

# AUTOMATIC SHOT BOUNDARY DETECTION USING GAUSSIAN MIXTURE MODEL

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**Abstract:** The basic step for video analysis is the detection of shots in a given video. A shot is sequence of frames captured in a single continuous action in time and space using a single camera. The boundary between two adjacent shots may be an abrupt change (hard cut) or gradual change. In literature, many shot boundary detection algorithms have been proposed for detecting the hard cut or gradual changes like fadein/out and dissolve. The performance of these algorithms degrades with zooming, lighting change conditions, and fast moving type of videos. In this paper, a novel algorithm based on Gaussian Mixture Model (GMM) is developed for shot boundary detection. The behavior of GMM with abrupt and gradual change is used for detection of hard cut, fadein/out and dissolve. Experimental results shows credibility of the proposed algorithm with zooming, lighting change conditions, and fast moving type of videos.

## 1 INTRODUCTION

With the overwhelmed collection of videos over Internet and other video libraries, automatic video analysis for semantic indexing and retrieval has emerged as a promising area of research. The foremost step in any video analysis is the detection of shots in a video. Some of the common methods used for detecting the shot boundary (SBD) are pixel difference, histogram comparison, edge change, compression ratio, and motion vectors. Performance comparison of these algorithms can be found in (Lienhart, 1999).

Zhang et al. (Zhang, 1995) proposed a method in which block by block difference is used instead of pixel difference to overcome sensitivity to camera motion and noise. To improve the performance of histogram based SBD, Huang et al. (Huang, 2003) have proposed the use of row and column histograms in addition to global histogram. Hardware implementation of the local histogram based SBD can be found in (Boussaid, 2007). However, histogram based methods lack spatial information and are also sensitive to changes in illumination and noise.

To avoid costly decompression of frames, many compression domain techniques based on compression difference or motion vectors (Tardini, 2005) have been proposed. Zabih et al. (Zabih,

1995) have proposed SBD based on determining the number of incoming and outgoing edge pixels called edge change ratio (ECR). Hard and gradual changes are detected by analyzing the characteristics of ECR time series. To make the SBD algorithm robust, many researchers have proposed to use multiple features (Bruyne, 2006) (Fang, 2006). Even though the performance of these algorithms are better than histogram and pixel difference based methods, the complexity in extracting the feature vectors is high making them less suitable for real time applications.

To overcome the above drawbacks, in this paper a GMM based shot boundary detection algorithm is proposed. At each frame, probability that the present frame fits into the GMM estimated up to the previous frame is calculated. The probabilities obtained at each frame are analyzed to detect hard cut and gradual change. As the GMM are inherently immune to noise and can handle the lighting change condition efficiently, the proposed algorithm can detect the shot boundaries more efficiently. The remainder of the paper is organized as follows. Section 2 describes the GMM and the proposed algorithm. Experimental results are presented in section 3 and the concluding remarks are given in section 4.

## 2 SHOT BOUNDARY DETECTION ALGORITHM

In surveillance applications, GMMs are widely in use for modeling the static background for detecting the foreground objects (Stauffer, 1999). Mo and Wilson (Mo, 2004) used multiresolution GMMs to capture both spatial and statistical aspects of the video. Based on the log-likelihood derived from the model, significant scene changes are detected. Next, we give an introduction to GMM, following which the proposed algorithm is discussed.

### 2.1 Gaussian Mixture Model

Gaussian mixture models are the probabilistic models for representing a distribution. GMM can also be viewed as a form of generalized radial basis function network in which each Gaussian component is a basis function or 'hidden' unit. Let us represent the  $k^{th}$  Gaussian component in a mixture model by  $N(\mu_k, \Sigma_k)$ , where  $\mu$  is the mean value and  $\Sigma$  is the variance. The probability that a sample value  $x$  belongs to a GMM is given by

$$p(x) = \sum_{k=1}^n w_k * p(x / N(\mu_k, \Sigma_k)) \quad (1)$$

where  $n$  is the number of components in a Gaussian mixture and  $w_k$  is the normalized weight factor associated with that Gaussian. Gaussian probability density function for  $N(\mu_k, \Sigma_k)$  is calculated by

$$p(x / N(\mu_k, \Sigma_k)) = \frac{1}{2\pi |\Sigma_k|^{1/2}} \exp\left\{-\frac{1}{2}(x-\mu_k)^T \Sigma_k^{-1}(x-\mu_k)\right\} \quad (2)$$

An *expectation-maximization* algorithm is used for fitting the GMM with a given set of training data. This algorithm is the best approach to train the stationary data. As the present algorithm is dealing with time varying data, this maximum likelihood algorithm is not suitable. Hence, an approximation to the *expectation-maximization* is used for updating the GMM over the time.

### 2.2 Proposed Method

The algorithm is implemented in compression domain. Partial decoding of the data is required for DC value extraction. This is another added advantage of the proposed algorithm. Each component is modeled with separate Gaussian mixture.

GMMs are initialized for each block with first frame of the sequence. First component of each GMM is initialized with the DC values corresponding to  $R$ ,  $G$ , and  $B$  as given below

$$\mu_{R1}^i = R_{DC}^i \quad \mu_{G1}^i = G_{DC}^i \quad \mu_{B1}^i = B_{DC}^i \quad (3)$$

where  $\mu_{R1}^i, \mu_{G1}^i$  and  $\mu_{B1}^i$  are the mean values of the first Gaussian.  $R_{DC}^i, G_{DC}^i$ , and  $B_{DC}^i$  are the  $R$ ,  $G$ , and  $B$  DC components of  $i^{th}$  block. Rest of the Gaussian components are initialized with zero value. Weights and variances of all the components are initialized with initial parameters.

To update the model from frame to frame, for every block of current frame find the best matching GMM in  $2 \times 2$  neighborhood blocks of the previous frame. The probability of fitting  $i^{th}$  block's DC value in the previous frame's  $j^{th}$  block GMM is calculated by distance function

$$d_k(i, j) = \sum_z^{R,G,B} \frac{1}{w_{zk}^i} \frac{(z_{DC}^i - \mu_{zk}^j)^2}{\Sigma_{zk}^j} \quad (4)$$

Equation 4 is approximately equal to the Mahalanobis distance with off diagonal elements of covariance matrix zero. Zero off diagonal elements means,  $R$ ,  $G$ , and  $B$  components are independent and have the same variance. Even though this assumption is not true, it avoids us to do costly matrix inversion at the expense of some accuracy. Using equation 4, find the minimum distance Gaussian component and corresponding block number as given below

$$D_k^i = \arg \min_d (d_k(i, j)) \quad (5)$$

$$l_k^i = \arg \min_j (d_k(i, j))$$

where  $j$  is the  $2 \times 2$  neighborhood of  $i^{th}$  block in previous frame.

For finding the shot boundary and shot transition type, count the number of blocks with  $D_k^i > T_d$ , where  $T_d$  is the distance threshold. Let us represent this count with  $N_1$ . If  $N_1$  is plotted against the frame number, it exhibits a different characteristic for hard cuts, dissolves, and fades as shown in Figure 1. From Figure 1(a), it can be observed that, for hard cut the change in the value of  $N_1$  is sudden. After a sudden change there is a gradual decrease of  $N_1$  value in the following frames as GMM gets updated.

Dissolves type of shot boundary transition exhibits a bell shape as shown in Figure 1(b). During the dissolve, the number of blocks with no best fit GMM increases gradually. After a few frames, as the GMMs get updated over a few blocks, the Mahalanobis distance curve decreases gradually. In case of fade-ins/fade-outs, as DC values increase/decrease continuously, the blocks without best fit GMMs peak for a few frames. This looks like a trapezoidal shape as given in Figure 1(c).

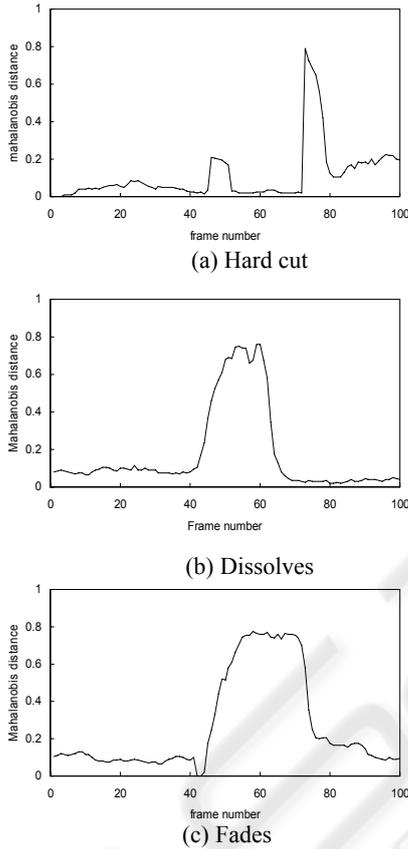


Figure 1: Typical pattern of Mahalanobis distance vs frames for hard cut, dissolve and fades.

Flickering type of lighting conditions can be detected by finding  $N_2, N_3, \dots, N_n$  for other Gaussian components similar to that of finding  $N_1$ . If there is a sudden change in  $N_1$  and at the same time if for any other Gaussian component  $k$ ,  $N_k$  is less, it is characterized as flickering.

The updating of GMM of blocks of current frame is as given in equation 6

$$\begin{aligned} \mu_i &= (1 - \alpha)\mu_{i-1} + \alpha I \\ \Sigma_i &= (1 - \alpha)\Sigma_{i-1} + \alpha(I - \mu_i)^2 \\ w_i &= (1 - \alpha)w_{i-1} + \alpha \end{aligned} \quad (6)$$

where  $I$  is  $R$ ,  $G$ , or  $B$  component and  $\alpha$  is the learning rate. If no matching GMM is found, then assign the spatial corresponding block GMMs of previous frame and initialize the last component of GMM with the DC component of the current block. After updating the GMM, weights are normalized. Based on the normalized weights, components of GMM are rearranged.

### 3 EXPERIMENTAL RESULTS

In this section, performance of the proposed algorithm is tested with different type of videos. For initialization of a GMM, initial weight and variance are taken as 0.2 and 225 respectively. The number of Gaussian components is selected as 3. Threshold value  $T_d = 1.0$  and  $\alpha = 0.2$  is chosen after testing with different types of videos.

Experimental results with the proposed method are presented for four different test sequences, namely, news, documentary, soccer, and basketball. These sequences are selected as they have lot of zooming, light changing, and fast moving effects. For all test sequences, the ground truths are generated manually with precise location and type of transition. Ground truth of these sequences is given in Table 1.

Performance of the algorithm is measured by using three types of measurements:

- **Correct detection ratio** is the ratio of shot transitions correctly detected to the actual number of transitions.
- **Miss detection ratio** is the ratio of number of shot transitions not detected to the actual number of shot transitions.
- **False detection ratio** is the ratio of number of shot transitions falsely detected to the actual number of shot transitions

Table 1: Ground truth of test sequences for hard cut (H), dissolve (D) and fades (F).

Test sequence	Duration (min)	H	D	F
News	7.00	44	0	0
Documentary	12.00	87	16	2
Soccer	11.00	45	30	0
Basketball	15.36	95	41	0

Table 2: Performance results for hard cut (H), dissolve (D) and fades (F) detection.

Test sequence	Correct Detection			False Detection		
	H	D	F	H	D	F
News	44	0	0	0	0	0
Documentary	87	8	2	10	2	2
Soccer	41	24	0	8	2	0
Basket-ball	90	37	0	39	4	7

The results with the proposed method are presented in Table 2. From Tables 1 and 2 it can be observed that hard cut detection ratio is 99.67% while dissolve detection ratio is 79.3%. Only two fade-outs are present in the documentary sequence and the two are detected correctly. Miss detection ratio for hard cut is 3.32% and for dissolve it is 20.22%. False detection ratio for hard cut and dissolve are 21% and 9.2% respectively. Results indicate that the performance of hard cut detection is very high and in most cases, dissolve detection is also correct. Our observation is that false detections occur in closeup shots. Specifically, these can be observed very prominently in the basketball sequence where players are showed closely while moving fast. For the qualitative evaluation of the proposed method, we refer the results presented with various algorithms in (Lienhart, 1999). In (Lienhart, 1999), Lienhart evaluated the best known algorithms and presented improvements to them. With these improvements, Lienhart achieved correct and false detection ratios for hard cut as 95% and 5% and for dissolve as 80% and 20% respectively. Even though, our test data is not as big as that Lienhart used, the results do bring out the merits of our method. As we have selected by carefully considering the various types of camera actions and events, the results can be considered as consistent over a large data set as well.

## 4 CONCLUSIONS

This paper presents a novel algorithm for shot boundary detection using Gaussian mixture models. Performance of the algorithm is verified by testing with different types of test sequences. Results indicate that proposed method can handle zooming, lighting change, and fast moving scenes effectively. However, the performance degrades with closeup shots with fast moving camera action or activity. These are due to the delay in updating the GMMs.

Handling of these types of problems for reducing the false detection is considered in part of our on going work.

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