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Replay Frames Classification in a Cricket Video Using Correlation Features and SVM

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Abstract: In this paper we propose a new framework meant for replay frames detection in cricket video. Our framework is based on a block of score bar which is present in non replay frame and not present in replay frame. Correlation is a signal matching technique used for obtaining similarity between two signals. Support Vector Machine (SVM) is a supervised machine learning technique meant for binary classification. A block of score bar from non replay frame and replay frame are selected as template1 and template2 respectively. A training set of thousand frames containing five hundred non replay frames and five hundred replay frames used for training SVM. Feature vectors are calculated using correlation coefficient between templates and the training frames in the training set. We evaluate our framework using publicly available cricket dataset provided by Mr.Dipen Raghuwani available at [1]. Our experiments have shown significant results compare to already existing frameworks. Our results have achieved an average recall of 96% and precision of 99%.

Key words: Replay frame • Cricket • Svm • Correlation • Video • Score board

INTRODUCTION

In recent years, a huge amount of video data is produced and stored by different sports, news and entertainment TV channels. Rapid improvement in storage technology allowed users to generate huge volumes of video content [2].

Sports videos have large fan following compare to other videos. Sports videos became popular throw ought the world as a medium of entertainment. A number of TV channels have evolved to broadcast sports videos. The main challenge faced by these TV channels is maintaining huge volumes of sports video data [3].

First top most viewing sport in India and second top most in the world is cricket. Cricket is a sport played in different formats like T20, one day and test. Large volumes of sports video content is generated for a single cricket match broadcasted by different TV channels. Manual indexing of such large volumes of video data is a big challenge.

Efficient video indexing and retrieving frameworks are needed to facilitate a user to retrieve interesting segments in a video. There is a huge demand for automatic indexing and retrieving techniques helpful for effective usage of video content. The indexing and retrieving techniques depends on video's visual, audio and text content [4].

Most of the users are interested in viewing important and interesting events in sports videos rather than watching the whole video [3].

Replay refers to something important that has occurred in a broadcasting video. In other words, the video having previously been shown live, is "re-played" a second time in order to facilitate the viewers to examine once again what has taken place. Thus, replay segment highlights the occurrence of significant and exciting events in a sports video [5].

Replay has been used in cricket to examine the areas of run outs, stumping, doubtful catches and whether the ball has crossed the boundary or not, for a six and for a four [6].

Classification of cricket video frames in to replay frames and non replay frames is useful to analyze the video semantically and extract important event segments [7].

Few of the replay frame/segment detection techniques reported in the literature are, M.H. Kolekar *et al* [8] in their paper they have proposed an algorithm to detect replay segment in a cricket video using logo transition frame and shot frequency. Mahesh Goyani *et al* [9] proposed a method to locate replay frame using hue, saturation histograms and connected component analysis. Jinjun Wang *et al* [7] in their paper

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introduced a novel replay detection method using scene transition structure analysis. Pan *et al* [10] proposed a framework to detect the replay segments using the editing effects present before and after the replay segments. Kobla *et al* [11] used macro block information and vector flow information to detect replay frame. Pan *et al* [12] introduced a novel technique to detect replay frame by zero crossing measure within a sliding window.

The Main Contributions of this Paper Are:

- We propose a new supervised framework for detecting replay frames in cricket video
- Our proposed work is less content dependent and less time consuming.

Rest of the paper is organized as follows. Section 2 presents the concept of correlation coefficient and a brief introduction about support vector machine (SVM), Section 3 presents our proposed algorithm, Section 4 presents experimental setup and results and Section 5 concludes the paper with future work.

Correlation Coefficient and Support Vector Machine: In this section we briefly discuss about the concept of correlation coefficient and Support Vector Machine.

Correlation Coefficient (CC): CC is a measure to find the similarity between two data sets or two variables. The mathematical equation to compute the CC between two variables x and y is given by

$$r = \frac{n\sum xy-(\sum x)(\sum y)}{\sqrt{n(\sum x^2)-(\sum x)^2}\sqrt{n(\sum y^2)-(\sum y)^2}} \quad (1)$$

Where r represents correlation coefficient and n is the number of pairs of data present in x and y.

Correlation coefficient can be of three types they are positive correlation, negative correlation and no correlation. Correlation coefficient value ranges between -1 and +1.

Two variables are said to be strongly correlated if the value of correlation coefficient is greater than 0.8 and is said to be weakly correlated if the value is less than 0.5, for more information reader is advised to look at [13].

The mathematical notation for finding the correlation coefficient between two images I1 and I2 is given by,

$$r = \frac{\sum_m \sum_n (I1_{mn}-I1_{mean})(I2_{mn}-I2_{mean})}{\sqrt{(\sum_m \sum_n (I1_{mn}-I1_{mean})^2)(\sum_m \sum_n (I2_{mn}-I2_{mean})^2)}} \quad (2)$$

Where I1 and I2 are two same size images with m rows and n columns. $I1_{mean}$, $I2_{mean}$ are mean values of I1 and I2 respectively.

Support Vector Machine (SVM): Support vector machine is a popular pattern recognition tool used for binary classification of data. In other words, SVM classifies a group of data points in to two groups by fitting an optimized hyper plane (linear decision function) as shown in below figure 1 [14].

$$w_0.z + b_0 = 0 \quad (3)$$

Let the above equation (3) represents the optimal hyper plane where w_0 is given by

$$w_0 = \sum_{supportvectors} \alpha_i z_i \quad (4)$$

Then the linear decision function is given by

$$I(z) = sign\left(\sum_{supportvectors} \alpha_i z_i.z + b_0\right) \quad (5)$$

Where z_i represents support vectors, z is a vector in feature space and $z.z_i$ is the dot product.

SVM can be used as linear classifier, non-linear classifier and multiclass classifier.

Proposed Framework: In this section we propose our novel method to classify replay frames in a cricket video. Our method is based on a block of score bar as shown in figure 2. From each and every frame we use only the portion marked in pink color (shown in figure 2) in our proposed method to classify a frame either a replay frame or non replay frame. This shows how much less amount of information we use in our proposed method for classification of frames.

Our proposed framework's block diagram is as shown in Figure 3.

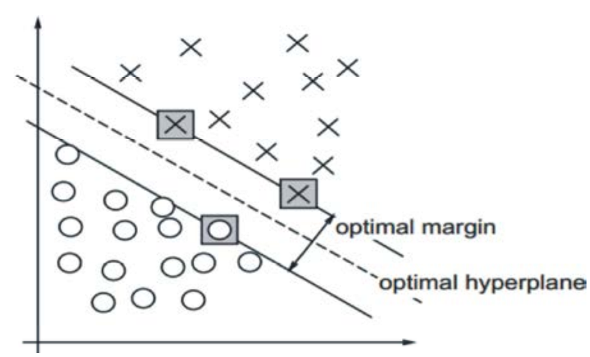

Fig 1: An example of SVM Optimized hyper plane [14]

Fig 2: (a) Replay Frame (b) Non-Replay Frame Block of score bar (marked in pink color) used in our proposed method

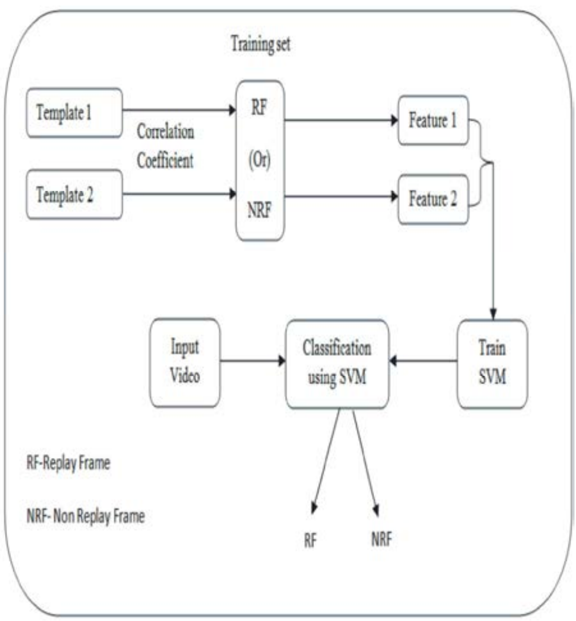

Fig 3: Block diagram of Proposed Framework

Proposed Algorithm:

Step 1: Select template 1 from a non replay frame and template 2 from a replay frame as shown in Figure 4.

Step 2: Select Training set of Five Hundred replay frames and five hundred non replay frames from the dataset.

Step 3: Calculate correlation coefficient between template1, frame(i) and correlation coefficient between template2, frame(i), (where frame(i) is a frame from the training set of 1000 frames).

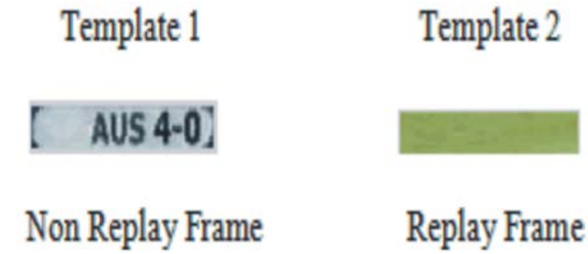

Fig 4: Templates used in our proposed Method

For frames 1 to 1000 calculate the Feature vector set of [r1 r2] using the following equations. Where [r1, r2] - are correlation coefficients between [template 1, template 2] and a training frame

$$r1 = \frac{\sum_m \sum_n (t1_{mn} - t1_{mean})(f(i)_{mn} - f(i)_{mean})}{\sqrt{(\sum_m \sum_n (t1_{mn} - t1_{mean})^2)(\sum_m \sum_n (f(i)_{mn} - f(i)_{mean})^2)}}$$

$$r2 = \frac{\sum_m \sum_n (t2_{mn} - t2_{mean})(f(i)_{mn} - f(i)_{mean})}{\sqrt{(\sum_m \sum_n (t2_{mn} - t2_{mean})^2)(\sum_m \sum_n (f(i)_{mn} - f(i)_{mean})^2)}}$$

In the above equations t1- is template 1, t2- is template 2, f(i) - i^{th} frame from the training set.

Step 4: Utilize the set of Feature vectors calculated in step 3 to train the Support Vector Machine.

Step 5: Classify the frames in the test video as replay frame or non replay frame using the trained support vector machine.

The very first step in the proposed algorithm is selecting template 1 and template 2 from a non replay frame and replay frame respectively. An example pair of templates is as shown in Figure 4.

The second step is finding the correlation coefficient between the templates and training set frames using equation (2). Example feature vectors calculated for five replay frames (1-5) and five non replay frames (6-10) are as shown in Table 1.

The training set consists of five hundred replay frames and five hundred non replay frames used for training support vector machine.

Likewise as shown in Table 1 we calculate feature vector set for all the frames in the training set.

Third step is training the Support vector machine with the feature vector set obtained in step 2.

Figure 5 shows the optimized hyper plane fit by the SVM, based on the feature vectors provided to it.

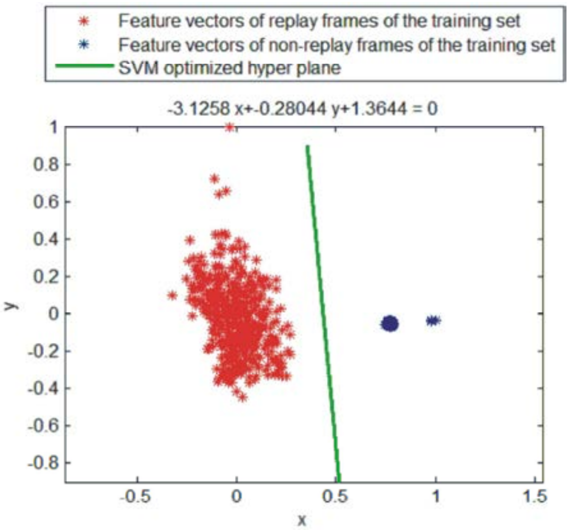

Fig 5: SVM optimized hyper plane for classification of frames

Table 1: Example Feature vectors [r1 r2] calculated for few of the training frame used to train SVM.

S.no	Result of Correlation coefficient between template 1 and training frame isFeature Vector 1 - r1	Result of Correlation coefficient between template 2 and training frame isFeature Vector 2 - r2
1	-0.0123885226980540	-0.227884320341331
2	-0.0110099660320351	-0.0226276592017390
3	-0.148319226064159	0.0253898057016962
4	-0.0208997529558105	-0.148852314178939
5	-0.00665631123876236	-0.0238782200160002
6	0.772700486258799	-0.0553183427620016
7	0.778831005142237	-0.0518041204683965
8	0.776908184339652	-0.0499743691146311
9	0.775981132543449	-0.0520871369099899
10	0.775132431424732	-0.0607036791840243

Table 2: Statistics of video segments used to test the performance of proposed classification algorithm

Video	Number of frames	Number of Replay frames	Number of Non-Replay frames
1	1000	384	616
2	1000	482	518
3	1000	771	229
4	1000	367	633
5	1000	358	642
6	1000	188	812
7	1000	431	569
8	1000	178	822
9	1000	294	706
10	1000	392	608
11	1000	408	592

After training of the SVM, we perform testing to find the efficiency of proposed classification algorithm.

RESULTS

In this section we discuss about the implementation details of our algorithm. We have implemented our proposed method in MATLAB 2011a. To implement our proposed method we have used the cricket data set available at [1]. The dataset we have used for our experiments is a ten over's match between Sri Lanka and Australia.

As discussed in the previous section the training set used to train the SVM consists of thousand frames (in which five hundred are replay frames and five hundred are non replay frames).

The trained SVM is used to classify the frames in the test data. Video segments that are used to test the efficiency of our classification method along with their statistics are as given in Table 2:

As shown in the above table the video segments are taken from the data set available at [2], in such a way that each segment consists of replay frames as well as non replay frames.

We find the efficiency of our framework using precision and recall measures. Precision is the measure used to find the percentage of selected items that are correct and recall is the measure used to find the percentage of correct items that are selected.

We obtain precision and recall using the following equations:

$$precision = \frac{(tp)}{(tp + fp)}$$

$$Recall = \frac{(tp)}{(tp + fn)}$$

Where tp – is true positive, fp – is false positive and fn – is false negative.

True positive represents the number of frames that are correctly classified by the SVM as replay frames. False positive represents the number of frames that are wrongly classified by the SVM as replay frames. False negative represents the number of replay frames that are not classified by the SVM as replay frames.

We have evaluated our proposed method on the video segments given in table 1 and results of our proposed method are as shown below in Table 3.

Where NARF – is the Number of Actual Replay Frames, NRFD – is the Number of Replay Frames Detected by the proposed method, NERFD – is the Number of Extra Replay Frames Detected by our method, NMRF – is the Number of Missed Replay Frames, P – Percentage of

Table 3: Experimental results of the proposed framework.

Video	NARF	NRFD	NERFD	NMRF	P	R	T
1	384	384	2	2	99.48	99.48	17.04
2	482	481	2	1	99.79	99.59	17.46
3	771	776	5	0	99.36	100	17.09
4	367	373	6	0	98.39	100	17.24
5	358	364	6	0	98.35	100	17.39
6	188	194	6	0	96.91	100	17.26
7	431	437	6	0	98.63	100	15.63
8	178	184	6	0	96.74	100	16.70
9	294	300	6	0	98	100	17.10
10	392	398	6	0	98.49	100	16.33
11	408	413	5	0	98.79	100	17.95

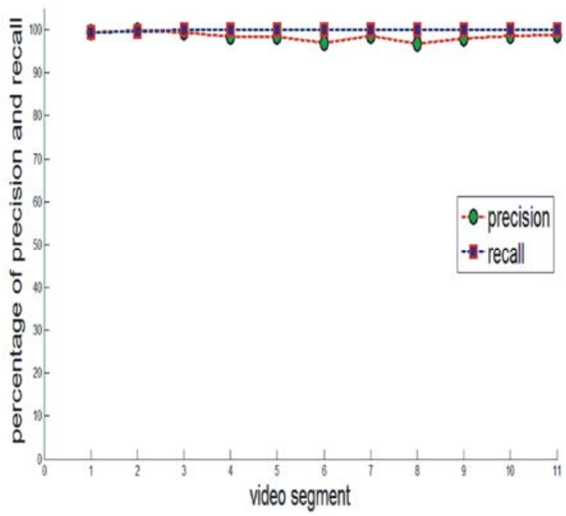

Fig 6: Precision and Recall graph of our method

Precision obtained by our proposed method, R– Percentage of Recall obtained by our proposed framework, T – is the amount of time taken in Seconds, by the SVM for classification of frames in the corresponding video segment.

The graph for precision and recall is as shown in figure 6.

CONCLUSION

In this paper we have proposed a SVM based replay frame detection framework using the small block of score board as shown in template 1, this shows that our proposed method uses only little amount of information from each frame to perform the task of replay frame classification. As shown in table 3 the amount of time taken to classify the frames in the test video segments is very low. Our proposed algorithm is able to detect almost all replay frames in every test video segment. Our results are significant and up to the mark compare to already existing methods. On an average we have obtained a recall of 96% and a precision of 99%.

In our future work we will try to improve the performance of the proposed method by increasing the size of training data set and also increasing the number of feature vectors provided as training data to the support vector machine.

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