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Propose shot boundary detection methods by using visual hybrid features

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ABSTRACT

Shot boundary detection is the fundamental technique that plays an important role in a variety of video processing tasks such as summarization, retrieval, object tracking, and so on. This technique involves segmenting a video sequence into shots, each of which is a sequence of interrelated temporal frames. This paper introduces two methods, where the first is for detecting the cut shot boundary via employing visual hybrid features, while the second method is to compare between them. This enhances the effectiveness of the performance of detecting the shot by selecting the strongest features. The first method was performed by utilizing hybrid features, which included statistics histogram of hue-saturation-value color space and grey level co-occurrence matrix. The second method was performed by utilizing hybrid features that include discrete wavelet transform and grey level co-occurrence matrix. The frame size decreased. This process had the advantage of reducing the computation time. Also used local adaptive thresholds, which enhanced the method's performance. The tested videos were obtained from the BBC archive, which included BBC Learning English and BBC News. Experimental results have indicated that the second method has achieved (97.618%) accuracy performance, which was higher than the first and other methods using evaluation metrics.

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1. INTRODUCTION

A video structure is a composition of scenes, shots, and frames. A video scene comprises a sequence of shots that are made up of interrelated events recorded at various camera positions. A video shot contains a sequence of interrelated frames taken by a single camera action. A frame is the smallest unit in a video where each frame represents a single image [1]–[4]. Shot boundary detection (SBD) in video is also called shot segmentation, and it is a technique of segmenting a video sequence into shots, which are smaller temporal units. SBD is the fundamental step that plays an important role in video processing tasks such as video analysis, summarization, retrieval, indexing, tracking an object, search, and content-based methods. Therefore, SBD's efficient method improves video processing [5]. This paper proposes a technique for shot boundary detection based on hybrid features.

Video SBD is an essential technique in video processing tasks which divides video sequences into smaller temporal parts called shots. A shot contains a sequence of interrelated frames of actions taken by a single camera. The main concept of the SBD technique is extracting efficient visual features from frames. Then, comparing the similarity between frames with a threshold value that is predefined after that, detecting a shot when the feature difference is greater than the threshold [6]. There are two types of shot boundaries, which are cut transition (abrupt) and gradual transition. This paper proposes a technique for cut-shot boundary detection. The first type is cut transition, which occurs as an abrupt change between two consecutive shots. That means only one frame is separated between two consecutive shots without the editing process. Whereas the second type is gradual transition, which occurs gradually between two consecutive shots, and this means that there are several frames separated between two consecutive shots during the editing process. The gradual transition has several types, such as: fade in, fade out, and dissolve [7], [8]. There are various SBD techniques, such as those based on histogram, pixel, block, edge, statistical, motion-estimation, clustering, and machine learning [1].

Features extraction process is an essential step in data analysis tasks used to extract important information from multimedia data [9], [10]. Features are defined as a descriptive parameter. The features extracted include color, texture, and shape. The color models like YUV, YCbCr, and HSV separate the chrominance from the luminance component, where this has advantages for distinguishing illumination changes, shadows, and noise because these two components are independent from each other. The texture features are grey level co-occurrence matrix and wavelet [11]–[14]. The details of the grey level co-occurrence matrix and wavelet are defined in the following sections.

The discrete wavelet transform (DWT) has become a powerful texture feature. DWT is one of the most widely used multi-resolution transforms. It is used in video and image processing tasks for transitioning data from the time domain to the frequency domain, being offers flexibility, robustness performance, and it splits the low and high frequency contents, so it needs less memory space [15], [16]. Typically, DWT was applied to every block of the frame to decompose the frame into LL, LH, HL, and HH subbands at different levels of resolution. Each subband contains a different type of frame information, with the LL subband containing the majority of the important frame features [17]–[19].

A grey level co-occurrence matrix (GLCM) is a robust texture feature. The texture feature contains information about the structure of surfaces by knowing the relationships of the neighboring pixels. For each texture feature extracted, there are several used approaches, one of which is the grey level co-occurrence matrix, which has the advantage of simple and fast implementation [20], [21]. GLCM is a second-order statistical approach that analyses the distribution of grey-level pixels. It is obtained by calculating the frequencies of a neighboring relationship between pairs of pixels at a specific angle of orientation and distance, then normalizing the co-occurrence matrix. The direction of the angle is usually calculated in four orientations, which are horizontal, vertical, and two diagonals that correspond to 0°, 90°, 45°, and 135°, whereas distance ranges from 1 to the dimension of the image [22], [23]. The contribution of this paper is to use a hybrid features method for detecting the cut shot boundary from a video sequence, which provides robustness and improves detection performance by selecting strong and flexible features.

Gygli [24] suggested a video shot boundary detection method based on convolutional neural networks. The suggested deep network consists of four layers of 3D convolutions; therefore, the deep model is fully convolutional in time. They used cross-entropy for the loss function. The input to the model was 10 frames, which it resized to 64×64 resolution, thus speeding up processing time. Furthermore, they created a dataset with one million frames and labeled frames as transitions or not in order to train the network. The created dataset includes an entire period of 3.5 hours of 79 videos gotten from YouTube. However, the experimental results were evaluated on the RAI dataset that showed an average F-measure of around 88%. He has also suggested enhancing the limitations of the proposed method in the future, which were that it was difficult to learn the transitions that were not included in the training set and to include the real data in the training set. Zhang *et al.* [25] have suggested a shot boundary detection method based on hue-saturation-value (HSV) color space. The suggested implementation for both types of transition, gradual and cut. The mechanism was first tested by taking single frames and breaking them into blocks. Then it was converted into an HSV model. In the HSV color space, the H value was quantized into 16 levels, while both S and V values were quantized to 4 levels, and then normalization was performed. After that calculation, histogram difference and give weight to the center region of a block higher than the peripheral region. They have used the K-means algorithm for specific threshold values. In a larger cluster, the point close to the center was chosen as a threshold for cut shots. When the value of the histogram difference was larger than the threshold value, it was considered a cut shots boundary. Whereas for gradual transition, a local pixel mean feature was used. The histogram difference was calculated between the first and last frames of the monotonic interval. When the value of the histogram difference is larger than the threshold value, it is considered a gradual shot boundary. However, the experimental results show the average F-measure is around 95%. They suggested enhancing the adaptability of parameters. Asha and Latha [26] have also suggested an approach for video SBD based on the discrete Haar transform. In this method, the discrete Haar transform was used to extract features such as edges, textures, motion vectors, and color. Then the correlations were used to compute the similarity of those feature vectors. After that, the corresponding continuous signal was calculated and used for shot detection. However, the experimental results were evaluated on the TRECVID 2001 dataset that showed the average F-measure for the cut shot was 93.26%. Sulaiman and Mahmood [27] have proposed an approach for SBD based on mean shift and dynamic time warping (DTW). The concept of this method was first performed by first performing preprocessing, which included converting the frames into YCbCr color space and dividing each frame into blocks. Then DTW was used as a distance measure to calculate differences between successive frames, and next normalized it. After that, a shift mean technique was used for shot boundary detection. Finally, for each shot, extract key frames that have higher content change. However, the experimental results that evaluated random videos and got from the open video project (OVP) dataset showed the average F-measure was 97.5%. Idan *et al.* [28] proposed a method for SBD that has achieved speed and accuracy depending on the moments and algorithm of support vector machine (SVM). The mechanism was performed by selecting an active area that contains the important information so that it reduces computation time. Then compute the moments for those active areas. The squared Tchebichef-Krawtchouk polynomials were used to extract features and use adaptive threshold. Furthermore, SVM was used to detect the cut boundary. However, the experimental results that evaluated the TRECVID 2001, 2005, 2006, and 2007 datasets showed the average F-measure was 96.15%. They have also suggested performing their method on different types of shot boundary and various applications in the future. Table 1 demonstrates the comparison methods of related work focusing on methodology, datasets, and average value of evaluation measure for video shot boundary detection methods.

Table 1. Comparison methods of related works

References	Methodology	Dataset	F-Measure
[24]	based on convolutional neural network	RAI	88%
[25]	based on HSV color space	____	95%
[26]	based on discrete Haar transform	TRECVID 2001	93.26%
[27]	based on mean shift and dynamic time warping	Open Video Project (OVP)	97.5%
[28]	based on moments and support vector machine	TRECVID 2001, 2005, 2006, and 2007	96.15%

2. RESEARCH METHOD

This paper has proposed two methods and compared them for cut shot boundary detection based on visual hybrid features that enhance the performance of detecting shots by selecting the strongest features. A detailed description of the proposed method with a general block diagram and algorithm for each method will be discussed as follows.

The first method for detecting cut-shot boundaries in video used hybrid features such as HSV color space statistics histograms and GLCM. The details are described in this section for each step. The first step is preprocessing, which includes extracting frames from video. Then resize the frames to 256×256. This step has the advantage of reducing the computation time.

The next step is extracting the first feature; this is a fundamental step in detecting shot boundary. The first feature is about visual color features, which includes extracting the chrominance feature from HSV color space. This feature is not affected by low-cal motion. Then it computes histograms of the chrominance feature and performs normalization. The histogram describes the distribution of color and disregards the spatial relationships, so it is robust to changes in scale, rotation, and camera movement. Then, from these histograms, it extracts the statistics. Features that include mean, median, standard deviation, skew, and entropy. So, each frame is represented as a vector of five features.

After that, the second feature is extracted to represent the texture feature. This includes converting frames into grayscale and extracting the GLCM feature, which is a powerful feature. GLCM calculates frequencies of a neighboring relationship between pairs of pixels at angles of 0°, 45°, 90°, and 135°, and distance 1. The GLCM is then normalized, and the correlation is computed.

Then a similarity matching step is done. This step matches the similarity between consecutive frames' features. Similarity matching is calculated for first and second features by using the Euclidean distance. After that, it computes the average of matching vectors of both features and returns the vector of average matching.

Finally, it calculates the local adaptive threshold, which is better than the global threshold. Using a global threshold for all frames is not an efficient approach because the video content is changed dramatically, making it hard to find a global threshold that fits all frames. While local thresholds are variable along with the content of video frames, therefore, in the proposed method, local thresholds are calculated based on the mean and standard deviation (STD) for an average matching vector of window size of 250 frames. Where local thresholds are computed using (1),

$$Th = (mean + std) \times c \tag{1}$$

where the value of *c* is specified as (3.7) and is obtained by experimental means until the best performance results are achieved. Then, a comparison is established between the average matching vector of the frames and a threshold value. If it is greater than the threshold value, the frame that corresponds to the index is considered as a cut shot boundary detection. Figure 1 illustrates the general block diagram of the first proposed method. Algorithm 1 proposed cutting SBD using hybrid features, which included statistics histogram of HSV color space and GLCM.

Algorithm 1. Cut SBD using statistics histogram and GLCM hybrid features.
```
Input: Video
Output: Frames that represent cut SBD
Process:
Step 1: Load video.
Step 2: Extract frames from video.
Step 3: Resize the frames.
Step 4: Extract first feature:
Step 4.1: Convert to HSV.
Step 4.2: Compute histograms for H of HSV and perform normalization.
Step 4.3: Compute statistics features for histograms that include: mean, median,
          standard deviation, skew, and entropy.
Step 5: Extract second feature:
Step 5.1: Convert frames to grayscale.
Step 5.2: Compute GLCM then perform normalization and correlation.
Step 6: Compute similarity matching for first and second features.
Step 7: Compute the average of similarity matching (Hybirdmatch[i]) for hybrid features.
Step 8: Calculate local thresholds (LTH[j]) for every M frame.
Step 9: Compare if Hybirdmatch[i] > LTH[j].
Step 10: Then it considered as cut SBD.
Step 11: Get frames that correspond the cut SBD.
Step 12: End.
```

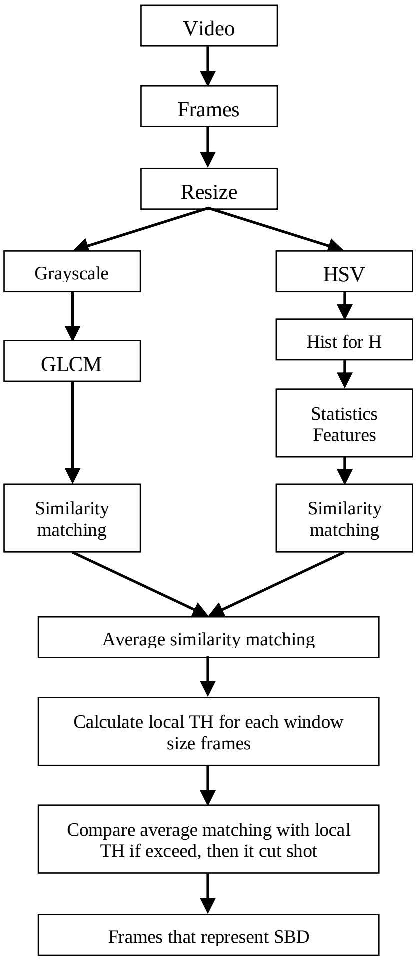

Figure 1. Block diagram of the first proposed method

The second method for detecting cut shot boundaries from video employs hybrid features including DWT and GLCM. The details are described in this section. The steps of the second method are the same as the first method except for the extraction of the first feature. DWT is used rather than the statistics histogram of HSV color space. The first feature is about texture features. That includes converting frames into grayscale. Then, when computing DWT, the Haar wavelet function is used within the DWT. This feature is an efficient, flexible, and robust feature selection. Then, for each frame, extract the low low (LL) sub band from DWT, which contains the most important feature information. Figure 2 illustrates the general block diagram of the second proposed method. Algorithm 2 proposed cutting SBD using hybrid features including DWT and GLCM.

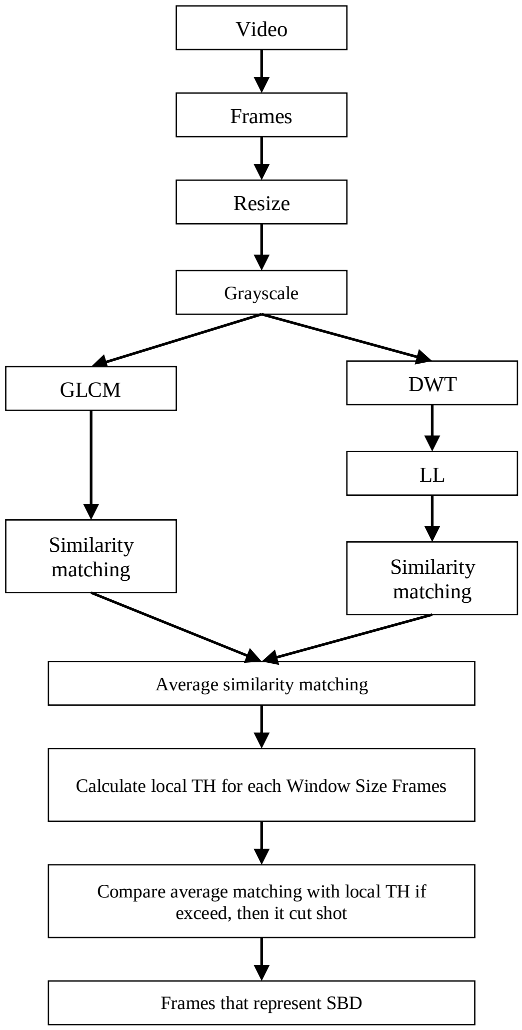

Figure 2. Block diagram of the second proposed method

Algorithm 2. Cut SBD using DWT and GLCM hybrid features.

```
Input: Video
Output: Frames that represent cut SBD
Process:
Step 1: Load video.
Step 2: Extract frames from video.
Step 3: Resize the frames.
Step 4: Convert frames to grayscale.
Step 5: Extract first feature:
Step 5.1: Compute DWT and extract LL.
Step 6: Extract second feature:
Step 6.1: Compute GLCM then perform normalization and correlation.
Step 7: Compute similarity matching for first and second features.
Step 8: Compute the average of similarity matching (Hybirdmatch[i]) for hybrid features.
```

```
Step 9: Calculate local thresholds (LTH[j]) for every M frame.
Step 10: Compare if Hybirdmatch[i] > LTH[j].
Step 11: Then it considered as cut SBD.
Step 12: Get frames that correspond the cut SBD.
Step 13: End.
```

3. RESULTS AND DISCUSSION

In this section, experimental discussions of the tests were exhibited to show the capability of the suggested shot boundary detection techniques. It holds information about the tested videos that were used to evaluate the performance of suggested techniques and, furthermore, a comparison with some previous techniques. All the tested video materials were downloaded from the BBC archive, which includes BBC Learning English and BBC News. Table 2 contains the details of tested video files that involve video duration, the number of frames, and also the number of ground truth of cut shots boundary.

Table 2. Details of tested videos materials

Name of the video	Duration	No. of frames	No. of ground truth of cut shots
BBC Learning1	9:43	14578	68
BBC Learning2	8:18	12453	45
BBC Learning3	8:1	12026	72
BBC Learning4	9:40	14505	76
BBC News	2:36	3917	16

To evaluate the performance of the proposed shot boundary detection techniques, evaluation metrics were applied, which were precision, recall, and F-measure. These metrics were evaluated by computing the number of true, false, and missed detections compared with the ground truth of shots. Whereas the high value of these metrics indicates perfect performance. Tables 3 and 4 illustrate the performance of the first and second proposed SBD techniques, respectively, using precision, recall, and F-measure applied to test videos.

According to both Tables 3 and 4, it is noticed that there are high values of evaluation metrics which indicate that proposed methods have achieved high accuracy performance. The average value of the F-measure of the first proposed method has been achieved (93.85%). While the average value of the F-measure of the second proposed method was achieved (97.618%). It seems that the second method using DWT and GLCM hybrid features has achieved higher accuracy performance than the first method using statistics histogram of HSV color space and GLCM hybrid features. Table 5 displays the comparison performance of the suggested method with other SBD methods according to the average value of the F-measure.

The high value of F-measure indicates an accurate performance. Therefore, according to Table 5, it seems that the proposed method had better performance than others. The big challenge in the SBD method is obtaining the optimal threshold value. According to experimental results, changing the way to compute threshold values was performed when using local adaptive thresholds improved method performance compared to when using one global threshold.

Table 3. The performance of first SBD proposed method

Name of the video	Precision	Recall	F- measure
BBC Learning1	96.6%	83.82%	89.76%
BBC Learning2	97.67%	93.33%	95.45%
BBC Learning3	89.87%	98.6%	94.04%
BBC Learning4	90%	100%	95%
BBC News	95%	95%	95%

Table 4. The performance of second SBD proposed method

Name of the video	Precision	Recall	F- measure
BBC Learning1	95.77%	100%	97.84%
BBC Learning2	100%	97.78%	98.88%
BBC Learning3	93.42%	98.6%	95.95%
BBC Learning4	94.81%	96.1%	95.42%
BBC News	100%	100%	100%

Table 5. Comparison of different SBD methods

Methods	Average F- measure
[24]	88%
[25]	95%
[26]	93.26%
[27]	97.5%
[28]	96.15%
The proposed second method	97.618%

4. CONCLUSION

This paper has introduced two strategies and compared them for cut shot boundary detection from video files based on visual hybrid features and exhibits a general framework and algorithm for each strategy. Furthermore, a comparison of the proposed technique with other techniques was presented. The frame size was decreased, where this step had the advantage of reducing the computation time. Using local adaptive thresholds has improved the method's performance compared to global thresholds. Evaluation metrics such as precision, recall, and F-measure were used to evaluate the performance of the proposed techniques. The tested videos were obtained from the BBC archive, which includes BBC Learning English and BBC News. Experimental results have indicated that selecting the strong features as in the second method, which is based on DWT and GLCM hybrid features, has achieved higher accuracy performance than the first method based on the statistics histogram of HSV and GLCM and also higher than those other methods.

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