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COD Detection for Injury Prevention Using Sports Analytics

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***Abstract*—ith the emergence of data science and wearable body sensors, sports analytics is becoming very important study field where sports scientists and coaches are able to track player activities and performance for early injury prevention. Electronic Performance Tracking Systems (EPTS) equipped with inertial sensors and GPS have been widely used for this purpose. The real challenge is to understand the data and translate it into meaningful information; visualizing relevant results for coaches' or sports scientists. Activity distance, speed and time can be measured using GPS data. These parameters are suffered from slow sample rate and high error tolerance which are not sufficient for predicting injury or reducing stress or fatigue. Workload estimation using inertial measurement unit (IMU) has been used for training and monitoring purposes. However, sports scientists need a closer look at the behavior of the data to identify the cause, and hence, able to prevent injury. This paper presents an algorithm for estimating the acceleration/deceleration at every change of direction and visualizing athlete's movement for the entire session based on IMU and GPS data. The visualization results from our on-field athlete's data have shown that the proposed algorithm can provide much more useful information for sport analytics purposes than the workload. ith the emergence of data science and wearable body sensors, sports analytics is becoming very important study field where sports scientists and coaches are able to track player activities and performance for early injury prevention. Electronic Performance Tracking Systems (EPTS) equipped with inertial sensors and GPS have been widely used for this purpose. The real challenge is to understand the data and translate it into meaningful information; visualizing relevant results for coaches' or sports scientists. Activity distance, speed and time can be measured using GPS data. These parameters are suffered from slow sample rate and high error tolerance which are not sufficient for predicting injury or reducing stress or fatigue. Workload estimation using inertial measurement unit (IMU) has been used for training and monitoring purposes. However, sports scientists need a closer look at the behavior of the data to identify the cause, and hence, able to prevent injury. This paper presents an algorithm for estimating the acceleration/deceleration at every change of direction and visualizing athlete's movement for the entire session based on IMU and GPS data. The visualization results from our on-field athlete's data have shown that the proposed algorithm can provide much more useful information for sport analytics purposes than the workload. W**

Wearable body sensors, Inertial sensors, Accelerometer, GPS, PlayerLoad, Sports analytics, Athlete performance tracking

I. Introduction

As wearable body sensors are being used in sports to track players' movement, sports analytics is gaining more importance in the sports industry. Using a combination of positioning and inertial measurement unit (IMU), now it is easier to manufacture these performance tracking systems [1] and [2]. As the demand is increasing rapidly, many suppliers are providing similar performance tracking solutions. The task is to extract valuable information from these sensor's raw data. Algorithms, that can generate meaningful and accurate results are useful for coaches and sports scientists.

Tracking performance can be benefical for coaches in preventing players from injury and fatigue [3] and [4] Sports scientists require quantifiable data to measure performance of an athlete [5], [6], and [7]. GPS is used to track player's position, speed and velocity [8] and [9]. Authors in [10], [11], [12], and [13] found GPS to be less reliable when used to track intense movements of players like rapid change of direction or speed. Accelerometers can also be used for this purpose.

An accelerometer is a device which is used to measure the acceleration and converts acceleration into an electrical signal. By using an accelerometer both dynamic and static acceleration can be measured. Dynamic acceleration is explained as the acceleration due to any force except the gravitational force applied on a rigid body while static acceleration is due to the gravitational force which is also called gravitational acceleration. The accelerometer can give output in analog or digital form. In the analog case, the output voltage (the duty cycle of a square wave) and acceleration are directly proportional to each other. While on the other hand, by using protocols such as SPI the output of a digital accelerometer is directly retrieved. There are different accelerometers for a variety of practical purposes. Additional parameters such as the number of axes, maximum swing, sensitivity and bandwidth are also need to be considered. For measuring acceleration of a player in X,Y and Z domains, triaxial accelerometer is used which calculates player's workload. Calculating $Playerload^{TM}$ (Catapult Innovations, Australia), in Eq.(1), is another method to calculate a player's workload using triaxial accelerometer. It is possible that two players have been on the field for the same amount of time and travelled the same distance have different $Playerload^{TM}$. A player that accelerates/decelerates quickly or changes direction sharply or having higher workload on the field will have higher $Playerload^{TM}$.

$$Playerload^{TM}(accumulated)_{t=n} = \sum_{t=0}^{t=n} \sqrt{(fwd_{t=i+1} - fwd_{t=i})^2 + (side_{t=i+1} - side_{t=i})^2 + (up_{t=i+1} - up_{t=i})^2} \quad \forall\, t \in [0, 0.01, \ldots, N] \qquad (1)$$

In [14] and [15] authors mentioned that $Playerload^{TM}$ is reliable during treadmill tests. However, they identified a research gap about reliability of $Playerload^{TM}$ during sports activities. They performed experiments to measure total distance, acceleration/deceleration, and triaxial $Playerload^{TM}$ for players playing at different positions. This study, was the first of its kind to identify differences in triaxial $Playerload^{TM}$ and

acceleration/deceleration, in competitive youth football. Athlete exerts more force on the body at change of direction than running [16] and [17]. At change of direction, athlete exerts force to decelerate before the change. After change of direction, athlete again exerts force to accelerate. Due to this reason, sports scientists and coaches always considers acceleration/deceleration at change of direction.

Earlier, due to lack of technology it was not an easy task to analyse athlete’s acceleration/deceleration at every change of direction. Now visualizing athlete’s movements at every instance, it will be easier to track athlete’s motion as he/she exerts force to accelerate/decelerate. As previously there was no mechanism to track these movements and workload of an athlete, due to this while preparing for an important match some athletes used to end up injuring themselves during intensive training sessions. Similarly, if an athlete exerts too much force to accelerate/decelerate, he/she might suffer any injury in future. But, if coaches can analyse their movements, injuries can be prevented and athlete’s performance can also be enhanced. Due to this reason, athletes’ movement is tracked with GPS and the algorithms presented in this paper are synchronized with reference to that GPS movement.

To calculate $Playerload^{TM}$, data is collected using $OptimEye^{TM}\ S5$ from Catapult innovations. Table.I represents data acquired for visualization. As the accelerometer’s refresh rate is 100Hz while GPS’s refresh rate is only 10Hz, at every 10^{th} accelerometer reading there is a GPS time stamp. If GPS data was used as a reference, there will be loss of accelerometer’s data. Hence, sample rate (Sample Data) was used to track athlete’s acceleration against movement. The main advantage of the algorithm on visualizing $Playerload^{TM}$ is that after a training session or match, coaches and athletes can go back and analyse how much force an athlete exerted at any specific position and time. This analysis is known as on-field analytics.

Similarly, acceleration algorithm will be useful in visualizing what changes in acceleration occurs, as the athlete moves around the field and just before and after any change of direction. The data is plotted on a 3-dimensional plot. $Playerload^{TM}$ can show a higher value when the athlete abruptly accelerates as well as when he/she decelerates. To overcome this shortcoming in $Playerload^{TM}$ visualization, an acceleration algorithm is proposed. Its visualization clearly differentiates between these movements. As $Playerload^{TM}$ is only calculated using accelerometer data, the acceleration algorithm also considers, only the acceleration data. The challenging task was to use filtering and other techniques to precisely match the acceleration/deceleration visualization with the athlete’s movement.

A. Summary of Contributions

Following are the main contributions of this paper

- On-field analytics-based acceleration algorithm is proposed. The algorithm represents the athlete’s acceleration/deceleration, identifying change of direction without magnetometer data.
- Algorithm to visualize athlete’s $Playerload^{TM}$, with simultaneous tracking of athlete’s movement is presented.
- From on-field athletes’ data, both algorithms are compared for better performance visualization and injury prevention.

The rest of the paper is organized as follows: In the next section related work is discussed, third Section is the experimental setup, explaining how real world athletes’ data is acquired for the experiment. Section four in the proposed algorithm. Section five is results and discussion and last section is conclusion.

TABLE I: Accelerometer and GPS data from Catapult Device, placed on the back of an athlete

Sample Data	Forward	Sideways	Up	GPSTime
0.012195486	-0.627	-0.105	0.822	’..’
0.012195602	-0.632	-0.096	0.819	’..’
0.012195718	-0.641	-0.096	0.816	’..’
0.012195833	-0.627	-0.098	0.816	’..’
0.012195949	-0.617	-0.117	0.81	’..’
0.012196065	-0.62	-0.137	0.802	’..’
0.012196181	-0.615	-0.152	0.776	’..’
0.012196296	-0.615	-0.147	0.762	’..’
0.012196412	-0.618	-0.143	0.749	’..’
0.012196528	-0.613	-0.149	0.743	’..’
0.012196644	-0.611	-0.144	0.719	’..’
0.012196759	-0.612	-0.16	0.712	’11:42:06’
0.012196875	-0.617	-0.169	0.693	’..’
0.012196991	-0.622	-0.182	0.707	’..’
0.012197106	-0.639	-0.19	0.726	’..’
0.012197106	-0.66	-0.183	0.733	’..’
0.012197222	-0.652	-0.197	0.748	’..’
0.012197338	-0.661	-0.177	0.742	’..’
0.012197454	-0.658	-0.161	0.727	’..’
0.012197685	-0.668	-0.149	0.682	’..’
0.012197801	-0.669	-0.179	0.678	’
0.012197917	-0.656	-0.204	0.654	’..’
0.012198032	-0.648	-0.212	0.619	’..’

II. Literature Review

Motion tracking attracts much attention from areas such as sports science, animation production and medicine. Authors in [18] and [19] perform kinematic and biomedical analysis for taekwondo and martial arts, respectively. Multiple motion capture cameras are used to track the movement of the subject with artificial passive markers and to automatically analyse 3D movements, thanks to pattern recognition algorithms.

The GPS is more frequently used to identify the athlete’s speed as opposed to the position. In addition to GPS accelerometer data can also be used better to verify the actual position and speed of the athlete. The accelerometer tri-axial data can be used to understand the acceleration and deceleration of an athlete.

Authors in [5] and [20] found accelerometers to be more reliable than GPS for tracking players’ movements involving intense and rapid movement. Authors in [21] found acceleration and high speed running are the most important parameters to measure in elite football. In [22] recommended that acceleration at each instance should be recorded and used for analysis. Authors in [23] analysed running pattern and recommended a system that can be beneficial for jogging. According to [23] this movement pattern can only be acquired from the sensor’s data and not from visual recording.

Studies exists that developed human step detection systems using accelerometer [24][25][26]. [27] used them in snow boarding for aerial aerobatics. Authors in [26] used a tri-axial accelerometer for healthcare purposes. For athlete performance monitoring, inertial sensors are widely used. Authors in [28][29] used it analyse collisions and tackles in Australian rules football. Authors in [30][31][32][33][34] estimated position using micro-electromechanical systems and various positioning techniques for a rigid body. Authors in [35][36][37][38] used inertial sensors for monitoring human activity.

Authors in [39] found tri-axial piezoelectric accelerometers along with GPS as a reliable device in laboratory and field setting while [40] considers sports specific applications. [41] found inertial measurement units as a cheap and reliable alternate to monitor athletic performance. Authors in [42] questions whether GPS is capable to identify body movements that incurs little displacement. [43] found accelerometer more reliable for collision based team sports than GPS. Similarly in this paper, algorithm

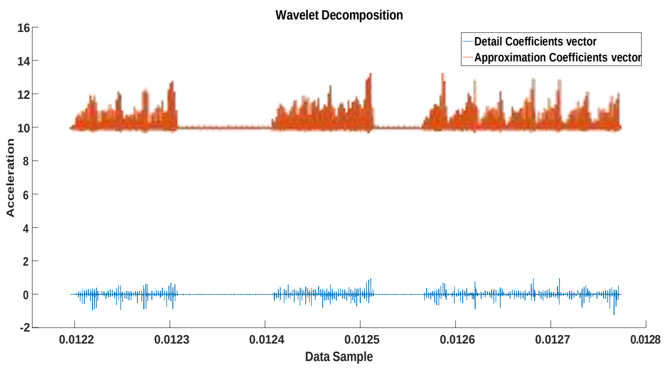

Fig. 1: Applying discrete wavelet transform on the acceleration data

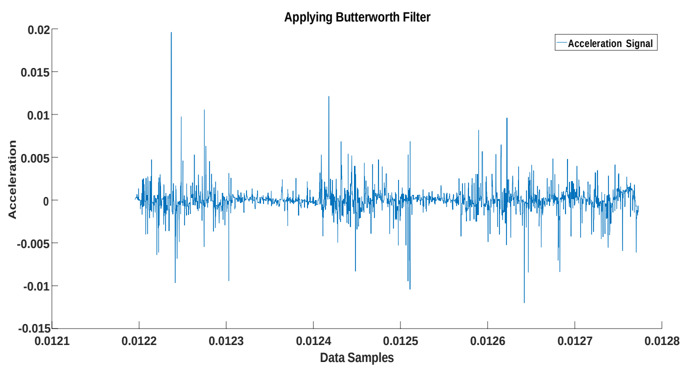

Fig. 2: Applying Butterworth filter to the filtered data

uses accelerometer data for visualization of instantaneous acceleration at each direction change and calculating $Playerload^{TM}$.

III. Experimental Setup

As mentioned in [17], to track an athlete's movement and specific instances of change of direction, GPS is used as a reference. Six male athletes (age $= 29\pm0.5$ **years) volunteered for the study. All athletes were briefed about the experiment. It is ensured that none of them had suffered any lower-body injury during past six months. For acquiring GPS and accelerometer data, commercially available** $OptimEye^{TM}$ $S5$ **from Catapult Innovations (Melbourne, Australia) was used. Formula to find an athlete's workload,** $PlayerLoad^{TM}$ **is also from the manufacturers of this technology. Players wore a vest and device was tightly placed in that, between the shoulder blades. The GPS receiver has a refresh rate of 10Hz while accelerometer samples at 100Hz with** ±16**g output range. It can be observed from the data that GPS gave a reading after 9 instances. This is due to the difference in sampling rate of GPS(10Hz) and accelerometer(100Hz).**

Each athlete completed 5 laps on a defined path where change of directions is marked. Different angles are considered to study impact of various directional changes on an athlete.

GPS played a vital role in finding the location of the player at various intervals of time. The GPS data is plotted in a 3-dimensional plot to precisely compare acceleration and workload. The algorithm doesn't require GPS data for calculating acceleration or workload. But it was used as a reference to know when the player is approaching a turn, the instance he/she is turning and then exiting the turn. $Playerload^{TM}$ **is calculated from the data of tri-axial accelerometer.**

IV. Proposed Algorithm

Steps of algorithm that can acquire acceleration/deceleration of an athlete is given below. Fig.?? is the logical flowchart of the algorithm while pseudo code is given in algorithm 1.

A. *Measuring Acceleration Deaccleration of an athelete*

Algorithm 1 Extracting Acceleration and Deceleration of an Athlete

```
Input: Sliding window median filter {MeanWin}
Output: Acceleration {MWacc}, deceleration {MWDeacc}
Initialize fs = 1000, fc = 0.1/36, order = 6;
Highpass Butterworth Filter ← (order,fc)
b1,a1 ← Highpass Butterworth Filter
AccFilt ← Zerophase Digital filtering (b1,a1,MeanWin)
AccSmooth ← applying smoothing filter on ACCFilt
AccShift ← (AccFilt − AccSmooth)
MeanWin ← AccShift
LenMW ← length(MeanWin)
for i ← 1 : (LenMW-1) do
    if MeanWin(i+1) > MeanWin(i) then
        MWAcc ← MeanWin(i)
    else MeanWin(i+1) ⩽ MeanWin(i)
        MWDeacc ← MeanWin(i)
    end if
end for
```

Algorithm 2 Calculating Athlete's Playerload

```
Input: Length of sliding window median filter {LenMW}
  Accelerometer data along X,Y,Z axis {accx, accy, accz}
Output: PlayerLoad(i), calculation for number of windows
  {NumWin}, each window {eMW}
Initialize WinWidth = 5, SlideIncr = 1
for i ← 1:LenMW do
    Playerload is calculated
  PlayerLoad(i) ← from accx, accy and accz and eq 5,
end for
PlayerLoad ← PlayerLoad^T
LenPlayerLoad ← length(PlayerLoad)
Calculation for number of windows
  NumWin ← LenPlayerLoad − WinWidth ÷ SlideIncr
for i ← 1:NumWin do
    Calculation for each window
  eMW(i) ← median (PlayerLoad (i : i + WinWidth))
end for
```

1) *Acquiring Accelerometer Data:* **Accelerometer data in 3D is recorded by placing the tri-axis accelerometer at the back of the athlete and made him run a certain track which includes sharp turns. As the athlete reaches a turn, he/she decelerates and after the turn he/she again accelerates. Accelerometer data is recorded simultaneously with the 10Hz GPS data. GPS data is used to track the location. Location information represents when the athlete is about to make a change of direction (decelerates) and then, when he/she will again start accelerating again.**

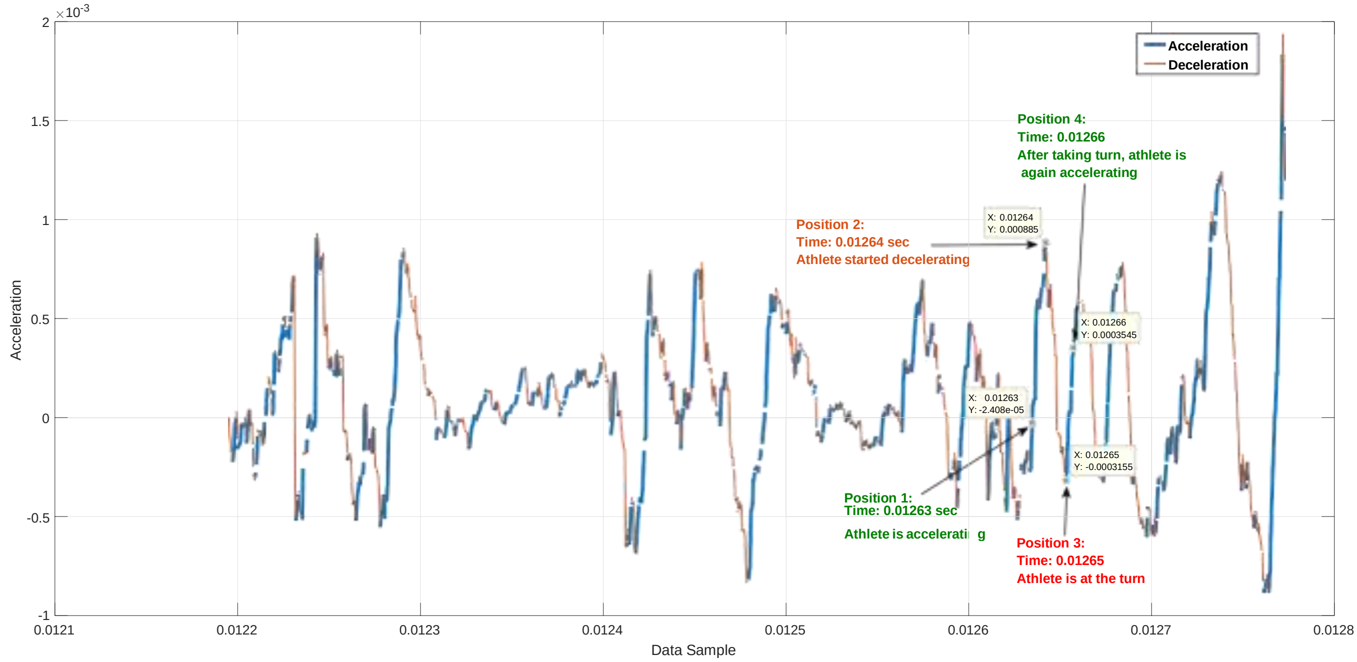

Fig. 3: Acceleration of athlete

2) Calculating Resultant Vector: **Accelerometers' output is relative to free falling point instead of acceleration related to a stationary point. Accelerometer data has the effect of gravity in it. The acceleration recorded for an object that is stationary with respect to the earth will therefore be 1 G ($1 * 9.81 m/s^2$) upwards to the earth axes.**

When we are dealing with multiple measurements we often need to calculate a resultant vector to understand their combined effect. The resultant is a one-dimensional vector whose effect is equal to the total effect of all vectors added together. Cartesian coordinate system is used in this case. The magnitude, r, of resultant vector is the net acceleration and is given by

$$r = \sqrt{(x^2 + y^2 + z^2)} \quad (2)$$

3) Discrete Wavelet Transform: **DWT is used in signal processing of accelerometer's data for analysing acceleration in gait analysis. A key advantage of DWT is its temporal resolution. DWT captures both location and frequency information. This is essential for analysing an athlete's acceleration and determining, if it is increasing or decreasing with time.**

For the analysis DWT is used before applying median filter. Median filter generalizes signal as well as noise in the data. Using median filter prior to DWT was distorting the visualization. One dimensional DWT is used, which returns values of approximate coefficient vector and detailed coefficient vector as shown in Fig.1. For the desired analysis, most relevant data was found in detail coefficient vector.

4) Median Filter to Remove Noise: **DWT is applied but there is fluctuation in the data. Median filter and moving average filter are used. But, moving average filter removes peaks in the data. For the visualization signal peaks are crucial and hence median filter is used. Median filter does not remove peaks from the data. Median filter sliding window slides over the data.**

5) Fourier Transform: **The Fourier transform is used to know that where most of the data exists. From Fourier transform provides cut off frequency of the data, butterworth filter will be designed in next step. This assumption is based on the calculation of the fourier transform, which is the basis for all spectral analysis discussed in this paper. The finest frequency resolution is**

$$df = fs/N \quad (3)$$

A lower value of df is preferred for resolution.

6) Butterworth Filter: **As this is the case of a human body, which is a flexible body, signal has more noise than a rigid body. If the athlete moves along one axis, due to flexible body and the way human body moves, there will be movements recorded on other axes as well. Due to this, there is always large fluctuation in data recorded from a human body than any rigid body. As there is still noise in the data, butterworth filter is designed to remove that noise.**
From Fourier transform, cut off frequency was calculated. Now a butterworth filter, as shown in Fig.2 is designed based on that cutoff frequency. The Butterworth filter is a filter designed for flat frequency response in the passband. There are no ripples in the response and due to this nature it is also known as maximally flat filter. The disadvantage of this flat response is at the cost of relatively wide transition region, from pass band to stop band.

7) Smoothing: **Zero phase filtering is applied to the signal extracted from Butterworth filter. Signal from Butterworth filter is further smoothed using moving average filter. To further enhance the shape of signal and to make acceleration and deceleration clearly distinguishable, two signals are substituted.**

8) Determining Acceleration and Deceleration: **The sliding window is used again for finding athlete's acceleration and deceleration. Based on certain consecutive readings of accelerometer it is determined if the athlete is accelerating or decelerating. Sliding window is used to find this. If the trend in accelerometer data is increasing, this means that the athlete is accelerating. If the trend is decreasing this is equivalent to the athlete deceleration. Furthermore, the data is mapped to show the location where the data started accelerating and where the data started de-accelerating.**

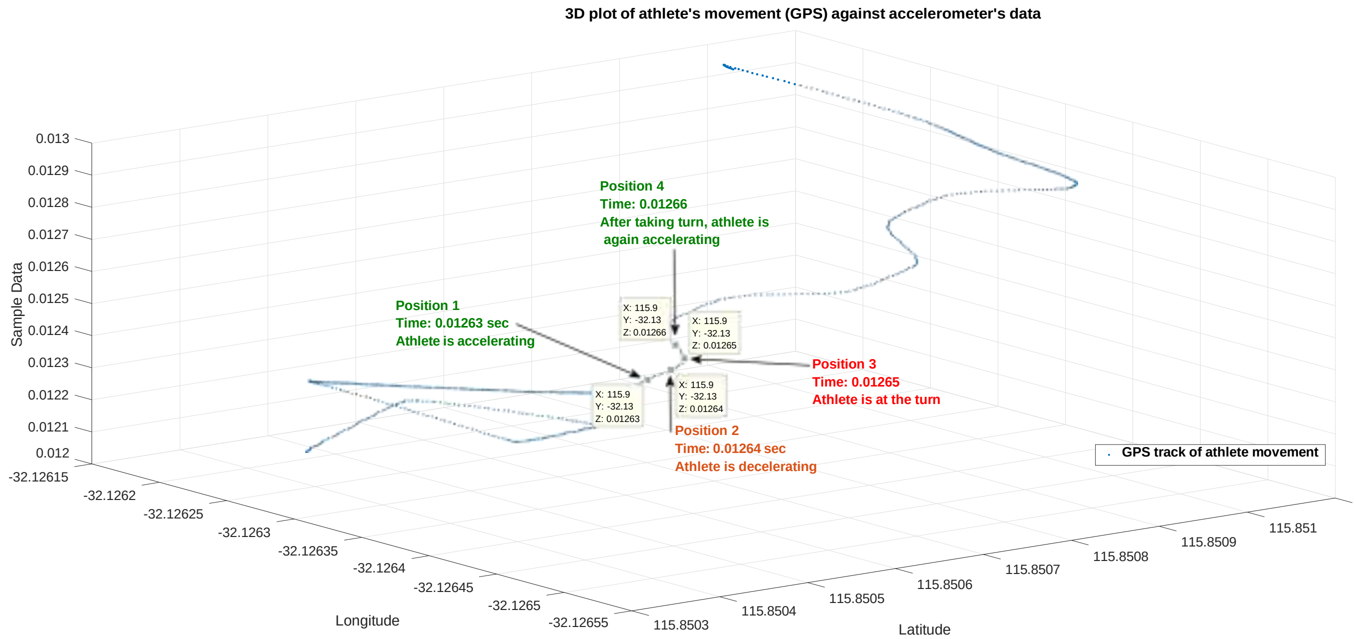

Fig. 4: Athlete's movement w.r.t GPS's longitude, latitude and sample data

B. Playerload

$PlayerLoad^{TM}$ is a measure of how intense body movements an athlete has performed while on field. Two athlete's running together on the same track and covering same distance may have different $Playerload^{TM}$. It may be due to difference in those players' running technique. Derived from tri-axial accelerometer, $Playerload^{TM}$ is the measurement of an athlete's instantaneous rate of change in acceleration. It is measured by combining athlete's movement along X,Y and Z axis. After filtering sensor's raw data, based on equation.5, $Playerload^{TM}$ is calculated. Steps to find $Playerload^{TM}$ are in algorithm 2. Fig.5 graphically represents an athlete's $Playerload^{TM}$ for the session.

V. Results and Discussion

Fig.3 represents the acceleration in blue and deceleration in red. When the athlete was about to take the turn, just before the turn his/her acceleration goes down, athlete decelerates. After taking the turn on running, acceleration again starts increasing. Fig.4 represents the movement of athlete with respect to sample data . Athlete took some very sharp turns where athlete needs to exert much force to turn.

Rapid change of direction and acceleration/deceleration has critical impact on the performance of an athlete. Measuring distance covered, average speed or time on field do not provide these valuable insights.

A. Results

Fig.4 represents movement of an athlete in GPS coordinates plotted against sample data. Fig.3 shows the acceleration/deceleration of an athlete, as he moves on the track and changes direction. Fig.5 shows the $Playerload^{TM}$ of the athlete during the movement.

1) Position 1: **At position 1, the athlete is accelerating forward. During this time, athlete acceleration is increasing, as shown in Fig.3. In the case of $Playerload^{TM}$ spike can be seen in Fig.5. As the athlete isn't close to any change of direction, it is important to observe that how the athlete is accelerating. His/her acceleration should be smooth, without abrupt changes. A professional athlete will gradually increase of decrease his/her acceleration, resulting in less workload and fatigue for the body.**

2) Position 2: **As the athlete approaches towards the change of direction, he/she stops accelerating and starts to decelerate as shown in Fig.5. There is a point of maximum acceleration, afterwards the athlete starts to decelerate. Two types of responses can be observed here. First, as the athlete is well aware of a change of direction ahead, he/she starts decelerating from a certain distance to the turn. Than slowly performs the change of direction and then gradually accelerates back to his/her running speed. This type of movement can be visualized with smooth transitions and certain gap between the maximum acceleration and minimum acceleration(deceleration). Less workload will be done in such movement and body will experience minimum fatigue.**

The other way to approach this turn is that the athlete keeps accelerating or continues with his/her speed. Very close to the direction change the athlete exerts much force to decelerate. He/she abruptly slows down and after the turn, again starts to accelerate. In this case there will be very abrupt transition between the two point of maximum acceleration and minimum acceleration(deceleration). Athlete's body will be exposed to too much fatigue as he/she makes abrupt changes. If an athlete has similar movement pattern, due to suffering more fatigue, he/she wont be able to perform as good as other players for a long time. Due to fatigue he/she will get tired early and performance will degrade. If this pattern is prolonged, athelet may suffer injury.

Using this algorithm, coaches will be enable to analyse these flaws in athlete's movement and correct them. This will benefit in two ways. Due t suffering less fatigue the athlete can perform better on the field, won't get tired during practice session or matches and it also prevents athletes from suffering any injury.

3) Position 3: **This is the instance at which the athlete is taking the turn. As can be seen in Fig.3, the acceleration decreases. The athlete exerts force as he/she decelerates. This movement (as the athlete changes direction) involves higher workload then running on a straight path. This higher workload can also be observed in Fig.5, where the $Playerload^{TM}$ has**

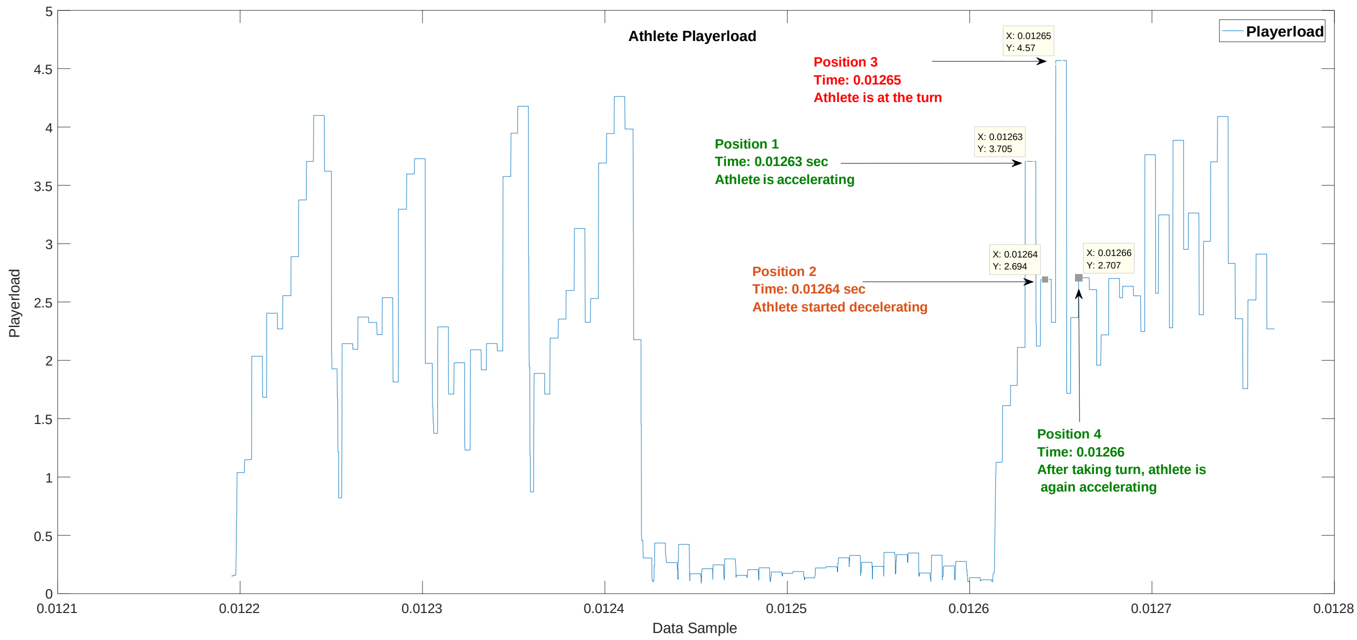

Fig. 5: Playerload of an athlete

increased higher than it was recorded at earlier two positions. At this position acceleration is lowest. Sharp transitions between acceleration and deceleration shows that the athlete exerts more force on his/her body.

It can also be observed from Fig.4 that athlete changed directions in left as well as right. Some athletes have improper change of direction in one direction while in other direction they make smooth change of direction. These flaws in movements can also be determined from Fig.3.

4) Position 4: After the athlete took the turn, he/she again started to run forward and increase acceleration. This can be observed at position 4 in Fig.3, where the athlete is accelerating. At this position the $Playerload^{TM}$ is similar to the $Playerload^{TM}$ at position 2 when the athlete was at maximum acceleration. In the case of $Playerload^{TM}$, this information is not possible to extract. Either the athlete decelerates from accelertion or wise versa, $Playerload^{TM}$ will increase, while in the proposed acceleration algorithm, it is possible to differentiate.

B. Discussion

Two athletes have different approach to take the same turn. One athlete gradually decreases his/her speed as he/she approaches a turn and after taking turn he/she gradually increases his/her speed. Second athlete rapidly decreases his/her speed upon approaching a turn and then rapidly increases his/her speed after the turn. Although both athletes travelled the same distance and performed the same body movement, but there is still major difference in their pattern. This difference can be very critical for an athlete's health and his/her performance on the field.

In the case of first athlete, there will be less stress on the body while second athlete exerted much more stress on the body as he/she rapidly accelerated and deaccelerated. Fig.3 can demonstrate this difference explicitly. The second athlete will have sharp peaks with higher amplitude while athlete one's graph will show less sharper peaks and amplitude.For the same task/movement two athletes performed in a very different manner. Improper running/movement causes stress and develops fatigue. For the second athlete, exerting unnecessary stress will result in decline of his/her performance during the match. If this movement pattern is prolonged, it can create fitness issues or it may causes athlete to suffer injury.

Sports scientists are interested in this meaningful information extracted from the raw sensor data. After a game, looking at their acceleration and deceleration pattern they can differentiate between athletes and the stress on their body during a match. They can find athletes that are exerting too much stress on their body, which may be due to some short coming in their approach to play game. This is also beneficial in selecting the players for a game. This information provides insight about an athlete's game technique and fitness.

The parameter that is presently used in sports science is $Playerload^{TM}$. $Playerload^{TM}$ is also measured from the data of tri-axial accelerometer. It does provide information about the stress an athlete exerted on his/her body. But, the above algorithm is useful in providing detailed information about the movement on field.

1) Acceleration and $Playerload^{TM}$: Considering the above four positions of athlete, the $Playerload^{TM}$ increased for both positions 1 and 3, although the physical activity of athlete's movement was very different. At position 1, the athlete was running forward in one direction, while at position 3, the athlete was changing direction. Athlete exerts more force for taking a turn than merely accelerating. $Playerload^{TM}$ does not provide this differentiation of movement.

Similarly for position 2 and 4, athlete's $Playerload^{TM}$ is same, making it more difficult to analyse nature of movement. While in the case of acceleration algorithm, based on the movement trend it is possible to determine nature of athlete's movement. Comparing Position 1,3 and 2,4, it can be understood that visualizing athlete's acceleration is more useful than $Playerload^{TM}$.

VI. Conclusion

Two algorithms are visualized on real world data for athletes' performance tracking and injury prevention. First an algorithm is proposed that visualizes athlete's acceleration and deceleration. Another algorithm is proposed, that visualizes acceleration based

on $Playerload^{TM}$ (workload) formula. It is found that proposed algorithm on visualizing acceleration/deceleration provides more useful information for athlete's performance evaluation and injury prevention than algorithm based on workload. Any force exerted by an athlete on his/her body (acceleration/deceleration) results in increase of workload while acceleration algorithm clearly differentiates between acceleration and deceleration. This provides better visualization for coaches as they can identify how much force athlete exerts before and after each change of a direction. The major hurdle in visualization was the noise and distortion in the acceleration signal as the device was mounted on a flexible human body.

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