1}, \frac{f_i G_i + G}{f_i + 1}, \frac{f_i B_i + B}{f_i + 1})$  and
17         $aux_i \leftarrow \{\min(I, \hat{I}_i), \max(I, \hat{I}_i), f_i + 1, \max(\lambda_i, t - q_i), p_i, t\}$ 
18      for each codeword  $c_i$  do
19         $\lambda_i \leftarrow \max\{\lambda_i, ((m \times n \times t) - q_i + p_i - 1)\}$ 
20      if  $t > N$  then
21         $\Psi \leftarrow BGS(F_t)$ 
22        set the pixels which are in the convex hull of each
23        contour detected in  $\Psi$  to foreground pixel ( $t_1$ ).
24         $\varpi \leftarrow Threshold$  (convert  $F_t$  from RGB to
        grayscale)
25        set the pixels which are in the convex hull of each
26        contour detected in  $\varpi$  to foreground pixel ( $t_2$ ).
27         $r \leftarrow Intersect^1(t_1, t_2)$ 
28       $t \leftarrow t + 1$ 

```

The figure 1 illustrates results obtained by the intermediate steps of the proposed algorithm.

IV. EXPERIMENTAL RESULTS AND PERFORMANCE

In this section, we present the performance of the proposed approach by comparing with the codebook algorithm [1] and mixture of gaussian algorithm [2]. The section consists on two subsections. The first subsection presents the experimental results whereas the second presents and analyzes the performance of each algorithm.

A. Experimental Results

For the validation of our algorithm, we have selected two benchmarking datasets from [16] covered under

¹ $Intersect(t_1, t_2)$ returns an image. The result's pixels are considered to be foreground pixels if the corresponding pixels are considered as foreground pixels both by t_1 and t_2 .

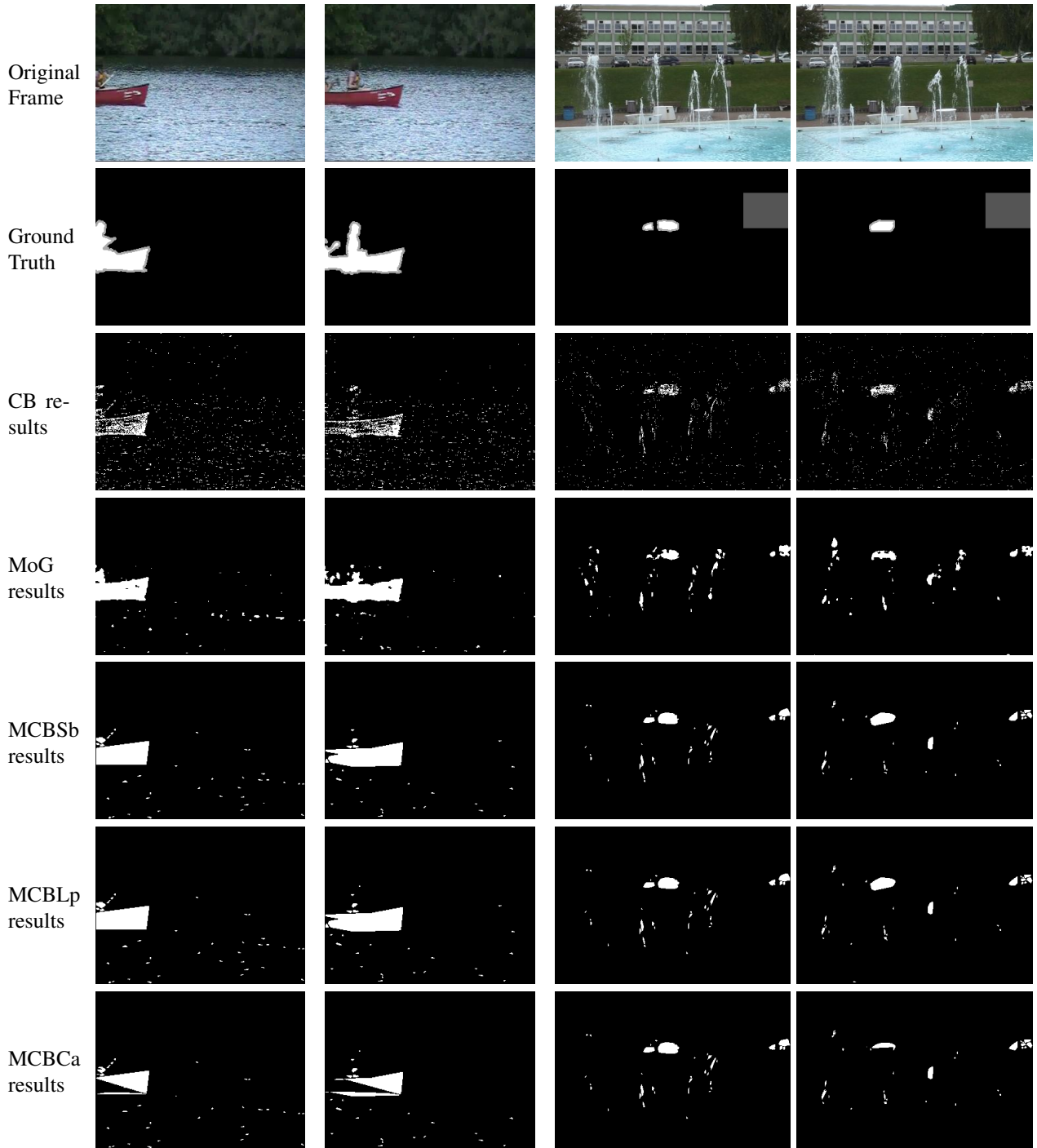


Figure 2. Segmentation results

the work done by [17]. They are “Canoe” and “fountain01” datasets. The experiment environment is Intel-Core7@2.13Ghz processor with 4GB memory and the programming language is C++. The parameters settings for mixture of gaussian were $\alpha = 0.01$, $\rho = 0.001$, $K = 5$, $T = 0.8$ and $\lambda = 2.5\sigma$. These parameters were suggested in [2]. According to [1], for codebook, parameter α is between 0.4 and 0.7, and parameter β belongs [1.1 1.5]. In this work, we take $\alpha = 0.4$ and $\beta = 1.25$. The parameter θ of our proposed method depends on the dataset. For “Canoe”

dataset we use $\theta = 0.85$ whereas for “fountain01” dataset we use $\theta = 0.80$. The results of segmentation are given in Figure 2. We assume that :

- CB means codebook;
- MoG means mixture of gaussian;
- MCBSb means combination of codebook and Sobel;
- MCBLp means combination of codebook and Laplacian of Gaussian operator;
- MCBCa means combination of codebook and Canny edge detector.

Algorithm 2: procedure *Threshold*

Input: grayscale image G **Output:** thresholded image t

```
1  $t \leftarrow \text{detectedge}^2(G)$ 
2 for each pixel  $p_i$  of  $t$  do
3   if intensity of  $p_i \geq$  maximum of  $t$ 's pixel
   intensity  $\times (1-\theta)$  then
4     intensity of  $p_i \leftarrow 255$ 
5   else
6     intensity of  $p_i \leftarrow 0$ 
```

B. Performance Evaluation and Discussion

In each case, we use an evaluation based on ground truth to show the performance of the segmentation algorithm. The ground truth has been obtained by labelling objects of interest in the original frame.

The ground truth based metrics are : true negative (TN), true positive (TP), false negative (FN) and false positive (FP). A pixel is a true negative pixel when both ground truth and system result agree on the absence of object. A pixel is a true positive pixel when ground truth and system agree on the presence of objects. A pixel is a false negative (FN) when system result agree of absence of object whereas ground truth agree of the presence of object. A pixel is a false positive (FP) when the system result agrees with the presence of object whereas ground truth agree with the absence of object. With these metrics, we compute other parameters which are:

- **False positive rate (FPR)** using formula (5);

$$FPR = 1 - \frac{TN}{TN + FP} \quad (5)$$

- **True positive rate (TPR)** using formula (6);

$$TPR = \frac{TP}{TP + FN} \quad (6)$$

- **Precision (PR)** using formula (7);

$$PR = \frac{TP}{TP + FP} \quad (7)$$

- **F-measure (FM)** using formula (8);

$$FM = \frac{2 \times PR \times TPR}{PR + TPR} \quad (8)$$

We also compare the segmentation methods by using **percentage of correct classification (PCC)** and **Jaccard coefficient (JC)**. PCC is calculate with formula (9) and JC is calculate with formula (10).

$$PCC = \frac{TP + TN}{TP + FN + FP + TN} \quad (9)$$

$$JC = \frac{TP}{TP + FP + FN} \quad (10)$$

We present the results in Table I and Table II. In these

²detectedge refers to the edge detector (Sobel operator, Laplace of Gaussian operator and Canny edge detector).

Table I
COMPARISON OF DIFFERENT METRICS ACCORDING TO EXPERIMENTS WITH DATASET "CANOE"

Metrics	CB	MoG	MCBSb	MCBLp	MCBCa
FPR	1.62	0.36	0.29	0.31	0.24
PR	41.01	89.82	86.29	86.01	81.89
FM	35.08	88.17	63.08	65.09	43.39
PCC	95.98	99.18	97.94	98.01	97.27
JC	21.27	78.85	46.07	48.24	27.71

Table II
COMPARISON OF DIFFERENT METRICS ACCORDING TO EXPERIMENTS WITH DATASET "FOUNTAIN01"

Metrics	CB	MoG	MCBSb	MCBLp	MCBCa
FPR	1.09	1.59	0.43	0.45	0.43
PR	2.24	4.01	6.82	7.31	6.79
FM	4.17	7.63	11.58	12.50	11.53
PCC	98.86	98.40	99.51	99.49	99.51
JC	2.13	3.97	6.14	6.67	6.11

Tables, we assume that, value in bold are the optimal value of the row. We analyzed the results in Table I and Table II through two steps. At first, we make a comparison between codebook, mixture of gaussian and our method based on the combination of codebook and edge detector. At the second stage, we make a comparative study of the performance of the system obtained after combination of codebook with the three edge detectors.

All experiments confirm that when codebook is combined with an edge detector, we get better result than original codebook. Experiments with "canoe" dataset prove that mixture of gaussian has good result than codebook. According to our results, the choice between mixture of gaussian and our method based on the combination of codebook and edge detector depends upon the application and the dataset's characteristics. Experimental Results with dataset "fountain01" show that our method is better than the mixture of gaussian approach. However, according to results of experiments with dataset "Canoe" we have two cases :

- 1) if we want to minimize the false alarms then FPR should be minimized. In this case, experiments show that method based on the combination of codebook and edge detector has the best result;
- 2) if we don't want to miss any foreground pixel we need to maximize TPR and FM. In this case, Experiments with allow us to use mixture of gaussian for segmentation.

The experimental results also prove that the choice of edge detection algorithm depends upon the application. For example, for an application in which the real-time parameter is not important, the use of Canny operator is recommended if we want to minimize the false alarms. But if we need to improve TPR then we use a Laplacian

of Gaussian operator. If we want to make a real-time application, we need to use Sobel operator, because the complexity of Sobel operator is less than Laplacian of Gaussian operator and Canny operator. The using of Sobel operator increases the codebook algorithm processing time by 19.55% (23.33% for laplacian of Gaussian and 28.15% for canny edge detector).

V. CONCLUSION

In this paper, we present a novel algorithm to segment moving objects with an approach combining the codebook and edge detector. Firstly, we segment sequence using codebook algorithm. This segmentation help us to know background pixels and foreground pixels. After that, by using edge detector, we show the object boundaries in each sequence. Then we set all foreground pixels which are not object's pixel to background pixel. The results can be summarized as follow :

- our method outperforms the codebook algorithm [1] in accuracy;
- in [1], authors claimed that codebook algorithm works better than the mixture of gaussian algorithm. This is not always true;
- the choice between our algorithm and the mixture of gaussian algorithm [2] depends on the input dataset's characteristics and the final application;
- the choice of edge detection algorithm which combines with codedook algorithm depends also on the characteristics of the sequence and the final application .

In the future, we will propose an extended version by adding a region based information in order to improve the compactness of the foreground object.

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