A Hybrid Intelligent System for Recovery and Performance Evaluation After Anterior Cruciate Ligament Injury

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Abstract—**This paper presents a hybrid intelligent system for recovery and performance evaluation of athletes after anterior cruciate ligament (ACL) injury/reconstruction. The fuzzy logic and case based reasoning approaches have been combined to build an assistive tool for sports trainers, coaches and clinicians for maintaining athletes' profile, monitoring progress of recovery, classifying recovery status and adjusting the recovery protocols for individuals. The kinematics and neuromuscular data are collected for subjects after ACL injury/reconstruction using self adjusted body-mounted wireless sensors Upon feature extraction and transformation using principal component analysis, the fuzzy clustering with automatic detection of clusters is employed to group the data according to current recovery status. A knowledge base has been designed to store subjects' profiles, recovery sessions' data and problem/solution pairs. The recovery classification and selection of similar cases has been done using fuzzy k-nearest neighbor (*f-knn*) and cosine similarity measure. Once relevant cases are selected, adaptation is performed and the performance evaluation will be done. The proposed system has been tested on a group of healthy and post-operated athletes and the classification accuracy of the system is found to be more than 94% using leave-one out cross validation method for walking/running activity.**

Keywords-Case Based Reasoning (CBR);Fuzzy Logic (FL); Anterior Cruciate Ligament (ACL);Wireless Sensors; Knee Injury;Recovery Monitoring

I. Introduction

The use of intelligent techniques combined with wireless body-mounted sensors is becoming prevalent in the field of medical diagnosis and pathology classification [1, 2]. The common applications of this blend are in the fields of stroke diagnosis, hand gesture recognition, stress monitoring, identification of hand motion commands, post-stroke rehabilitation, electromyography (EMG) classification for neuromuscular diseases and in general for human motion/gait analysis [3-8]. In these applications, generally, the kinematics, kinetics, neuromuscular or other relevant signals are acquired through wearable sensors and then pattern matching and/or soft computing techniques are used for data classification. These computational intelligent techniques have provided assistive tools to clinicians to assess the subjects under different health conditions. In few applications, the data from multiple sensors are integrated before applying the intelligent mechanisms. This provides a broad analysis of patients while using a more detailed feature set rather than relying only on few parameters [9].

Rehabilitation after any injury or trauma is one of the main areas where light-weight body-mounted wireless sensors have been used recently [7, 10]. Different machine learning and Artificial Intelligence (AI) techniques have been utilized for rehabilitation of lower limb movements after neurological disorders and implantation of artificial limbs [11]. However, few efforts have been done for developing an intelligent assisting tool for monitoring recovery of athletes after Anterior Cruciate Ligament (ACL) injury and reconstruction. ACL injury, being more common in female athletes, is one of the knee injuries causing deterioration in the sports performance or premature end to the career for athletes [12]. A major difference between the rehabilitation of athletes from other subjects/patients is to bring them not only to their normal activity level but also to assist them to rejoin sports within shorter period and return to their original sports performance level.

An end-to-end system would be ideal which may help in ACL injury prevention, intelligent rehabilitation monitoring and prediction of athletes sports performance after ACL reconstruction. In order to build such an exhaustive system, a knowledge base of athletes' profiles is required to be developed which could store current and past information (i.e. before and after ACL injury/surgery) about athletes' knee dynamics and other relevant parameters. A suitable approach to build such system is to use Case Based Reasoning (CBR) methodology which solves the new problems by using or adapting the existing solutions and maintain a knowledge base of solved problems [13]. CBR has been used in variety of medical applications for data analysis and classification. A diagnosis and prognosis system has been developed using CBR in [3] for stroke patients. A gait disorder analysis system has been proposed in [14] for general practitioners using CBR approach. It uses accelerometer data for lateral and forward movements of center of mass to retrieve similar cases based on experts' knowledge. CBR has also been combined with other techniques including fuzzy logic and neural network to develop more robust classification systems. A fuzzy CBR has been used to design a decision support system for stress diagnosis in different subjects [5].

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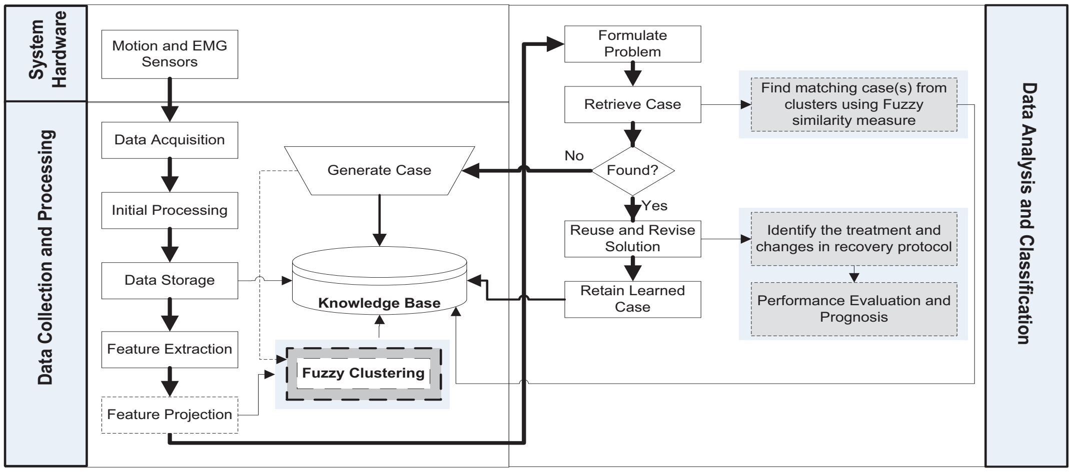

Figure 1. Hybrid intelligent system for ACL recovery classification and performance evaluation

The imprecision and uncertainty in sensors' measurements was dealt by using a fuzzy similarity metric for case retrieval. Alahakone [15] proposed a hybrid system combining Self Organizing Maps (SOM) and CBR for evaluating postural control based on trunk sway obtained during a tandem Romberg stability test. The prediction accuracy of the system was claimed to be more than 90%.

This paper presents a novel approach for monitoring and classification of recovery status and evaluating athletes' sports performance after ACL reconstruction by combining fuzzy logic and CBR system. The kinematics and neuromuscular data for subjects are collected through body-mounted wireless sensors after ACL injury/reconstruction. After feature extraction and data processing a knowledge base has been designed to store subjects' profiles, recovery sessions' data and problem/solution pairs. The case retrieval is performed using fuzzy *k-nn* and case selection is done by using cosine similarity metric. The system can be utilized by sports trainers, coaches and clinicians for multiple purposes including maintaining athletes' profile, monitoring progress of recovery, classifying recovery status, adapting recovery protocols and predicting athletes' sports performance.

II. Hybrid Intelligent System For Recovery Classification

The hybrid intelligent framework for ACL recovery classification and performance evaluation is shown in Fig. 1. The components and sequential operations of the system are elaborated in the following sub-sections.

A. System Hardware

The system hardware is composed of wireless body-mounted motion and electromyography sensors, and a video camera. The sensors record kinematics and neuromuscular signals from the subjects, and the camera provides the visualization of human motion by capturing the video of the experiments. These sensors can provide required parameters during ambulation, one leg jumping or balance testing activities without obstructing the lower limb movements.

B. Data Collection

In order to collect data and perform initial processing, following steps are performed.

1) Data Acquisition: The sensing units are setup for recording signals from the motion and EMG sensors. The motion sensors are attached to the thighs and shanks of both legs to note the knee joint movements. The EMG sensors are placed on the quadriceps and hamstring muscles on both legs. The raw signals from sensors are acquired using the software modules provided with the sensing systems. These raw signals (angular rate, acceleration, raw EMG data) are then stored in the files for further processing.

2) Initial Processing: The raw signals are filtered and transformed into the required format for visualization and feature extraction. The knee angle computation, EMG rectification and envelop generation are done at this stage.

3) Data Storage: Initial-processed data is stored in the knowledge base and a preliminary profile of the subject is created. This data can be mainly used for visualizing the superimposed kinematics and neuromuscular signals for each subject.

4) Feature Extraction: Different time, frequency and time-frequency features are extracted from both kinematics and neuromuscular data [16]. Both signals are first synchronized (if the sampling rates are different) and then based on the monitored activity (walking/running, jumping or balance testing), the features extraction and selection step is performed. For this study, following features were extracted using disjoint segmentation. The length of the segment varies with the activity monitored.

a) Knee flexion/extension: The knee angle was calculated using angular rates and acceleration from thigh and shanks of each leg.

b) Integrated EMG (IEMG): The integrated EMG for each muscles is calculated as the summation of absolute values of EMG signal.

$$IEMG = \sum_{i=1}^{N} | emg_i | \quad (1)$$

where emg_i is the value of each part of the segment, and N is the length of the segment.

c) Mean Absolute Value (MAV): The mean absolute value for each muscles is calculated by adding the the value emg_i in a segment and dividing it by the length of the segment.

$$MAV = \frac{1}{N} \sum_{i=1}^{N} | emg_i | \quad (2)$$

d) Root Mean Square (RMS): The root mean square value of each muscle for different segments is calculates as follows:

$$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^{N} emg_i^{\ 2}} \quad (3)$$

e) Waveform Length (WL): The waveform length is the cumulative length of the waveform over the segment. follows:

$$WL = \sum_{i=1}^{N-1} | emg_{i+1} - emg_i | \quad (4)$$

f) Mean Frequency (MNF): For frequency *fi* and power spectrum *Pi*, the *MNF* is calculated as follows:

$$MNF = \frac{\sum_{i=m}^{n} f_i P_i}{\sum_{i=m}^{n} P_i} \quad (5)$$

g) Continuous Wavelet Transform (CWT): CWT of an EMG signal *emg(t)* is defined in (6) where *s* represents the scale parameter, τ represents the translation diameter of time shifting and the basis function ψ^* is obtained by scaling the mother wavelet at time τ and scale *s*.

$$CWT_{emg}(s, \tau) = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} emg(t) \psi^* \left(\frac{t - \tau}{s} \right) dt \quad (6)$$

5) Features' Selection/Reduction: The proposed set of features for recovery classification is based on kinematics and neuromuscular signals. In this study all of the above features were extracted for walking/running activity at different speeds. The length of the data segments for feature extraction was defined as the selected phases of the gait namely Load Response (*LR*), Mid Stance (*MSt*), and Terminal Swing (*TSw*) phases. The selection of these phases was due to the fact the selected muscles (vastus medialis, vastus lateralis, semitendinosis and biceps femoris) are mostly active during these phases. The *MSt* was further divided in to two halves as *MSt_1* and *MSt_2* to reduce the segment length and make the distinction among muscles more clear. Let K_i^G and E_i^G represent the kinematics and EMG features' set for G^{th} gait cycle and i^{th} subject, respectively then

$$K_i^G = \{k_p^n\}, \ E_i^G = \{m_{1p}^l, m_{2p}^l, m_{3p}^l, m_{4p}^l\} \quad (7)$$

where k_p^n represents the n^{th} kinematics feature (*n=1* for this study) for p^{th} phase, m_p^l represents the l^{th} EMG feature (*l=1..7* for this study) for p^{th} phase for muscles. The value for *p* depends on the activity being monitored (*p=1..4* for walking/running). Let f_i^G represents the feature vector for G^{th} gait cycle for the i^{th} subject and total feature set is *F* then

$$f_i^G = \{K_i^G\} \cup \{E_i^G\}, \ F = \{f_i^G\} \quad (8)$$

The feature vector length for walking/running activity is 116 (7 EMG features × 4 muscles × 4 phases + 1 kinematics feature × 4 phases). In order to reduce the feature vector length, different feature selection and reduction algorithms were investigated. The feature selection algorithms select only a subset of the features to represent the model while the feature projection/ transformation algorithms try to determine the best combination of the original features to form a new and smaller feature set. The features selection techniques discard some of the features completely and so the information provided by those features is completely lost. In order to avoid this problem, Principal Component Analysis (PCA) is applied to reduce the dimension of data and still not rejecting some of the features completely from the data set. PCA transforms the original feature set of variables $f \in F \subseteq R^N$ into a new feature set of variables $v \in V \subseteq R^M$ of reduced dimension by minimizing the mean-square error (MSE) between the original set *F* and projected set *V* [17].

6) Case Generation: The case generation is a semi-automatic process where the extracted features and recommendation from the clinicians are used to generate a case (problem/solution pair) and stored in the knowledge base.

C. Fuzzy Clustering

In order to retrieve the most similar cases efficiently, the clustered case base organization has been used. Due to the imprecise nature of motion and neuromuscular parameters, the fuzzy clustering has been adopted as opposed to the crisp/classical clustering algorithms which assign an object to only one group. This is generally difficult in domains like recovery classification or gait analysis where variations in data are more common and one object may belong to different groups with different degree of memberships. Fuzzy clustering partitions the sample space and organizes the data into approximate clusters. O'Malley et al. [18] has applied fuzzy clustering for classifying gaits of children with cerebral palsy into different groups. Fuzzy clustering approach has also been used to identify the effect of temporal patterns on the walking speed based on foot switches [19].

The fuzzy *C*-means (FCM) has been applied to the transformed feature set '*V*' of kinematics and neuromuscular data collected during walking at different speeds on the treadmill. The *fcm* function in Fuzzy Logic Toolbox from MATLAB starts with an initial guess for the cluster centers for marking the mean location of each cluster. Each feature vector as a data point is then assigned a membership grade for each cluster. *fcm* follows an iterative process to minimize the objective function and then decides the right cluster centers and membership grade for each feature vector. In order to avoid a pre-assigned number of clusters, the cluster validity measure proposed in [20] has been modified. In [20], a simple validity measure based upon the intra vs. inter cluster distance has been designed for *K*-means clustering. This measure has been adapted, as in (9), by including fuzzy membership value μ assigned to each of the clusters and minimum validity index has been selected.

$$Validity = \frac{\left. \sum_{i=1}^{k} \sum_{\forall v \subseteq V} \mu_{vc_i} \times \left\| v - c_i \right\|^2 \middle/ KN \right.}{\min(\left\| c_i - c_j \right\|^2)} \tag{9}$$

where c_i and c_j are the cluster centers, N is the number of records in the data set, k is the maximum number of clusters, v is a subset (selected features) of V and $|| v - c_i ||^2$ and $|| c_i - c_j ||^2$ represent the intra and inter cluster distances, respectively.

D. Data Analysis Using Case Based Reasoning System

The data analysis and classification of recovery is done by using fuzzy case based reasoning approach. CBR paradigm is based on the concept of solving new problems by using/modifying the similar previous experiences (problem-solution pairs). CBR is a four -step process:

- Retrieve: Finding similar case(s) from the knowledge-base whose problem description best matches with the given problem
- Reuse: Reusing the solution of most similar case to solve the new problem
- Revise: Adapting/Modifying the chosen solution according to the differences in new problem
- Retain: Storing the new problem-solution pair as a case once it has been solved

The details about these processes and other components of the CBR system designed for this study are discussed in next subsections.

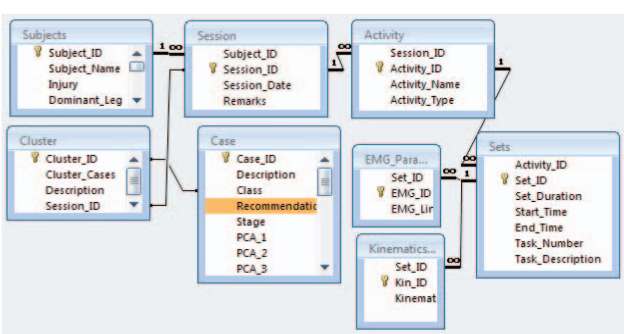

Figure 2. Knowledge base implementation using relational database

1) Case Representation: Each case in the knowledge-base is composed of problem-solution pair and a case description. The problem part is represented as attribute/value pairs for the selected kinematics and EMG features and the corresponding solution part is made up of the recovery classification, treatments at different stages and the performance evaluation/prognosis for the athletes. The case description contains the subject's biographical, sports and other relevant clinical information. This information may provide assistance in refining the retrieval and adaption of similar cases.

2) Knowledge-base (KB): In order to manage the knowledge-base repository, a relational database has been used (see Fig. 2). The knowledge-base will evolve with the time-period when new problems are presented and new cases are added to the system. This evolution process makes it more useful for domains where subject's specific monitoring and prognosis mechanisms are required. The important components of the KB are briefly explained as below:

a) Subjects and Session: The *Subject* table contains the biographical and some injury related information for each subject. This *Session* table contains the information about each session of the experiments i.e. whenever the data is acquired from the subject (pre-injury, post-injury or post surgery), a new session is created. *Pre-injury data* may be utilized in comparing the post-injury or post-operated performance differences when in case an athlete gets an ACL or other knee injury. *Post-injury data* may be utilized to compare the pre and post-operated changes in attributes. *Post-operated data* are recorded during different recovery stages and additionally a solution part is also stored along with the case.

b) Activity and Sets: During each session, data for different activities (walking/running, one leg jumping and balance testing etc.) can be recorded. In the post-operated data collection, the selection of activity depends on the current stage of recovery for an individual. For each activity, multiple datasets are stored to avoid any error and identify outliers.

c) Kinematics and EMG Data: The data recorded during each set is stored in these tables after data processing step. The link to the corresponding raw data file is also stored along with each record.

d) Cluster and Case: The clustering is performed in order to group the subjects according to their similarities. This table contains the cluster indices and cases under each cluster. The *Case* table contains all information related to each solved case stored in the repository including problem description, transformed attribute/value pairs, recovery stage, class, recommendations and protocols followed during rehabilitation etc.

3) Retrieval of Similar Cases: In order to retrieve the most similar cases for the given scenario, a two step process is performed. In the first step, the best matching class is identified for the new problem (after transforming it using PCA coefficients) by using *f-knn* algorithm on the clustered data [21]. In the second step, the most similar cases are retrieved from the identified cluster by using cosine similarity metric. The retrieved cases are arranged in the descending order of similarity and first *k* cases are selected where *k* is the user's choice. The result of the the retrieval step is the recovery classification of the given problem i.e the recovery classification of the athlete based on the values of currently measured parameters and retrieval of cases for adaptation process.

4) Reuse and Repair of Cases: After retrieving the most similar case, the next step is to use and adapt the solution of this case to improve the recovery process of the athlete for the next stage. This semi-automatic process requires the involvement of the clinicians/physiotherapist to decide any changes in the rehabilitation protocol based on the recommendations and indication of performance level from the retrieved case. Additionally, modifications may also be done in the recommendation section of the previous stages of the new problem.

5) Retaining the Learned Case: The new case may be retained in the library after formulating a solution based on the adjustments of parameters for individuals. Whenever a new case is added, the fuzzy clustering algorithm generates new clusters (if required) and assigns different membership grades to the related cases. The cluster table is also updated in the KB.

III. Results And Discussion

In order to test the proposed system, multiple sets of kinematics and neuromuscular data from 11 subjects (6 unilateral ACL reconstructed and 5 healthy i.e. without any knee/ACL injury) were collected for walking/running activity (at 2 and 3 km/h) on a treadmill. The kinematics and electromyography signals were recorded using KinetiSense (ClevMed, Inc.) motion sensors and BioCapture (ClevMed, Inc.) monitoring system, respectively. The healthy subjects were having a mean age of 25.6±6.10 years, mean height 168.4±3.20 cm, and mean weight 69.2±13.98 kg. For ACL reconstructed subjects, the mean age, mean height and mean weight were 31.2±6.20 years, 166.2±14.72 cm and 66.8±15.64 kg, respectively. The ACL reconstructed subjects were at different stages of rehabilitation. A total of 116 features (time, frequency and time frequency) were extracted and then by using PCA the feature set was reduced. A careful analysis of principal components (PCs) showed that 20 PCs were appropriate to be selected to increase the cumulative distribution to 95% (see Fig. 3). The coefficients matrix and these transformed features were stored for data analysis. Fig. 4 shows the original data projected on first two PCs. It is visible from Fig. 4 that the PCA is also useful in identifying the subjects who have very different values of the input parameters (bottom-left). The transformed features were clustered using FCM to form the groups of subjects who were healthy or at similar stage of recovery. Three clusters were identified using proposed validity index (11) which were manually verified and found to be appropriate. Fig. 5 shows 3-D scatter plot for the first three PCs and the cluster centers identified by FCM where clusters 1, 2 and 3 represent subjects within 3 months after surgery, subjects after 6 months of surgery and subjects without ACL injury, respectively. Some of the data points lie on the boundary of second and third clusters which depicts that some of the subjects belong to both clusters with certain high grades and cannot be completely categorized into a single recovered group. This is natural as even after following the same rehabilitation protocol, the recovery may depend on individuals' other physical parameters.

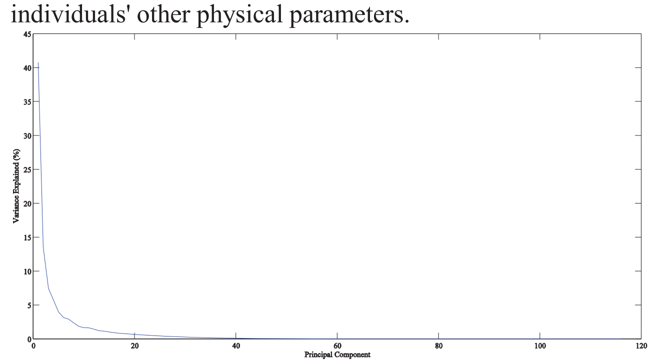

Figure 3. Percentage of variance explained by all principal components

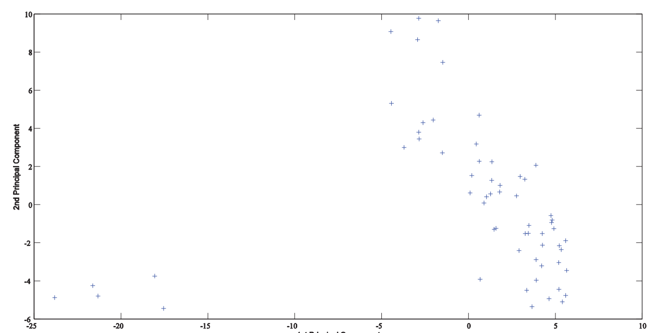

Figure 4. Original data projected on first two principal components

TABLE I. Classification Performance

Walking Speed	Class	Sensitivity (%)	Specificity (%)	Precision (%)
2 km/h	1	100.00	100.00	100.00
	2	95.65	100.00	100.00
	3	100.00	96.42	100.00
3 km/h	1	100.00	100.00	100.00
	2	91.66	95.65	93.10
	3	95.65	91.66	96.42

In order to classify a new subject, the input parameters were first transformed using the coefficient matrix and then *f-knn* was used to classify the subject based on trained clustered data. Due to small sample size, the Leave-One-Out Cross Validation (LOOCV) method was utilized to test the validity of the classifier [22]. The *f-knn* was trained on *N-1* samples from the dataset and one sample was left as the validation sample (N=60 for 2 km/h and N=51 for 3 km/h data sets). This process was repeated *N* times and the overall classification accuracy was found to be 98.33% for 2 km/h speed and 94.11% for 3 km/h speed data set. The classification n performance of the system is shown in Table I. After classifying the recovery stage, the relevant cases are selected using cosine similarity metric. The performance of each subject is compared with the most similar retrieved cases by using their recommendations and next stage results.

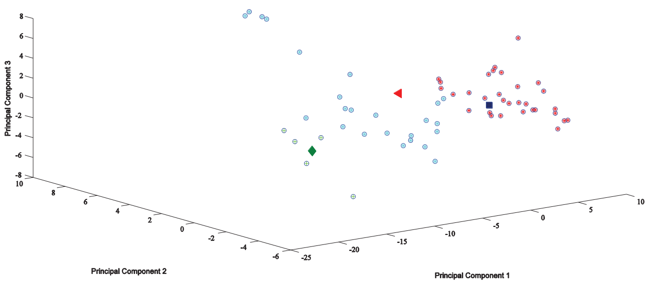

Figure 5. Clusters' centers identified by FCM - cluster 1 (♦) cluster 2 (▲) cluster 3 (■)

IV. CONCLUSIONS

A system determining an athlete's ACL injury profile and potential knee joint/neuromuscular problems during rehabilitation would be valuable in clinical environment as decision support system. In this work, a hybrid intelligent system has been proposed for ACL recovery classification and performance evaluation of athletes. This system helps in building a knowledge base of with athletes' pre-injury, post-injury and post surgery profiles, and possible set of solutions for assistance during rehabilitation period. The system has been tested for walking/running activity for a small group of ACL reconstructed and healthy subjects and the accuracy of the system is high for the monitored activity. In future, balance testing and one leg jumping activities will also be included during tests for enhancing the subjects' profile. Moreover, the pre- and post injury data will also be collected to compare the performance differences after ACL reconstruction. Additionally, the system will be enhanced for injury prevention and performance prediction of athletes.

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