CORNER EVENT DETECTION BASED SOCCER VIDEO SUMMARIZATION

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Abstract— The translation of low level content in video sequences into high level semantic concepts is a research to pic that has received much interest in recent years. We propose fully automatic and computationally efficient framework for analysis and summarization of soccer videos using event based features. The processing framework includes some novel low-level soccer video processing algorithms, such as dominant color detection, robust shot boundary detection, and shot classification as well as some higher level algorithm such as corner event detection. We have used different methods such as morphological image processing method which is used for extracting the interested area, which is in our case corner of the ground, segmentation for detecting the corner vertical pillars, which are extracted through Canny Edge Detection method. We have conducted large number of exp eriments to show effectiveness and robustness of the approach.

Index Terms— Dominant green pixel ratio (DGPR), HIS(histogram) , RGB (red, green, blue)

I. INTRODUCTION

Today technologies that enable people to easily capture and share digitized video data are rapidly developing. With progress in video compression and communication technologies, demand of digital video is increased dramatically. Internet is growing in terms of bandwidth and number of users. Home users have high bandwidth cable connection to watch TV-quality videos. Personal computers are powerful enough to handle computational demand of digital video applications and high storage capacity. DVD, which provides high storage capacity, delivers high quality digital video to consumers. It is now quite easy to capture a video and load it into computer memory as advance digital cameras are introduced. Advanced mobile and multimedia technologies, such as web-enabled cellular phones, multimedia messaging allows people to interact with multimedia data everywhere. People have large repositories of videos, such as training, educational, sports, news, home videos etc. All these indicate that future for the world of digital video is promising. This increased generation and distribution rate of digital video content has created a new problem: Management of the content. A video sequence normally contains a large number of frames. In order to ensure that humans do not perceive any discontinuity in the video stream, a frame rate of at least 25 fps is required, that is, 90000 images for one hour of video content. This sheer volume of video data is a barrier to many practical applications, and therefore, there is a strong demand for a mechanism that allows the user to gain certain perspectives of a video document without watching the video in its entirety. There is no feasible way to enable a quick browse of a large collection of video data and to achieve efficient content access and representation. To address these issues, video summarization techniques have emerged. Video summarization is the process of condensing video content into a shorter descriptive form. It provides a solution to the problem of managing video content. Automatic video summarization aims at creating efficient representations of video for facilitating browsing, search and management of digital multimedia content. Automatically generated summaries can support users in navigating large video archives and in taking decisions more efficiently regarding selecting, consuming, sharing, or deleting content. For event-based content, since the types of events of interest are well-defined, one can use knowledge-based event detection techniques. In this case, the processing will be domain-specific and a new set of events and event detection rules must be derived for each application domain, which is a disadvantage. However, the summaries produced will be more reliable than those generated using general summarization algorithms [2].

II. EVENT BASED VIDEO SUMMARIZATION

If the application domain of the summarization algorithm is restricted to event-based content, it becomes possible to enhance summarization algorithms by exploiting domain specific knowledge about events. Summarization of sports video has been the main application for such approaches. Sports programs lend themselves well for automatic summarization for following of reasons. The interesting segments of a program occupy a small portion of the whole content. Compact representations of sports programs have a large potential audience. Often there are clear markers, such as cheering crowds, stopped games, and replays, that signify important events [2]. Sports video follows production rules. During any excitement event camera will move over different parts of the ground. Semantic events are the collection of a temporally ordered set of different views. So by analyzing temporal sequence of the views, events can be detected. Figure below shows general procedure of event based video summarization.

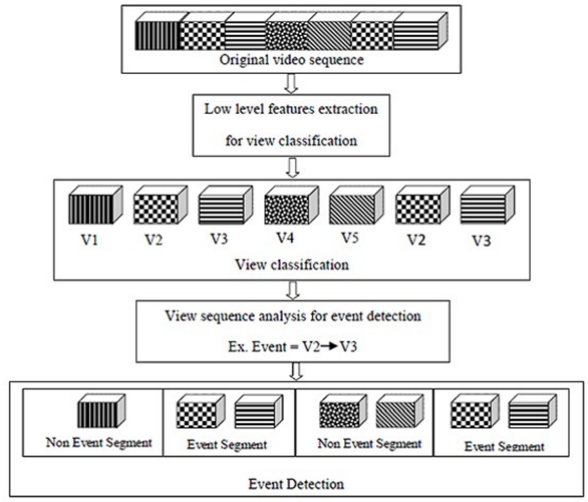

Figure 1 Event based video summarization

2.1 HIDDEN MARKOV MODEL BASED APPROCH

Chung-Lin Huang and Chih-Yu Chang have proposed a system to analyze and summarize the video shots of the baseball game into fifteen categories. System consists of three modules: feature extraction,

Hidden Markov Model (HMM) training, and video

shot categorization. In feature extraction, feature vector for each frame is generated using the motion estimation, color, texture information analysis and vector quantization. HMM is trained with this feature vector for each content class of video shots. For a query video sequence, the probabilistic decoding sequence calculates the sequence of HMMs that maximizes the probability of having generated the corresponding feature vector sequence. The model with the highest score is selected as the recognized video shot [23]. An algorithm for parsing the structure of soccer programs is presented in [24]. Two states of the game are defined: Play and Break. Domain-tuned feature set, dominant color ratio and motion intensity are selected. With percentage of grass field, shots are divided into wide, medium and close up shots. A play is usually captured by wide shots interleaved with short medium shots or close ups; and a break usually has a majority of close up and medium shots. Motion intensity is computed as the average magnitude of motion vectors in a frame. Wide shot with high motion intensity often results from player motion during a play;

while a static wide shot usually occurs during break. The stochastic structure within a play or a break is modeled with a set of HMMs. A multi-layer soccer game event detection framework is described in [25]. In the midlevel of this framework visual and audio keywords are created from low-level features and the original video is converted into keyword sequence. Support Vector Machine (SVM) classifiers are used to group these features into predefined groups and each group is labeled with a keyword. Such keyword sequences are combined to form a keyword vector stream which is then processed in the high-level layer to detect semantic event. In the high-level the temporal pattern of keyword sequences are analyzed by HMM classifier. Color, motion and texture are used to create the keywords: Far Middle-Field View, Far Goal-Field View, Close-Up View, Audience View, and Replay. Detected events are: "Goal, Corner kick, Shot and Goal kick. The creation of visual and audio keyword can help to bridge the gap between low-level features and high-level semantic. The use of HMM classifier can automatically find the temporal change character of the event. Guoying Jin, Linmi Tao, Xinghua Sun and Guangyou Xu have presented an algorithm based on hidden Markov models for cues fusion and events inference in soccer video. Five extracted cues are: shooting scale, playback, goal mouth appearance, blurs football trajectory. Shooting scale is classified into global, zoom in and close-up shot using hue of soccer field. Playback is detected using Viterbi algorithm. The goalposts are detected by searching vertical white strip by Hough Transform, with the help of the net texture detection. Football in zoom-in shots is detected by a simple approximate method: detecting white round area in certain amount of successive frames. The observation of HMM is defined as the combination of these five cues. Given observation sequence produced from training data HMM is trained. Event detection is done using Viterbi algorithm. Finally four events: shoot, foul, offside and normal playing, are detected [26]. A statistical method to detect highlights in a baseball game video is described in [27]. The input video is first segmented into shots, within which the camera motion is continuous. Each scene shot is then compared with the learned view models, and the probability of being any of them is calculated. Statistical models for each type of scene shots with products of histograms, and then for each type of highlight, a hidden Markov model is trained to represent the context of transition in time domain. Finally given the stream of view classification probabilities, the probability of each type of highlight can be computed by matching the stream of view classification probabilities with the trained HMMs. Highlight extraction process discussed by Kamesh Namuduri is consists of three steps: Shot boundary detection: A video is segmented into shots by considering three consecutive frames, previous, current and next frames. Shot boundary is detected when the difference between the histogram values of previous-current and current-next histograms exceeds a threshold. After segmenting the video into shots, key frames are identified in each shot. First frame is selected as a key frame and compare it with consecutive frames. A frame whose dissimilarity is more than a threshold is considered as the new key frame. Classification of shots into views: Four views are identified to describe the video: 1) close-up view, 2) medium view, 3) audience view and 4) pitch view. Shots of same type usually have the same kind of color, texture, number of edge pixels and motion distributions. The same sets of features are extracted from all key frames and the view classification is done based on these features. Five features, which are considered here, are: 1) grass color, 2) pitch color (sand color), 3) audience texture, 4) motion activity and 5) number of edges. **Extraction of highlights:** HMM, which takes the initial probabilities and the transition probability matrix of the states as input is developed to extract highlights [28]. A semantic event detection algorithm in structured video is proposed in [29]. A hybrid method that combines HMM with SVM to detect semantic events in video is proposed. Video is segmented by shot change detection. Then video shots are clustered and categorized into event depending on the semantics of the shot. The state diagrams of the event are constructed based on the categorized shots. Visual features that could distinguish the states are selected as an input of HMM and HMM is trained. For event detection low level features are extracted from each shot and then fed into HMM. Viterbi decoding is used in finding event sequence that produces maximum output probability.

III. THE PROPOSED SOCCER VIDEO SUMMARIZATION APPROACH

The proposed methodology is considered to be one of the most important sections. It explains how we are going to handle the main problem of project. Here I have created proposed methodology in the manner of flowchart. The flowchart is divided into 3 parts i.e. process1, process2, process 3. Each process describes the flow of research. In this section the process 1 of proposed method describes the flow of getting dominant pixel color ratio. In process 2 the classification portion of the soccer video is described. As we can see that based on dominant pixel color ratio the video is classified into two main categories i.e. far view and non far view. At the end of the classification we will be getting the corner view which is the first step of detecting corner event. In the process 3 based on the outcome of process 2 we will achieve corner event detection which is the second goal of the research work. At the end of this process 3 we will be able to do summarization of corner events. Now we will discuss each and every process mentioned in the proposed method in detail.

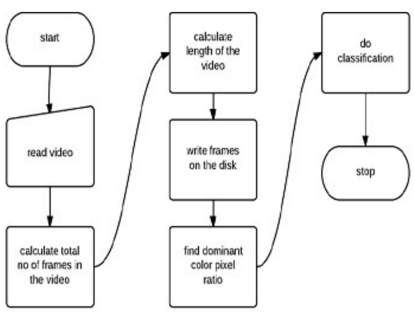

Figure 3.1 proposed method phase 1

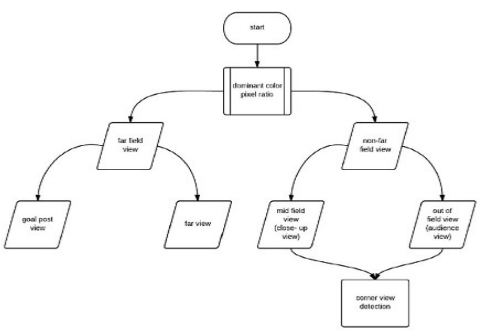

Figure 3.2 proposed method phase 2

For the classification process mentioned in process-2, we require calculating the dominant color pixel ratio mentioned in process-1. Dominant color pixel ratio is described by the mean value of each color component which is computed around their respective histogram peaks. We do the classification process by means of KMEANS algorithm. After calculating the dominant color pixel ratio we manually specify one threshold value by doing some analysis. The classification process starts by comparison of dominant color pixel ratio and the threshold value.

3.1 ROBUST DOMINANT COLOR REGION DETECTION

The dominant color is the color that fills most of the given area, and it is different for various play fields. Here we are concerning only with the soccer game, which has a green color for the playing field. As dominant color extraction is challenging due to effects on the play-field such as shadow, lighting, low resolution and other environmental factors, there are several color spaces that have been used for the dominant color detection including HIS and RGB. The soccer field has 1 distinct dominant color that may vary from stadium to stadium and also due to weather and lighting condition within the same stadium. We do not assume specific value for color of the field in our framework. Therefore only assumption is the existence of a single dominant color that indicates the soccer field. The statistics of this dominant color in the HIS space are automatically updated to adapt to temporal variations. Dominant field color is described by the mean value of each color component which is computed around their respective histogram peaks.

The figure below shows the example of dominant color pixel identification.

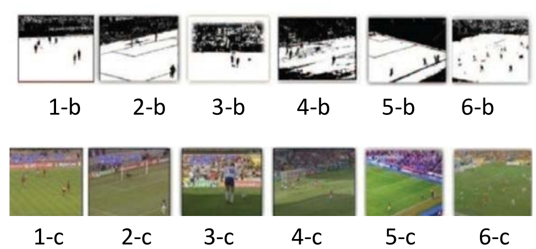

Figure 3.3 (1-6) c original frames, (1-6) b dominant color regions shown in white using RGB space

3.2 K-MEANS

K-means is most commonly used partitioning method. The algorithm takes the input parameter, k, and partitions a set of n objects into k clusters so that the resulting intra-cluster similarity is low. Cluster similarity is measured in regard to the mean value of the objects in a cluster, which can be viewed as the cluster's centroid. The K-means method proceeds as follows. First, it randomly selects k of the objects, each of which initially represents a cluster mean or center. For each of the remaining objects, an object is assigned to the cluster to which it is the most similar, based on the distance between the object and the cluster mean. It then computes the new mean for each cluster. This process iterates until the criterion function converges. Typically, the square-error criterion is used and it is defined as,

$$E = \sum_{i=1}^{K} \sum_{P=Ci} |P - mi|2 \quad (1)$$

Where, E is the sum of the square error for all objects in the data set; p is the point in space representing a given object; and mi is the mean of cluster Ci (both p and mi are Multi-dimensional). In other words, for each object in each cluster, the distance from the object to its cluster center is squared, and the distances are summed. This criterion tries to make the resulting k clusters as compact and as separate as possible [30]. As mentioned in process 2, after dominant color region detection we do classification frames between far field view and non-far field view. For classification we use K-means algorithm. The flow of algorithm is shown below.

K-means algorithm

The number of clusters: 2, A data set containing n
values: DGPR **Output:** A
set of 2 clusters.

Method:

- Arbitrarily choose 2 values from DGPR as the initial cluster centers;
- Repeat
- Assign each DGPR value to the cluster to which the value is the most similar, based on the mean value of the DGPR in the cluster;
- Update the cluster means, i.e., calculate the mean value of the DGPR for each cluster; until no change.

After classification of Far Field view and Non Far Field view, algorithm is applied on those frames which belong to Non Far Field view to classify Medium field view and Outfield view. Based on the outcome of the dominant color ration identification, by using the KMEANS clustering algorithm in MATLAB we will do the further classification. KMEANS clustering algorithms will divide the frames into two clusters by calculating the distance of the each and every pixel from the specified center points. Here we will decide that particular frame belongs to far field view or non far field view. The far field view specifies that in particular frame we can easily identify maximum number of dominant color pixels. While in the non far field view the numbers of dominant color pixels are comparatively less. To differentiate between these two categories we require identifying the threshold value which will divide the number of frames according to their category.

If dominant color pixel ratio > threshold
Then far field view
Else
Non-far field view

After dividing all the frames into above two categories we proceed further. For the next step we do classification by using Hough Transformation method. After applying the Hough Transformation we divide all the available categories into separate classes. At the end of the classification process it provides 4 different class values. We have mainly four types of views/shots available for soccer video. Next step we do is view or shot classification base on the far field view and non-far field view. Shot is defined as a sequence of frames captured by a single camera in a single continuous action in time and space [16]. Separated views come from multiple cameras positioned at different locations. It can be realized that while changing from one camera to another, this indicates a start and marks a boundary of a new shot. We use two set of features to detect a shot: 1) the difference between dominant colored pixel ratios of two frames (Gdistance) and 2) the difference in color histograms based on HSV color space (Hdistance). We define these thresholds to detect the boundaries with three different ranges as shown in Table below.

Threshold	*Value*
$G_d \geq$	0.5
$H_d \geq \& \; G_d \geq$	0.8 & 0.2
$H_d \geq$	1.6

Table 3.1 Thresholds adjusted from soccer videos

3.3 SHOT-TYPE CLASSIFICATION

After applying the shot classification algorithms the output will be as shown in the figure 3.4 below.

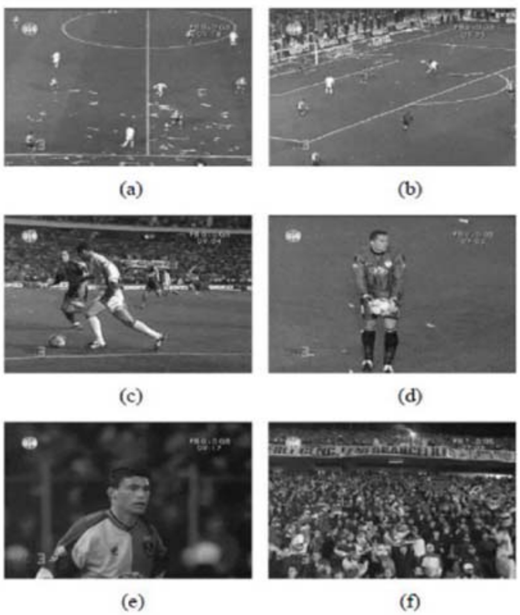

Figure 3.5 (a), (b) Long view, (c), (d) in-field medium view, (e) close-up view, and (f) out of field view

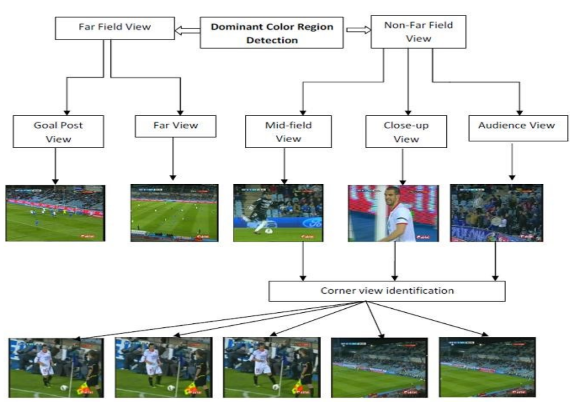

Figure 3.6 view classification The process-3 for proposed algorithm is depicted in the figure below

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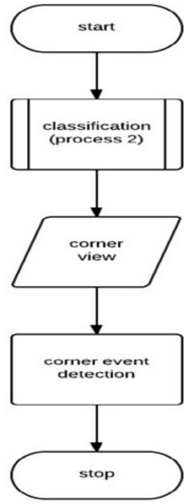

Figure 3.7 proposed method phase 3

3.4 CORNER VIEW DETECTION

As a part of phase 3 of proposed methodology we apply following algorithm in order to achieve corner view.

Corner View Detection

- Apply vertical Sobel filter in order to detect vertical lines.
- Apply erosion operation in order to extract the area of our interest. Here vertical pole is our area of interest.
- Apply Hough transformation.
- Now find out 5 peak values and plot them on the eroded image.
- Calculate length of the plotted line.

If the length if between the specified length, it is a corner view otherwise it is not.

The outcome of the corner view detection algorithm is represented below.

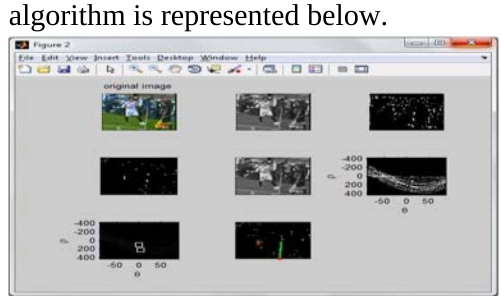

Figure 3.8 outcome of corner view detection algorithm

IV. EXPERIMENTAL RESULTS

Video summarization proposed techniques have been applied on many types of videos e.g. home videos, sports, surveillance, news. However, among all these types of videos surveillance and sport genre have their interesting applications related to security and commercial interest. Sport videos are itself in dynamic nature and experience high motion as well as sudden changes. Hence it poses a stiff challenge to generate to generate a good video summary. The experiments were conducted on the soccer videos of different conditions. In order to evaluate performance of the proposed algorithm we experimented on 6 different videos. Each video has different number of frames. Here we use frame rate of 25frames/s. The frame size of the video was 352 × 288. The experiments were conducted on Intel® Pentium® dual processor with 1.73 GHz and 2 GB RAM. Implementation tool used for experimentation is MATLAB 7.8(R2009a). Used dataset of video is shown in the table 4.1.

Number	Name of video	No. of frames
1	Video 1	20000
2	Video 2	40000
3	Video 3	16700
4	Video 4	18000
5	Video 5	18000
6	Video 6	18000

Table 4.1 Soccer video sequence used for experiments

4.1 VIEW CLASSIFICATION RESULTS

During the classification we divide frames into 4 different class values. 1. Goal post view

2. Far field view

3. Close up view/ mid field view

4. Audience view/ out of field view

Output of view classification is shown in the table 4.2. Table specifies total number of frames belongs to goal post view , close up view/ mid field view, audience view , out of fields view.

Number	Name of match	No. of frames belongs to class 1	No. of frames belongs to class 2	No. of frames belongs to class 3	No. of frames belongs to class 4
1	Video 1	9893	7196	2501	410
2	Video 2	23816	1740	12007	2437
3	Video 3	1112	240	12881	2467
4	Video 4	1224	88	16144	544
5	Video 5	7021	190	10147	642
6	Video 6	285	188	15319	2208

Table 4.2 result of view classification

4.2 corner vies with different angles

Figure 4.1 corner views of experimental video 1

4.3 RESULT OF CORNER VIEW DETECTION

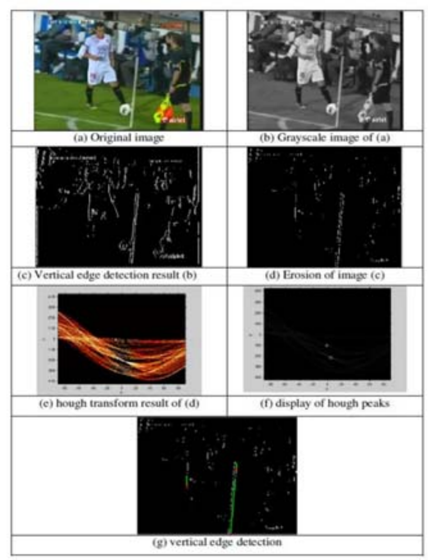

Figure 4.2 Corner view detection in experimental video 1

2.3 ACCURACY ANALYSIS OF CORNER EVENT DETECTION

Number	Name of match	Corner event		Result%
		Actual	Detected	
1	MP4_Apr17_192654_0	4	2	50
2	MP4_Apr18_182145_0	1	1	100
3	MP4_May04_125300_0	1	1	100
4	MP4_May16_013051_0	1	1	100
5	MP4_Sep29_120103_0	3	2	66
6	MP4_Sep30_111317_0	1	-	-

Table 4.3 corner event detection result

Event	Detected	Miss	Recall
11	7	4	64%

Table 4.4 accuracy analysis of event detection

V. CONCLUSION AND FUTURE WORK

The literature survey reveals that video summarization based on event detection can help to bridge the gap between low level features and high level semantic events. Various approaches for event detection are available. The proposed system is using frame based feature extraction approach rather than shot based approach. So classification is done more accurately. For field view classification, K-means algorithm is applied on DGPR values, which dynamically creates three clusters of far field view, medium field view and out-field view. So, method avoids defining static threshold. Goal post detection method using Hough transform is able to detect goal post captured by different orientation of cameras. Apart from that Sobel operator, erosion, Hough transformation methods are used for corner view detection. Various approaches have been proposed for event detection. But these are domain specific approaches. So, there is a lack of a generic event detection framework that can be applied to various domains. The performance algorithm has been evaluated on different video dataset of varying conditions. Obtained result reflects that even under the varying conditions of the dataset algorithm achieves favorable results.

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