IARJSET

ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Vol. 8, Issue 9, September 2021

DOI: 10.17148/IARJSET.2021.8921

Identification of Pose Gesture of Serving in Volleyball and three pointer shot in Basketball using Baysian classification& Image Edge Feature Extraction.

Dr. Ashish Shukla[1] , Mr. Vishwanath D Kale[2]

[1]Sports & Physical Education, SIES (Nerul)College of Arts, Science & Commerce

[2]IT Department, SIES (Nerul) College of Arts, Science & Commerce

Abstract: This paper addresses pose gesture from image sequences by converting them as classification problem. The first step of this work consist of a method to Extract edge features of image and classify images using optimum(bayes) statistical classifier method. We label the extracted data by viewpoints and actions. Next we define classes. Pose detection is based on optimum (bayes) statistical classifier method. We input data using CNN for image for grayscales conversion, smoothening of resultant image. Our proposed work gives results about the difference between pose detected during training and expected pose.

Keywords: pose gesture, Baysian Classifier, CNN,

INTRODUCTION

This paper introduces the methods of pose gesture of players of, volleyball and basketball. During the practice of above games, digital camera captures the multiple frames of player. Using Image processing algorithm we detect the edges of image and extract different features of postures of player. This data was pass as input to supervise model of AI (CNN network). After training of data the output layer information used for further analysis of pose gesture. The propose model process the data through 4 different aspects i.e. elimination of unwanted image components, hierarchal features extraction with symbolization, object detection based on unique factors and classification no different complex scenes. In our work we use pose of serving in volleyball and three pointer shot in basket ball as Master or base image. These images can be act as training data set of User level input images.

TERMINOLOGIES

Basketball players usually score more points during the game by using the jump shot. For this reason it isknown that the basketball jump shot is one of the most important shots of the game. Shooting the ball consists of a correct technique to ensure that the ball goes through the hoop. The aim of this analysis is to analyse the optimal shooting technique of Stephen Curry who is known as one of the premier shooters of theNBA (National Basketball Association).

PRE-CONTACT PHASE - STANCE & HOLDING A BALL

1. Server does their pre-serve routine. Ball is in non-dominant hand and the server is deep enough to make a three-stepapproach.
2. The server starts their approach with the non-dominant foot at a 45-degree angle. The ball is still held in front of the body.
3. The second step is taken with the dominant foot as the player picks-up speed. The hitting arm is behind the body as it wouldnormally be while running but is prepared to move up into ready-to-hit position.
4. The non-dominant foot becomes the take off step as the ball leaves the hand of the server in a low toss. The eyes are focusedon the ball. The shoulders are still at a 45-degree angle and the dominant hand is lifting above and behind the head.

CONTACT PHASE - LIFTING, THROWING & HITTING A BALL

5. The arm that tossed the ball starts lowering down as the abdominal muscles initiate the rotation of the body to bring thedominant hand on the ball. The hitting hand is open with a tight wrist.
6. The ball is contacted in front of, and in line with the hitting shoulder. Ideally, there is a straight line from the contact pointthrough the shoulder and through the hip. The hips and shoulders now face the direction of the serve.

IARJSET

ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Vol. 8, Issue 9, September 2021

DOI: 10.17148/IARJSET.2021.8921

POST-CONTACT PHASE - FOLLOW THROUGH

7. The arm stays extended as it follows through in the direction of the serve. The legs get ready for landing.
8. Landing is balanced with the non-dominant foot touching ground ahead of the non-dominant foot. The server lands in running stride and gets positioned to play defence.

COMPUTATIONAL METHODOLOGY

Gesture recognition methods are highly dependent on the robustness of pose classification, and the pose identification requires efficiency to perform in real time. To solve this multi-class classification problem, we propose aoptimum (BAYES) statistical classifier approach, where the classifier recognise image patterns. Finally, we would like the user to be able to, at any moment, provide labelled training data to correct and improve the classifier robustness, whilekeeping it efficient.

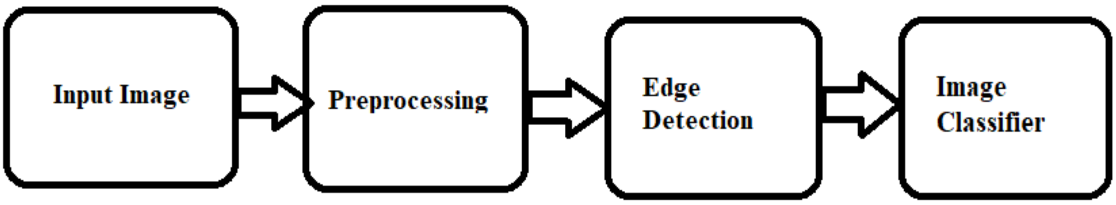


Fig 1: Flow architecture on uderstanding on the basis of edge detection and Optimum(bayes) Classifier

As shown in Fig. 1. First stage comprised of acquisition of image and preprocessing including resizing, gray scale conversion from RGB colour space. While, to remove noisy effect, median filter is applied.

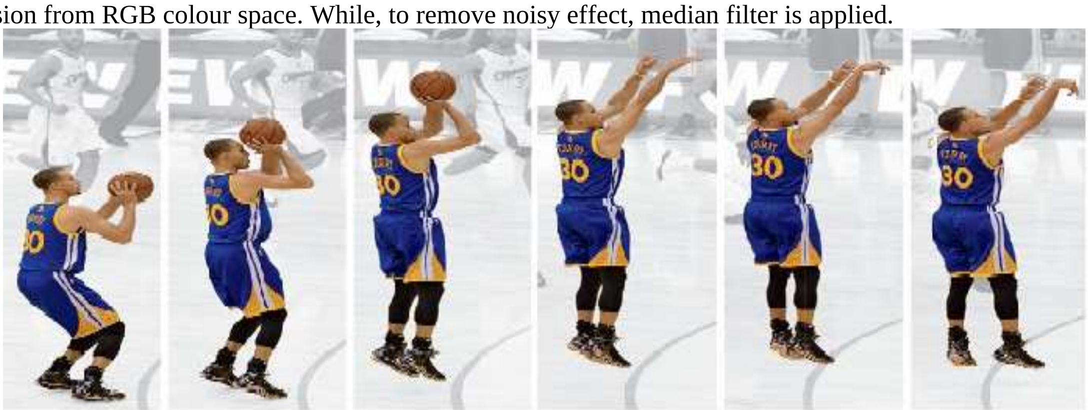
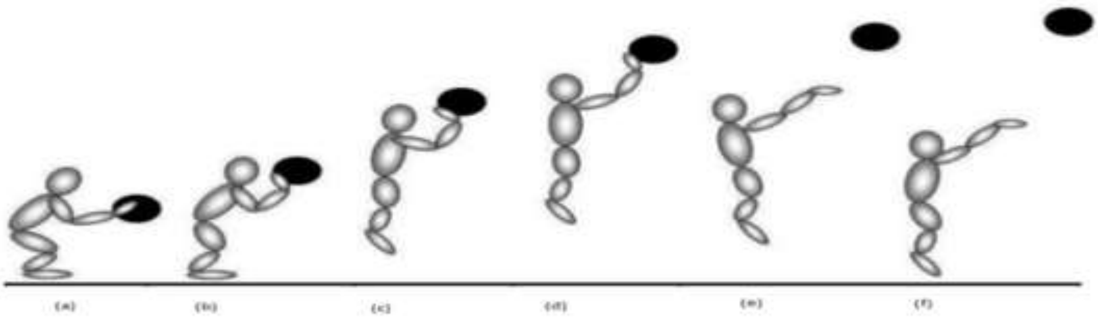


Fig : Image to define Classes in stance & holding balls, lifting balls Throwing & hitting & Follow through

The images we capture are in RGB so we convert them into grayscale to avoid the computational complexity.



Phase I (a) and (b) as Preparation and Ball Elevation phase.
Phase II (c) and (d) as Stability and Ball Release phase.
Phase III (e) and (f) as Inertia and Follow through phase.

IARJSET

ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Vol. 8, Issue 9, September 2021

DOI: 10.17148/IARJSET.2021.8921

This grayscale image we then process by using median filter to reduce noise and enhance edge detection.

II] Optimal Statistical Classifier

To begin, let us consider image involving three pattern classes ( ) Nc = 3 governed by Gaussian densities, with means m1,m2 and m3 and standard deviations s1, s2 and s3, respectively.

$$d_j(x) = p(x/c_j)P(c_j)$$

$$= \frac{1}{\sqrt{2\pi}\sigma_j} e^{-\frac{(x-m_j)^2}{2\sigma_j^2}} P(c_j) \qquad j = 1, 2$$

Where the patterns are now scalars, denoted by x. if the three classes are equally likely to occur, then Pc Pc () () , 1 2 3 = = 1 2 3and the decision boundary is the value of x0 for which px c px c ( ) ( ).

01 02 03= This point is the intersection of the three probability density functions, Any pattern (point) to the right of x0 is classified as belonging to class c1. Similarly, any pattern to the left of x0 is classified as belonging to class c2. When the classes are not equally likely to occur, x0 moves to the left if class c1 is more likely to occur or, conversely, it moves to the right if class c2 is more likely to occur. This result is to be expected, because the classifier is trying to minimize the loss of misclassification. For instance, in the extreme case, if class c2 never occurs, the classifier would never make a mistake by always assigning all patterns to class c1 (that is, x0 would move to negative infinity). In the n-dimensional case, the Gaussian density of the vector

III] Edge Detection

Fig 3 : Image for Edge detection and Compare with Fig 3 statestical data

Edge detection is a technique of image processing used to identify points in a digital image with discontinuities, simply to say, sharp changes in the image brightness. These points where the image brightness varies sharply are called the edges (or boundaries) of the image.

You must have recognized the objects in above image – Stance & holding ball, Lifting of ball, Throwing & follow through. Edge detection features considered while differentiating each of these images. After Classification and compare the images we can detect performance as follows

IARJSET

ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Vol. 8, Issue 9, September 2021

DOI: 10.17148/IARJSET.2021.8921

Table 1: EVALUATION OF THE PROPOSED MODEL UJSINGGAUSSIAN NAÏVE BAYES (MASTER DATA SET)

Image Classes	Stance & Holding Ball ACCURACY % (Master)	Lifting Ball, Throwing & hitting Ball ACCURACY (Master)	Follow Through ACCURACY % (MASTER)
volleyball	93.23	92.13	83.30
Basket Ball	77.18	82.30	79.51
Overall Accuracy	**91.03**	**87.20**	**83.35**

Table 2 : EVALUATION OF THE PROPOSED MODEL UJSINGGAUSSIAN NAÏVE BAYES (SIES DATA SET)

Image Classes	Stance & Holding Ball ACCURACY % (SIES Dataset)	Lifting Ball, Throwing & hitting Ball ACCURACY (SIES Dataset)	Follow Through ACCURACY % (SIES Dataset)
volleyball	89.20	89.24	75.30
Basket Ball	62.45	75.42	68.32
Overall Accuracy	**75.82**	**82.33**	**71.81**

All the experiments performed in Mat lab 2017 and Jupyter Notebook (Python) using Intel Pentium Corei3 (2.0 GH) witha RAM of 6 GB. We performed training and testing using cross- valuation phenomenon for SIES sports dataset 5 Scenes natural and indoor dataset. Table I shows the segmentation results by comparing with annotated ground truth of SIES sportsdatasetand5SceneNaturalandoutdoorscenesdataset. Results shows remarkableperformance.

CONCLUSION & RESULT

In this paper, an effective approach for pose recognition is proposed by applyinstatistical bayes model which exploits classification technique in a sequence of four stages. The morphological operators including dilate, erode and reconstruct methods that are applied to clearly segregate the object from the background. Segmented object is processed by Edge detection and classification to cluster the object with similar features. Finally Gaussian Naïve Bayes classifieris applied for pose (images) recognition using unique features. We validated our system on SIES sports data set and 5 Master images dataset as well

REFERENCES

[1] A.JalalandS.Kamal,“ImprovedBehaviorMonitoringandClassification Using Cues Parameters Extraction from Camera Array Images,” IJMI, 2-18.
[2] A. Jalal, Y.-H. Kim, Y.-J. Kim, S. Kamal and D. Kim, “Robust human activity recognition from depth video using spatiotemporal multi-fused feature,” Pattern recognition, vol. 61, pp. 295-308,2017.
[3] F.Farooq,A.Jalal,L.Zheng,“Facialexpressionrecognitionusinghybrid features and self-organizing maps”, in proc. of ICME, pp. 409-414, July 2017.
[4] G. Zhengyang and Z. Le, “Improved adaptive median filter,” in IEEE ICCIS, pp. 44-46,2014.
[5] B. Bruno, F. Mastrogiovanni, A. Sgorbissa, T. Vernazza and R. Zaccaria, “Analysisofhumanbehaviorrecognitionalgorithmsbasedonaccleration data,” in Proc. of the IEEE ICRA,2013.
[6] Leandro Miranda, Thelas Viera, “Real Time Gesture recognition from depth data through key poses learning and decision forest.”
[7] Gregory Rogez, Jonathan Rihan, srikumarRamlingum, Carlos Orrite, “Randomized Trees for Human Pose Detection”
[8] Guanghui Yang, Lijun Wang, Xiaofeng Xu, and Jixiang Xia, “Footballer Action Tracking and Intervention Using Deep Learning Algorithm.
[9] A. Agarwal & B. Triggs. Recovering 3rd human pose from monocular images. IEEE trans. 28(1) 44-58, 2006