Impact of intelligent biofeedback during rehabilitation of professional athletes: a model for next generation smart healthcare system

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Abstract

This paper presents a general framework of intelligent biofeedback for smart healthcare system and its impact on healthcare of professional athletes, especially during rehabilitation monitoring. The application of machine learning techniques along with various wireless wearable sensors facilitated in building a knowledge base system for healthcare monitoring of the subjects and providing a visual/numeric biofeedback to the clinicians, patients and healthcare professionals. The validated system can potentially be used as a decision supporting tool by the clinicians, physiotherapists, physiatrists and sports trainers for quantitative rehabilitation analysis of the subjects in conjunction with the existing recovery monitoring systems. Based on the results achieved, a conceptual design and model for next generation smart healthcare system/devices for professional athletes has been proposed.

Index Terms: biofeedback, smart healthcare, machine learning, wireless sensors

1. Introduction

Various tasks and activities are performed by the athletes during their training sessions/regimes as well as in the field. In order to improve and optimize their sports performance and prevent them from any action leading to injury, a continuous monitoring of their health conditions is crucial. Moreover, in case of an injury, observing their recovery progress becomes vital for timely return to sports and avoiding further injuries.[1] Evidence-based, informed decisions are required to be made regarding structuring training and evaluation of individuals. Thus, powerful tools are needed to be developed for performance evaluation, training enhancements, injury screening, and return-to-play assessment for a variety of athletes and sport disciplines.[2] Recording of the appropriate data/bio-signals interfaced with intelligent techniques can assist in solving this problem by designing a knowledge-based system as a decision supporting tool for clinicians, healthcare professionals, sports trainers and the athletes as well.[2,3] Such a system can provide visual and numeric biofeedback in real-time or off-line in order to improve the health conditions and/or sports performance of the athletes.[3]

This paper presents an overview of the design of an intelligent biofeedback system and its effectiveness in assessing the healthcare and sports performance of athletes having knee injury and surgery. The overall recovery evaluation performed by the developed system was found in accordance with the assessment made by the physiotherapists using standard subjective/objective scores with additional useful information. Further, the statistical results demonstrated that the use of visual biofeedback improved the rehabilitation performance of the subjects. Based on these results, a conceptual design and model for next generation smart healthcare system for professional athletes has been proposed in this paper.

2. Experimental approach

Overview of the Developed System

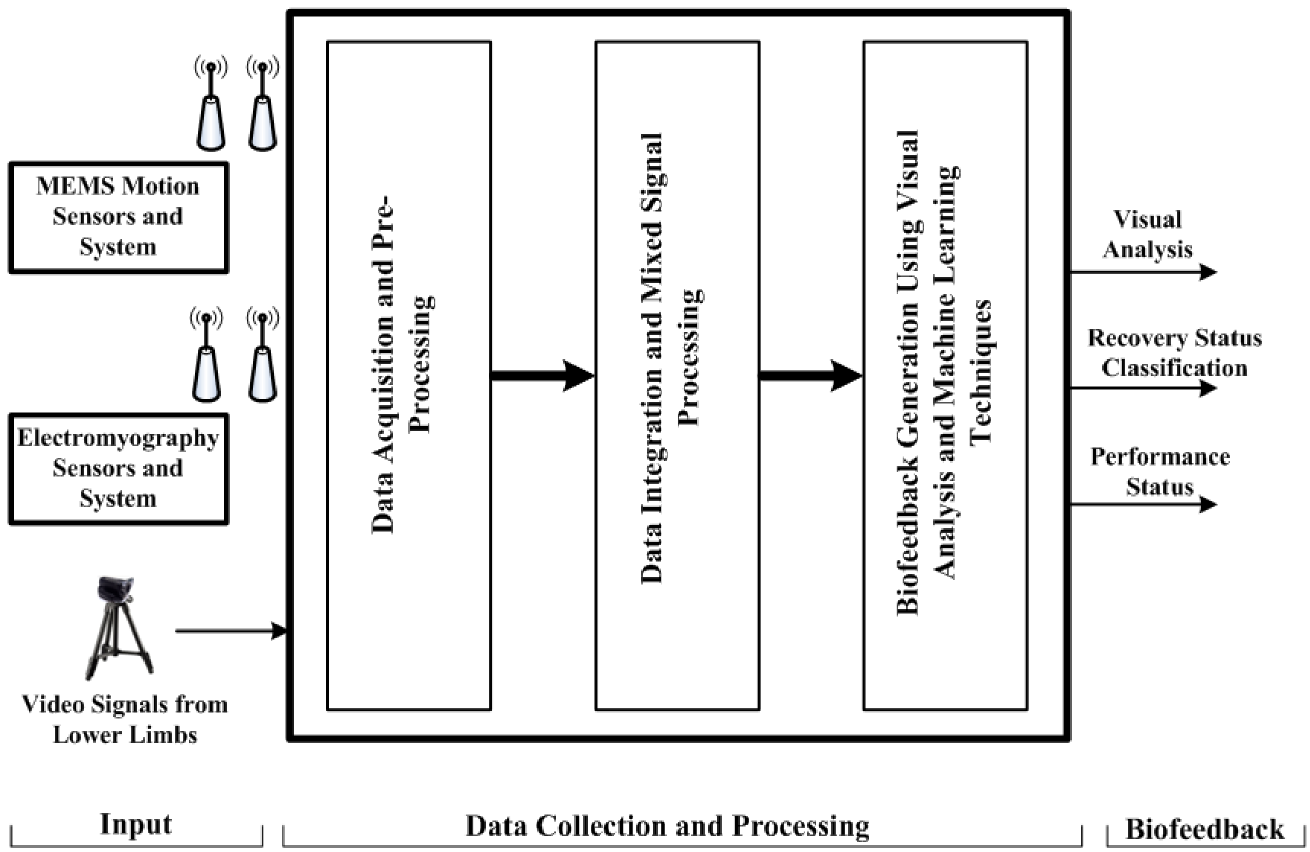

Figure 1. Components of the system

An intelligent extensible framework was designed and developed for monitoring and assessing the recovery status of athletes, and evaluating their sports performance after having knee injury or surgery. This system was developed using non-invasive body-mounted motion and electromyography (EMG) wireless sensors to capture the kinematics and neuromuscular data from human lower extremity during ambulation and single leg balance testing activities. This framework was developed in order to facilitate the clinicians, physiotherapists, physiatrists and sports trainers in determining the recovery stage of the subjects based on the data collected during different rehabilitation testing activities and identifying the subjects lacking behind the desired level of recuperation. Additionally, the feedback/solution from the previous cases was provided to assist them for taking the required therapy/training measures or accelerating their ongoing activity level.

The overall structure of the developed system is shown in ***Figure 1***. The system mainly consists of three components: 1) input (signals from wireless sensors attached to the lower extremity of subjects), 2) data collecting and processing software module and 3) output (visual analysis, recovery and performance status). Initially, the output with corresponding input pattern set is used to create a knowledge base (KB). After forming the KB, the system provides a biofeedback (recovery and performance status) to clinicians, physiatrists and physiotherapists for the test subjects and the KB is enriched/updated if the test pattern is new and/or repaired pattern.

Knowledge Base (KB)

A knowledge base (KB) is a centralized repository for information related about a particular field or domain. In this study, a KB was created in order to manage the information about the subjects' profiles and their health/rehabilitation conditions. The KB contains different types of information including raw and processed data, domain knowledge, historical data available for subjects (pre-injury, post-injury), session data during convalescence, case library (problem-solution pair for rehabilitation monitoring), reasoning and learning models (trained intelligent methods) and other relevant data (e.g. subjects' profiles, gender, type of sports etc.). In general, the information in KB can be represented as

$$\text{KB} = [\ pre\_inj\_I_S^i,\ post\_inj\_I_S^j,\ post\_op\_I_S^k,\ \mathfrak{I}(pre\_inj\_I_S^i),\ \mathfrak{I}(post\_inj\_I_S^j),\ \mathfrak{I}(post\_op\_I_S^k),\ \mathfrak{S}_p,\ \mathfrak{D},\ \mathfrak{C},\ \mathfrak{M}_t\ ]$$

where

$pre\_inj\_I_S^i$: raw input data set (kinematics, EMG and video) of a group of subjects '*S*' for different sports activities at pre-injury (i.e. healthy) stage for *i* sessions ($i \geq 1$)

$post\_inj\_I_S^j$: raw input data set (kinematics, EMG and video) of a group of subjects '*S*' for different sports activities after knee injury (i.e. before surgery) for *j* sessions ($j \geq 1$)

$post\_op\_I_S^k$: raw input data set (kinematics, EMG and video) of a group of subjects '*S*' for different sports activities after knee surgery (i.e. rehabilitation after surgery) for *k* sessions ($k \geq 1$)

$\mathfrak{I}(pre\_inj\_I_S^i)$: processed input data set (kinematics, EMG and video) of a group of subjects '*S*' for different sports activities at pre-injury (i.e. healthy) stage for *i* sessions ($i \geq 1$)

$\mathfrak{I}(post\_inj\_I_S^j)$: processed input data set (kinematics, EMG and video) of a group of subjects '*S*' for different sports activities after knee injury (i.e. before surgery) for *j* sessions ($j \geq 1$)

$\mathfrak{I}(post\_op\_I_S^k)$: processed input data set (kinematics, EMG and video) of a group of subjects '*S*' for different sports activities after knee surgery (i.e. rehabilitation after surgery) for *k* sessions ($k \geq 1$)

$\mathfrak{S}_p$: profile (e.g. gender, age, weight, height, type of injuries, sports activities etc.) of *p* subjects

$\mathfrak{D}$: domain knowledge (e.g. type of protocols followed for subjects after surgery, local/standard norms for different rehabilitation testing activities etc.)

$\mathfrak{C}$: case library consisting of problem-solution pairs (processed input, rehabilitation procedure followed, outcomes and possible suggestions) related to individuals or different group of subjects

$\mathfrak{M}_t$: trained intelligent models for each activity *t* to be monitored.

The designed KB is not a static collection of information, but it acts as a dynamic resource which has the capacity to learn and evolve with the passage of time when new problems are presented and new problem-solution pairs are added to the system. This evolution process makes it more useful for domains where subject's specific monitoring and prognosis mechanisms are required. Thus, as an integral component of rehabilitation and performance monitoring system, this KB has been used to optimize collection, organization and retrieval of relevant information for subjects.

System output - Biofeedback

In order to observe the rehabilitation progress and performance of knee injured subjects, the developed systems provides a set of outputs '$\mathfrak{O}$' consisting of visual biofeedback (*VBF*) and recovery progress indicators (*RPI*) for physiotherapists, physiatrists and clinicians.

$$\mathfrak{O} = (VBF, RPI)$$

Visual Biofeedback (VBF)

The developed visual biofeedback system provides a visual monitoring of individual and superimposed signals (kinematics and EMG) in order to identify the knee joint abnormality and muscles strength during ambulation and balance testing activities performed by the knee injured subjects. The system can present different types of individual/superimposed processed signals for inter- and intra-subject comparisons e.g.

- Knee flexion/extension with each of the processed EMG signals (envelopes) from different muscles for each rehabilitation testing/monitoring activity
- Knee abduction/adduction with each of the processed EMG signals (envelopes) from different muscles for each rehabilitation testing/monitoring activity

- Knee rotation with each of the processed EMG signals (envelopes) from different muscles for each rehabilitation testing/monitoring activity
- Comparison of activation timings, duration and normalized strength of different muscles monitored for each rehabilitation testing activity within same and/or different legs of an knee injured subject and with the average of these parameters of a group of healthy subjects
- Comparison of 3-D knee movements (flexion/extension, abduction/adduction and rotation) of non-injured (anterior cruciate ligament intact) and injured (anterior cruciate ligament reconstructed) leg of the same subject for each rehabilitation testing/monitoring activity
- Comparison of 3-D knee movements (flexion/extension, abduction/adduction and rotation) of injured leg of a subject with average 3-D movements of healthy subjects for each rehabilitation testing/monitoring activity

Recovery Progress Indicators (RPIs)

For objective assessment and recovery analysis of a knee post-operated subject during rehabilitation period, four outputs are provided by the developed system using integrated kinematics and EMG feature set.

- Current recovery stage/phase for each activity
- Percentage of the recovery progress for each activity as compared to the healthy group
- Percentage of the recovery progress within a identified stage/phase for each activity
- An overall combined recovery state for all activities monitored

Decision making

The objective biofeedback provided by the developed system is used as a supporting tool by clinicians, physiatrists, physiotherapists and sports trainers for observing the subjects with ambulation and balance impairments after knee surgery and timely intervening during the rehabilitation regimen. The current recovery progress evaluation and previously stored experiences in KB (if any) help in focusing on specific recovery problem areas and modifying the rehabilitation protocols for individuals as per the requirements.

In order to make a decision about the recovery state and performance of a subject, first the input parameters '$post\_op\_I_S^k$' are collected through sensors and video camera for each activity during a rehabilitation monitoring session and system outputs '$\mho$' (as described in section 2.2) are generated using the processed data. These system outputs (indicating the objective and quantitative recovery progress of a subject) and other standard tests are then used by physiatrists, physiotherapists and trainers for suggesting and/or modifying the training and exercises during the next phase of rehabilitation. The subject is re-assessed after further rehabilitation training and the improvements or deteriorations are objectively identified. This process continues till a subject fulfils the required criteria of recovery evaluation before joining any high level sports or other demanding activities. Thus, this complementary decision support system can help in reducing duration and cost of recovery, and improving the rehabilitation process by providing accurate and timely information about the individual subjects' knee functionality after surgery.

Experimental setup

This section briefly describes the experimental setup for the study. Wireless motion and EMG sensor systems were used for data acquisition method and setup of sensors was performed using standard procedures.[2,5] Twenty six subjects (10 healthy and 16 unilateral anterior cruciate ligament reconstructed i.e. post operated knee) athletes were recruited from Performance Optimization Centre (POC) in Ministry of Defence and Sports Medicine and Research Centre (SMRC) in Ministry of Youth, Culture and Sports, Brunei Darussalam. The healthy subjects (4 females and 6 males) had no previous history of knee injury and ambulation/postural control impairments at the time of data acquisition. These subjects were having following mean and (S.D) readings: age of 29.4 (4.15) years, height 169.3 (4.30) cm, and weight 72.8 (14.17) kg. Knee post-operated subjects (6 females and 10 males) were in range of 2 to 13 months post reconstruction with mean 7.25 (3.53) months. The mean (S.D) age, height and weight of this group were: 25.6 (4.15) years, 164.5 (5.34) cm and 68.5 (12.54) kg, respectively. All procedures were carried out according to the ethics guidelines approved by Universti Brunei Darussalam's Graduate Research Office and Ethics Committee.

Biosignal processing

In order to design and test the proposed system, 3-D kinematics and EMG parameters were recorded for healthy and post-operated subjects for five different activities: normal walking on flat surface at comfortable speed, two high speed walking activities (7 km/h and 8 km/h) on a treadmill and two single leg balance testing (eyes open - EO and eyes closed - EC) on a balance training platform (***Figure 2*** and ***Figure 3***). The selection of these activities was based on the recommendations from physiotherapists and due to presence of post-operated subjects at varying level of recovery.

The raw input data set obtained through the sensors and video recordings is processed by using a system-software developed in MATLAB 7.0. The system software has a layered architecture where each layer performs one or more tasks and the results are transferred to the next layer for further processing or output generation.

Figure 2. A test subject walking on a treadmill wearing wireless motion and EMG sensors

Figure 3. A test subject standing on single leg on a balance trainer wearing wireless motion and EMG sensors - front and back view

Relevant and key features from kinematics and EMG data were extracted during subjects' motion in order to collect data for generating data sets and then applying recovery classification and evaluation mechanisms.[2,5] A data set for each activity was formed by using the kinematics and EMG feature sets. The data set for each ambulation and balance testing activity consisted of 78 feature vectors (26 subjects × 3 trials per activity) with corresponding feature vector length. A single gait cycle (averaged gait cycle for a trial) during each ambulatory activity was represented by a feature vector of length 903 (840 EMG features + 63 kinematics features). For balance activities, the feature vector length was 159 (150 EMG features + 9 kinematics features) for each time segment per activity. Thus, a total of 9 data sets (3 for ambulation activities + 3×2 for balance testing activities) were generated for further processing. In order to remove the redundancy in feature vector/set and making the recovery evaluation system more efficient, principal component analysis was applied successfully.[2,5] The subjects were grouped into four categories based on their health condition using semi-automatic process and distribution of subjects' data points in these groups were verified by the physiotherapists. The groups were labelled as "Healthy Subjects", "Subjects at Stage 3", "Subjects at Stage 2" and "Subjects at Stage 1" representing different stages of health/recovery condition of the subjects (stage 1 represents the initial level of recovery and stage 3 represents the advanced level of recovery). The identification of current class/status of gait/balancing patterns of a new subject provides useful complementary information in order to make adjustments in his/her rehabilitation process. Based on the patterns of 3-D kinematics and neuromuscular data, an automated identification of class/stage of gait/balance patterns of a subject for an ambulation/balancing activity is done by training and testing various intelligent classifiers.[5] Thus, for each ambulation/balancing testing activity, the class of gait/balance patterns of a subject is determined as per his/her performance during the test trials for that particular activity. An overall recovery progress output for a subject is computed by combining the results of all activities monitored during a session. Various data processing and the intelligent techniques were used for providing the recovery progress evaluation. [5]

For generating the visual biofeedback, the raw EMG data with zero mean for different muscles were full wave rectified and low pass filtered to generate linear envelopes. The linear envelopes provide useful information for assessing the strength/activation of different muscles for inter- and intra-subjects comparison. For comparing the EMG amplitude, the data were normalized for each subject using mean value of the signal of each stride/balance segment for respective muscles and data were represented as a percentage of mean.[3,5] The estimated knee orientation (flexion/extension, abduction/adduction and internal/external rotation) in three planes and EMG envelopes from different lower limb muscles were superimposed to observe the changes in both type of signals simultaneously.

3. Results and Discussion

This section reports the effectiveness of the design and impact of the results for healthcare monitoring of the subjects. It mainly describes the comparison of the performance of recovery stage classifiers, their validation and the impact of the overall biofeedback in order to improve the recovery of the professional athletes (details can be found here).[5]

Comparison of the recovery classifiers' performance

In order to determine the recovery stage of the subjects, three different classifiers adaptive neuro-fuzzy inference system (ANFIS), fuzzy unordered rule induction algorithm (FURIA) and support vector machines (SVM) were trained and tested for each activity based on the respective clustered data for healthy and post-operated subjects, and their performance measures were compared. The cross validations of all models were done by partitioning the data into two groups: training data (75% of the total data) and test data (25% of the total data). The training/testing phase for all classifiers was repeated 10 times and the average values of different performance measures were computed.

Both ANFIS and FURIA based classifiers generated the rules after training phase and these rules (models) were saved for further validation and re-suing for new data. However, it was found that the number of rules generated by FURIA based classifiers were, in general, less than the rules generated by ANFIS models for different activities which indicates the efficient rule learning/pruning mechanism in FURIA. The number of rules generated by ANFIS and FURIA models for four different activities is shown in T***able 1***.

Table 1. *Number of rules generated by ANFIS and FURIA classifiers for different activities using combined 3-D kinematics and EMG features*

Activity\Technique	***ANFIS***	***FURIA***
Normal walking	6	6
Walking at 7km/h	5	4
Walking at 8km/h	7	4
Single leg balance (EO)	10	4
Single leg balance (EC)	6	6

In order to evaluate the performance of different classifiers for various rehabilitation testing activities, Friedman's test (omnibus) and the Nemenyi test (post-hoc test) were used. The purpose of statistical significance testing is to help us gather evidence of the extent to which the

Table 2. Percentages of classification accuracies for all classifiers for different activities using combined 3-D kinematics and EMG features

Activity/Classifier	*FURIA*	*ANFIS*	*Linear SVM*	*Quadratic SVM*	*RBF SVM*
Normal walking	96.23	95.36	98.04	98.11	97.06
Walking at 7km/h	100.00	98.48	99.27	99.00	99.27
Walking at 8km/h	100.00	99.46	100.00	100.00	100.00
Single leg balance (EO)	97.22	84.13	99.67	93.33	84.67
Single leg balance (EC)	95.24	80.87	82.24	97.62	97.76

Table 3. Ranks of each classifier based on classification accuracies for different activities using combined 3-D kinematics and EMG features

Activity/Classifier	*FURIA*	*ANFIS*	*Linear SVM*	*Quadratic SVM*	*RBF SVM*
Normal walking	4.00	5.00	2.00	1.00	3.00
Walking at 7km/h	1.00	5.00	2.50	4.00	2.50
Walking at 8km/h	2.50	5.00	2.50	2.50	2.50
Single leg balance (EO)	2.00	5.00	1.00	3.00	4.00
Single leg balance (EC)	3.00	5.00	4.00	2.00	1.00

results returned by an evaluation metric are representative of the general behavior of our classifiers. All the classifiers were ranked based on their classification accuracies on each activity separately (***Table 2*** and ***Table 3***). For each classifier *j*, the sum of their ranks (R_j) obtained on all the activities is computed and then Friedman statistic is calculated using equation below.

$$\chi_{F^2} = \left[\frac{12}{n \times k \times (k+1)} \times \sum_{j=1}^{k} (R_j)^2 \right] - 3 \times n \times (k+1)$$

where n represents the number of activities and k is the number of classifiers.

The null hypothesis is that all the classifiers perform equally better, and the rejection of the null hypothesis means that there exists at-least one pair of classifiers with significantly different performances. By using the above equation, the value of χ_{F^2} was found 10.04. For a 2-tailed test at the 0.05 level of significance, the critical value is 7.8. Since the value of χ_{F^2} >7.8, so the null hypothesis is rejected. In case of the rejection of the null hypothesis, the omnibus test is followed by a post-hoc test whose job is to identify the significantly different pairs of classifiers. The Nemenyi test was used as a post-hoc test which computes a statistic q_{yz} between two classifiers y and z as follows:

$$q_{yz} = \frac{\overline{R}_y - \overline{R}_z}{\sqrt{\frac{k \times (k+1)}{6 \times n}}}$$

where $\overline{R}_y$ and $\overline{R}_z$ represent the mean rank of classifiers y and z, respectively.

Table 4 shows q_{yz} statistic computed using Nemenyi test for all classifiers. For level of significance 0.05 (i.e. α=0.05), q_α is 2.55. In order to reject the hypothesis that classifiers y and z perform equally well q_α must be larger than $|q_{yz}|$. Based on the results in ***Table 4***, the null hypothesis cannot be rejected for all combinations except for ANFIS-Linear SVM comparison (q_{yz}=*2.6*).

Table 4. q_{yz} statistic computed using Nemenyi test for all classifiers

Combination of Classifiers	*q_{yz} Statistic Value*
FURIA-ANFIS	-2.5
FURIA-Linear SVM	0.1
FURIA-Quadratic SVM	0
FURIA-RBF SVM	-0.1
ANFIS-Linear SVM	2.6
ANFIS-Quadratic SVM	2.5
ANFIS-RBF SVM	2.4
Linear-Quadratic SVMs	-0.1
Linear-RBF SVMs	-0.2
Quadratic-RBF SVMs	-0.1

Table 5. Area under curve (AUC) for all activities for different groups of subjects using combined 3-d kinematics and EMG features with FURIA classifiers

Activity/Subjects	*Healthy*	*Stage 3*	*Stage 2*	*Stage 1*
Normal Walking	1	1	0.9679	0.9889
Walking at 7 km/h	1	1	1	1
Walking at 8 km/h	1	1	1	1
EO Balance Testing	1	1	0.9944	0.9083
EC Balance Testing	0.9899	0.9986	0.9653	1

Table 6. Area under curve (AUC) for all activities for different groups of subjects using combined 3-d kinematics and EMG features with SVM (quadratic kernel function) classifiers

Activity/Subjects	*Healthy*	*Stage 3*	*Stage 2*	*Stage 1*
Normal Walking	0.9971	0.9858	0.9881	0.9805
Walking at 7 km/h	1	1	0.9959	0.9918
Walking at 8 km/h	1	1	1	1
EO Balance Testing	0.9915	1	0.9833	0.9167
EC Balance Testing	0.9839	1	0.9917	1

Table 7. Overall classification accuracy (percentage) of recovery stage identification for all activities based on combined 3-D kinematics and EMG features using trained classifiers (ANFIS, FURIA and SVMs) for new subjects to test the framework

Activity	*FURIA*	*ANFIS*	*Linear SVM*	*Quadratic SVM*	*RBF SVM*
Normal walking	95.83	94.34	95.23	94.71	94.24
Walking at 7km/h	100.00	97.50	100.00	99.00	99.00
Walking at 8km/h	100.00	100.00	100.00	100.00	100.00
Single leg balance (EO)	91.67	88.89	88.89	91.30	86.89
Single leg balance (EC)	94.12	76.19	80.95	90.72	92.65

Although, the statistical analysis show that almost all classifiers perform more or less similar in terms of their classification accuracies, a close analysis of other measures including sensitivity, specificity, F-measure, AUC (***Table 5*** and ***Table 6***) and number of rules generated suggest that FURIA classification models may be preferred over other models. In order to verify this, the trained models for each activity were stored and a data set for each activity consisting of data (three trials per activity) from 5 new subjects with known classes was used for evaluating the retrieval process. PCA coefficient matrices were applied on the given data, and five classification models were used to identify the classes. The classification performances of these models were compared (***Table 7***) and it was found that FURIA based classification model performed better than the other models for data from new subjects. The performance of each subject during each activity are compared with the most similar retrieved cases by using their recommendations and next stage results.

Validation of the recovery evaluation mechanism

In order to validate the proposed system, a data set of testing activities from 5 new post-operated subjects with known recovery status was used. PCA coefficient matrices were applied on the collected kinematics and EMG data (average of 10 gait cycles per trial for ambulation activities and 3 trials of 15 sec segments of balance testing activities) for new subjects, and different proposed metrics were used to determine their level of recovery condition based on transformed features. ***Table 8*** presents the mean(S.D) of percentage of recovery progress, recovery stage (using FURIA trained models) and percentage of recovery within the identified stage for three trials for five subjects during different activities monitored for testing. The percentages of different measures in ***Table 8*** are reported to the nearest whole percentile.

In order to verify the recovery evaluation of subjects, subjective assessments from two experts (the physiotherapist, and physical strength and conditioning coach) were used. An overall

Table 8. Recovery Evaluation for Five Subjects for Different Activities

Subject	***Activity***	***Recovery Progress (S.D) (%)***	***Recovery Stage***	***Recovery Progress within Identified Stage (S.D) (%)***
1	Normal Walking	80(1.85)	Stage 3	91(1.00)
	Walking at 7km/h	83(1.74)	Stage 3	91(1.10)
	Walking at 8km/h	82(1.72)	Stage 3	91(0.95)
	Balance (EO)	79(2.1)	Stage 3	88(1.24)
	Balance (EC)	68(2.54)	Stage 2	87(2.05)
2	Normal Walking	81(0.75)	Stage 3	95(0.45)
	Walking at 7km/h	83(0.78)	Stage 3	96(0.35)
	Walking at 8km/h	83(0.78)	Stage 3	96(0.38)
	Balance (EO)	81(0.98)	Stage 3	92(0.40)
	Balance (EC)	79(0.90)	Stage 3	89(0.70)
3	Normal Walking	95(1.20)	Healthy	96(0.95)
	Walking at 7km/h	93(1.05)	Healthy	96(0.87)
	Walking at 8km/h	95(0.95)	Healthy	95(0.89)
	Balance (EO)	90(1.20)	Healthy	92(0.92)
	Balance (EC)	81(1.10)	Stage 3	90(1.02)
4	Normal Walking	69(2.85)	Stage 2	91(2.10)
	Walking at 7km/h	67(2.23)	Stage 2	90(1.92)
	Walking at 8km/h	68(2.45)	Stage 2	90(1.90)
	Balance (EO)	67(1.89)	Stage 2	89(1.50)
	Balance (EC)	66(1.85)	Stage 2	88(1.45)
5	Normal Walking	70(1.97)	Stage 2	92(1.05)
	Walking at 7km/h	69(1.86)	Stage 2	91(1.01)
	Walking at 8km/h	69(1.86)	Stage 2	91(1.10)
	Balance (EO)	70(1.75)	Stage 2	89(1.01)
	Balance (EC)	69(1.86)	Stage 2	89(0.96)

assessment of current recovery status for each subject was given by these experts based on their judgments and standard physical fitness test scores (Tegner/Lysholm scores, assessment of leg press, hamstring curls, half squat and vertical/horizontal jumps etc.) for the subjects with post-operated knee. The assessment system used by the physiotherapists had four grades (Excellent, Good, Fair and Poor), each representing the health condition of a subject based on some subjective/partially objective measures. Similarly, the assessment system used by the strength and conditioning coach had five levels of grading (A, B, C, D and E), each representing the health condition of a subject based on certain subjective/partially objective tests. ***Table 9*** shows the comparison of overall subjective assessments (grade and percentages) given by the experts and an overall recovery value (stage and average percentage of recovery progress for all activities) obtained using proposed system by combining the The value of λ was found to be -0.8795. By calculating the $g(A_i)$s and $h(y_i)$s, the Choquet integral was used to compute the final recovery evaluation. The subjective assessments and the recovery stage identified by the proposed method are mostly consistent for all subjects. The percentages mentioned in the parentheses vary as these depend on the range assigned by different experts and techniques used to compute the values. The average percentage of recovery progress for all activities computed by the proposed system depends on the formation of respective clusters (groups identified for each stage of recovery). The number of clusters may vary due to the types of subjects available (after having knee surgery) for formation of the groups. However, for the given five subjects, a similarity

Table 9. Comparing subjective assessment and recovery evaluation computed by the proposed system

Subject	***Subjective Evaluation***		***Overall Evaluation by Proposed System***
	Physiotherapist	**Strength and Conditioning Coach**	
1	Good (~86.0%)	B (~80.0%)	Stage 3 (78.56%)
2	Good (~89.0%)	B (~86.0%)	Stage 3 (81.37%)
3	Excellent (~92.0%)	B (~93.0%)	Healthy (90.77%)
4	Fair (~73.0%)	C (~70.0%)	Stage 2 (67.36%)
5	Fair (~78.0%)	C (~73.0%)	Stage 2 (69.13%)

trend can be noticed between the recovery evaluation values computed by the proposed system and provided by the experts. The subjects having lower percentage of subjective assessments (subjects 4 and 5) also have low percentage of recovery value computed by the proposed system. Similarly, the subjects with higher percentage of subjective assessments (subject 1, 2 and 3) also have high percentage of recovery value computed by the proposed system.

Visualization of Biosignals' Patterns

The biofeedback system provides visual monitoring of individual and superimposed signals (kinematics and EMG) to physiotherapists, physiatrists and clinicians, as well as to the subjects. At the same time, this allows monitoring of the progress based on all processes and effectively matching with the motion patterns (previous patterns from the same subject or average patterns of healthy subjects or other knee post-operated groups/subjects) stored in the knowledge base.

This can also help in determining the time a subject might take to get back to the original performance or near original performance, or he/she might not be able to return to the previous level. This visual biofeedback has been found effective in improving the knee extension and muscle strength for the knee injured/post-operated subjects. Some examples of visualization of knee kinematics, EMG signals and their overlapping are shown in ***Figure 4*** through ***Figure 9***.

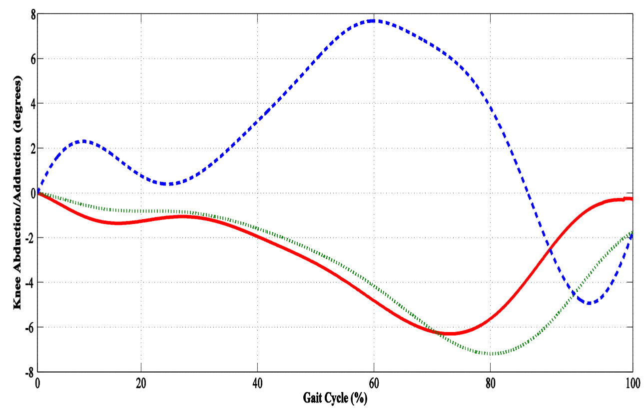

Figure 4. Knee abduction/adduction variations in the subjects during normal walking - Mean angle values in the post-operated leg (---) vs. healthy leg (....) for a subject 2 months after surgery and mean angle values for a healthy subject (____)

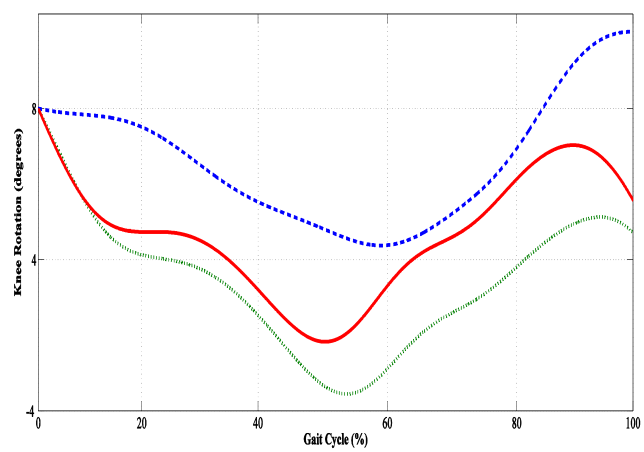

Figure 5. Knee rotation variations in the subjects during normal walking - Mean angle values in the post-operated leg (---) vs. healthy leg (....) for a subject 2 months after surgery and mean angle values for a healthy subject (____)

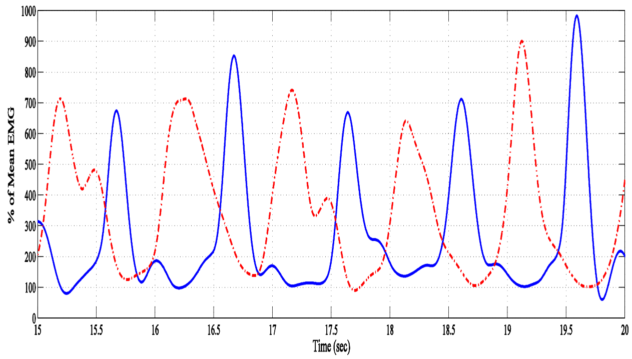

Figure 6. Comparison of percentage of mean strength and activation for biceps femoris muscles of healthy leg (– – –) and post-operated leg (___) of a subject 1 year after surgery walking at a high speed (7 km/h), representing more or less similar strength for muscles in both legs

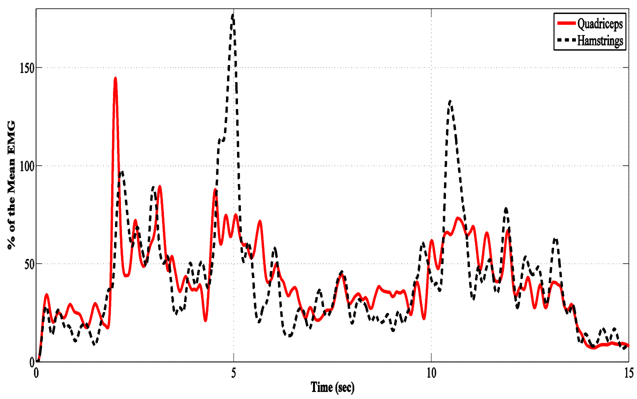

Figure 7. Comparison of the percentage of the mean EMG of quadriceps and hamstrings muscles for EO single balance testing activity for a subject after two months of surgery

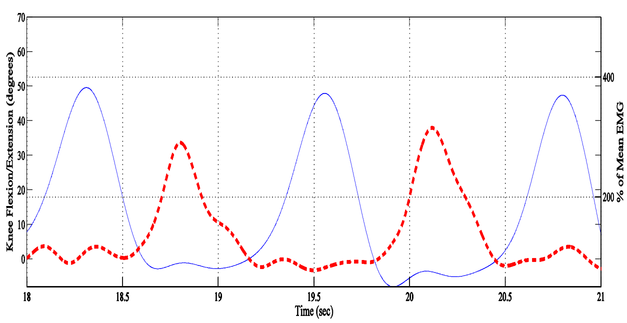

Figure 8. Activation timings and strengths of (a) biceps femoris, (b) semitendinosus and (c) vastus lateralis (---) vs. knee flexion/extension (____) of a healthy subject walking at a normal speed

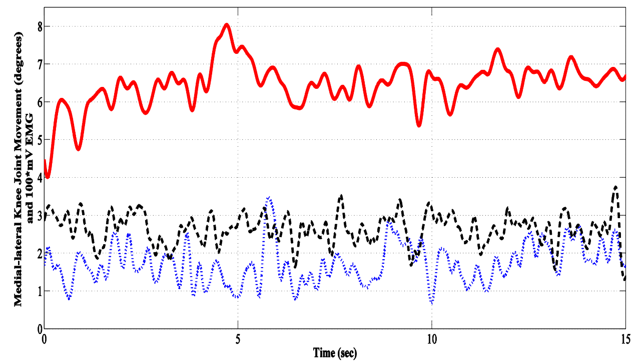

Figure 9. Superimposition of the medial-lateral knee joint movements (____), and vastus lateralis (----) and semitendinosus (-.-.-) EMG envelopes (100×mV) for a subject 2 months after knee surgery during EO single leg balance testing activity

Impact of the biofeedback

Based on the analysis of recovery stage and the visual biofeedback, vital muscle movements and kinematics signals during different gait phases and balance control for the subjects with knee surgerywere identified by the physiotherapist and the head of physical strength and conditioning, and focused training and exercises were instituted to restore the normal knee kinematics and required muscle strength for these subjects. The effectiveness of the biofeedback was evaluated by randomly assigning the subjects with knee surgery from recovery stage-2 to one of two groups: either with biofeedback (n=3) or without biofeedback (n=3). Similarly, the subjects from recovery stage-3 were also randomly allocated to one of two groups: with biofeedback (n=4) or without biofeedback (n=3). There were only 3 subjects with knee surgery found in recovery stage 1 so statistical testing of the impact of biofeedback has not been conducted. The data for these subjects were collected and monitored during the first session. In addition to following the same rehabilitation protocol as the other subjects, visual representation of the data for the subjects in the biofeedback group were used to identify the muscle movements and knee dynamics and take appropriate measures. Different parameters during ambulation at different speeds (the average knee extension angle during the terminal stance and swing phase, the peak knee flexion, the average abduction/adduction and rotation during pre-swing phase and the normalized peak values for

Table 10. p-values for different parameters using biofeedback for the subjects in recovery stage 2 during ambulation activities

Parameter Observed	*Normal Walking*	*Walking at 7km/h*	*Walking at 8km/h*
average knee extension angle during the terminal stance	0.041	0.036	0.035
average knee extension angle during the swing	0.047	0.042	0.043
peak knee flexion	0.035	0.031	0.031
average abduction/adduction during pre-swing phase	0.045	0.042	0.041
average rotation during pre-swing phase	0.205	0.195	0.191
normalized peak values for the vastus lateralis	0.042	0.040	0.040
normalized peak values for the vastus medialis	0.041	0.038	0.035
normalized peak values for the semitendinosus	0.150	0.098	0.110
normalized peak values for the biceps femoris	0.115	0.096	0.092

Table 11. p-values for different parameters using biofeedback for the subjects in recovery stage 2 during balance testing activities

Parameter Observed	*Single leg balance (EO)*	*Single leg balance (EC)*
average AP knee joint movements	0.047	0.041
average ML knee joint movements	0.043	0.040
average area of the distribution of AP-ML movements	0.025	0.038
normalized peak values for the quadriceps muscle strengths	0.039	0.038
normalized peak values for the hamstrings muscle strengths	0.189	0.176
normalized peak values for the gastrocnemius muscle strengths	0.105	0.101

the vastus lateralis, vastus medialis and hamstring muscle strengths) and single leg balance testing activities (average anterior-posterior and medial-lateral knee joint movements during the testing segment, the normalized peak values for the quadriceps, hamstrings and gastrocnemius muscle strengths) were noted for all the subjects after a period of around six weeks, to evaluate the effects of the biofeedback. An independent sample Mann-Whitney test, with $p < 0.05$ considered as the significance threshold, was used to test the differences between the groups. Significant differences ($p < 0.05$) were observed in the knee extension during the terminal stance and swing, the peak knee flexion and the average abduction/adduction during pre-swing phase, average AP and ML knee joint movements, and the average area of distribution of AP-ML movements during the testing segment for the subjects from recovery stage-2 who were treated using biofeedback as a complementary tool, in comparison with the subjected treated without biofeedback. Moreover, significant differences ($p < 0.05$) were also noted in the normalized peak values for the vastus lateralis and vastus medialis muscles for all ambulation and balance testing activities. However, no significant differences were noted between the two groups (with biofeedback and without biofeedback) in the average rotation during pre-swing phase and normalized peak values for the hamstring and gastrocnemius muscle strengths. ***Table 10*** and ***Table 11*** show the p-values for different parameters for the subjects from recovery stage 2. Significant differences ($p < 0.05$) were observed only for the average knee extension angles during the terminal stance, average abduction/adduction during pre-swing phase, average AP and ML knee joint movements, average area of distribution of AP-ML movements during the testing segments and the normalized peak values of the strength of the vastus medialis in subjects from recovery stage 3 who were treated with biofeedback compared to those treated without biofeedback.

Table 12 and ***Table 13*** show the p-values for different parameters for the subjects from recovery stage 3. Hence, these results indicate prospects of using the developed system as part of existing rehabilitation monitoring procedures to achieve a more effective and timely recovery of subjects.

Table 12. p-values for different parameters using biofeedback for the subjects in recovery stage 3 during ambulation activities

Parameter Observed	*Normal Walking*	*Walking at 7km/h*	*Walking at 8km/h*
average knee extension angle during the terminal stance	0.043	0.042	0.040
average knee extension angle during the swing	0.047	0.045	0.045
peak knee flexion	0.205	0.172	0.175
average abduction/adduction during pre-swing phase	0.189	0.175	0.171
average rotation during pre-swing phase	0.221	0.198	0.199
normalized peak values for the vastus lateralis	0.181	0.210	0.205
normalized peak values for the vastus medialis	0.039	0.032	0.033
normalized peak values for the semitendinosus	0.162	0.092	0.090
normalized peak values for the biceps femoris	0.150	0.146	0.142

Table 13. p-values for different parameters using biofeedback for the subjects in recovery stage 3 during balance testing activities

Parameter Observed	*Single leg balance (EO)*	*Single leg balance (EC)*
average AP knee joint movements	0.041	0.040
average ML knee joint movements	0.047	0.045
average area of the distribution of AP-ML movements	0.040	0.042
normalized peak values for the quadriceps muscle strengths	0.028	0.021
normalized peak values for the hamstrings muscle strengths	0.210	0.197
normalized peak values for the gastrocnemius muscle strengths	0.150	0.135

4. Next Generation Smart Healthcare System for Professional Athletes

The need for smart healthcare system is ever increasing. Hence, more efforts are being made to transform reactive care to proactive and preventive care, clinic-centric to patient-centered practice, and episodic response to continuous well-being monitoring and maintenance. Due to easy availability of low-priced and high performance sensors and computational intelligent techniques such efforts can be turned into practical system. The combination of big data analytics, intelligent knowledge-based system and health informatics can help in creating a smart healthcare system (***Figure 10***).

Layered Architecture

As a future work, we propose a general layered/modular architecture for smart healthcare system for professional athletes (***Figure 11***). Brief description about each layer is given as follows:

Layer 1: This layer consists of different types of hardware components (e.g. motion sensors, EMG sensors, EEG sensors, motion capture system, video cameras, BP/heart-rate monitor etc.) for collecting various relevant physiological, biomechanical and video signals/data for analysis. The selection of hardware components depends on the type of training/activity to be analyzed.

Layers 2 & 3: Each sensor/hardware component may have its unique data collection method. Hence, appropriate techniques need to be employed for data acquisition, storage (if required) and then filtering and pre-processing. These methods may vary based on the real-time or off-line feedback required by the user.

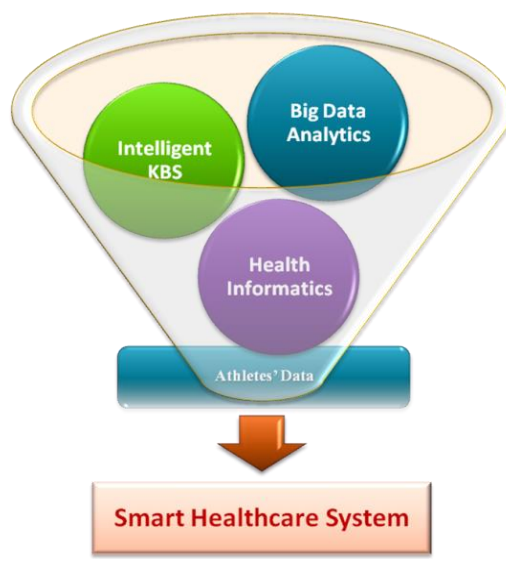

Figure 10. Smart healthcare system - major components and domains

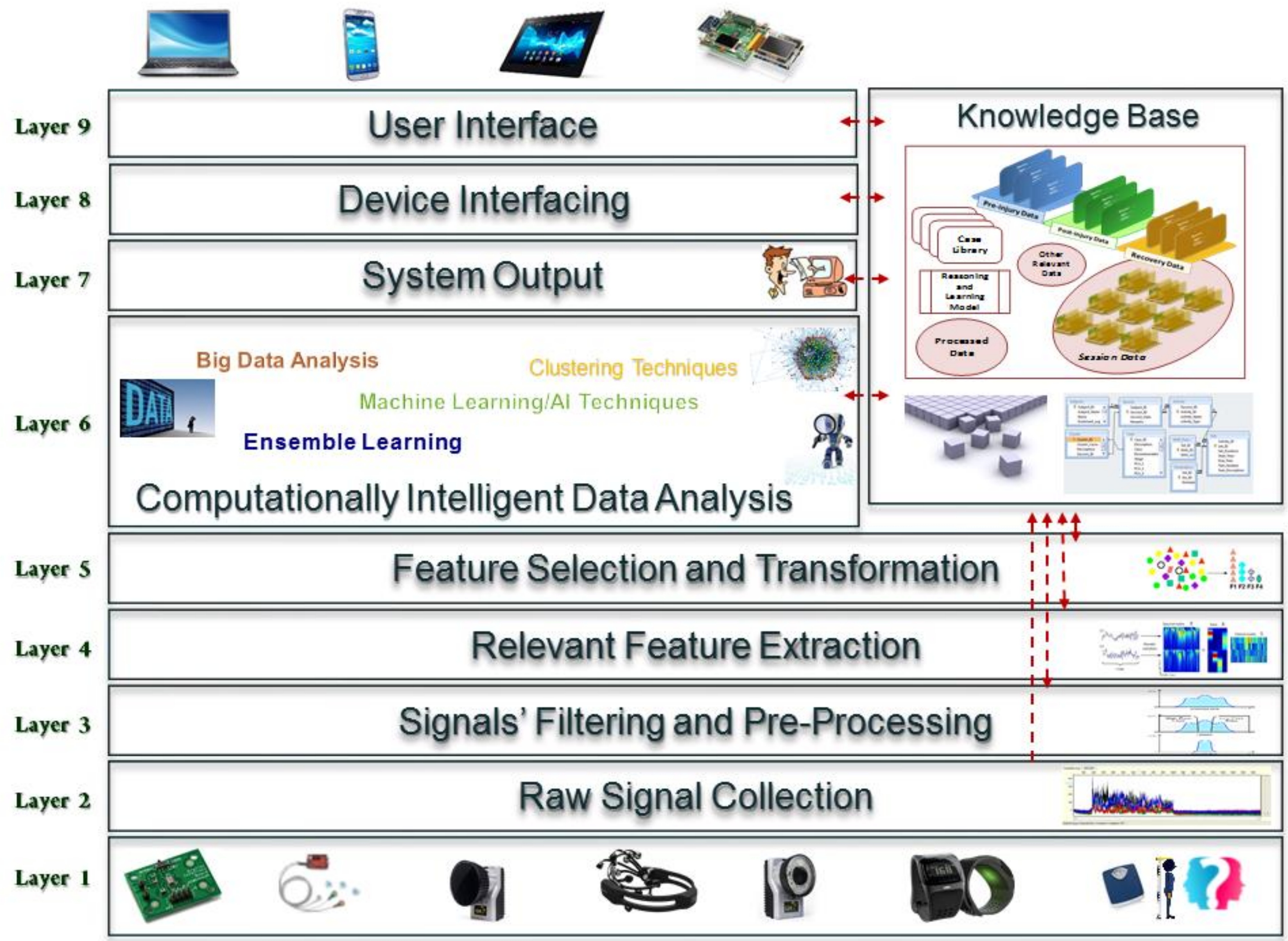

Figure 11. *Layered architecture of the proposed smart healthcare system*

Layer 4: From filtered and pre-processed data, relevant features for each type of signal will be extracted so that important information from the data can be gathered for further processing.

Layer 5: In order to efficiently apply the intelligent mechanism and retrieve the results, feature selection and transformation step may be required. This step is required for those types of signals where large number of features are available. Data fusion and integration techniques can be used for combining various types of signals.

Layer 6: Various intelligent data analysis techniques can be applied and explored in order to cluster and classification of the signals. Further, different intelligent techniques can be combined (if required) to achieve the best possible solution for classification and prediction problems. The possible usage of these techniques can be in the areas of grouping athletes based on different characteristics, recovery stage classification, classification of performance during a sports training activity, prediction of injury, prediction of time-to-return to sports, performance optimization and real-time/off-line biofeedback etc. Further, big data analytics can also be explored with the data collected from different sources (sensors, sports trainers, physiatrists and physiotherapists etc.) and stored in knowledge-base.

Layer 7: The system would be able to provide output in real-time and/or off-line. Accordingly, appropriate measures will be taken for data processing and extracting results from intelligent mechanisms.

Layer 8: The system output/biofeedback could be directed to different types of output devices including computers/laptops and hand-held devices (mobile phones, tablets etc.) as well as to other wearable devices such as smart watches. Hence, a device interfacing mechanism would be required for directing the system output.

Layer 9: Appropriate data visualization and user-interface designing techniques will be used in order to provide easy to understand results for users of the system.

Knowledge management, design of efficient data retrieval mechanisms and data access and security issues will also be handled in the system design.

Possible benefits and contributions

Possible benefits and contributions of the Next Generation Smart Healthcare System for Professional Athletes are briefly mentioned below:

- Design of an extensible integrated framework for health/performance monitoring and intelligent diagnosis for Brunei Athletes
- Monitor and track record during various activities/sessions
- Centralize data obtained from multiple sources or devices, long-term data storage and analysis – suitable for longitudinal studies
- Predict changes in athletes' fatigue, recovery and performance readiness
- Prevent staleness and overtraining, reduce injuries
- Plan training based on the objective and scientific results, monitor and individualize training and recovery strategies more effectively
- Objective assessment → Improve motivation, build trust and involvement
- Real-time and offline feedback with accessibility (remotely) on multiple devices
- Development of healthcare data analysis expertise in Brunei – Exploring new venues
- Replication of the system for other than health informatics – Large scale data analysis

5. Conclusion

This study presented the summary of the overall results achieved and conclusions reached by developing and applying a novel approach for monitoring the recovery progress of the knee injured/post-operated subjects based on a knowledge-based framework using the hybrid intelligent techniques, visual biofeedback and multi-modal feature integration mechanism. The system has been implemented in such a way that additional tools and routines can be added based on more activities and features identified in the clinical environment. Thus, this system can be used as a complementary decision supporting tool, in conjunction with the existing rehabilitation monitoring mechanisms, to enable the clinicians, trainers and physiotherapists to objectively monitor the rehabilitation progress of athletes and their compliance to the rehabilitation protocol during different convalescence stages. This will help them accomplishing required training within specified time period and timely return to the pre-injury activities. Furthermore, based on the results achieved during the pilot study, a conceptual model for smart healthcare system for professional athletes has been proposed.

Acknowledgements

The authors acknowledge the Universiti Brunei Darussalam (UBD) for funding this research (Grant no. UBD/PNC2/2/RG/1(195) - 'Integrated Motion Analysis System') and providing academic and computing facilities to carry out this study. We would also like to acknowledge the staff at Performance Optimization Centre in the Ministry of Defence and the Sports Medicine and Research Centre in the Ministry of Culture, Youth and Sports, Brunei Darussalam for providing athletes as test subjects for this study and their continuous support and feedback during experiments. Further, this research grant led the completion of PhD of Owais A. Malik with significant outcomes as reported.

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