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Umpire Gesture Detection and Recognition using HOG and Non-Linear Support Vector Machine (NL-SVM) Classification of Deep Features in Cricket Videos

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ABSTRACT
Gesture Recognition pertains to recognizing meaningful expressions of motion by a human, involving the hands, arms, face, head, and/or body. It is of utmost importance in designing an intelligent and efficient human–computer interface. . In recent years, there has been increased interest in video summarization and automatic sports highlights generation in the game of Cricket. In Cricket, the Umpire has the authority to make important decisions about events on the field. The primary intention of our work is to design and develop a new robust method for Umpire Action and Non-Action Gesture Identification and Recognition based on the Umpire Segmentation and the proposed Histogram Oriented Gradient (HOG) feature Extraction oriented Non-Linear Support Vector Machine (NL-SVM) classification of Deep Features.
Key words: Computer Vision, Machine Learning, Umpire Detection, Umpire Segmentation, Umpire Gesture Recognition, Histogram of Oriented Gradients (HOG), Non-linear Support Vector Machine Classifier.

I. INTRODUCTION

Background

Content portrayal and naming of video successions have developed into critical examination regions with the objective of naturally depicting the subjective video. Separating significant rank semantics from video information is a troublesome issue. Since sports recordings are unscripted in nature, it is a serious moving errand to create the features in sports recordings. An effective method to produce features in sports recordings is to recognize the occasions in that game. Since the occasions in various games are not comparable, we can't utilize a typical strategy for creating client favoured video cuts from sports recordings. Among the games, Cricket is a famous game having high viewership rating from one side of the planet to the other. The game term ranges from one day to five days. Removing the significant occasions from the cricket match-up assists with featuring the client's intrigued cuts with regards to a brief period. An umpire is available, who has the power to settle on choices during game-play.

Literature Review

This segment uncovers the writing audit of a few techniques identified with umpire present identification, pitch outline order, batting shots acknowledgment, occasion, and action discovery are portrayed and broke down as follows: Chambers, G.S et al.[1] developed an approach for Automatic labelling of sports video using umpire gesture recognition using Hierarchical hidden Markov model. It considers gestures at different levels of abstraction and handles extraneous umpire movements. But however, it failed to use the filler model ratio to provide more insight. A Heickal, H et al.[2] presented an approach for real-time 3D gesture recognition using depth image adopting Naive Bayes and neural network classifier. It attained better accuracy as 98.11% using neural network and 88.84% using Naive Bayes method and failed to use the features, like finger positions. Hari, R. and Wilscy, M et al.[3]developed the K-means segmentation algorithm for occasion identification in cricket recordings utilizing power projection profile of Umpire signals.This algorithm effectively recognizes the occasions in the cricket video. This calculation yields an awesome outcome for put away cricket video, which can likewise be utilized progressively with devoted equipment support. The method does not consider excusals of a batsman by getting the ball by the defender of inverse side are not flagged as expected by the Umpire. Bhansali, L.and Narvekar, M [4] employed Gradient Method for Gesture recognition to make umpire decisions and It was capable of recognizing a group of six umpire gestures from the game of cricket and performs best once using a feature set. The main drawback of this method is, the performance of segmenting gestures from a stream of continuous gestures by selecting candidate gestures by the existence of movement was poor.

Cricket Dataset Description

For Umpire Gesture Detection and Recognition, we utilize One Day International World-Cup2013 cricket video matches of range 2:12:38 seconds. Appropriately making a total of 20 accounts of at regular intervals and complete edges are 1, 93,000 open in the dataset. Test dataset SNWOLF traces are shown in figure 1. In our proposed approach, we haphazardly and manually selected 80% of
Umpire Action and Non Action frames from total Dataset frames for Feature Extraction using Histogram Oriented Gradient algorithm .

Existing System

Signals are known as expressive, significant body development which includes actual development of the fingers, hands, arms, head, face, or body with the purpose of 1) appointing significant data or 2) interfacing with the climate. As of late motions are generally utilized by people to associate with PCs and machines. The human signal comprises of significant developments of hands, arms, face, head, or different appendages.

This is a non-verbal method of correspondence and is appropriate for human-machine cooperation. Sports authorities perform numerous signals which are demonstrative of what is happening in the game. Their signals can give something significant about a player, a group, or the whole game. On the off chance that the tokens of these authorities can be perceived, significant data can be determined.

We allude to a signal as a purposeful activity whereby a piece of the body is moved in a predefined approach to show a particular occasion. Recognizing these occasions empowers programmed age of features and all the more significantly, rich, relevant naming of video.

Disadvantages

- Person who updates the score board has to continuously observe the umpire
- He/she may miss few umpire signal

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Proposed System

In this project, an umpire action and non-action detection and classification is developed based on Histogram of Oriented Gradients (HOG), Non-Linear SVM classifier and CNN. The general methodology of the proposed technique includes division, highlight extraction, and umpire activity and non-activity outlines arrangement.

At first, the Umpire video frames are extracted from the Umpire Frames Segmented database and the 80% of Umpire Action and Non-action frames are selected manually and feature extraction is performed based on HOG and trained to Non-Linear SVM classifier and CNN. After that, the remaining 20% of the frames, feature extraction is performed using HOG and tested using trained NL-SVM Classifier and CNN, which categories the Action and Non-action Umpire Frames.

Advantages

- Automatic score board update
- No human involvement to update the score
- Less error

Umpire Action Dataset

We have arbitrarily gathered 80% of pictures of umpires performing different activities relating to occasions, for example, "Six", "No Ball", "Wide" "Out", "Leg Bye", and "Four". These pictures have been gotten from One Day International World-Cup-2013 cricket video matches of length 2:12:38 seconds. The dataset includes six classes of information outlines. Every one of the six classes having a place with the six activities and one Non-Action class in which the umpire Action doesn't exist as displayed in figure. 3. The umpire Action class consists of 1040 images for all six classes.

Block Diagram

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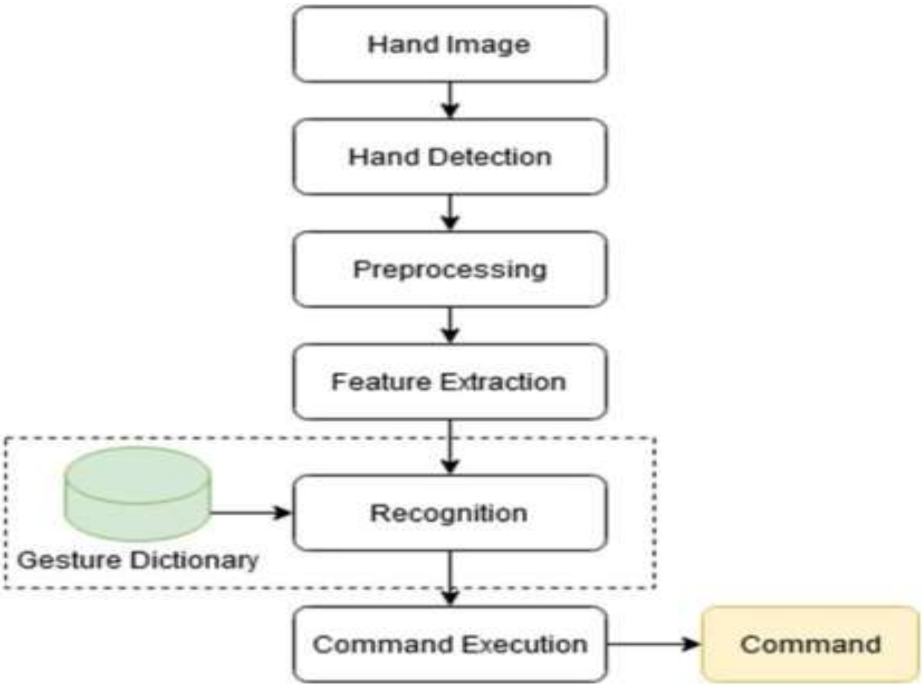
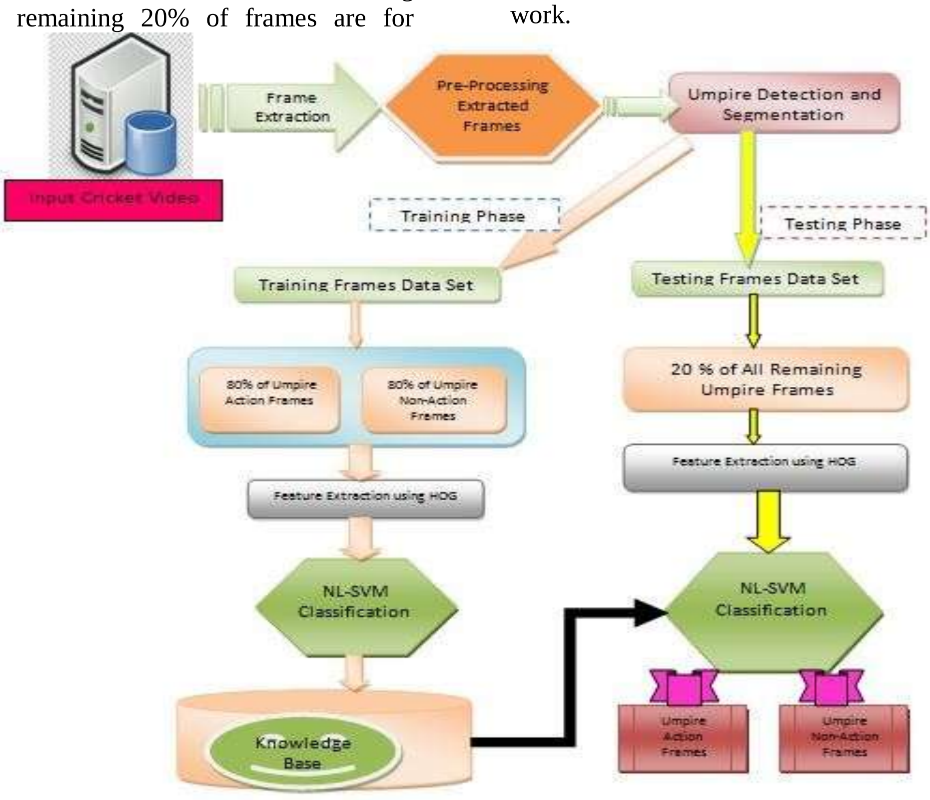


II. METHODOLOGY

Our proposed strategy employments One Day International Cricket Video of length 2:12:38 seconds having 1,93,000 edges named SNWOLF Dataset. The 80% of frames are randomly selected for each Umpire Action and Non-Action classes from total SNWOLF dataset for NL-SVM training purpose and remaining 20% of frames are for Testing purpose. It is sufficient & thoroughly examined as information and yield will be Umpire Action and Non-Action class Classification out of Testing experiment using Knowlwdge Base generated out of Pre-trained network phase of Non-Linear Support Vector Machine. The figure 4. Exhibits the proposed methodology and suggested work.



Algorithm: Umpire Action/Non-Action Frames HOG features Extraction
Step1: Read Umpire Action /Non-Action images from Training Action /Non-ActionDataset folder
Setp2: Set Training Ratio to 0.8
Step3: Extract HOG features from true color or grayscale image I and returns the features in a 1-by-N vector for each image in Umpire Action/Non-Action Set
Step4: Label “1” for each image in Action Dataset and Label “2” for image in Non-Action Dataset

Algorithm: Extract HOG features for Testing Dataset at Testing Phase

1. Read remaining 20% of frames from SNWOLF database
2. Pre-process the current frame
3. Detect the people in the frame
4. Detect the Umpire and Segment the Umpire frame
5. Extract the HOG features and assign class label for each frame in Testing Dataset
6. Forward HOG features and class labels of Testing Dataset to NL-SVM for Testing to classify into Umpire Action or Non-Action class by using Knowledge base created at Training Phase.
7. The test exactness is determined dependent on the excess 20% of the concealed information.
8. The Highest Result Accuracy is seen through confusion matrix

III. RESULTS

At first, the HOG highlights were determined for 80% of each Umpire Action and NonAction pictures. However, while calculating the HOG features for the Umpire Action and Non-Action images, which are contributions to the classifier, the cell size utilized is 16 x 16.

The Radial Bias Kernel Function algorithm based NL-SVM classifier is implemented for the preparation and testing of the order stage. One Day International Cricket Match of duration 2:12:38 seconds having 1, 93,000 images Dataset named SNWOLF is utilized. It was picked in light of the fact that it gives a different subset of information base cantered towards the various assignments engaged with a Umpire Gesture Recognition, namely People Detection, Umpire Detection, Umpire Segmentation and Classification for overall system evaluation. For preparing of classifier, it gives 1040 physically chose positive (or Umpire-Action) pictures and 5399 physically chose negative (or Umpire Non-Action) pictures.

A classifier prepared with additional preparation information would be better proficient at precisely recognizing an Umpire Action and Non-Action images of remaining 20% data frames. Hence to bring in more Umpire Action and Non-Action present situations, the SNWOLF dataset utilizes Umpire competitor pictures of the Umpire Segmented dataset. The demonstrated work uses 80% of 1040 Action and 5399 Non-Action Umpire images for training of classifier to generate the knowledge base. For testing, the described work uses a total of 832 Umpire Action and 1079 NonAction images by using knowledge base generated at training phase.

IV. CONCLUSION

In this paper, execution of two key squares in the Umpire Gesture Detection, Recognition and Classification structure, specifically include extraction and grouping are introduced. Histogram Oriented Gradient highlights are carried out for include extraction, with a cell size of 16x16 (for computational accelerate) and a proficient standardization technique (for enlightenment invariance). A soft-margin Non-Linear SVM, based on the HOG algorithm is used for implementation of the classification module. The classifier uses a subset of the SNWOLF Cricket Sports Dataset, which is specifically aimed at the training and testing of the classification stage. The outcomes got show high Umpire Action and Non-Acton Umpire order exactness (TP) of 98.60 % and a general arrangement precision (TP+TN) of 97.95 %. Henceforth, the carried out include classifier gathering can go about as a quick and strong structure block for a total Umpire Gesture Recognition and Classification. Anyway the future work can likewise be planned to additionally ad lib the consequences of the introduced work, measures like expanding the measure of preparing information of the classifier and utilizing an appropriate confirmation methodology — to lessen the quantity of false positives incurred—can be embraced.

REFERENCES

[1]. Hand Guesture Recognition Systems With The Wearable Myo Armband, Author:Engin Kaya, Tufan Kumbasar, (2018)
[2]. Gesture Recognition To Make Umpire Decisions,Author: Lesha Bhansali, Meera Narvekar, (2019)
[3]. Detecting Third Umpire Decisions & Automated Scoring System Of Cricket

Author: Md.Kowsher, M Ashraful Alam (2019)
[4]. RGB-H-CbCr Skin Color Model For Human Face Detection Author: Nusirwan Anwar Bin Abdul Rahman, Kit Chong Wei & John See (2019)
[5]. A Vision Based Dynamic Gesture Recognition of Indian Sign Language on Kinect based Depth Images Author: Geetha M, Manjusha C, Unnikrishnan P & Harikrishnan R (2018)
[6]. A New 2D Static Hand Gesture Color Image Dataset for ASL Gestures Author: A.L.C. Barczak, N.H. Reyes, M. Abastillas, A. Piccio & T. Susnjak (2018)
[7]. A Color Hand Gesture Database for Evaluating and Improving Algorithms on Hand Gesture and Posture Recognition Author: Farhad Dadgostar, Andre L. C. Barczak (2019)
[8]. Low cost approach for Real Time Sign Language Recognition Author: Matheesha Fernando, Janaka Wijayanayaka (2018)
[9]. Static Hand Gesture Recognition Based on Convolutional Neural Networks Author: Raimundo F. Pinto Jr. , Carlos D. B. Borges, Antoˆnio M. A. Almeida , and Ia´lis C. Paula J (2019)
[10]. An Approach to Automate the Scorecard in Cricket with Computer Vision and Machine Learning Author: Md.Asif Shahjalal1,Zubaer Ahmad2 (2017)
[11]. Robust Real-Time Face Detection Author: Paul Viola & Michael J.Jones
[12]. Machine and deep learning for sport-specific movement recognition Author: Kevin Ball & Sam Robertson (2018)