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Review on badminton players hand-grip analysis and tactical dynamics prediction using egocentric vision

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ABSTRACT

Many works have already been carried out on computer vision-based sports analytics, activities in egocentric vision to improve player performance. But less is explored in terms of vision based kinematic analysis in badminton where shuttle trajectory is explored, angles are derived from features and analyzing biomechanics of the player first person vision cameras. This paper reviews existing research on badminton hand-grip analysis and tactical prediction using egocentric vision. It highlights key methods, datasets, and challenges in applying computer vision techniques to sports analytics. The review focuses on computer vision approaches for analyzing hand-grip patterns and predicting tactical dynamics in badminton using egocentric video data. The study summarizes current advancements, identifies research gaps, and outlines future directions for improving egocentric-vision-based sports analytics.

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1. INTRODUCTION

Computer vision, as the name states (a computer’s vision) analyzes images and videos, and predicts the characteristics of the objects present inside them using different machine learning methods [1]. Egocentric vision or the first-person vision (FPV) or ego vision corresponds to recording a video when a wearer wears the camera (example in front of their forehead). It helps to see things from his perspective. Now-a-days increase in work towards egocentric vision has helped in understanding hand movement, hand localization and hand recognition [2], [3]. Videos have been recorded for longer hours especially when travelers are going for longer rides. Those videos have been labelled and summarized as egocentric datasets, which are in turn kept for the researchers for further use [4].

Badminton is one of the famous racket sports along with tennis and squash. It involves playing two to four people on either side of the court, within the team or against each other. The shuttle weighs from 4.75 to 5.5 grams [5] which can travel up to 565 km/h [6]. Grip is an essential part of the game. In badminton, there are two types of grips, forehand and backhand grip. When a shuttle is coming towards the right side of the body, it must be played with the forehand grip or overhand grip. When the shuttle comes to the left side of the body, it can be played with a backhand grip [7]. In backhand grip, the thumb comes close to the racket and is placed parallel to the face of the racket, whereas forehand grip includes holding the racket with the palm like a firm handshake.

Recent advances in computer vision have enabled detailed analysis of sports performance, including player movement, grip techniques, and tactical strategies. Despite growing interest in sports analytics, limited research has explored the use of egocentric vision to analyze badminton hand-grip techniques and tactical decision-making.

Devices such as smartwatches and smart glasses are available on a large scale [8]. ‘Wearcam’(and the concept of FPV) was first introduced in 1998 [9]. Considering the demand, Microsoft presented ‘sensecam’ and Google introduced project glass into the market (2012) to meet the consumer needs [10]. The position of the camera has been changing with time to capture more accurate and dynamic movements (example: placing camera over the chest or wrist-’wristcam’) [11]. Rise in demand for these devices extended the use of egocentric vision into multiple fields.

- Group activity: egocentric videos have been analyzed to understand the behaviour of a group. Sousveillance [12], a system to actively monitor groups of people helpful in the larger surveillance networks. Ibrahim and Mori [13] worked on structuring relations between people in a scene.
- Human activity recognition: research has been carried out on human activity recognition (HAR) in non-uniform environments like terrains and mountains, calibration of mountain trails with terrain transitions and fatigue variations by using data segmentation and labelling methods [14].
- First person vs third person videos: characteristic analysis of first-person videos versus third person videos was performed based on low level features like color and contrast without adding annotations [15]. Personal locations were predicted by using the transfer learning and entropy-based rejection in the egocentric videos [16].
- Summarization and segmentation: egocentric videos were explored on indexing and identifying the locations based on memory [17], [18]. Sparse graphs were used to represent the large-scale video data and spotted it with the help of graphical algorithms. Egocentric video summarization is explored [19], to predict important objects based on their distance, gaze and frequency of their occurrence. Segmentation of long egocentric videos was done based on the wearer’s motion cues using cumulative displacement curves [20]. Egocentric vision helped in creating a driver assistance system which monitors the driver’s gaze and then predicts whether the driver is looking inside the scene of the drive or outside. Bag of words has been used to extract the features from the scene and then vector classification using support vector machine (SVM) has been done [21].

With the help of computer vision, sports have evolved in creating advanced training networks, personal training assistant systems and analyzing player biomechanics, which resulted in improvement of game for the players [22]. Key movements in dancing like jumping and lifting with the help of wearable sensors were identified for ballet dancers [23]. Research has been carried out to identify and classify the change of direction movements in tennis [24]. StagNet [25] was proposed based on a recurrent neural network (RNN) to understand the player movements in group activity. SoccerNet [26] is another neural network which summarizes hours of soccer content with sufficient annotations and does the task of event spotting in soccer videos. In badminton [27], a training system based on body sensor networks (BSN) was proposed using the hidden Markov model (HMM). Multivariate sequencing patterns were used to identify various tactics adopted in sports like tennis and badminton [28], [29]. Analysis of various strokes in table tennis are performed helping coaches to increase their players’ performance [30]. Classification of sports activity was done by attaching sensors to the hand and ankle [31]. A multi sports dataset was presented based on spatio-temporal localized sports actions [32].

In basketball, first person basketball videos were analyzed for predicting the group trajectory [33]. They used a neural network to predict the future movement of players. They analyzed visual semantics of group movements through the work. Some studies [34] have used second order polynomial regression to calculate the trajectory of the path travelled by ball, and they went ahead and used it to predict whether the likelihood of ball hitting the base. In badminton, during women’s singles [35], a player’s style of play is studied, and last 3 shots were predicted before scoring. Surprisingly, it came out that she has scored her points using a baseline high lift with 56% of the rally with the opponent. In one of the studies [36], they used a convolutional neural network (CNN) classifier to predict the player’s shot, after recognizing the object using a lighter you only look once version 5 (YOLO-V5) model and a deep sort for tracking the object in the sports video. A player’s next movement has been predicted based on the previous shot using a graph-based model. They constructed a relation between player’s shot and the next move using a dynamic graph [37]. Real-world badminton datasets have been taken and transformers’ encoder-decoder architecture used to predict the next stroke of the player in badminton [38]. Some studies have completely left the sequence-to-sequence models and graph-based models, and they adapted transformer-based models to form a correlation between shot and player’s movement, and they have used the same to predict the next move of the player [39].

2. METHOD

The review was conducted by analyzing peer-reviewed studies related to badminton analytics, egocentric vision, and grip analysis published in major scientific databases. Computer vision, egocentric vision and sports are taken as three separate entities, and search across google scholar, IEEE and PubMed resulted in few papers. Those papers were then, narrowed by combining keywords like "sports + egocentric vision", and "badminton + egocentric vision", All the papers were considered that combines both egocentric vision and badminton. A summary of the various papers along with their tasks and keywords are shown in Table 1.

Table 1. A summary of the papers with their keywords and tasks achieved

Reference	Year	Algorithm used	Task	Keywords	Limitations
[40]	2022	ReLu, SoftMax	Sports activity recognition, sensor based	Sports, activity recognition	Generic to all sports, not specific to badminton
[14]	2021	CNN (deep learning (DL))	HAR	Egocentric vision	Not related to badminton
[15]	2014	Color based	First-person view (FPV) vs third-person view (TPV)	Egocentric vision	
[23]	2020	DL (3 levels)	Key ballet movements (jumping and lifting leg)	Egocentric vision	
[41]	2022	Reinforcement learning	Tactics evaluation	Sports, badminton	Discussed racket sport on a whole, not specific to badminton
[16]	2017	Entropy based rejection algorithm, SVM	Location recognition, reject negative frames		
[42]	2020		Event detection	Sports, computer vision	Generic sports comparison
[43]	2011	Unsupervised algorithms (clustering)	Action recognition	Egocentric vision, sports	Generic sports with egocentric data. Not specific to badminton
[24]	2020	Random forest (RF)	Player tracking, Tennis	Computer vision, sports	Not related to badminton
[27]	2016	HMM	Action recognition, stroke classification	Badminton, egocentric vision	Relative to both badminton and egocentric vision. However, they used sensor-based networks
[19]	2015	Reinforcement learning	Object recognition	Egocentric vision	Egocentric data but not related to badminton
[20]	2014	Cumulative displacement curves	Segmentation	Egocentric vision	

The methodology outlined in this review is conceptual in nature and derived from the synthesis of existing literature. Instead of presenting a fully implemented system the proposed framework serves as a reference model that highlights key stages involved in egocentric vision-based badminton grip analysis including data acquisition preprocessing, feature extraction analysis and coaching feedback.

- System design setup and data collection: to choose the camera position (head/shoulder/chest). Second, collect data with variation in samples.
- Data pre-processing: to pre-process the data from the collected samples. It is necessary to do object localization and object segmentation.
- Analysis and integration: analyse the processed data by passing it in multiple machine learning algorithms. Analyse grip patterns by using various algorithms.
- Tool development: develop a user interface (UI) tool to understand and display the results provide training protocols on improving player performance.
- Documentation and reporting: validate the results and document the reports.

The analysis of badminton performance remains predominantly reliant on third-person cameras or inertial/body sensors despite extensive research in egocentric vision and sports analytics independently. Currently existing egocentric vision studies in sports focus largely on team sports, activity recognition or general hand-object interaction without exploiting fine-grained grip analysis. In addition, current badminton studies emphasize stroke classification or tactics using broadcast videos or wearable sensors leaving a critical gap in vision-only grip analysis. There is no unified framework that leverages the head-mounted egocentric vision to understand grip analysis, stroke intent and actionable coaching insights.

When considering the intersection of egocentric vision, badminton biomechanics and grip analysis, this study doesn't propose a new algorithm but takes a systematic and analytical look at existing knowledge in this area. This paper shows the problem of badminton grip analysis as a biomechanical issue that relies on vision and lays the groundwork for the use of head-mounted, egocentric vision as a standalone method of tracking, something that hasn't been well-covered in the literature so far.

There are many surveys on egocentric vision or sports performance analysis, but this review focusses on badminton grip analysis with the help of egocentric vision. This paper has put together egocentric vision, racket sports biomechanics and grip analysis all under one roof. This work solves the problem at hand from a vision-only perspective, presenting head-mounted cameras as an alternative for sensor-heavy approaches. It also identifies the limitations and unexplored research opportunities specific to badminton.

3. RESULTS AND DISCUSSION

In various review papers were analyzed related to usage of computer vision in sports [42], [44], [45] egocentric vision [2], [4], [46], [47]. However, since the focus is towards badminton, the search has been refined to racket sports (especially badminton, tennis and table tennis). Apart from the above-mentioned datasets, there are many broadcasting videos available on YouTube. But since the point of interest here is to have a dataset from a first-person perspective, and playing badminton, it is very limited or no data is available on the internet. Hence, a new data set based on wearable cameras must be prepared and record video for multiple skill levels and multiple strokes focusing on the forehand and backhand grip in badminton. Summary of different available datasets has been presented in Table 2. Many approaches were present for HAR. Let us look at the comparative analysis of various approaches used over the years for HAR (shown in Table 3).

Table 2. Summary of available datasets on different sports

Dataset	Sport	Year	AR	OD	SG	LO	Limitations
Badminton olympic [48]	Badminton	2018	✓	-	-	✓	No egocentric data
Stroke forecasting [49]	Badminton	2022	✓	-	-	-	
ACASVA [50]	Tennis	2011	✓	-	-	-	Not badminton related datasets
THETIS [51]	Tennis	2013	✓	-	-	-	
TenniSet [52]	Tennis	2017	✓	-	-	✓	
OpenTTGames [53]	Table tennis	2021	-	✓	✓	-	
Stroke recognition [54]	Table tennis	2022	✓	-	-	✓	

Note: AR: activity recognition, OD: object detection, SG: scene/strategy generation, and LO: localization.

Table 3. Comparative analysis of various approaches used over the years

Method	Description
2-stream CNN [55]	A spatio-temporal network based on neural nets where the spatial network is responsible for identifying objects and scenes whereas the temporal network finds distance, velocity
Temporal segment networks (TSN) [56]	TSN uses segment-based sampling in long range videos to deal with temporal information
R(2+1)D network [57]	A mixed convolution network where input is passed through (2+1)D convolutions to increase the non-linearity
Temporal shift module (TSM) [58]	TSM is a video understanding network to find the flow of information between the adjacent frames
Slow fast network [59]	A network where slow pathway corresponds to spatial information in low frame rates whereas fast pathway corresponds to temporal information in higher frame rates
Temporal pyramid network [59]	It is a 2D or 3D backbone network which employs single or multi pyramid to achieve richer semantics in spatial dimensions

4. CONCLUSION

Even though much research has been carried over in egocentric vision and badminton as an individual, there is a notable gap in using egocentric vision (especially wearable cameras) for analyzing player dynamics in badminton. This paper aims to bridge the gap of analyzing badminton videos through first person perspective which can help players and coaches in analyzing and increasing their performance. This review highlights the potential of egocentric vision for analyzing badminton hand-grip techniques and tactical dynamics. The reviewed studies demonstrate that computer vision methods can effectively capture grip patterns and player movements, enabling deeper tactical analysis in badminton. There is a scope for future research to focus on enhancing deep learning models, building larger egocentric datasets, and developing a real-time analytics system to improve the accuracy of grip recognition and tactical prediction.

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C : Conceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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