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3-D Kinematics and Neuromuscular Signals' Integration for Post ACL Reconstruction Recovery Assessment

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***Abstract*— An intelligent recovery classification and monitoring system (IRCMS) for post Anterior Cruciate Ligament (ACL) reconstruction has been developed in this study. This system provides an objective assessment and monitoring of the rehabilitation progress by integrating 3-D kinematics and neuromuscular signals recorded through wearable motion and electromyography sensors, respectively. The data from a group of healthy and ACL reconstructed subjects were collected for normal/brisk walking (4-6km/h) and single leg balance (eyes open and eyes closed) testing activities. Fuzzy clustering and fuzzy nearest neighbor methods have been used to classify the collected data into different groups for each activity. The classification accuracy of the system is found to be 94.49% for 4 km/h walking speed, 95.41% for 5 km/h walking speed, 96.00% for 6 km/h walking speed, 94.44% for single leg balance testing with eyes open and 95.83% for single leg balance testing with eyes closed. The recovery status of a subject is evaluated based on different activities assessed and the overall assessment is done using Choquet integral fusion technique. Further, biofeedback mechanism has been developed using a visual monitoring system which provides the variations in strength/activation of knee flexors/extensors and 3-D joint kinematics. This integrated system can be used as an assistive tool by sports trainers, coaches and clinicians for monitoring overall progress of athletes' rehabilitation and classifying their recovery stage for multiple activities.**

I. Introduction

Anterior cruciate ligament (ACL) injuries are common in sports, like soccer, basketball and tennis, which require pivotal movements and frequent maneuvering of lower limb joints [1]. ACL injury generally results in changes in spatiotemporal, kinematics, neuromuscular and kinetics parameters of the subjects during motion. These changes not only restrain an athlete to rejoin sports temporarily or permanently but they also may lead to cartilage degeneration and osteoarthritis over the period of time [2]. Three-dimensional kinematics changes in knee can still persist even after one year of ACL reconstruction (ACL-R) followed by rehabilitation [3]. Additionally, the muscle strength decreases after ACL surgery and regaining the muscle strength plays an important role in dynamic knee joint stability [4]. In more demanding activities, like one leg jumping, deficits in the dynamic postural-control after landing has also been observed in female athletes after more than two years of ACL reconstruction [5]. In order to avoid late discovery of such alterations and minimizing the risk of re-injury, a timely action can be taken during the recuperation regimen if a robust rehabilitation monitoring system is available.

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Subjective or partially objective measures are used to assess the recovery progress of subjects undergoing activity based ACL rehabilitation protocols. These measures, in general, do not provide the insight of recovery issues e.g. recruitment of different muscles in each phase of an activity, co-contraction of muscles and their effects on corresponding knee joint movements etc. Timely intervention during rehabilitation phases can be done if the recovery status is properly quantified and a biofeedback is provided. This paper describes an intelligent recovery classification and monitoring system (IRCMS) to provide an objective assessment and monitoring for the recovery status after ACL reconstruction by integrating 3-D kinematics and neuromuscular features. Data are recorded non-invasively through wearable wireless 3-D motion and electromyography sensors and a fuzzy logic based system has been used to classify the recovery level of each activity. Normal/brisk walking and balance testing activities during rehabilitation protocol are included to test the proposed approach. The overall recovery classification is computed by using Choquet fuzzy integral fusion [6]. A visualization system for monitoring the synchronized bio-signals has also been developed to evaluate the subjects at individual level and identify the specific muscle performance or knee movements during each activity. The system can be utilized as an assistive tool by sports trainers, coaches and clinicians for monitoring overall progress of athletes' rehabilitation and classifying their recovery for multiple activities.

II. Methodology

The ACL recovery classification model based on multiple activities along with the placement of sensors on human lower extremities is depicted in Fig. 1. The overall recovery classification is a four step process as explained below.

A. Data Acquisition

In order to test the proposed system, four activities were selected from the rehabilitation protocol followed by the athletes: walking on treadmill (4 km/h and 5 km/h), brisk

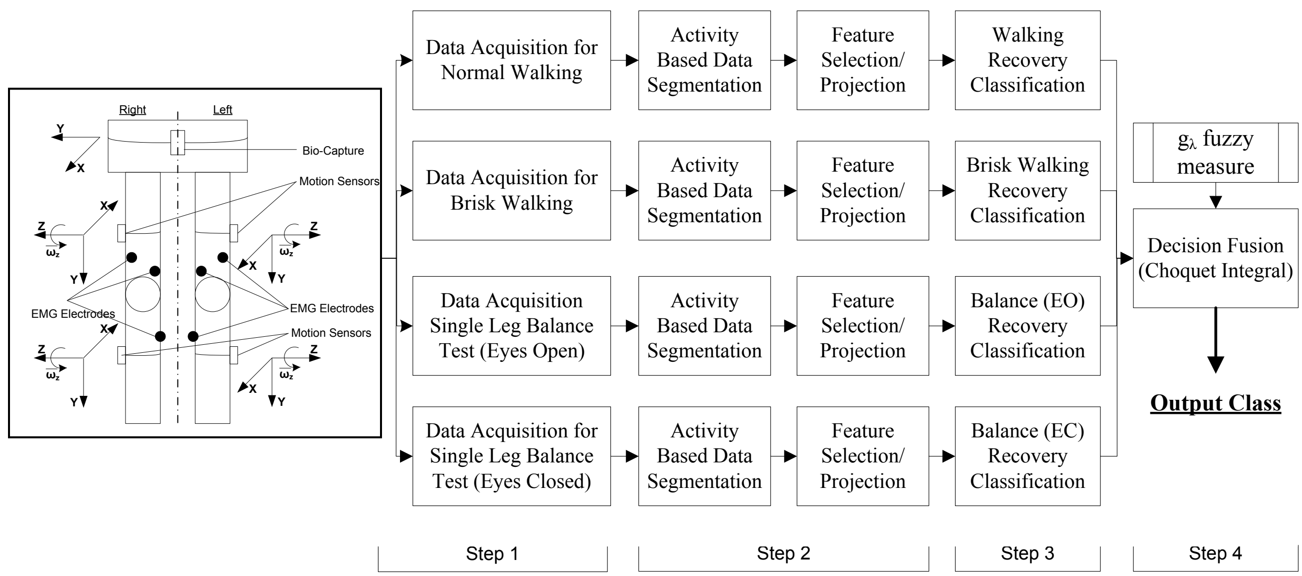

Figure 1. Multi-Activity based overall ACL recovery calssification model and sensor placement on human lower extremities (front view)

walking on treadmill (6km/h), and single leg flat surface balance testing with eyes open and eyes closed. The 3-D kinematics and neuromuscular data were recorded for subjects from both lower limbs (healthy and ACL reconstructed) for two sessions of 30-35sec for each walking speed and two sessions of 15-20sec for each balance test. The KinetiSense (ClevMed, Inc.) 3-D motion sensors and BioCapture (ClevMed, Inc.) monitoring system were used to record the kinematics and electromyography signals for these activities, respectively. The data from sensors were wirelessly transferred through USB receiver to the computer at a sampling rate of 128Hz where the KinetiSense software recorded the readings for each experiment. Each subject was setup with four motion sensors attached to his/her both left/right thighs and shanks to note the 3-D angular rates and accelerations of lower limb extremities during all four activities (Fig. 1). The neuromuscular signals were recorded using surface EMG sensors from vastus medialis, vastus lateralis, semitendinosus and biceps femoris muscles for walking activities and wirelessly transferred to the BioCapture software. For balance testing activity, data from gastrocnemius medialis were also recorded in addition to the above four muscles. The BioCapture records the data at a sampling rate of 960Hz (12/16 bits A/D) so re-sampling was done in order to synchronize both kinematics and EMG signals. All further processing was done by using MATLAB 7.1 software.

B. *Feature Extraction*

Two types of feature sets were generated for all activities based on kinematics and EMG signals recorded.

1) Kinematics Feature Set: The kinematics feature set included 3-D joint movements of the knee namely knee flexion/extension, abduction/adduction and internal/external rotation. These parameters were computed by using angular rates and accelerations recorded from motion sensors. Each gait cycle for walking activities was segmented by detecting the heel strike and root mean square (RMS) value for above three parameters were calculated for each phase of a gait cycle. A feature vector for kinematics data was then generated for 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 quadriceps and hamstrings muscles are mostly active during these phases [7]. 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. For balance testing activities, a time based segmentation was done. The total time for each balance testing activity was divided into segments of 4 seconds and the RMS value for three parameters were calculated for three segments (out of 4 or 5 segments).

2) EMG Feature Set: The raw EMG signals were transformed to generate time, frequency and time-frequency parameters of relevant muscles during all four activities. The features investigated in this study are integrated EMG (IEMG), mean absolute value (MAV), root mean square (RMS), wave length (WL), mean frequency (MNF) and maximum/minimum continuous wavelet transform (CWT) coefficients . These parameters have been found effective in classification using EMG signals previously [8]. The values for these parameters were computed corresponding to the gait phases (for walking activities) or fixed time duration (for balance activities).

C. *Feature Projection*

The feature vector length for walking activities for single gait cycle for one leg was 124 (7 EMG features × 4 muscles × 4 phases + 3 kinematics feature × 4 phases). For balance activities, the feature vector length was 38 (7 EMG features × 5 muscles + 3 kinematics feature) for each segment for each leg. In order to reduce the feature vector length, Principal Component Analysis (*PCA*) was applied which projects the high dimensionality of data to the low dimensionality. *PCA* transforms the original feature set of variables $f \in F \subseteq R^N$ into a new feature set of variables $v \in V \subseteq R^M$, known as Principle Components (PCs), of reduced dimension by minimizing the mean-square error (MSE) between the original set *F* and projected set *V* [9].

D. Activity Based Recovery Classification (RC_A)

The classification of each subject's data for four different activities (Fig. 1) is done by using fuzzy clustering technique [10]. Fuzzy clustering partitions the sample space and organizes the data into approximate clusters. 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 is quite suitable [11]. 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 and balance testing activities. Based on the available data, four clusters were generated for each activity. The assignment of data points to each cluster was based on their similarity to each other rather than time since ACL reconstruction. Once the clusters are generated for a specific activity, the cluster for healthy subjects is identified with cluster center 'C_H' and the distance of 'C_H' from other clusters' centers has been used as a metric to identify the recovery stage of the subjects. The recovery status of data in a cluster is classified as close to healthy or away from healthy based on their distance from 'C_H'. In order to validate the classification, Leave-One-Out (LOO) cross validation technique was used in conjunction with fuzzy nearest neighbor (*f-knn*) method [12]. Due to intra-subject variability, data points belonging to the same subject for an activity may fall into multiple clusters with higher membership values. This results in classifying a subject in two or more groups at the same time based on his/her feature vectors' variations. This problem has been resolved by taking the average of membership grades for each class for an activity to which a subjects' data belong and then the class with the highest membership value is chosen as the output class for the subject for that particular activity. By using this technique, overall membership values are assigned to the subjects for each class for all activities.

E. Overall Recovery Classification

Different classifiers may assign different classes to the same subject base on his/her performance during each activity or due to misclassification. In addition to evaluate the output of an individual activity of a subject, an overall assessment can also be helpful to categorize the recovery stage of a subject after a certain rehabilitation period. The classification results of multiple activities for each subject's data have been combined using Choquet integral method. The Choquet integral is a non-linear functional defined with respect to a fuzzy measure g_λ, where g_λ is completely determined by its densities (g^i - degree of importance of classifier y_i towards final decision). The fusion of different classifiers is computed based on (1) and (2) [6]

$$\begin{cases} g^i = \beta p_i, & i = 3 \\ g^i = (1-\beta) p_i, & i = 1,2,4,5 \end{cases} \tag{1}$$

$$\sum_{i=1}^{n} (h(y_i) - h(y_{i-1})).g(A_i) \tag{2}$$

where p_i (classification rate) and β (scaling factor for classifiers) are in interval [0,1], and $h(y_0)=0$ and $h(y_1) \leq h(y_2) \leq \dots \leq h(y_n)$. The value of $i=3$ is chosen based on the higher accuracy rate of the third classifier.

F. Visualization of Bio-Signals

In order to provide a biofeedback, a visualization system for monitoring the neuromuscular and kinematics bio-signals has been developed. The differences of recuperation among individual subjects can be examined by observing the activation of different muscles and knee joint movements simultaneously for ACL intact and ACL-R legs, during walking and balance testing activities. Moreover, overlapping of neuromuscular and kinematics signals can depict the contribution of muscles in controlling the 3-D joint movements and thus a more targeted recovery process can be initiated.

G. Participants

Four healthy (3 males and 1 female) and eight unilateral ACL reconstructed (6 males and 2 females) subjects were recruited for the purpose of study from Sports Center and Ministry of Defense in Brunei Darussalam. The healthy subjects were having a mean age of 31.00± 8.29 years, mean height 164.50±13.03 cm, and mean weight 65.25±20.17 kg. The ACL reconstructed subjects were at different stages of rehabilitation (from 3 months to more than a year after ACL reconstruction) with mean age: 31.00± 4.07 years, mean height 167.75±7.85 cm, and mean weight 70.50±15.44 kg. An informed written consent was taken from all of the participants. The study was carried out as per the guidelines approved by UBD Graduate Research Office and Ethics Committee.

III. Results and Discussion

Before applying clustering technique, the multivariate analysis of variance (MANOVA) was employed to evaluate the difference of the entire set of means for multiple features between healthy and ACL-R groups. The *p*-value depicts the significant difference between two groups for four selected activities ($p << 0.05$). In order to reduce the large feature set and selecting the most significant features, PCA was successfully applied. More than 98% variation is explained by selecting first 40 PCs for walking activity and 10 PCs for balance testing activity. The transformed features were clustered for each activity using *FCM* to form the groups of subjects who were healthy or at similar stage of recovery to compute RC_A. Four clusters were identified as "Healthy", "ACL-R > 1 year", "ACL-R < 1 year" and "ACL-R <= 6 months" represented as "Group A", "Group B", "Group C" and "Group D", respectively. Fig. 2 shows the clusters identified by *FCM* for walking (4km/h) activity for different groups (data are plotted for only first two PCs). Some of the data points lie on the boundary of groups A, B and C clusters which depicts that some of the subjects' data belong to different 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. Another possible reason for this overlapping is the intra-subject variability which can cause falling some of the data of the same subject into neighboring cluster. Fig. 3 shows the clusters formed for brisk walking (6km/h) activity. It was found that clusters became more distinct for high speeds and the overlapping between clusters reduced as we moved from lower to higher speeds. The clusters identified during balance testing were found to be more distinguishable for both eyes open and eyes closed tests for all groups.

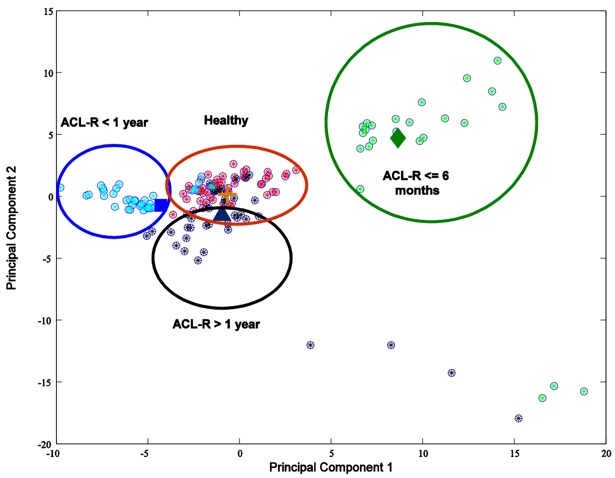

Figure 2. Clusters' centers identified by FCM (4km/h Speed) - Healthy (+), ACL-R > 1year (▲), ACL-R < 1 year (■), ACL-R <= 6 months (♦)

The performance evaluation of the cluster-based classification was done by using LOO cross validation technique. The *f-knn* was trained on *N-1* samples from the dataset for each activity and one sample was left as the validation sample (*N*= total number of samples in an activity). The input parameters of the testing sample were first transformed using the coefficient matrix of PCA and then *f-knn* was used to classify the subject based on trained clustered data. This process was repeated *N* times for each activity and the classification accuracy was found to be 94.49% for 4 km/h walking speed, 95.41% for 5 km/h walking speed, 96.00% for 6 km/h walking speed, 94.44% for single leg balance testing with eyes open and 95.83% for single leg balance testing with eyes closed. The classification precision values for four groups (A, B, C and D) for walking at 4km/h speed were 98.04%, 89.74%, 92.31% and 91.30% respectively. For walking at 5km/h, the classification precision values for groups A through group D were found to be 93.62%, 100.00%, 91.30% and 100.00%. For walking at 6km/h, the classification precision values for groups A through group D were found to be 97.50%, 90.48%, 95.00% and 100.00%. For single leg balance testing with eyes open, the classification precision values for groups A through group D were found to be 91.67%, 100.00%, 85.71% and 100.00%. For single leg balance testing with eyes closed, the classification precision values for groups A through group D were found to be 100.00%, 100.00%, 88.89% and 100.00%.

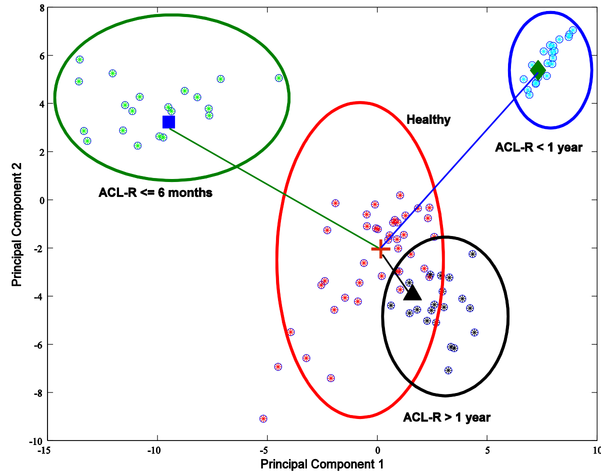

Figure 3. Clusters' centers identified by FCM (6km/h Speed) - Healthy (+), ACL-R > 1year (▲), ACL-R < 1 year (■), ACL-R <= 6 months (♦)

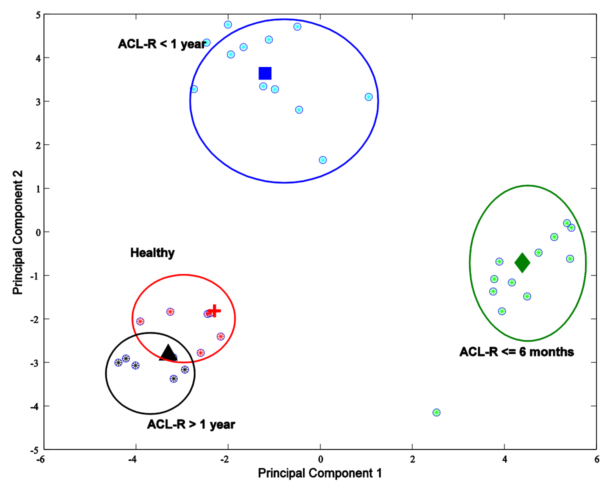

Figure 4. Clusters' centers identified by FCM (single leg balance test with eyes open) - Healthy (+), ACL-R > 1year (▲), ACL-R < 1 year (■), ACL-R <= 6 months (♦)

In order to obtain an overall recovery value, the Choquet integral was used. The fuzzy densities of each classifier were computed as $g^1=0.373$, $g^2=0.384$, $g^3=0.576$, $g^4=0.377$, $g^5=0.383$ by using (1) with $\beta=0.6$. The value of λ was found to be -0.914. Table I reports the results of combining classifiers for different activities for four subjects using (2). Based on the final output it can be noted that some of the activities were misclassified by classifiers but the fusion results match with the actual classes. The values in the parenthesis show the membership grade or confidence of the evaluation from *FCM*. The results of the fusion were manually verified. The comparison of different bio-signals for an individual subject is shown in Fig. 5. The differences between knee rotation of both legs is more visible for this subject even after more than 6 months of surgery.

TABLE I. RESULTS OF COMBINING MULTIPLE CLASSIFIERS BY CHOQUET INTEGRAL

Test Data	Actual Class	Activity Classification - Partial Decision					Fusion Output
		4 km/h	*5 km/h*	*6 km/h*	*Eyes Open*	*Eyes Closed*	
a	A	C (0.3478)	A (0.3124)	A (0.6675)	B (0.7047)	C (0.4382)	A
b	B	D (0.6485)	B (0.6359)	B (0.6347)	C (0.7839)	C (0.4214)	B
c	B	A (0.5737)	B (0.4891)	A (0.6433)	B (0.6977)	B (0.6007)	B
d	C	B (0.5422)	B (0.4891)	C (0.8923)	C (0.752)	D (0.7385)	C

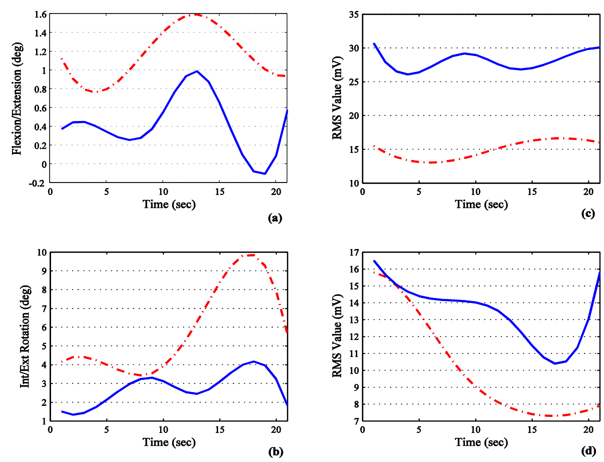

Figure 5. Comparison of ACL intact (___) vs.ACL reconstructed (-.-.-) leg during single lege eyes open balance test for a subject from Group C for knee angle (a), knee roation (b), vastus lateralis (c) bicep femoris(d)

Similarly, difference in muscle strength can also be noted for both legs. Observing variations in these parameters can be useful for physiotherapist or clinicians in identifying the deficiency of specific muscles or detecting any abnormality in the joint movements. Additionally, simultaneous monitoring of superimposed kinematics and neuromuscular data for multiple activities can provide correlation of both signals and thus any anomalous patterns can be detected.

IV. CONCLUSIONS AND FUTURE WORK

The integration of 3-D kinematics and neuromuscular signals proved effective in classifying the recovery of subjects after ACL reconstruction. This classification will be beneficial in timely identification of athletes with delayed or partial recovery, requiring early intervention to accelerate or modify rehabilitation program besides minimizing later stage problems such as re-injury or knee osteoarthritis. It can also be used to evaluate athletes' performance before their re-embarking to sports activities. In addition, more refined assessments can be done by recognizing varying patterns of different parameters using simultaneous visualization of multiple bio-signals. In order to further validate the system, data are being collected from more athletes with ACL reconstruction. Moreover, a comprehensive analysis of the subjects can be obtained by including more activities (e.g. single leg jumping/hoping and running) and taking into consideration other parameters (e.g. gender, age, type of sports).

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