Wearable Sensors for Real-Time Kinematics Analysis in Sports: A Review

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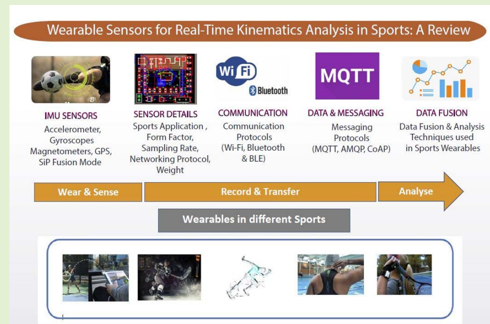

***Abstract*—Wearable Inertial sensors have revolutionised the way kinematics analysis is performed in sports. This paper aims to present a comprehensive review of the literature related to the use of wearable inertial sensors for performance analysis in various games. Kinematics analysis using wearable sensors can provide real-time feedback to the players about their adopted techniques in their respective sports and thus help them to perform efficiently. This article reviews the key technologies (IMU sensors, communication technology, data fusion and data analysis techniques) that enable the implementation of wearable sensors for performance analysis in sports. The review focuses on research papers, commercial sports sensors and 3D motion tracking products to provide a holistic and systematic categorisation & analysis of the wearable sensors in sports. The review identifies the importance of sensors classification, applications and performance parameters in sports for structured analysis. The survey also reviews the technology concerning sensor architecture, network and communication protocols, covers various data fusion algorithms and their accuracy while throwing light on essential performance matrices for an athlete. This review paper will assist both end-users and the researchers to have a comprehensive glimpse of the wearable technology pertaining to designing sensors and solutions for athletes in different sports.**

***Index Terms*—Wearable inertial sensors, IMU sensors, data analytics, accelerometer, gyroscope, magnetometer, kinematics analysis, performance analysis, 3D motion tracking.**

I. Introduction

THE aspiration for prolific achievements in sports, by an individual or a country, motivate researchers, sports' scientists and sportspersons to explore better training and performance analysis methods. A little gain of a single second or even an 'mm' in any athlete's performance can be a significant differentiator over other players. Technology has evolved to such an extent that the study of various performances indicators and analysis parameters are now allowing players to gain and achieve optimal results. Performance analysis in sports is the process of assessing techniques, strengths and weaknesses of players during their respective games to develop an understanding of motion and postures that can help in optimizing their performance and support both coaches and players in achieving the desired goals. Quantification of players' moves and positions in sporting events is essential as it enables coaches to evaluate the performance of the athlete and their rehabilitation and recovery from injuries [1].

Fig. 1. Multiple camera-based video motion capture system - Nike Sports Research Lab [1].

Collection of data related to players' activities during training/game sessions is vital for players/coaches to identify the strong and weak points in the techniques of the players. Traditionally, all these years, performance analysts have been recording training or game sessions and creating video highlights to collect information about all the events happening 'on the ground [2]. This information is provided to players and coaches for the analysis and evaluation of the performance. The primary technique for such analysis is the deployment of video-based sensors that capture images and videos to recognize athletes' movements during training and actual games.

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Fig. 2. A wireless wearable IMU sensor system launched in 2016 for tennis players used to count shots and accuracy level [3].

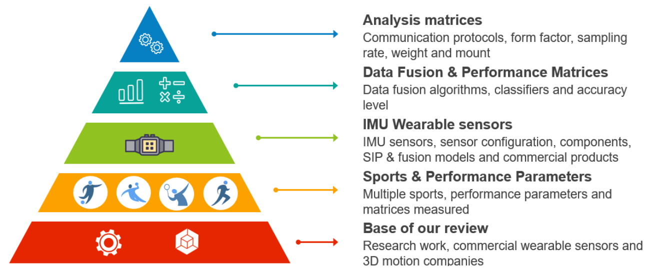

Fig. 3. Methodology used in the review paper.

These video-based techniques are rigid, bulky and are operational only in a fixed environment. These are also not suitable for real-time analysis due to more time requirement for video transfer, tedious post-processing, extraction and analysis of the collected data. There are also possibilities of user privacy and capturing irrelevant data as well. These camera-based performance analysis systems are enormous and require costly hardware setup. A complete and comprehensive profile of a player's performance can be extracted from a setup consisting of multiple synchronized video cameras is needed, thus making this video camera-based system more exclusive and expensive [5].

The above shortcomings of video-based analysis methods call for alternative tools for providing faster and real-time solutions for performance analysis in sports. It has been observed from modern trends for activity and motion analysis that the wearable sensors technology consisting of inertial measurement units (IMUs) is an accessible and suitable alternative for a faster, reliable and cost-efficient process [6], [7]. The recent advancements in sensor technologies and a significant drop in the prices of wearable devices have driven the implementation of wearable IMU sensors in athlete's activity detection and measurement. Use of IMU sensors-based wearable technology that is accessible, small, and flexible in implementation is finding its place in the field of sports analytics and becoming popular.

Recent developments in communication technology, microelectronics, MEMS sensor technology and data analysis techniques have also revolutionized the application of wearable technology for human activity detection and motion analysis [4]. This analysis has allowed the athletes to take advantage of these small, inexpensive and accessible sensors (MEMS-Micro Electromechanical Systems accelerometers, gyroscopes and magnetometers) for monitoring their techniques and activities [5]. Wearables sensors are user friendly with plug and play set up that is easy to use without any complicated arrangement. Moreover, wearables consisting of IMU sensors are proficiently used to classify activity and effort levels. These sensors are unobtrusive and improve reliable data acquisition in different environmental conditions and challenging terrain, unlike video setups that are very difficult to work under the water and on the mountains [6].

This article aims to present a comprehensive review of the application of wearables sensors, data fusion and kinematic analysis in multiple sports. Research work carried out in last ten years in different sports, commercial wearable products for sports application available in the market and 3D motion tracking and analytics solutions by motion tracking companies form the core of this review work. A total of 21 multiple sports-specific research work consisting of data fusion algorithms and the reported accuracies have been included in this article. Data sampling rate and output matrices for 16 wearable sensors are also included in the review. Performance parameters for 17 different sports identified have also been presented in the paper that can be measured using wearable sensors [7]–[9]. 3D motion tracking and analytics solutions from three global companies have also been discussed from the perspective of their application in sports. A detailed analysis of IMU sensors, components and configurations including SiP (System in Package) fusion mode sensors and their examples have also been provided [6], [10]. A discussion on Data fusion algorithm and their sports-specific application along with resultant output and accuracy is also presented. Finally, a summary of 16 commercial wearables sensors used in sports has also been discussed focusing on their form factor, size, weight, communication protocols and mounts. A pyramidical representation of the review process and methodology is shown in Fig. 3.

In general, the studies conducted using the wearable sensors in sports have focused on extracting and using the data for an informed and productive decision making to improve the performance of the athletes as learnt from the literature reviewed. Based on this learning, the review paper has been organized as follows; Components of wearable sensors, including accelerometers, gyroscopes, magnetometers and their suitable combination and classification, have been presented in section II. A detailed analysis of recent research works for specific sports have been presented in section III. Data fusion techniques and algorithms used in sports analytics have been presented and discussed extensively in section IV. Commercially available wearable sensors and products for sports analytics have also been included in section V. For the extensive review, different motions and their effects on the performance of an athlete have also been discussed. Discussion on the review, technology gaps and future scope have been discussed in section VI. The review paper is concluded with section VII.

II. Wearable IMU Sensors for Kinematics Analysis in Sports

Kinematics is a branch of physics that deals with the study of the motion of objects and not concerning the cause of it.

The motion components are displacement, velocity, and acceleration; IMU sensors are used for the kinematic analysis in sports. Kinematics in games allows coaches and athletes to study their technique, analyze sports movements and minimize injury risks. Wearable inertial sensor technologies for sports applications have undergone continuous changes to reduce the form factor of the sensor and optimize power consumption, improving data storage, enhancing processing power, and making them widely available at low cost.

Technically, the term "Inertial Measurement Unit (IMU)" refers to the sensor unit containing inertial sensors which are used to track movement and orientation of the object. The IMUs, when combined with sensor fusion software, can provide orientation concerning the global coordinate system. An IMU sensor unit measures angular acceleration, linear acceleration (force) and sometimes magnetic field also. For instance, an accelerometer measures the time derivative of velocity so that they can be used for kinematics study and orientation using components of accelerations along the three axes. Gyroscopes measure angular acceleration about a single axis and can be used to determine orientation in an angular coordinate system. A magnetometer measures magnetic field strength. An IMU sensor having both 3-axis accelerometer and a 3-axis gyroscope is referred to as a 6-axis IMU sensor. If the sensor includes an additional 3 axis magnetometer, then it is a 9 DOF IMU sensor. Using a combination of multiple sensors allows the building of robust systems that can achieve higher levels of accuracy for activity detection and analysis. Complex sequences of motion can be analyzed using various synchronized wearable IMU sensors.

The primary purpose of these sensors is to measure human movements and orientation with respect to the global coordinate system. A triaxial (3D) Gyroscope or accelerometer provides a detailed and more useful data for orientation and kinematics study contrary to single (1D) axis sensors. Therefore, it can be concluded that a system of synchronized nodes of 9DOF IMU sensor with are best suited for the highest level of analysis.

This 9 DOF IMU sensor is the major component of a wearable sensor in sports where there is a need to measure the kinematics parameters of the athlete. These sensors have low power consumption, small form factor and less weight that makes them best suitable for wearables. However, the principal disadvantage of an IMU sensor is that they accumulate error over time due to not having a fixed reference point location. These accumulated errors are called "drift". These errors must be taken care of for an accurate analysis else the whole purpose of incorporating IMU sensors in wearables is defeated. In a 9DOF sensor, there are three different types of sensor configuration to choose from to design a wearable sensor for precision measurement by eliminating these accumulated errors as discussed below.

A. Individual IMU Sensor System

Separate accelerometer, gyroscope and magnitude sensor of required specification communicating with an external MCU and RF unit to form a wearable sensor. These sensors are bulky with a significant form factor as each sensor have its area and volume. An example of an individual sensor system along with the minimum form factor is given in Table I. It comprises of a 3D accelerometer, gyroscope and magnetometer. In this article LIS3DH, L3GD20H and LIS3MDL from STMicroelectronics are used as an example to constitute the components of the sensor unit. LIS3DH is a 3-axis, ±2.5 g full-scale accelerometer, L3GD20H is a gyroscope sensor, and LIS3MDL is a magnetometer [26]–[28].

TABLE I
IMU SENSOR CONFIGURATION

Configuration	Components	Sensors	Size (mm^3)	Area
Individual IMU Sensor System	Magnetometer	LIS3MDL [28]	2.0 x 2.0 x 1.0	64 mm^2
	Accelerometer	LIS3DH [27]	5 x 5 x 1.7	
	Gyroscope	L3GD20H [26]	3 x 3 x 1	
SIP IMU Sensor	Magnetometer Accelerometer Gyroscope	LSM9DS1 [30]	3.5 x 3 x 1.0	10.5 mm^2
SIP IMU Sensor Fusion	Magnetometer Accelerometer Gyroscope 32-bit MCU	BNO055 [10]	3.8 x 5.2 x 1.13	19.76 mm^2

B. System in Package IMU Sensor

In these types of sensor configuration, a single SiP MEMS sensor contains a 3D accelerometer, 3D gyroscope and 3D magnetometer. This single SIP communicates with the MCU and RF module to form a wearable sensor unit. The data extracted from the sensor is in unprocessed raw form. Individual values from accelerometer, gyroscope and magnetometers are subject to drifts and errors [5], [29]. Acceleration values accumulate errors due to drifting; gyroscope orientation shows depended values for each rotation forming a gimbal lock, and magnetometer values are affected by an external magnetic field created by any small source. Hence, data fusion techniques like Low pass, high pass, Kalman and other stabilizing filters are required to extract true raw values using an MCU. LSM9DS1 is a SiP sensor from STMicroelectronics. The LSM9DS1 has a linear acceleration full scale of ±2g/±4g/±8/±16 g, a magnetic field full scale of ±4/±8/±12/±16 gauss and an angular rate of ±245/±500/±2000 dps [30].

C. SIP IMU Sensor Fusion

In these types of sensors beside from 3D accelerometer, 3D gyroscope and a 3D magnetometer, an MCU is also integrated with the SiP to provide stable raw value from the sensor. The raw output values from the SIP sensor is a result of intra sensor data fusion that provide stable values irrespective of the external environment. They are immune to drift errors

TABLE II
COMMERCIALLY AVAILABLE WEARABLE SENSORS FOR SPORTS ANLAYTICS

Company	Wearable Device	Application	Connection protocol	Mount	Sensor Components	Size	Weight	Matrices Measured
Stance Beam [15]	Stancebeam Striker	Cricket	BLE	Cricket Bat	3D Accelerometer & 3D Gyroscope	29mm x 29mm x 15 mm	10gm	Speed, Power, Timing, 3d Swing Analysis Angle and Direction Session Details
Str8bat [14]	str8bat	Cricket	BLE	Cricket Bat	3D Accelerometer & 3D Gyroscope & 3D Magnetometer	80mm x 50mm	15gm	Shots swing speed, Impact speed, Bat lift angle, Timing index
Zepp [31]	Zepp Baseball	Baseball	BLE	Bat	Dual axis accelerometer	27.94 mm x 27.94 mm 10.16mm	9gm	Bat speed, Hand speed, time-to-Impact, Attack angle
Zepp [32]	Zepp Golf	Golf	BLE	Glove	Accelerometer, Gyroscope, Magnetometer	27.94 mm x 27.94 mm 10.16mm	9gm	Club speed, Club plane, Tempo, Backswing length
Zepp [33]	Zepp Tennis 2	Tennis	BLE	Racquet	3D Accelerometer & 3D Gyroscope	27.94 mm x 27.94 mm 10.16mm	9gm	Racquet speed, Potential ball speed, Spin, Backswing time, and Impact time.
Zepp [34]	Zepp Play Soccer	Football	Bluetooth 4.2	Calf Sleeve	3D Accelerometer & 3D Gyroscope	7.2mm 38mm 27.2mm	6.84g	Track on-field stats including Kicks, Sprints, Distance, Max speed
Kinexon [35]	Kinexon Perform	Football, Basketball, Hockey, Handball	RF	sensors can be mounted in different ways (shirts, clips for trousers etc.)	Accelerometer, Gyroscope, Magnetometer	30.75x25.4mm	14g	Changes of direction Accelerations Decelerations High metabolic power distance Max. speed Max. acceleration Max. deceleration
Motus [36]	Motus THROW	baseball	Bluetooth	compression sleeve on the throwing arm	Accelerometer, Gyroscope	38 mm x 25 mm x 9 mm	6.8gm	Acute and Chronic Workloads Arm Stress (elbow valgus torque) Throw Count Arm Speed Arm Slot at Release Max Shoulder Rotation

TABLE II
(Continued.) COMMERCIALLY AVAILABLE WEARABLE SENSORS FOR SPORTS ANLAYTICS

Company	Wearable Device	Application	Connection Protocol	Mount	Sensor Components	Size	Weight	Matrices Measured
Motus [37]	Motus QB	Quarterback Throwing Analysis	Bluetooth	Compression sleeve or wristband	3D Accelerometer & 3D Gyroscope	29.9 x 22 x 9.9 mm	6gm	Total Throws High Effort Throws Elbow Distraction Force Elbow Valgus Torque Arm Speed Arm Angle Shoulder Rotation Fingertip Velocity
Motus [38]	Motus VB	volleyball	Bluetooth	compression sleeve or wristband	3D Accelerometer & 3D Gyroscope	29.9 x 22 x 9.9 mm	6gm	Day Workload Chronic Workload A:C Ratio Arm Health Tracking impact Speed Ball Speed Potential
Actofit [20]	Actofit Badminton Tracker	Badminton	Bluetooth	Badminton Racquet	3D Accelerometer & 3D Gyroscope	29.9 x 22 x 9.9 mm	6gm	Drive, Lift, Drop, Block, Slice Smash Shot count
Actofit [39]	Actofit Edge	Real Time Auto Activity Tracker	Bluetooth	Wrist Straps	Accelerometer & Pedometer	23mm x 15mm x 10mm	18gm	Heart rate & daily steps, Distances, Calories
Targetize [40]	Targetize	Shooting	BLE	Gun	9 axis IMU	35mmx45mm	28gm	Handgun Accuracy: Hand position
Catapult [41]	ClearSky T6	athlete monitoring	BLE	Back shoulder	9 axis IMU	84mm x 42mm x 21mm	42gm	Activity, Heart rate, distance,
Catapult [21]	Playertek	athlete monitoring	BLE	Back shoulder	Accelerometer, GPS	48mm x 40mm x 6mm	53gm	Physical and tactical performance
Catapult [22]	Catapult Vector	Sport Specific Application, any field game	BLE	Back shoulder	9 axis IMU, GPS	81mm x 43mm x 16mm	53gm	Load, Intensity, impact, speed, rotation, counts (depending on sports)

and external magnetic field. BOSCH BNO055 is a SIP sensor Fusion packages that deliver sensor fusion data in quaternion, Euler and polar coordinate system [10]. Stable linear acceleration data along with independent AHRS data are extracted from its 16g accelerometer, 2000deg/s gyroscope and a magnetometer data fused together in a 32-bit cortex M0+ microcontroller [10]. The data can be directly used as true raw values for further analysis that saves time and resources for the developers in product development.

III. Related Research Works

Wearables for sports analytics is a relatively new field where the majority of products have been launched in the last ten years. In the last few years, data analytics in sports became popular, mainly due to the availability of affordable and small wearable sensors. In this section, a summary of research works available in support of the use of wearable sensors for analyzing the techniques and performance for different sports has been presented.

A. Wearable Sensors in Tennis

Tennis is a technique and strength orientated game. Multiple sensors mounted on arms and body provide the much-required data for performance and technique analysis.

In [9], three wearable IMUs equipped with 3D accelerometer and 1D gyroscope were used for analyzing the skills of tennis players. Angular velocity data from the upper arm, chest and the hands were used for skill evaluation and skill acquisition of players in Tennis.

In [54], tennis stroke recognition has been discussed by using a single IMU sensor that is mounted on players dominant arm to detect the spike in accelerometer reading when the ball hits the tennis racket. The strokes and non-stroke events are filtered. The strokes are classified into serve, backhand or forehand using either accelerometers, magnetometers or gyroscopes data. Naive Bayesian classifier was used to classify strokes into serves, backhands and forehands.

Authors in [12] developed an analytics system for tennis shot detection and classification on the basis of data acquired from a wearable sensor worn on the wrist by the player. The data for shot detection were collected from the players using gyroscope and accelerometer sensors. Quaternions based Dynamic Time Warping (QDTW) classifier was used to classify shots. A two-level hierarchical classifier was used. At the first level, shots were classified into forehand, backhand or serve by applying classical Dynamic Time Warping (DTW) on accelerometer and gyroscope data. At the second level, shots were classified into sub-shot type by applying QDTW on quaternion time series calculated for shots.

In [55], a wearable system to gather data for motion and movements of shot to capture the kinematics of tennis players has been implemented. Commercially available EXLs3 IMUs consisting of 3D accelerometer, 3D gyroscope and 3D magnetometer were used. One sensor was placed on a tennis racket, and two sensors were attached to each shoe of the player. LCSS (Longest Common Subsequence) algorithm [56], [57] was employed for classification of shot movement. The data from the gyroscope allowed to distinguish shot movements more precisely during play movement. The data was first discretized using k-Means algorithm, and then LCSS was applied. The type of steps performed during a game was classified using the data from the gyroscope sensor mounted on foot. Dead reckoning [5], [29] was used to identify the steps.

In [58], a methodology based on data fusion for sports training has been presented. A system was developed to assess the performance of a tennis player. The system recorded the data, created a profile for each player, provided a feature to browse the history of stored data and performed identification and classification of tennis strokes based on the data acquired from the sensors mounted on the players' wrists.

B. Wearable Sensors in Football

In [59], impact velocity, acceleration and frequency during tackling events in Australian football have been described and quantified by implementing video and motion tracking wearable technology. Velocity and acceleration of the players were assessed using Minimax X S4 placed on the upper back of the player. During the tackles, speed and force of impact were measured. Based on the observed values, tackles were categorized into three different intensity groups viz. low, medium and high. At every point of contact between the players, peak Global Positioning System (GPS) and accelerometer data were observed.

An algorithm has been introduced in [60] to detect a kick in soccer based on data acquired from a wearable inertial sensor placed on the back of the ankle of the kicking leg. The wearable sensor used consisted of a 3D accelerometer, a 3D gyroscope and a 3D magnetometer. The algorithm searches for backward/forward swings of kicking to verify kick motions, which can give relevant data to assess features for the quality of kicks in soccer. It was observed that for a valid kick motion, acceleration and the derivative of acceleration (jerk) [61] change drastically at the moment of impact.

In [62], a system called "StreamTeam" has been introduced for football to monitor, analyze, and visualize the actions of players in real-time in highly dynamic and mobile environments in a robust and scalable way. Authors demonstrated the application of "StreamTeam" to generate data from sensors mounted on football players. "StreamTeam – Football" analyzes the raw data generated from the sensors and produces output data similar to data abstraction approach used in Herakles [63]. "StreamTeam" also consists of a real-time web client that captures these output analysis results and displays them in a meaningful way. Overall, this workflow generates data streams of positions, current match time, play direction, identifies changes in ball possession, shots, kick-offs, passes and interceptions, calculates pass statistics, produces heatmaps, and develops a virtual offside line.

In [64], "SoccerMate" has been demonstrated that assists players to enhance soccer skills. Two wrist-worn wearable devices with integrated 3D accelerometer have been used to gather various attributes of a football player for performance analysis. Deep learning-based method Restricted Boltzman Machine (RBM) has been implemented to analyze various

TABLE III
MULTI SENSOR MOTION TRACKING AND ANALYTICS PRODUCTS

Company name	**XSENSE** [23]			**VICON** [50]	**STT SYSTEMS** [25]
Sensor System	MVN Link [51]	MVN Awinda [51]	Xsens Dot [52]	Blue Trident [53]	iSEN [25]
No of Nodes	17 WIRED	17 WIRELESS	5 Wireless	4 Nodes	17 wireless nodes
Communication	One Wi-Fi access point	One Wi-Fi access point	Bluetooth 5 with an access point	Bluetooth 5	Wi-Fi
Sampling Rate	240 Hz Output	60Hz Output	60Hz Output	Upto100 Hz	25 Hz Output
Range	20m	50m	20m	20m	Normal Wi-Fi Range
Dimensions	Suit available in 5 sizes	47 x 30 x 13 mm	36 x 30 x 11 mm	42 x 27 x 11mm	56 (64) x 38 x 18 mm
Weight	Not Available	16gm	10.8gm	9.5gm	46gm

soccer events like in-possession, pass, kick, sprint, run, ball touch and dribbling.

C. Wearable Sensors in Swimming

In [65], automatic detection of main events of breaststroke swimming using two IMUs worn on the right arm and right leg of players has been discussed. The IMUs used consists of a 3D accelerometer and 3D gyroscope. One of the IMUs were mounted at right forearm and another IMU was placed on the tibia just above the medial malleolus. Hidden Markov Model (HMM) was used to study the kinematics signal patterns to detect the temporal phases during the breaststroke.

In [66], a review on the use of IMU sensors for motion analysis in swimming has been provided. It has been observed that IMUs, including accelerometers and gyroscopes are able to assist in performance analysis. The approach of using inertial sensors for monitoring swimming performance was compared with typical video analysis, and the main strengths and weaknesses were highlighted.

Researchers in [67] demonstrated the use of inertial sensors to identify the push-off time point in swimming. [68] supports the use of wearable inertial sensors to identify the longitudinal rotation of the tumble turn action in freestyle swimming. This study showed that the inertial sensors could be used as a tool to evaluate and monitor the secondary rotation of a swimmer. The authors highlighted the capabilities of the inertial sensor to identify turn kinematics with the help of fused video data.

The effectiveness of a wearable device measuring combination of acceleration data and GPS data for kinematics analysis in swimming has been evaluated in [69]. In the study conducted, twenty-one swimmers performed 3 rounds in a 50 m swimming pool which included one round of breaststroke, one round of butterfly and one round of freestyle. The velocity of the swimmer at the halfway mark along with the number of strokes for each trial was calculated from the wearable device, which consisted of a GPS and a 3D accelerometer. For breaststroke and butterfly, the stroke count observed with the accelerometer was found to be strongly similar to the measures obtained using video analysis. For freestyle and breaststroke, the velocity recorded using GPS was similar to the velocity recorded using the video-based method. The velocity recorded using GPS and velocity recorded using video criterion were significantly different for butterfly. The combination of accelerometer and GPS device has been found to be a precise instrument for the measurement of strokes in swimming.

Authors in [6] performed the motion analysis in swimming, canoeing and kayaking using wearable IMU sensors. Multiple IMU devices with 6 DOF inertial sensors consisting of 3-axis accelerometer and 3-axis gyroscope were used to quantify temporal and kinematic features like angular velocity, acceleration peaks, stroke frequency, stroke duration, stroke symmetry, etc. in above-mentioned three water-sports.

Authors in [70] proposed an inertial motion capture system for performance analysis in swimming. The attitude of swimmers was estimated using multi-sensor data fusion technique. The postures of swimming were recreated as biomechanical model. The system can record motion of lumbar spine of a swimmer in four competitive swimming styles. A kinematic analysis of the motion of lumbar spine stipulates that the patterns of motion of lumbar spine of swimmers can be used to assess performance and provide feedback data to swimmers. An orientation estimation algorithm paired with human biomechanical models have been used to assess the motion of the lumbar spine of swimmer. In the proposed method, the Gradient Descent Algorithm (GDA) was adopted for analysis.

D. Wearable Sensors for Running, Race-Walking

It has been observed that mostly fitness runners train by recognizing their skills themselves. A structured evaluation of kinematics is restricted to elite athletes that have access to camera-based laboratory environments. Identification of running asymmetry can help in potential injury identification and management. Minute asymmetries in running are not visually identified and may not be known to the athlete. Hence, there is a need of a data-backed analysis to identify running asymmetries. Generally, camera-based motion capture systems are used in rigid laboratory environments to assess joint kinematics. Force-plates are also used in combination with camera-based techniques to determine body joint/segment loading.

In [18], authors developed a small and lightweight inertial measurement unit (IMU), optimized for on-field analysis

TABLE IV
WEARABLE SENSORS AND DATA FUSION TECHNIQUES USED FOR PERFORMANCE ANALYSIS IN VARIOUS SPORTS

Ref	Sport/ Activity	Purpose	Sensors	#IMUs	Mount	Data Fusion/Analysis Techniques	Remarks
[54]	Tennis	Stroke Recognition: Forehand, Backhand and Serves	Accelerometer; Gyroscope; Magnetometer	1	Forearm	Stroke Classification: Naive Bayesian Classifiers; Accuracy: 10-fold cross validation	First Step Classification: Stroke or Non-Stroke Event; Second Step Classification: Serves, Backhands or Forehands
[58]	Tennis	Tennis Strokes Detection and Classification	Accelerometer; Magnetometer	1	Wrist-worn Pebble Watch sensor	Classification: k-NN and Logistic Regression; Accuracy: 10-fold cross-validation and leave-one-out evaluation	Stroke Classification: Serves, Backhands or Forehands
[16]	Badminton	Badminton stroke detection and classification	Accelerometer; Gyroscope	1	Bottom of Racket Handle	Classification: Random Forest Classifier Accuracy: 10-fold cross-validation	Stroke Detection; Stroke Classification: Clear, Drop, LOB, Drive, Smash, Net play and Serve
[72]	Race-Walking	Assessment of performances and infringements	Accelerometer	1	end of athlete's column vertebra	Statistical Analysis	Data Collection: Loss of Ground Contact (LOGC); Step Length Ratio (SLR); Step Cadence (SC); Smoothness (S)
[73]	Race-Walking	Investigation of feasibility of using machine-learning algorithms fed with inertial data for auto identification of race-	Accelerometer; Gyroscope	7	Hip, left and right thigh, left and right shank, and left and right	Classifiers: DTf, SVMl, SVMq, SVMc, kNNf, kNNc, kNNcu, kNNw, and ANN Accuracy: cross-validation	108 Machine learning Algorithms were compared for every player as combinations of: 4 body segments x 3 datasets x 9 classifiers
[74]	Thrusters	sensor-driven evaluation of athletes	Accelerometer	3	wrist, hip and ankle	Support Vector Machine (SVM)	Automatic classification of thrusters; discriminating beginner athletes from advanced athletes
[13]	Swing Sports	Shot detection	Accelerometer; Gyroscope	1	Wrist	Hierarchical classifier; AVA classifier; Logistic Regression; CNN based classification; BLSTM based classification	used Samsung smartwatch Gear S2 to capture and store data at 100Hz from 3-axes accelerometer and gyroscope sensors embedded in the watch
[8]	Detection of Daily Activities	Activity Recognition	Accelerometer; Magnetometer	2	Wrist, hip	Four different classifiers were used: custom decision tree; automatically generated decision tree; artificial neural network (ANN); and hybrid model	The aim of this study was to examine how well the daily activities and sports performed by the subjects in unsupervised settings can be recognized compared to supervised settings
[75]	Golf	Golf Swing Classification	Accelerometer; Gyroscope	1	Upper back	Classifiers: Support Vector Machine (SVM) Classifier; Deep Convolutional Neural Network (Deep CNN) Accuracy: 10-fold Cross-Validation	Classification Accuracy: Deep Convolutional Neural Network (Deep CNN):95.04%; Support Vector Machine (SVM) Classifier:86.79%
[76]	Swimming	Stroke Count and Stroke Recognition: freestyle, breaststroke, backstroke swimming and turns	Accelerometer	2	Wrist, Upper Back	LDA classifier; QDA classifier	The paper focused on recognition of swimming style; counting of strokes, swimming intensity estimation; and comparison of different sensor placements

TABLE IV
(Continued.) WEARABLE SENSORS AND DATA FUSION TECHNIQUES USED FOR PERFORMANCE ANALYSIS IN VARIOUS SPORTS

Ref	Sport/ Activity	Purpose	Sensors	#IMUs	Mount	Data Fusion/Analysis Techniques	Remarks
[77]	Football	Kinematics analysis of Head Impact	Accelerometer, Gyroscope	2	Helmet and mouthguard	Statistical analysis	Applicability of commercially available HITS & X2 wearable sensors for kinematics analysis of head impact in football
[60]	Soccer	Detection of kick in soccer	Accelerometer, Gyroscope, Magnetometer	1	Back of the ankle of the kicking leg	Mathematical modeling for impact measurement and kick detection in soccer	Proposed an algorithm for detection of kick in soccer using wearable sensors
[64]	Soccer	Kinematic assessment in soccer	Accelerometer	2	Wrist	Restricted Boltzman Machine (RBM) used for classification of soccer events	Results obtained using proposed model "SoccerMate" were compared with the performance parameters evaluated using ZeppSoccer
[18]	Running	Kinematics analysis of runners	Accelerometer, Gyroscope, Magnetometer	12	Foot and shin	Pattern recognition, statistical and mathematical analysis	Used data from two ETHOS IMU units worn on foot and shin; Parameters measured: Foot-ground contact duration, type of foot strike, heel lift
[17]	Running	Kinematics analysis of runners	Accelerometer, Gyroscope, Magnetometer	12	Foot, legs, arms, back	Scatter plots; statistical analysis; Classification of runners: Nearest Centroid Classifier algorithm	Runners distinguished as Beginner, Intermediate, Advanced, Expert
[65]	Swimming	Detection of phases (temporal events) in breastroke	Accelerometer, Gyroscope	2	Forearm(right), tibia(right)	Statistical Analysis; Detection of phases: Hidden Markov Model; Accuracy: Leave-one-out cross validation	Phases in breastroke: Arm extension, Hand backsweep, Elbow Drive, Leg Flexion, Leg Extension, Lifting of Heels
	Swimming	Kinematics analysis in swimming	Accelerometer, Gyroscope	1	Lower back		
[6]	Canoeing	Kinematics analysis in canoeing	Accelerometer, Gyroscope	1	canoe	Statistical signal analysis	Observations: these three water sports have similar kinematic parameters for analysis of performance; temporal and kinematic features like angular velocity, acceleration peaks, stroke frequency, stroke duration, stroke symmetry, etc. were analyzed
	Kayaking	Kinematics analysis in kayaking	Accelerometer, Gyroscope	1	kayak		
[11]	Tennis	Classification of tennis activities	Accelerometer, Gyroscope	2	wrist, waist	Spectrograms, Multi-Layer Perceptron (MLP), Convolutional Neural Network (CNN)	Tasks preformed: Classification of Stroke or Non-stroke events; For tennis activities - classification of strokes; For non-tennis activities - detection of seven normal activities

in running. An exhaustive run was performed during trials by each runner wearing 12 ETHOS units. ETH Orientation Sensor (ETHOS) constitutes an inertial measurement unit (IMU), which includes a 3D accelerometer, a 3D gyroscope, and a 3D magnetometer sensor. The study presented kinematic feature extraction and analysis based on the sensors placed on the foot and shin (heel lift).

The work presented in [17] explores the possibility of using wearable sensors to extract kinematic parameters in running for data-based performance analysis and injury reduction. Twelve ETHOS units with small form factor were mounted on twelve runners. To distinguish between experienced and unexperienced runners, the kinematics parameters recorded from two acceleration sensors attached to foot and hip of the athlete were found to be sufficient.

In [71], a wearable analysis system to assess asymmetry in running while training has been demonstrated. Twenty-one runners with artificially induced asymmetry were used to evaluate the sensor's ability in the study. Two sensors were mounted on each leg, one above the knee on the thigh and another one below the knee on the lower leg. The system automatically identifies the running duration from other training activities and extracts data for every step sequence. Participants performed different activities like jogging, standing stationary, shuffling, stretching, walking and slow jogging in an indoor environment and running was performed on a treadmill. Random Forest classifier was implemented to categorize data into different activities.

In the work presented in [72], primary results on the implementation of a wearable system consisting of IMU measurement and management unit for performance analysis in race-walking have been discussed. The investigational results support the use of wearable inertial sensor system for on-field training in race-walking to help coaches and players in real-time and to create a customized profile of the race-walkers. Gait and posture analysis can also be performed using the wearable sensors.

E. Wearable Sensors in Hockey and Ice-Hockey

In [78], the use of wearable sensors for training and monitoring of the players in skating and hockey was demonstrated. Two wearable systems, "SkateTracker" and "GameTracker" were presented to quantify the kinematics of players for training and monitoring of skating and shooting in ice-hockey. "SkateTracker" monitors skating, related events like power strokes, breaking, turns, jumps and curves and generates statistical data for every motion. "GameTracker" identifies events of hockey which includes hits, shots, time in motion, etc. The use of a hockey stick equipped with IMU sensors, strain gauges and potentiometers for pressure measurement was demonstrated to measure the hand positions, motion and flexion of the stick during the game. The system can identify different shot types on its own and the skill levels of the players depending on the device usage pattern.

The main objective of the study in [79] was to explore the possibility of utilizing wearable accelerometers to analyze different skill levels and skating stages. 22 ice hockey trainees performed 30m forward skating sprints on an ice rink with two tri-axial accelerometers, one placed on their skate and the other wrapped around their waist. The data from the sensors calculated the contact & stride time along with the stride propulsion of a skating stride. These measurements were used to analyze skill levels, sprint phases, total sprint time.

It can be concluded that the use of wearable technology allows players to assess their performance in real time instead of doing a technical test in rigid video labs. The real-time analysis can be done during the training and on-field performances for instant decision making and data driven evidence-based analysis by the players and coaches in different sports. Wearables sensors and data fusion techniques for performance analysis find their application in ubiquitous sports and are presented in Tables IV and VI.

IV. Data Fusion And Analytics

Data fusion & analytics is essential for interpreting the vast volume of data generated by wearable sensors. Interpretation of these extensive data sets is a challenge because of the heterogeneous and random nature of the data. Heterogeneous nature of data arises as the data are generated from various sensing modalities. Data fusion techniques help in building a meaningful and detailed description of the performance of players. The collection of raw data from sensors is the first step in data-fusion based approaches to performance analysis. The data are collected from the wearable IMU sensors worn by the players. Then the data are transmitted wirelessly to a remote computational device (computer or smartphone). The data from these sensors are processed to extract the features about the physical performance that allows the coaches and physios to plan the recovery routine for the best and quickest recovery. A meaningful interpretation in the form of charts, plots, graphs is extracted after the implementation of data fusion algorithms for visualization and representation.

With the advent of wearables sensors and data fusion techniques, data analytics has started to play a significant role in the sports industry for analysis of players' technique, physical strength, training efficiency, performance. Every sport has different techniques and parameters that affect the performance of an athlete. Data fusion techniques allow us to measure these performance parameters in games, for instance, in swimming, hands and legs movement of the swimmers play a crucial role in training. Stroke frequency, head profile, the technique in swimming can be measured using a kinematic analysis system. Similarly, for a cricket bowler, elbow angle at the time of ball release decides the legality of the bowl bowled and, head and back movement also affect the quality of the bowling. Kinematics of these actions allow the player and coach to analyze the bowler's action and make adjustments for further improvements. Details of parameters for kinematic analysis for different sports are given in Table V. Extracting these data parameters forms the basis of applying wearable sensors in sports analytics. Table IV shows the essential details about the sensors whereas Table VI throws light on the literature reviewed in the paper in relation to data fusion techniques summarized in the paper.

Accuracy of data fusion techniques in analysing the performance and producing the results plays a crucial role in the

TABLE V
PARAMETERS FOR KINEMATICS ANALYSIS IN VARIOUS SPORTS

Sports	Type of Analysis
Cricket (Batsman) [80]	Angle of the bat (Straight bat); Elbow angle; Front leg angle; Weight distribution between the legs (need extra sensor for this); Head-bat-elbow line to play with straight bat; Impact of the ball at bat (not possible to detect the location); Bat lift angle
Cricket (Bowler) [81]–[84]	Angle between head and arm; Ball release angle from the hand; Front leg straight or bent; Follow through line after bowling; Elbow angle less than 15deg for legal delivery
100m sprint (Runner) [8], [17], [18]	Back angle (straight); Back leg and back line; Body in straight line (min yaw); Starting jump angle from the initial stance
Boxing [85]–[87]	Punch classification, reaction time, punch travel
Basketball [63], [88], [89]	Free throw shooting stance, pointers shooting stance, follow through
Skateboarding [90]	Identification of different tricks and their accuracy, 360 deg rotation, flips
Archery [91], [92]	Arrow Release angle, Deflection, accuracy of release
Volleyball [93]–[96]	Vertical Jump parameters, height
Weightlifting [74]	Back angle, head position, movement and techniques
Golf [13], [97]	Hand and wrist position, club rotation, swing and speed
Badminton [13], [16]	Shots count and classification
Swimming [67], [68]	Classification of swimming style, stroke frequency and efficiency
Alpine Skiing [98]	Movement and techniques
Tennis [99], [100]	Swing and rules (challenge)
Snowboard [7], [101]	Real-Time feedback of snowboarding
Martial Arts [24], [102]	Movement and techniques
Taekwondo [102]–[105]	Movement, techniques and rules (system)
General Sports [4], [106]	Classification of the modality or activity of the sport

acceptance of the fusion model as a whole. These techniques include statistics, classifiers, algorithms and machine learning for both analysis and analytics. Data fusion techniques and their accuracy in kinematics and performance analysis in sports like tennis, football, running events, water sports, golf and impact games are discussed below.

In [54], authors present the application of Naïve Bayesian classifiers for tennis stroke classification. Tennis stroke identification and classification based on IMU sensor mounted on player's forearm has been presented using individual data from accelerometer, gyroscope and magnetometer. Combination of accelerometer, gyroscope and magnetometer data also provide valuable data for stroke classification. A global feature vector was generated to filter stroke events from non-stroke events by using the accelerometer, gyroscope and magnetometer data separately. The spikes in the accelerometer data were used to detect the stroke. Another global feature vector was created, and all the stroke events were classified into serves, backhands and forehands using Naive Bayesian classifier from accelerometer data. The same process is repeated for gyroscope and magnetometer separately. Out of the three individual classification process, classification based on accelerometer data were found to be accurate. When the same filtration and classification of the strokes into serve, forehand and backhand was performed using sensor fusion of all the 3 sensors combined; the Naïve Bayesian Classifier achieved 90% accuracy in stroke classification. The data analyses in the research also presented the option to use any combination of 2 intra sensor data from the 9D IMU sensor.

The accuracy level of the data fusion technique applied is given in Table VI. The sensor used for the experiment is a Tyndall developed TennisSense WIMU system, which is based on Tyndall's 25mm Mote platform. This provides a small, lightweight and low-cost method for instrumenting human subjects to provide high-speed motion data. The sensor communicated using a 2.4GHz RF system with a data transfer rate of 100 red/s.

Another approach for stroke detection and classification into forehand, backhand and serve is presented in [12] combining acceleration and orientation data from the IMU mounted on the wrist of the players by applying Quaternions Dynamic Time Warping (QDTW) classifier. A Samsung smartwatch gear S was used to record the data which has the data transfer rate of 25 readings per second.

Data from the sensors was classified based on the peeks and spikes generated by the shots. A further classification of each shot was performed into shot type as flat, topspin and slice. DTW classifier used here measured and analyzed the variation in the data received from the Quaternion time series calculated for the shots. Authors are able to summarize players game from the results obtained. The data fusion applied recorded an accuracy level of greater than 99%.

The authors have successfully demonstrated that application of DTW & NBC for stroke classification in racket-based sports. These two classifiers and approach implemented can also be used for stroke classification in other racket or swing sports like cricket into the cover drive, pull shot, scoop, leg glance, cut, sweep etc. Classification of punches in boxing can also be performed using NBC over fused IMU data. Any sports parameter that can be recognized by measuring the peaks in the raw data, NBC can be used easily.

In tennis, apart from shot classification, other performance parameters have been analyzed using various data fusion techniques. Longest Common Subsequence Algorithm is employed for classification of shot movement made by the player in [56], [57]. Both accelerometer and gyroscope were used to identify and distinguish shot changes. The data from the gyroscope alone could classify the shot movements more precisely during play movement. Use of GPS could also be tried for validation and accuracy.

In [58], authors presented the three-level of data fusion process that includes signal level, feature level and the decision level for detection and classification of a tennis stroke. At the first level, Extended Kalman and Unscented Kalman filter were implemented to estimate the correct attitude from the accelerometer and gyroscope data. Authors used the pebble watch mounted on the wrist to gather the data for stroke detection and identification. The simple moving average algorithm

TABLE VI
WEARABLE SENSORS' DETAILS AND DATA FUSION RESULTS FOR THE LITERATURE REVIEWED

Ref	Sport/ Activity	Communication Protocol	Sensor Hardware	Size	Weight	Sampling Rate	Out-Put and Accuracy
[54]	Tennis	Wireless 2.4 GHz RF system,	TennisSense WIMU	25mm Mote Technology	Not-Available	100 Hz	Accelerometer & Gyroscope 82.5%, Accelerometer & magnetometer 86%, Gyroscope and Magnetometer 88%, Accelerometer, Gyroscope & magnetometer 90%
[58]	Tennis	Bluetooth 2.1 and 4.0 Low Energy	Pebble Smartwatch	52 mm × 36 mm × 11.5 mm	38gm	25 Hz	Stroke classification accuracy using k-NN and Logistic Regression Algorithm found to be 82.16% and 87.16% respectively.
[16]	Badminton	Sensor to mobile - Bluetooth 2.0	Usense for badminton	12 mm × 28 mm × 28 mm	8gm	Not Available	Random Forest implemented for stroke classification with an overall accuracy of 79.32% validated with 10-fold technique
[72]	Race-Walking	Bluetooth 3.0: sensor to Mobile	BTS 9DOF wearable inertial	70 mm x 40 mm x 18 mm	37gm	up to 200Hz	Step cadence and step length ratio varied from 3.03 steps/s to 3.28 steps/s and 66.5% to 76.1% respectively depending on velocity of the subject
[73]	Race-Walking	Wi-Fi communication using a common router	MVN Atvinda by Xsense	45 mm × 20.4 mm × 10.6 mm	16gm	60 Hz	SVM (Quadratic) was the best performing classifier with an F1 score and a goodness index equal to 0.89 and 0.11 respectively.
[74]	Thrusters	8-channel ultra-low power ANT module for wireless communication.	ETHOS sensors	14mm × 45mm ×5mm	21.7gm	100 Hz	SVM trained was able to classify experts and amateur with a 94% accuracy.
[13]	Swing Sports	Classic Bluetooth, Wi-Fi and 3G for 3 different functions	Samsung Gear S2	43.6 mm x 39.9 mm x 11.4 mm	47g	100 Hz	Feature based, CNN and BLSTM classified shots in tennis and squash with an accuracy of 93.8% and 93.6% respectively
[8]	Detection of Daily Activities	Low Energy Bluetooth	Samsung Gear S	5.08 mm x 5.08 mm x 1.2 mm	67gm	25 Hz	Dynamic Time Warping implemented for the shot detection and classification obtained an overall accuracy of greater than 99%
[82]	Swimming	Low Power Bluetooth	MSR Electronics GmbH	20 mm x 14 mm x 62 mm	18gm	50Hz	Classification of strokes into freestyle, breast stroke, back stroke and, turns was done using QDA classifier with an accuracy of 96.1%, 96.7%, 97.1% and 89.8% respectively.

TABLE VI

(Continued.) WEARABLE SENSORS' DETAILS AND DATA FUSION RESULTS FOR THE LITERATURE REVIEWED

Ref	Sport/ Activity	Communication Protocol	Sensor Hardware	Size	Weight	Sampling Rate	Out-Put and Accuracy
[77]	Football	On Board Recording	X2 mouthguard & HITS	Custom Helmet Size	500gm	1000 Hz: acceleration; 800Hz: Angular acceleration	HITS detected and classified the impacts with an accuracy of 96.1% whereas X2 did the same with a lower rate of 95.4%.
[60]	Soccer	2.4 GHz wireless communication with PC	Custom Sensor	Not Available	Not Available	100 Hz	Proposed a new algorithm to detect soccer kicks with a 90% accuracy
[64]	Soccer	BLE low energy Smart & USB 2.0 with mobile App	Actigraph GT3X and Empatics Embrace	44mm x40mm x16 mm	25gm	32 Hz	Restricted Boltzmann Machine classifier implemented for detecting soccer activities with an accuracy of 86.54%
[18]	Running	Wireless connectivity using ultra-low power ANT+ module	ETHOS sensors	14mm × 45mm ×5mm	21.7gm	100 Hz	Normalized Foot contact, heel lift and Foot strike type were measured from the accelerometer and gyroscope data using statistical analysis
[17]	Running	Wireless connectivity is provided by an integrated ultra-low power ANT+ module	ETHOS sensors	14mm × 45mm ×5mm	21.7gm	100 Hz	Nearest Centroid Classifier Algorithm achieved 100% accuracy in classification of experienced and unexperienced runners
[65]	Swimming	Bluetooth Technology	Physilog®, BioAGM	47.5 mm x 10 mm x 26.5 mm	11gm	100 Hz	Hidden Markov Model in detecting different phases in the breaststroke swimming types with an accuracy of 94.4% for legs and 93.5% for arms
[11]	Tennis	SensorTag CC2650STK 2.4 GHz wireless MCU with code compatibility across Bluetooth Smart	SensorTag CC2650STK	5 mm x 6.7 mm x 3.5 cm	63gm	20Hz	MLP classified strokes with an accuracy of 99.25% and 96.5% for a 1st time and 2nd time user respectively.

was implemented to remove the noise from the recorded data at the first level of the data fusion process.

At the second level, feature extraction based on Discrete Fourier Transform and Mel Frequency Cepstral Coefficients was performed using the acceleration data. Features extracted are fused together using two different classifiers that are k-Nearest Neighbours and Logistic Regression Algorithm. A 10-fold cross-validation procedure was used to generate the training and test set and trained the two classifiers. The authors were successfully able to classify the stroke in tennis and suggested the use of NBC for further study. The accuracy of the k-NN and Logistic regression algorithm was found to be 82.16% and 87.16% respectively.

In [16] authors, presented the use of USENSE, a wearables IMU sensor designed for badminton containing a microphone to collect sound of the stroke and Bluetooth for communication. The sensor is mounted on the racket for data collection. Random Forest, SMO with Polynomial Kernel, SMO with RBF Kernel and Naïve Bayes Random Classifier are implemented in a PC installed with WEKA for stroke detection. Random Forest Classifier was used for Stroke classification into Clear, Drop, LOB, Drive, Smash, Netplay, and Serve. The evaluation of the accuracy was done using the 10-fold validation technique and attained the stroke identification accuracy of 79.32%.

In [72] performance and infringement in race walking were assessed using a BTS 9DOF wearable inertial system by achieving optimal values of Step Length Ratio (SLR) and Step Cadence (SC) using statistical analysis from the acceleration data of the IMU system. The SLR and SC depend on the velocity of the runner. These are proportional to the velocity of the subject also. The Step Length ratio varied from 66.5% for 12 km/h velocity to 76.1% for 15.5 km/h velocity. Step Cadence also increased with velocity and varied from 3.03 steps /s to 3.28 steps/s.

In [73] Investigation of the feasibility of using machine-learning algorithms fed with inertial data for auto-identification of race-walking faults was performed. 7 IMU Atwinda Xsens sensor units were used, and data analysis was carried by applying DTf, SVMl, SVMq, SVMc, kNNf, kNNc, kNNcu, kNNw and ANN. Loss of contact and knee bend are the two variables for the investigation conducted using the classifiers. The SVMq was the best performing classifier with an F1 score and a goodness index equal to 0.89 and 0.11 respectively.

In [74], Three IMU sensors mounted on wrist, ankle and hip are used to detect thrusters exercise and differentiate professional from amateurs. ETHOS wearable sensor was used for collecting the required data at 100Hz sampling rate. Acceleration data from the sensors were used to extract thruster data using a non-linear optimization model to find the thruster parameters. An SVM, support vector machine was trained on the data for automatic classification of the thrusters. The system was able to identify experts and amateur using the IMUs sensors with a 94% accuracy.

In [13], authors have demonstrated the use of a wearable sensor mounted on wrist containing accelerometer and gyroscope for the swing analysis in tennis, badminton and squash. Samsung smartwatch GearS2 was used for the Feature-based classification. Conventional neural networks (CNN) and Bi-Directional Long Short-Term memory (BLSTM)network were used to classify the shots in tennis and squash with a 93.8% and 93.6% accuracy.

In [75] paper, authors investigated golf-swing data classification method based on Deep Convolutional Neural Network (Deep CNN) fed with multi-sensor golf swing signals. 10-fold cross-validation technique was used to validate the effectiveness of the Deep CNN and SVM classifier. The accuracy achieved was found out to be 95% and 86.8% respectively. Two orthogonally affixed strain gauge sensors, 3-axis accelerometer and 3-axis gyroscope sensors were used to collect real-world golf swing data from professional and amateur golf players.

In [76] Authors have been able to accurately track the swimming style, number of strokes and intensity of the swimmer using a 3D accelerometer by mounting the sensors on the upper back and wrist. Linear quadratic classifiers (LDA) and quadratic classifiers (QDA) were used to recognize the swimming style and intensity. Classification of strokes into freestyle, breaststroke, backstroke and, turns was done using QDA classifier with an accuracy of 96.1%, 96.7%, 97.1% and 89.8% respectively. The authors could have also used the IMU sensors containing both Gyroscope and accelerometer for improved accuracy. Orientation and rotation data generated from the wrist can assist the researchers in recognizing and counting the strokes. Application of NBC could have also improved the efficiency of stroke classification.

In [77], Authors demonstrated the application of Head Impact Telemetry System (HITS, Simbex, Lebanon, NH; Riddell, Rosemont, IL) and the X2 mouthguard (X2 Biosystems, Seattle, WA) in measuring the head impact frequency and magnitude in football. Statistical analysis using the mean, median, the standard deviation was performed using Matlab. HITS detected and classified the impacts with an accuracy of 96.1% whereas X2 did the same with a lower rate of 95.4%. The experiment was performed in a lab and needed to be done in real live condition with real players to establish the validity of results. The weight of the sensor assembly needs to be brought down from 500gm to make it easier for the players to use in field play.

In [60], authors demonstrated the application of an IMU sensor mounted on athletes' legs to detect the soccer kick during play. A new algorithm is proposed for kick detection using the angular velocity vector generated from the sensor data with a 90% accuracy. The author, although have been able to identify the kicks, the classification of types of kicks can also be performed for detailed analysis using kick impact data generated by accelerometer. In this literature, the author designed a new algorithm for kick detection in soccer for which the accuracy could be compared with another algorithm.

In [64], authors demonstrated the application of Restricted Boltzmann Machine to detect multiple soccer activities like passing, kicking, walking, running, standing, dribbling using Actigraph GT3X and Empatics Embrace with an accuracy of 86.54% for walking, running and standing events. Kick and passing were detected with a lower efficiency of 82% and 75%

respectively. The low sampling rate of 32 Hz could be increased for better accuracy. A custom sensor application with high data rate should be tried for better accuracy results.

In [18], Authors demonstrated the application of IMU sensors containing 3D accelerometer, gyroscope and magnetometer mounted on the athlete's legs for kinematic analysis. EHOS sensors mounted on leg and toes generated real-time data sampling rate of 128Hz. The normalized foot contact duration (NFC), Heel Lift and Foot strike types were the three matrices analyzed denote the percentage of time one foot is on the ground during one step cycle. NFC decreases with increasing skill level since shorter contact allow for faster running. Heel lift angle was found to be from 85deg-95deg for advanced and expert runners. The beginner and intermediate runners have the heel lift angle for 65 degrees to 75 degrees.

In [17], 12 ETHOS sensors mounted on the athlete's body are used to distinguish beginner, intermediate, advanced, and expert runners using statistical analysis and implementation of Nearest Centroid Classifier algorithm. The NCC algorithm gave an accuracy of 58% in classification of four types of runners but achieved 100% accuracy in classifying experienced and unexperienced groups of runners.

In [65], authors presented the use of Hidden Markov Model in detecting different phases in the breaststroke swimming types. Two sensors mounted on forearm and tibia assisted in the detection of various aspects in swimming. The output values include arms extension, back sweep, elbow drive, leg the hands and legs as suggested by authors in [65] to give more detailed parameters of stoke identification and classification.

In [11], Authors have demonstrated the implementation of Multi-Layer Perception classifier using a Sensor Tag CC2650STK IMU sensor to classify tennis stoke and non-tennis strokes. The stroke data was further classified into 4 strokes with an accuracy of 99.25% and 96.5% for a 2nd time user and first-time user respectively. Due to high-level accuracy, the same analysis can be done for other swing-based sports like badminton, cricket, baseball and others.

From the above study of the application of data fusion algorithms in sports, it can be concluded that the data fusion algorithms and classifiers are of prime importance in extracting the exact and accurate data. In the review, different sports are analyzed, ranging from racket & swing sports to impact sports for a holistic picture of data fusion algorithm and sports. 10-fold cross-validation technique is an accuracy and validation technique used by most of the researchers. More details about the analysis are given in Tables IV and VI that contains details about the data fusion technique used and output results achieved in various research conducted using wearable sensors in sports analytics.

V. Commercially Available Wearable Products for Sports Analytics

In the recent time, there have been advances in sports analytics, IMU sensors and data fusion techniques that have led to the application of the IMU sensors as wearable in sports for extracting and analysing specific performance and kinematics matrices. National and professional sports teams have started to incorporate wearable technology to add new data points and critical matrices for overall performance improvements in training and games.

Swing sports have seen a variety of sensors being launched for performance tracking and analysis [8]. Sensors like stance beam, str8bat have been recently launched for cricket to measure swing parameters of the cricket batsman. Similar sensors from Zepp and Actofit for baseball and badminton respectively have been used to perform the similar swing analysis and present sports-specific matrices like bat speed, hand speed, time-to-impact, Attack angle, Drive, lift, drop, block, slice smash shot count [15], [26]. Form factor and weight hold the key for easy adoption. Although most of the sensors are weighing from 10gm to 30gm, performance measurement sensors from catapult [14] for outdoor sports are much heavier that is mounted at the back weighing about 55-60gm as shown in Tables II, IV and VI. These sensors are capable of measuring activity level, heart rate, distance covered, load, intensity, impact force, speed, body rotation and step count as required by the sports. A special vest is required for the sensor mounting. Details of various sports with the different types of wearables used to satisfy the needs of athletes have been discussed. Some of the Wearable technologies available in the market for various sports have already been given in Table II. Below are some of the commercial products discussed in brief pertaining to their applications.

A. ShotTracker for Basketball

ShotTracker for Basketball [107] is a sensor system which is used to track players performance during basketball matches. The system is positioned to track the location of the ball and player, which in turn assists coaches in designing strategies and improve player's performance during the game. This wearable system consists of three parts: the sensor for the players, a sensor mounted in the ball and a sensor mounted in the court. This system gives real-time data to coaches for analysis. Players can see and compare their performance with each other. Fans can also track the stats of the game in real-time. Most of the professional teams in the US, including teams in NBA are using this system.

B. Catapult Sports

Catapult has been involved in sports science since 2006. Catapult Sports offers wearable analytic solutions for sports to over 2970 teams. The primary aim of Catapult is to prevent injuries during the high-intensity sports by monitoring data and generating alerts to the player about potential injuries. Catapult sensor monitors speed, acceleration, heart rate, distance covered etc. and then transmits all the data to the coaches in real-time [19]. Some of the wearable products of Catapult are Clearsky T6, Optimeye S5, and Optimeye S6. Catapult ClearSky [41] is a local positioning system (LPS) that gives precise locational and inertial data in different conditions. A revolutionary goalkeeper monitoring sensor, G5 has also been developed by Catapult that measures various movements of the goalkeeper.

These movements include the goalkeepers' direction and intensity of dives along with jumps made, any sudden change in accelerations/decelerations, changes of direction while

C. Kinexon Tracking System

During the year 2017-2018 Euro-league Basketball Adidas Next Generation Tournament Finals, the Kinexon Tracking System was used to measure the movements of players. The use of the Kinexon tracking system [35] is a way of adopting new and advanced technical innovations in basketball. The Kinexon's tiny, lightweight wearable sensor was mounted in between the shoulder blades of the players. The sensors record and transmit the information related to movement and position precisely using RF technology. Kinexon tracks the movements of the players, including jump and acceleration.

D. Garmin Swim for Swimming

Garmin is well known for offering different types of specialized sport wearables such as for biking, hiking, golfing and swimming. Its Swim watch (Garmin Swim) [108]is another cheap way to track distance, pace, stroke count and the gadget can automatically detect your stroke type [109]. The battery of this watch is replaceable and it can last for about a year before replacing it, and it comes with six physical buttons that correspond to each of the functions the device tracks. The data from the watch are in sync with Garmin Connect so one can view all the activities online.

E. ZEPP

ZEPP is a famous name in the wearable world. Now, Zepp is compatible with sports such as Golf, Softball, and Baseball [31], [32], [34], [97], [110]. Zepp Baseball is a single sensor device mounted on the baseball bat which presents a 3D analysis of the swing of the baseball bat. It also gives bat speed, impact time, angle of the bat at the time of impact and attack. The data from sensors evaluate the players' performance and presentation in the Zepp App in a meaning full representation. Zepp Play Soccer is a wearable designed for football/soccer. The sensor is mounted on the calf sleeve to track various data points including the number of kicks, sprints, distance covered etc. These stats are tracked in real-time, which provides complete insights about the players' performance. The next generation of Zepp Golf features the novel Smart Coach training system. With few swings, Zepp instantly calculates the areas of improvement and offers training plans that are personalized to player's swing. The sensor is attached to the player's glove. It performs 3D swing analysis, measures the most vital aspects of swing: club speed, club plane, tempo, backswing length and more. It provides instant analysis and evaluation to support training.

F. Stance Beam for Cricket

Stance Beam [15] is a single sensor-based product that is used in cricket. The sensor is mounted on the top of the cricket bat. The IMU sensor-based product gives a detailed analysis of the cricket batting shot. It tracks the direction of motion of the stroke, back lift, follow though angle, impact speed of the bat and presents a 3D infographic for the shot played for players and coaches to analyze the shots played.

G. Actofit Badminton

Actofit Badminton Tracker [20] is a made in India product for badminton players. The sensor is mounted on the badminton racket. Using Actofit equipped with a 9 DOF IMU sensor, players can track and map their shots. The sensor can detect over 100000 shots and classify them into drop, smash, drive, block, slice and clear. This data then allows players and coaches to understand the gameplay and techniques in post-match analysis. The sensor transfers the data in real-time to the actofit app.

There is still a void left where sensors can simultaneously present the activity level data matrices along with matrices for kinematics analysis that allows the player to learn and correct their techniques. The data is required to be gathered from multiple locations to understand the technical analytics behind the athlete's performance. There are very few specific companies dedicated to particular sports, although there are a few that give human motion, meaning using 3D motion tracking & analytics techniques. Marker-based methods have been the most reliable methods to generate and track 3D motion data but are confined to lab study and research work only. Some of them have started to find application in motion pictures and animation. Real-time motion tracking in sports has only been possible because of the wearable sensors. MEMS low power lightweight sensors have made a collection of data in fields outside the labs for more realistic analysis. Companies like Xsense, Vicon, STT systems have made it possible to record the kinematics data in real-time [23], [25], [50], [83].

Major 3 D motion analytics companies include Xsens, VICON and STT SYSTEMS which have recently introduced multiple wearable sensors for 3D motions tracking, measurement and analysis. Marker based methods have been used for this purpose. In the section, the main focus is on discussing their wearable sensor systems related to sports applications only.

1) Xsens: It is the leading innovator in 3D motion tracking technology and products. Its sensor fusion technologies enable a seamless contact between the physical and the digital world in consumer electronics devices and professional applications such as Motion Capture, Motion Analysis, healthcare, sports and industrial applications. X Sens has four different product lines, MTi series which are IMU sensor packages for custom applications. Other three are the MVN LINK and MVN AWINDA and DOT that are wearable sensors products for 3D motions tracking for multiple applications [52], [51], [111]. Technical specification and features are given in the Table III.

MVN Link is 17 IMU sensors embedded wearable suit with GNSS support for better translation motion tracking of the subject. All the 17 sensors are wired with one single battery that is sufficient to operate for up to 9.5h with an output data rate of 240Hz. The suit has an operational range of 50m indoor and 150m outdoor [23], [51]. On the other hand, MVN Awinda is a wireless sensor version of MVN Link where each sensor is discretely connected to a single base station. Due to its wireless nature, the output data rate is 60Hz with an indoor and outdoor operation range of 20 m and 50 m respectively. The latest and plugin play version of wearable sensors for motion tracking is Dot. The X-sense DOT sensor is small and lightweight for portability, with a quick and easy setup. This 5-sensor set is waterproof with a 6-hr battery life working on latest BLE technology. The sensors are lightweight, weighing 10.8gm. A custom mobile app records and displays the raw motion tracking that includes orientation, acceleration, velocity and magnetic field output data.

Exploring the application of MVN Link, MVN Awinda and Dot as wearable sensors for sports analytics each sensor system has its pros and cos. MVN link is a bodysuit with wired sensors that may affect the athlete's performance during any sports and training. Due to its bulky nature, it is mostly used in research purpose and animations assisted by 3D motion tracking. MVN Awinda, on the other hand, is a user-friendly and easier to use version of MVN Link when it comes to motion tracking in sports. Dot has been the latest form of sensors from Xsens which are designed to be used in sports although there are no direct applications and solutions from Xsens that can be used in sports directly. In sports, Xsens has conducted research and analysis in various sports focusing on motion tracking. In golf, the effect of intra-individual movement on psychological focus has been studied using the MVN sensors and MVN Analyze software [51], [112]. Xsense has also found its application in professional bike racing to understand the back and hip movements of the rider to find the ideal form and fit. Moreover, Xsens has also conducted motion tracking research and analysis in running events, tennis, basketball, drag and flick in hockey, kick optimization in rugby and ski jump analysis. Despite all the research, there is no direct plug-in-play solution for users and athletes that delivers the performance matrices in specific sports.

2) VICON: Vicon is a major 3D motion analytics company with a recent launch of IMU wearable sensor, BLUE Trident that boasts of its real-time analysis abilities both on land and water [50], [53]. The sensor is equipped with a Dual accelerometer with 16g and 200g as maximum acceleration measurement capacity clubbed with a 3 gyroscope and magnetometer weighing 12g. It uses Bluetooth 5 network connectivity. The Trident has conducted research and trials using its dual sensor system in sports such as basketball, cricket, swimming etc.

Blue Trident is a great sensor for a simpler analysis with upto to 4 sensors can be connected to the system that is able to generate very specific data matrices for a football kick or a cricket bowlers arm rotation but doesn't give the kinematics data for a complex system and intra-movement dependency for each motion.

3) STT Systems: STT's solution for inertial motion capture is another multi wearable sensor system [25]. The package includes all necessary hardware and software items to perform analyses quickly. iSEN can also acquire and synchronize data from different devices, and offers a range of utilities for signal processing, event detection, reporting and more. STT wireless wearable sensor system iSEN is a 17-sensor modular system that communicates using Wi-Fi [25]. The data transfer rate varies from 400Hz to 25 Hz depending on the number of sensors. The iSEN sensors connect to Wi-Fi common router as clients. A custom windows computer with iSEN software connects to the router access point where data is displayed from the sensors. The communication between sensors and router is always wireless. On the other hand, the communication between laptop and router can be either wireless or via Ethernet connection. There are no sports specific applications for the sensors.

VI. Discussion & Future Scope of Wearable Sensors

Wearable sensors have found their place in the field of real-time data analytics in sports. Recent developments in the MEMS and low power IMU sensors have accelerated the use of miniature sensors in wearables. Several gaps have been identified for the practical implementation of wearable sensor technology and data fusion in sports. Faster and efficient processing of real-time data from multiple sources in different environments is a requirement.

Building a complete and comprehensive performance profile of the athlete based on the gathered data is a challenging problem. For an accurate and reliable sensor system for a holistic analysis in sports, research and product development need to be done considering the points discussed below.

A. Wearable Sensor Unit

For the kinematics analysis, a combined solution of multi-sensors system, including GPS/GNSS sensors with IMU sensors needs to be developed that can track the linear motion of the players along with body kinematics. Xsens hardware is capable of tracking motion and position. However, there is no plug and play solution available specific to sports analytics that can track the kinematics as well as the position of the athlete at the same time.

B. Senor Architecture & Networking

Wearable IMU sensors need to have a minimum latency and work on synching up multiple sensor data with time scale is a design challenge for sensors application in sports analytics. Sports wearable companies need to implement multiple sensors and communication architecture, taking inspiration from XSENS [23], [112] that has a common networking router for the sensors. Sports wearable sensors also need to explore increasing the wireless transmission range. There is a need to implement low power Wi-Fi for long-range transmission required in sports.

C. Data Communication & Out Put Sampling Rate

Need for an efficient & faster data transmission protocol is a must in the wearable sensor for sports as a different of 1mm or 1 second can make a huge difference. MQTT could be the solution to transmit multiple sensor data in real-time with an acceptable sampling rate. In literature and products studied, the sampling rate drops down from 100Hz to 25 Hz for the wearable sensors as evident from Table VI. So, there is a need to at least have a sampling rate of over 60Hz even for a multiple sensor system for an accurate analysis.

D. Data Fusion and Analytics

The challenge is to design efficient data fusion techniques and mathematical models to analyze the performance of players and suggest the best technique and routine. With the introduction of wearables and real-time data analytics in sports, there has been an increase in the demand for the latest products that are smaller, efficient, faster and economical. In the literature reviewed, there are over 21 different data fusion algorithms used in the data analysis for performance and kinematic analysis in sports. NBC, SVM & QDA are a few popular algorithms used along with 10-fold validation technique for accuracy analysis [12], [55], [90]. Custom algorithm has also been successfully implemented in the research work [66] for detecting a soccer kick. Hence, researchers can look into designing custom algorithms for detecting various performance analyzing matrices in sports given in Table IV.

E. Performance Matrices in Sports

Matrices that were only qualitatively analyzed in the last decade can now be quantified due to the real-time data generated by sports wearable sensors. Efforts are required to made in collaboration with athletes and coaches to quantify multiple performance matrices in respective sports. Wearable sensors and data fusion can play a key role in quantifying those unexplored matrices and strategically make a positive impact in the lives of sports players

F. Form-Factor

Size of the wearable sensor hardware is an essential factor that decides the acceptance level of the product among the athletes. There is a need to reduce the size of the sensors and their mounting positions in such a way that the athletes remain unaware of their existence and concentrate totally on the activity being performed. Flexible sensors with provision to mount on the athlete's sportswear could be the answer to this challenge.

G. Battery Life

It is one of the biggest challenges in sports wearables, especially if the communication protocol used is Wi-Fi. Wi-Fi protocol is used for outdoor field events where real-time data is to be collected and displayed on a remote device. It consumes the majority of the power in transmitting that data. Efficient utilization of battery power is an essential aspect of designing a wearable sensor. Therefore, in order for the devices to run for a reasonable time frame, an efficient battery management system is required.

H. Ergonomics and Comfort

These are of prime importance in the wearable sensor system for sports application where sensors are required to be mounted on the athlete's body. In the best-case scenario, the player should be unaware of any external sensor being mounted on the body to prevent any distraction or discomfort. This level of comfort and ergonomics can be achieved with maximum packing efficiency of the hardware. This requires a lot of iteration and changes in the design based on constant feedback from players.

I. Antennae Integration

In wearable sensors integrating antenna is a design challenge for the designers considering the smaller form factor. Effective integration of antennae with required signal strength in a limited space is a challenging task. Flexible antenna design and its integration in the hardware could be a solution for the challenge. Conformal antennas are suitable for such an application where the whole antenna can be carved on the sensor casing. In GPS/GNSS enables devices, antenna size, and weight are an issue. Therefore, there is a need for a smaller GPS antenna also to promote the use of wearables sensors in analysing, both linear and rotation kinematics effectively.

VII. Conclusion

This detailed review aimed to investigate published literature, sports wearable sensors and 3D motions tracking products in kinematics and performance analysis in sports. It highlighted the importance of IMU sensors configuration, form factor and other matrices for sensor selection. These wearable sensors and solutions are ideal for on-field analysis, making technology accessible to the players and athletes. Integration of wireless communication and BLE in wearables sensors has made it easier for the players to record their performance in real-time for a detailed analysis. On-screen data display and analysis is limited to smartwatches and fitness sensors only. A detailed analysis requires data to be displayed in a remote device such as a phone or computers. Smartphones equipped with high processing power have become very common for the choice of remote display and processing.

Wearable sensors revived in the paper are consist of SIP sensors. Authors have focused on implementing stabilizing filters such as Kalman filter for improving the accuracy of the output data from the IMU sensors. A little has been discussed on the SIP fusion sensors that save a lot of coding and filtering work. It is advisable to use SIP fusion mode sensor to directly use raw data for data and kinematics analysis using data fusion algorithm. Since the majority of the literature reviewed used commercial sensors, there was no scope on experimenting with the sensor architecture. It can only be concluded from the review work that wearable sensors for sports analytics with a stand-alone sensor uses a remote BLE device for data transmission over Wi-Fi which is only for long-range transmission and multiple sensors application as in Xsens and STT Systems. A very little has been experimented with the data transmission protocols in the literature reviewed. Implementation of different data transmission protocol and comparing the sampling rate and latency could through light on improving sensor design and output data rate.

A smaller form factor sensor finds its easier for athletes to integrate into their sportswear or equipment. GSP enabled sensors are heavier and larger in volume due to the antenna and are mostly mounted on the back of the player. Efforts can be made to make wearable sensors lightweight and smaller.

Based on the study of literature, commercial products and 3D motion tracking systems, it can be summarized that the athletes are able to get quantifiable data and performance matrices in real-time by applying various data fusion techniques. It can be concluded that the trend now, is the development of sensor fusion techniques that combine multiple sensors for activity recognition and kinematics analysis in sports. Although there has been much research done in sports like tennis, swimming and football, but there are very few options available for the athletes in the market despite the popularity. It is expected that a complete and comprehensive performance profile of the athlete can be designed based on the data gathered from wearable IMU sensors. The accuracy of activity detection is also expected to increase with the implementation of multiple wearable sensors along with data fusion techniques in comparison to single-sensor systems. It is expected that the review paper would assist researches and users in designing next generation wearable sensor systems for sports analytics.

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