A Real-time Gait Monitoring System based on Edge Computing using Motion Capture Techniques for Knee Injury Analysis

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Abstract: Human gait analysis provides qualitative and quantitative information regarding the characteristics of walking of a given subject. Cost-efficient RGB-D cameras can estimate the 3D position of several body joints without the use of markers. The acquired information can be used to perform objective gait and injury analysis for sports people such as basketball, volleyball, handball, etc., in an affordable and portable way. Amateur or professional athletes have a high tendency of suffering Anterior Cruciate Ligament (ACL) injuries. On the other hand, the design of smart healthcare techniques is paving the way with the increase of Internet capabilities and advanced sensors. The integration of cloud, IoT, and edge become an important area of research to meet the time-critical requirements of smart healthcare services. In this contribution, a real-time gait monitoring system based on edge computing is presented for automatic gait analysis and knee injury analysis using a Microsoft Kinect camera. An algorithm to estimate the heel-strike events during a gait cycle, aiding in the measurement of spatiotemporal gait parameters is implemented. Few studies suggest that low flexion angle and high valgus angle tend to increase the strain on ACL. Using the proposed Kinect-based motion capture system, it should be possible to determine knee injuries due to valgus knee location by studying the Knee abduction angle and the Knee-Ankle separation ratio (KASR) in some gestures simulating dynamic movements of the jump oriented ball games. 3D kinematic algorithms were developed using Microsoft Kinect V2 environment to calculate lower limb joint angles for some sports activities. The results confirm the reliability of the Kinect apparatus for gait analysis and its analyzing capability of knee injury risks in professional ball games.

Keywords: Kinematics, Motion Capture Systems, varus-valgus, Anterior Cruciate Ligament, Edge Computing, Cloud, Internet of Things

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1. Introduction

The steady progressive growth of the Internet of Things (IoT) era increases the number of connected wearable sensors currently being in use to one billion in 2021 [40]. A single gait monitoring sensor generates 2 GB of data per day [20]. With the integration of technology, all the healthcare applications are bloomed by connecting IoT to cloud computing. The more the sensors are connected to the cloud, the more the data consumes the core network during its transmission to the central cloud. Though the cloud provides several computing resources to handle the large volume of diverse healthcare data, its centralized nature limits the scalability of the deployed applications to extend beyond [39].

The latest technology introduced to consume the resources available close to the end-users is called Edge Computing, which can be used with wearable/medical IoT sensors. The big volume of sensor data undergoes various data transformations, and the resultant minimal data will only be sent to the cloud. This enhances both the network utilization and performance of the service on the user end.

The related edge/fog-based architectures [39] for real-time health monitoring applications have been proposed where the healthcare IoT data processing and analytics are performed at the edge/fog node. The resulting real-time insights are conveyed to the end-users such as the monitored patients, their relatives, nurses, emergency services, doctors, or medical practitioners. The cloud server is used additionally to store the history of the person for a long time or sometimes it can be used for long-term analytics of non-real-time data.

Human Gait analysis finds its applications in various fields such as sports, fall detection, and gait impaired people’s assessment [36,37]. As an indicator of health, Gait analysis is important in diagnosing patients, who are recovering from accidents, traumatic brain injury [45], brain strokes, neurological disorders [25], musculoskeletal anomalies, and psychiatric disorders [35].

The method for Gait analysis can be categorized into the marker-based system and marker-less system. The marker-based system requires the usage of reflective markers on the body parts for gait recognition. These are expensive as well as more inconvenient for use during movement [29]. Recently, markerless motion capture devices have been introduced and wide usage of them can be found in human activity monitoring. One such device is Kinect introduced by Microsoft in 2010. It provides color images, infrared images, and depth information of the human body to realize several body joints. Having features such as cost economical, affordable, easily portable, and non-invasive, it is often used in the development of gait recognition systems [8].

Knee injuries are more common in people playing sports, either professionally or amateur. 1 in 3,000 people experience knee injuries, and 70% of those injuries are attributed to sporting activity [26]. The occurrence of knee injury ranges from 9-15% across basketball leagues [13] in North America & Europe, especially NBA (National Basketball Association) and the ACB (Spanish Basketball Professional League). In such a case, it is more common to have knee injury in the anterior/external compartment of the knee when compared to the lateral/internal compartment [4]. Few researchers [42, 31] have attributed this anterior compartment knee damage to certain gestures attributed to the game. This injury is broadly known as Anterior Cruciate Ligament (ACL) injury.

An ACL injury is a tear or sprain of the anterior cruciate ligament - one of the major ligaments in the knee that connects the thighbone (femur) to the shinbone (tibia) and helps stabilize the knee joint. The potential correlation to ACL injuries has been assessed by carefully examining lower extremity kinetic and kinematic parameters in athletes. The knee abduction angle which is a measure of the dynamic knee valgus has been linked significantly to ACL injury risk [6, 42, 44]. To further analyze this risk, a bilateral jump-landing task such as the Drop Vertical Jump (DVJ) can be utilized to obtain a knee abduction measure [24]. Dynamic Knee Valgus [7, 11,12] has been established as an abnormal movement pattern of the lower limb comprising excessive femoral adduction, femoral internal rotation, knee abduction, and external tibial rotation. The early identification and screening of such poor movement patterns play an important role in preventing the risk of ACL injury in athletes. Some researchers [2,9] have depicted the correlation between DVJ and the risk of ACL injury. The Knee-Ankle separation ratio (KASR) has been proposed as a potential substitute for knee abduction angle to assess the dynamic knee valgus during the DVJ. The KASR value is measured during the DVJ task at two different time points: Initial Contact (IC) and Peak Flexion (PF).

Through this study, it is possible to determine that knee injuries can be caused by transferring loads to the external compartment due to the valgus knee location by studying the abduction angle and the KASR in some gestures of the basketball game. A method for calculating KASR during DVJ activity of the subject by measuring kinematic 3D using MS Kinect is thus introduced in this study to screen ACL injury risk.

Also, a system for automated real-time gait analysis based on edge computing using a single and cost-effective RGB-D camera, namely Microsoft Kinect v2 is proposed. Gait recognition model analyses the video stream sequence recordings produced by the Kinect. The methodology then calculates gait parameters and the KASR value of the subject performing sports activity. It analyses the ACL injury risk for the person and reports the result to the end-users.

The key contributions of this research work are as follows.

1. An Edge-based real-time gait monitoring system for knee injury analysis is proposed, consisting of a multi-tier architecture. A computer system acting as an edge node implements the edge computing concept.
2. A method is proposed to calculate gait parameters of the subject performing jump and squat activity and to measure KASR to assess the dynamic knee valgus in the person performing the DVJ task by analyzing the data acquired by the Kinect sensor.
3. Experiments have been conducted with three volunteers asked to perform the activities. The resultant values show that the KASR value found during DVJ can be used to screen the possibility of ACL injury in the person.

The rest of this paper is organized as follows. Section 2 discusses the characteristics of markerless motion capture approaches and background information of cloud and edge computing technologies. Section 3 reviews some related works on edge computing frameworks, gait recognition systems, and deep learning approaches. The proposed edge framework for gait monitoring application is depicted in section 4. Section 5 discusses the methodology and algorithm to implement the system. In section 6, various gestures simulating the jump-oriented ball games have experimented with the volunteers and their results are shown.

2. Background

This section describes the limitations of marker-based motion-capture devices and the beneficial features of marker-less devices for gesture recognition. It also narrates the intention of edge computing for time-sensitive applications.

Gait recognition using marker-based solutions (e.g., Vicon, Qualysis), requires the employment of several IR cameras and retro-reflective markers needed to be placed at the specific body positions [29]. These procedures are accurate, but often more expensive and impractical to move. Additionally, passive or active markers must be correctly placed on the body before each capture session. Therefore, such processes are only suitable for laboratory settings. Force plates [38] are also used for gait analysis. Again, these systems are usually costly and are only found at laboratories and clinics. Sensors must be placed correctly and securely and must account for gravity, noise, and signal drift. Additionally, a single sensor is not enough to measure all gait parameters and so a matrix of sensors is required to obtain a comprehensive analysis [28]. They are also invasive in that the subject needs to be in contact with the sensor all the round for measurement which would be inconvenient to perform the activities. To overcome the aforementioned disadvantages of marker-based motion capture systems, the use of marker-less technology was proposed.

The marker-less motion capture method for gait recognition is recently evolved and is widely used in several kinds of research [18]. The Kinect sensor device is one of the tools for capturing motion without the requirements of the markers. The Kinect sensor can track 3-D movement through its depth sensor and output the location of 25 body joints in 3-D space at 30 Hz [18]. The procedure of detecting a movement or an activity by a person is fully automated with no manual or external intervention. When an activity is detected by the sensor, different gait cycles can be easily perceived from the acquired raw information, and gait features like stride time, stride length, cadence, and gait velocity are computed for each gait cycle (e.g.,) [27].

Cloud computing technology has evolved as a promising solution for the deployment of time-critical healthcare IoT applications. Such applications require minimum latency, desired QoS, efficient network utilization, and energy consumption [32]. The cloud cannot meet these requirements due to the rapid growth in network data volume. Edge computing is evolving technology, introduced by Cisco in 2014 [10], and inherits the features of cloud computing in the proximity to the end-users. Edge node utilizes the available limited computing capacity to process the data to obtain the desired insights and hence lowers the forwarding data to the cloud.

In this work, we propose to introduce an edge computing framework to implement a real-time gait monitoring system. It analyses the real-time sensor information about the gait parameters of the sportsperson and presents it to the appropriate end-users from the edge node itself. It reduces the latency resulting from the cloud architecture due to the long-distance travel of data and bottleneck in central cloud processing.

In our proposed architecture, a PC is configured as an edge node to connect with the Kinect sensor and process the depth image frames. Then, gait parameters are calculated, and KASR is calculated to identify the injury risk associated with the subject performing the intended activities. Experiments have been conducted with the three volunteers performing a jumping activity, squat position, and DVJ task. The results obtained from the experiment show that the proposed technique is simple and more efficient in identifying the possibility of knee injury risk.

3. Literature Survey

This section briefly presents the state-of-the-art gait monitoring procedures using marker-less devices and deep learning methods.

3.1 Silhouette based approaches

Lee et al. [22] proposed a person identification and classification mechanism using moments extracted from human walking video silhouettes. Each silhouette of a walking person is segmented into 7 regions fitted with ellipses and feature vectors are formed. Human identification and gender classification are performed based on the information in this feature vector. The gait feature had too much dependency on the appearance of the subject which could have been better solved by face recognition.

Liang Wang et al. [23] proposed a Spatio-temporal silhouette analysis-based gait recognition mechanism. The architecture is composed of detection/tracking, feature extraction, and classification. Principal Component Analysis (PCA) is used to reduce the dimensionality of the feature space. Since the cameras are not calibrated, views are foreshortened. Not much about gait can be obtained using this approach.

Ju Han et al. [19] proposed an individual recognition by gait across walking humans using Gait Energy Image (GEI). These features help characterize human walking properties and forecast gait properties under conditions like injuries, environment context, etc. The performance suffers amidst large silhouette distortion generated by differences in shoe, surface, clothing, and time.

Hu Ng et al. [16] proposed a method of extracting gait features of humans using silhouette images. It works in 6 stages: Preprocessing, Applying Bounding boxes, Silhouette segmentation, Skeletonization, Joint Angle extraction, and calculating Euclidean distance. The accuracy for the last subject was a mere 57% due to a large number of misclassifications of it to other subjects. Less number of gait features is extracted resulting in lower classification accuracy.

3.2 Marker-based motion capture approaches

Neelesh Kumar et al. [30] proposed a Gait measurement system consisting of active markers like LEDs positioned on anatomical landmarks for 2D tracking and extraction of spatiotemporal gait parameters. The image data acquired was captured using a Lumenera USB camera and analyzed using LabVIEW for gait determination. Flexion angle was calculated using a pattern matching algorithm on the preprocessed image. Measuring the distance between two successive minima of ankle marker trajectory using an imaging algorithm was used to determine Stride length. The total walkway distance in Field of view and frame rate were used to determine stride time. The major disadvantages comprise using costly LEDs and cameras.

Hewett TE et al. [15] proved the usage of kinematic analysis of the DVJ task in female athletes. The presented method clearly showed the difference between knee abduction angles between ACL injury and non-ACL injured groups. It also illustrated that ACL injured people would have high abduction angle at the two points - Initial Contact and Peak Flexion and low knee flexion angle when compared with the healthy groups.

3.3 Deep Learning-based approaches

Thomas Wolf et al. [41] captured the Spatio-temporal features for recognizing gait in multiple views by adapting 3D CNN. In order to allow detection of movements in all directions and also to preserve the temporal information, a 3x3x3 convolutional filter is used. ReLU is used as the activation function while the Softmax function is applied in the final layer. Since the available datasets suffer from subjects having different colors and clothing invariances, the RGB images are converted to grey-scale in order to learn gait features. This method faces the problem of overfitting due to smaller variances and small database sizes of CMU and CASIA datasets.

A deep learning approach for Gait Recognition was proposed by Sokolova et al. [1] using an optical flow of motion information is proposed instead of traditional silhouette-based methods. A Convolutional Neural Network(CNN) is used for this purpose and it comprises three parts namely input data preparation, extracting neural features, and classification of found features. Combining the CASIA and TUM-GAID datasets was not possible as the attributes were distinct.

Yang Feng et al. [47] proposed a CNN-based pose estimation method producing heatmaps that give the gait information in one frame. The LSTM network is used to model the gait sequence as they are found to be effective against unlabeled data. The model requires more training to learn transformations since heatmaps of synchronized frames under both the views could be different.

3.4 Edge-computing Architectures

A novel edge computing architecture for human-centric applications for healthcare 4.0 is developed in [32]. It utilized an edge gateway device to perform filtering and local processing which ultimately reduces the data load transferring to the cloud and request processing time. Another edge-computing approach [39] executed gait recognition models at the network edge using a single board computer. It proved efficient in terms of latency and local bandwidth in implementing machine learning models at the edge device.

An edge-based telemedicine framework based on 5G and artificial intelligence [48] is presented for remote automated disease diagnosis. A machine learning model is deployed at distributed edge nodes for medical information analysis to improve overall system efficiency. A fog-based IoT healthcare monitoring system [34] is designed to reduce latency and bandwidth consumption resulting from clod architectures. It implements a task scheduling algorithm at the fog layer which classifies the task according to priorities and schedules the virtual machines depending on the desired resources required by the incoming tasks.

As we have seen in this section, there are many kinds of research done based on gait analysis using markerless motion capture devices. Also, the integration of IoT, cloud, and edge computing has been attracting many researchers to propose many edge-computing frameworks for smart healthcare services. However, we did not find any works that merged real-time remote health monitoring and marker-less gait recognition systems. Hence the proposed framework serves the purpose of utilizing the edge computing concept in gait monitoring for screening the possibility of ACL injury risk factors associated with the sports athletes.

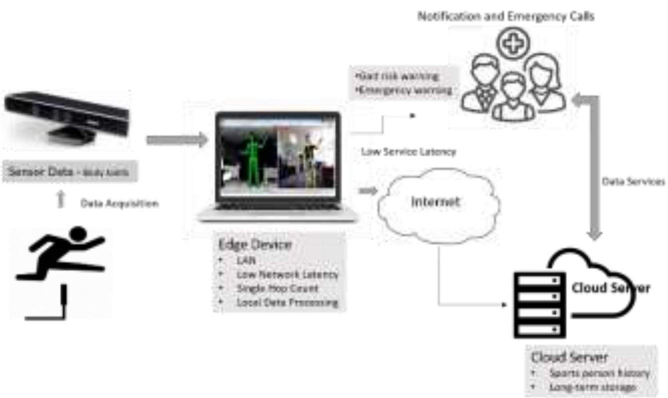

Figure 1: Edge Computing Architecture for Real-time Gait Monitoring System

4. Proposed Real-time Gait Monitoring System

In this section, the overview of the proposed multi-tier edge computing architecture is presented in Figure 1.

4.1 Architecture

In this paper, we propose a real-time gait monitoring system based on edge computing, whereby in this proposed work, the environment of the sports activity is equipped and the subject is monitored for his gait information.

The first layer of the architecture consists of the motion capture IoT sensor for acquiring 3D body joint information of a person and transmitting its data to the edge node. The second layer contains an edge device that uses a communication module to interface with the sensor. The topmost layer is based on a cloud to which the edge node can get communicated. The remote cloud server provides an enormous amount of storage and computational resources to the services. An application is developed to provide access to human activity statistics of the subject for real-time monitoring; therefore, identification of the risk factors associated with sports activity is performed at the edge node.

4.2 Sensor Layer

A motion tracking sensor is used to sense and transmit the obtained gait data of the subject. Kinect v2 is a motion capture sensor used in the proposed work which is non-intrusive and marker-less technology. It mainly consists of an RGB Camera, 3D Depth Sensor (IR Camera + Projector), and built-in Microphone Array using Time of Flight technology to perform real-time Gesture recognition, Speech Recognition, and body skeleton detection by enabling users a hands-free user interface with a computer system. The communication module is exploited for transmission of the sensor data to the edge node where they are analyzed to provide meaningful insights.

4.3 The Edge Layer

This layer contains an edge node to collect gait sequences from the sensors to perform the computation of gait parameters and their respective analysis. The edge node processes the incoming gait data and transfers the status of the gait information to the developed application for real-time monitoring. The data will be stored in the edge node for a specific amount of time and transferred to the remote database for maintaining the history of the person.

4.4 The Cloud Layer

This layer contributes to the cloud data server which is located far away from the user location. It offers extra storage capacity to the edge layer possessing limited capability. The storage module in the cloud server caches all up-to-date gait-related data for maintaining the subject's history. After consuming relevant data for gait identification, the edge nodes periodically submit the analyzed data for long-term storage in the cloud server. In our proposed model, the computational resources available at edge nodes are utilized for data processing and analytics, thus reducing the additional delay and network burden during communication with the remote cloud.

5. Methodology

This section briefly explains gait analysis and its application to knee injury analysis. It also discusses the methodology to calculate gait parameters and KASR value.

5.1 Gait Analysis:

Gait cycle describes the pattern of repetitive body movements during human walking events. The actual cycle begins when heel of one foot strikes the ground and completes when the heel of same foot strikes again. It is divided into two phases: stance phase and swing phase. The stance phase elapses between heel strike and toe-off the ground of right or left foot and the swing phase elapses between toe-off and heel strike the ground of the same foot [3,17]. Gait analysis is generally performed to obtain the spatial and temporal parameters: cycle time, stance time, swing time, step length, stride length and stride time, cadence and gait velocity. In our work, we estimate two types of gait parameters: kinematic parameters and Spatio-temporal parameters.

For kinematic analysis, intersegmental lower limb joint angles [14] which denote the joint ROM, are considered as salient variables. Characteristic analysis of these angles paves a stronger decision related to the injury risk. If the ROM during flexion exceeds the specific limit, then the probability of injury increases.

5.2 Application to Knee Injury Analysis

This research also examines the disparities in varus or valgus knee amongst subjects in a standing posture. When the distal part of the bone or a joint is more medial or when there is excess inward angulation, it is called varus. When the distal segment is more lateral, it is called valgus [5,43].

Around 70% of sports-related ACL tears are noncontact injuries [21], occurring during pivoting maneuvers or landing from a jump as illustrated in Figure 2. Noncontact ACL injuries are more common in females than in males [31]. It can be observed that when an athlete suffering from ACL injury lands after performing a jump, he/she exhibits greater dynamic knee valgus and increased joint knee load, resulting in subsequent meniscal injuries or even Osteoarthritis. Therefore, an algorithm for calculating the angles of the joints of the lower limb was implemented. The angles of the joints of the lower limbs [46] in the three anatomical planes for each recorded frame were obtained.

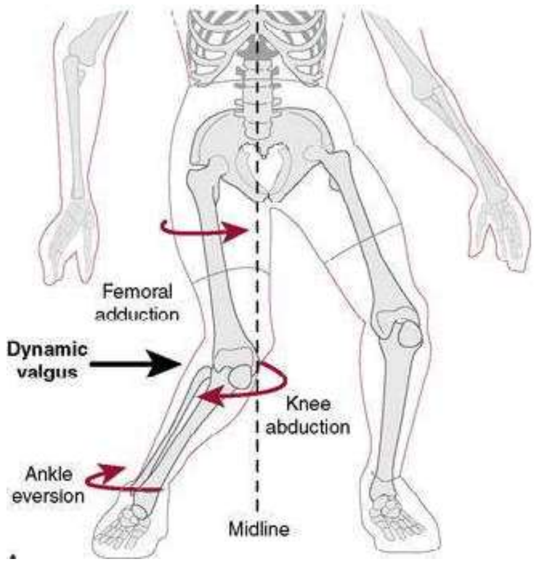

Figure 2: Dynamic Valgus

5.3 System Description

A desktop PC installed with Windows 8.1 OS is being used as an edge node in this work. The 3D kinematic system uses Microsoft Kinect® SDK (Software Development Kit) with its drivers and Developers Tool Kit with the examples and tools for the development of proposed applications on the Windows platform. The code creation is done using the Microsoft Visual Studio 2013 IDE employing .NET Framework 4.0.

5.4 Data Acquisition

Data provided by the Kinect were acquired at 30 frames per second (fps) [18], using our C# application running on the Windows platform. The application is responsible for the acquisition, processing, and recording of video. This application makes use of the libraries and components provided by the Kinect SDK. The Kinect data include infrared, depth, and 3-D body joint data. The subject walked in front of the camera positioned at a distance of 2.5m, with the sensor fixed at 0.6m height as shown in Figure 3. The sensor samples the skeleton data approximately at a rate of 30 fps and the edge node consumes the information to calculate the knee angle. Each frame of the depth image includes the 3-D position of the body joints.

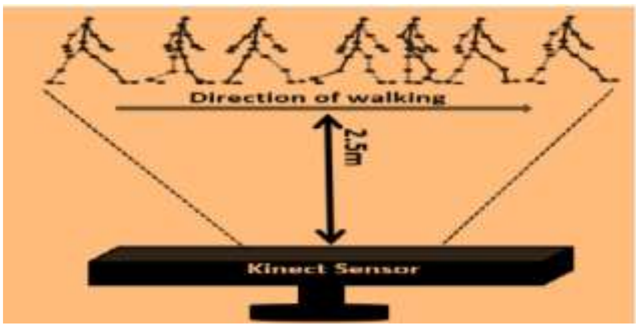

Figure 3: Kinect Sensor Positioning

5.5 Feature Extraction

The joint flexion angle at the knee is of special interest in this study as it predominantly describes the walking activity. The method to compute the knee flexion angle based on the definition of the dot product between two vectors is shown in Figure 4. The dot product is defined as the angle between two body parts: the shank and the thigh, adjacent to the knee joint, or on the other hand it is said as how much the knee bends during walking. In the figure, the body parts are depicted as two lines and the corresponding angle is indicated as α. Then this value is further post-processed to obtain the knee flexion angle. The knee flexion angle, represented as θ, is computed by making the complement angle of the dot product.

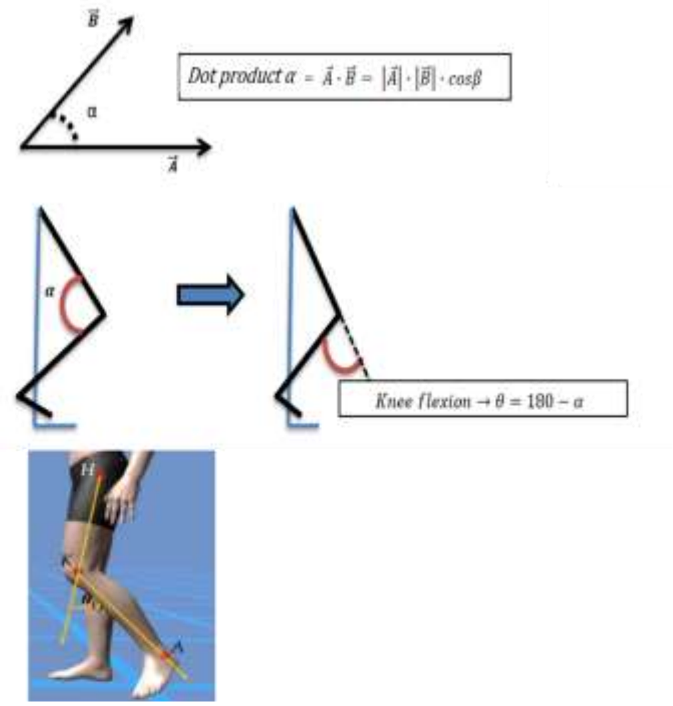

Figure 4: Knee Angle feature extraction

5.6 Gait Parameters Calculation

The method of calculation of kinematic and Spatio-temporal parameters in the proposed system is described in this section.

The kinematic measures are extracted at 30 frames per second and are useful for both gait analysis and activity recognition. θ_{kf} denotes the knee flexion angle calculated using the following equation (1).

$$\theta_{kf} = \cos^{-1}\left(\frac{\overrightarrow{HK}\cdot\overrightarrow{KA}}{\left\|\overrightarrow{HK}\right\|\left\|\overrightarrow{KA}\right\|}\right) \rightarrow (1)$$

where $\overrightarrow{HK}$ and $\overrightarrow{KA}$ are hip-knee vectors and knee-ankle vectors respectively.

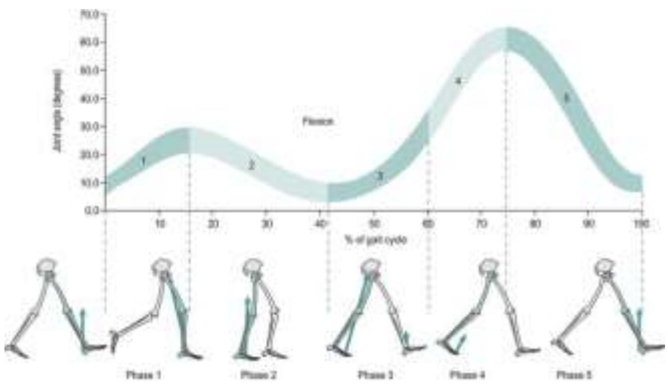

Figure 5: Knee Flexion observed during a gait cycle

Figure 5 shows the knee flexion angle observed during a sample walk. This performance is similar to the standard plot [33] and therefore it is possible to interpret the systems by considering all the negative peaks as heel strikes of the person. A peak detection algorithm is then employed and all the local minima events are estimated and equivalent timestamps are extracted, within the gait cycle. Using this information, Spatio-temporal parameters such as stride time, step time, stride length, step length, cadence, and gait velocity are measured. The proposed method to calculate the gait parameters from the knee flexion angle is given in algorithm 1. Three individuals with a mean age of 35 ± 5 participated in the study and their mean gait parameters were estimated as shown in Table 1.

Table.1 Estimated Gait parameters

Gait Parameters	Kinect Sensor Mean ± S.D	Normal Range
Step Length (m)	0.65 ± 0.05	0.6 – 0.7
Stride Length (m)	1.25 ± 0.1	1.2 – 1.5
Cadence (step/min)	105 ± 10	90 - 100
Gait Speed (m/s)	1.10 ± 0.1	1.0 – 1.3

5.7 KASR Calculation

The KASR is a ratio of the distances between the knees and ankles which is calculated at Initial Contact and Peak Flexion during DVJ [2]. The description of the KASR value and its respective risk possibility is described in Table 2.

Table.2 KASR value representation

KASR value	Description	Possibility
= 1.0	knee directly above the ankles	Normal knee
< 1.0 & >= 0.6	knee medial to the knees	Knock knee (Dynamic Valgus)
< 0.6	knee medial to the knees	Severe risk of Valgus
> 1.0	knees lateral to the ankles	Bowlegs (Varus)

The Microsoft Kinect Software Development Kit is also used to obtain a 1-dimensional KASR at IC and PF for the DVJ performed, obtained using the knee and ankle joint centers of the Kinect skeletal model. The IC and PF events are estimated by the Kinect V2 and extracted using two keyframes. The event IC represents when any of the feet hits the floor following the initial drop from the platform. The joint velocity starts to reduce at the IC. Therefore, using the ankle and foot joint centers, the point when the joint velocity decreases are calculated. The event PF represents the moment of high knee flexion angle after IC and before leaving the floor for the vertical jump. To identify this, firstly the average of the hip joint centers and the spine base is computed and the frame with the minimum joint centers relative to the floor is then identified.

The knee valgus angles were recorded at IC and PF. The joint coordinates were used to calculate the 2-dimensional KASR in the frontal plane.

With the x-axis aligned in the medial-lateral direction, the KASR was measured using the joint coordinates as estimated by the Kinect camera, using the following equation (2).

$$\mathrm{KASR}_{\mathrm{K}} = \frac{\left|x_{\mathrm{LeftKnee}} - x_{\mathrm{RightKnee}}\right|}{\left|x_{\mathrm{LeftAnkle}} - x_{\mathrm{RightAnkle}}\right|} \rightarrow (2)$$

Algorithm 2 shows the steps to measure KASR for the identification of injury risk factors. The implementation of the whole system is illustrated as a flowchart in figure 6.

Algorithm 1: Gait Parameters Calculation

Input: x, y coordinates of the knee flexion movement
Output: gait parameters and Knee flexion angle

1. Calculate the α:dot product of x and y
2. Find the complement of the angle, θ as shown in Figure 4
3. Calculate knee flexion angle, θ_{kf} using the equation 1
4. Call peak_detection() and estimate all the local minima points in the walking pattern of a subject
5. Calculate Spatio-temporal parameters: Step length, Stride length, Gait speed, Cadence

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Algorithm 2: KASR Calculation

Input: DVJ frame sequences
Output: KASR value

1. Find Initial Contact: Call decreasing(velocity(ankle-foot Joint)) and extract the first frame
2. Find Peak Flexion: Implement avg(hip-spine base joint) and extract the frame at the minimum position of joint relative to the floor
3. Find Knee Valgus angle at IC and PF
4. Calculate the KASR value using the equation 2
5. Display the value
6. If KASR < 0.6

Display "Severe Valgus Risk Possibility" and mark it as "important"

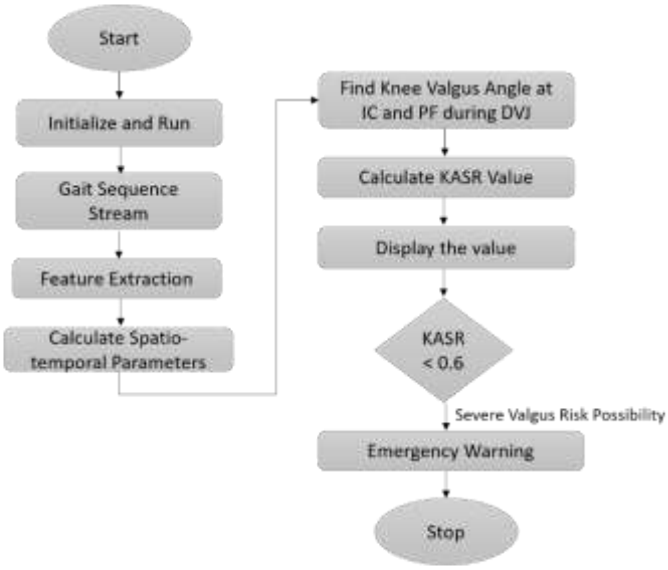

Figure 6: Flowchart for Proposed Methodology at the Edge node

6. Experiments and Results

This section illustrates some activities simulating the jump-oriented ball games that should be performed by the subjects. It also shows the respective results obtained for each gesture.

The movement of the volunteers performing two different tasks (as in a game of basketball/volleyball) was captured using a Microsoft Kinect sensor. Five repetitions for each of the gestures were recorded and the knee flexion/extension and knee abduction/adduction angles were estimated. The two tasks are defined as:

A. *Jump*: The subject was instructed to jump (as in the case of a free throw in basketball or defending/smashing in volleyball) after he was positioned within the coverage area of Kinect. The recording of data started with the subject standing and completed once he had returned to the start position, completing the jump.

B. *Squat:* Also, the subject is asked to perform DVJ activity to measure the KASR value for the assessment of risk factors. In this regard, the Kinect

V2 was positioned at a distance of 2.5m from the platform. A participant stood on the 31cm platform, dropped from the platform to the ground, and immediately performed a maximal vertical. 5 such jumps for a subject were recorded.

Also, the subject is asked to perform DVJ activity to measure the KASR value for the assessment of risk factors. In this regard, the Kinect V2 was positioned at a distance of 2.5m from the platform. A participant stood on the 31cm platform, dropped from the platform to the ground, and immediately performed a maximal vertical. 5 such jumps for a subject were recorded.

6.1 Experimental Results

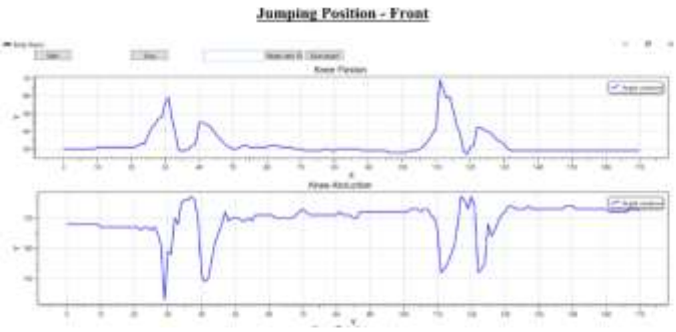

Figure 7: Knee angles of jump

Figure 7 shows the knee angles of a subject performing a jump similar to that in a basketball or volleyball game. It can be observed that the knee flexion peaks during the impulse and landing phase of the jump depending on the movement of each subject. The knee rotation was used to estimate these phases. This is since when the knee is stretched out, there is no pivot because of a blockage at this joint. It can also be observed the time difference between the occurrence of the flexion peak and the maximum angle of the knee valgus-varus. During the impulse and the landing phases, the varus angle observed during internal rotation of the knee is closely spaced, and has a spread ranging from 0º to -25º while the valgus angle is observed during external rotation of the knee is dispersed widely, ranging from 0º to 15º. Figure 8 shows the knee angles of a subject performing two squats with a pause in between. Here also, it can be observed that the knee flexion peaks when the knees are in the squatted position.

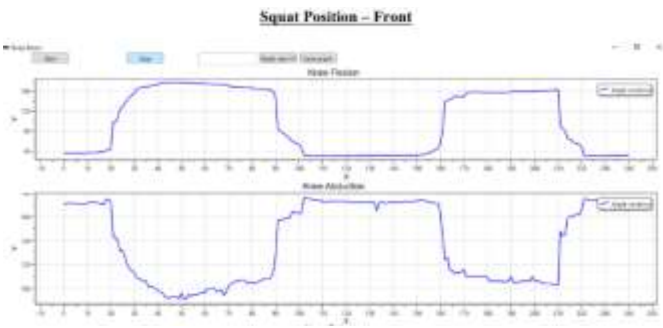

Figure 8: Knee angles during squat

Furthermore, the eligible subjects were divided into two groups: one who did an internal rotation of the knee during a jump and the second group who did an external one, recognizing that both the movements are related and that the subjects ultimately made one of the two rotations during jumps. The difference between internal or external rotation is used to determine whether the knee had the associated motion of a varus or valgus. The knee injury pertaining to the external compartment is connected with the valgus shift. As a result, the higher the valgus angle amplitude more is the risk of ACL injury. Although the knee abduction angle is a measure related to ACL injuries, further study into the predictive value of this angle is required.

Table.3 Summary of Drop Vertical Jump

Parameters	Subject 1	
	Initial Contact	Peak Flexion
Left Valgus (degrees)	4.86	5.26
Right Valgus (degrees)	-1.43	-2.64
Knee Ankle Separation Ratio	0.91	0.93

A summary of the jump performed, clearly showing the left/right valgus angles along with the KASR metric is demonstrated in Table 3. The application records the left/right valgus angles and KASR metric at IC and PF instances of the DVJ. The left and right valgus angles were averaged for each jump since the KASR metric is a bilateral lower extremity measure. An ensemble average taken across 5 successful jumps was used to compare the valgus angles against KASR. Since a coefficient of determination (r2 = 0.7) exists between valgus angles and KASR, there exists a strong linear relationship between the two. Since a more detailed analysis of this proposal is not the objective of this work, only preliminary results are discussed for illustration.

7. Conclusion

To ensure the provision of real-time risk analysis associated with sports activity, an edge-based gait monitoring system using a Kinect sensor is thus proposed. The sample experiments have been conducted with three volunteers performing the sports activity. The proposed method calculates gait parameters and KASR frontal plane value from the depth images sensed by the Kinect. The framework intimates the respective authorities if any injury risk is found with the activity performed by the subject.

In the proposed model, the gait features are extracted that would be useful in both medical and sports circumstances using a Kinect-based marker-less motion capturing system. The estimation of gait parameters using just one Kinect camera was a challenge, the achievement of which has encouraged the use of such technology where no other equipment is available. Gait parameters thus estimated were found to tally with reference values and the same can be extended to include subjects varying in age, gender, health conditions, etc. In the clinical context, this analysis has provided useful insight for detecting people walking with disabilities or improper walking techniques. The effect of the knee valgus on ACL injuries in athletes playing jump-oriented sports such as basketball, volleyball, handball, etc. has been quantitatively studied in this paper using Kinect. The KASR is a simple measurement that strongly correlates with the abduction angles resulting from the DVJ. Since there is no arduous task of estimating the hip joint center, the KASR frontal plane measure becomes a simple substitute for the Knee abduction angle, thereby offering immense promise to screen the risk of ACL injury during dynamic movement tasks. Thus, in the context of sports, it has provided useful information regarding injuries and their subsequent rehabilitation measures.

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