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An Adaptive Interval Type-2 Fuzzy Logic Framework for Classification of Gait Patterns of Anterior Cruciate Ligament Reconstructed Subjects

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***Abstract*— This paper aims to investigate a gait pattern classification system for anterior cruciate ligament reconstructed (ACL-R) subjects based on the interval type-2 fuzzy logic (FL). The proposed system intends to model the uncertainties present in kinematics and electromyography (EMG) data used for gait analysis due to intra- and inter-subject stride-to-stride variability and nature of signals. Four features were selected from kinematics and EMG data recorded through wearable wireless sensors. The parameters for the membership functions of these input features were determined using the data recorded for 12 healthy and ACL-R subjects. The parameters for output membership functions and rules were chosen based on the recommendations from physiotherapists and physiatrists. The system was trained by using steepest descent method and tested for singleton and non-singleton inputs. The overall classification accuracy results show that the interval type-2 FL system outperforms the type-1 FL system in recognizing the gait patterns of healthy and ACL-R subjects.**

Keywords—type-2 fuzzy logic; gait analysis; EMG; inertial sensors; kinematics; anterior cruciate ligament

I. INTRODUCTION

Altered gait patterns are common after anterior cruciate ligament (ACL) trauma [1, 2]. Although there is certain improvement in knee dynamics after ACL reconstruction but gait abnormalities persist even several months after surgery [3, 4]. These impairments may result in long term effects including early cartilage degeneration and osteoarthritis which are considered progressive processes occurring during cyclic loading of less intensive but frequent activities (e.g. walking) [5, 6]. An early detection of gait abnormalities may help in reducing the risk of such problems and other movement disorders by taking appropriate actions during rehabilitation regimen.

Computerized and sensors' based gait analysis methods have become more common in last two decades [7-9]. Different measurement techniques provide variety of data for human gait analysis such as spatiotemporal data (e.g. walking speed and step length), kinematics data (e.g. joint angles and acceleration), kinetics data (e.g. foot force and torques), electromyography data (e.g. muscles activation timings and levels) and electroencephalographic data (e.g. cortical activation). Several studies have reported changes in the above different types of data for ACL injured and reconstructed subjects as compared to healthy subjects [4, 5, 10-13].

Significant efforts have been made in order to analyze and classify gait data using different machine learning techniques including artificial neural network (ANN), support vector machines (SVMs) and fuzzy logic (FL) [14-17]. One of the main advantages of these techniques is their ability to deal with the complex non-linear relationships in gait data. However, one important issue about gait data is the intra- and inter-subject stride-to-stride variability of different parameters which are used for analysis [18-20]. This stride-to-stride variability is generally present in kinematics and electromyography (EMG) data which are frequently used for gait analysis of ACL reconstructed (ACL-R) subjects. In designing a classification system for gait patterns, uncertainties will be involved when such data (kinematics and EMG) are used. The uncertainties are also present in the actual measurements recorded through sensors due to noise and motion artifacts. Although the noise and artifacts can be minimized but these factors cannot be completely removed from the data which will result in imprecise input to the system. The existing fuzzy logic based (type-1) gait analysis/classification systems handle the imprecise data by choosing precise membership function value but these systems lack modeling of uncertainty involved in the measurements, definitions of input and output fuzzy sets, and rules [21].

In this study, interval type-2 fuzzy logic has been used for assessment of gait patterns of ACL-R subjects. An automated adaptive classification system has been investigated for distinguishing the gait patterns of healthy and ACL-R subjects at different stage of recovery. The kinematics and EMG signals are recorded through wearable wireless sensors. The recorded signals are filtered and processed for extracting the relevant features from kinematics and EMG data. The parameters for the membership functions (MFs) of antecedents are extracted from the historical data recorded for healthy and ACL-R subjects during experiments and the parameters for MFs of consequent are determined based on the recommendations/observation of physiotherapists and physiatrists. Theses parameters are tuned by using steepest descent method. The classification performance of the proposed system was tested for singleton and non-singleton inputs and results were compared with type-1 FL system.

II. METHODOLOGY

A fuzzy logic based general framework for classification of gait patterns of ACL-R subjects is shown in Fig. 1. The framework mainly consists of two modules: data collection and processing of different types of input signals and an adaptive fuzzy logic based classification module. Due to alterations in various physiological parameters in subjects after ACL trauma, different types of signals/features can be used for classifying the gait patterns of ACL-R subjects. In this study integrated kinematics and neuromuscular features have been used to develop a fuzzy logic based classification model for gait patterns. The details about different components and design of the proposed system are described in the following sections.

A. Participants

A total twelve subjects (four healthy and eight unilateral ACL-R) subjects were recruited for this study from Sports Medicine & Research 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 2 months to around 1 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.

B. Data Collection and Processing Module

The kinematics and EMG parameters were recorded from healthy and ACL-R subjects using wireless micro-electro-mechanical systems (MEMS) motion sensors (Fig. 2) and surface EMG monitoring unit with Ag/AgCl electrodes (Fig. 3), respectively. Each subject walked at 4km/h speed on a treadmill for duration of 30-40 seconds and data were collected for two sessions/trials for all subjects. Two motion sensors were attached to the thigh and shank of one of his/her legs (operated leg for ACL-R subjects and any leg randomly selected for healthy subjects) using flexible bulk and Velcro straps. These body-mounted motion sensors (sampling rate of 128Hz, 12 bit analog/digital resolution within a frequency range 0-20Hz) were used to measure the subject's lower extremity motion during walking in terms of angular rate and linear acceleration. These angular rates and linear acceleration were then used to compute the knee joint movements in sagittal plane (Fig. 4). The electromyography sensors (sampling rate of 960 Hz, 12 bit Analog/Digital conversion) provided the muscle recruitment pattern for knee extensors and flexors. The surface EMG signals were recorded by placing foam snap electrodes on vastus medialis (VM), vastus lateralis (VL), semitendinosus (ST) and biceps femoris (BF)

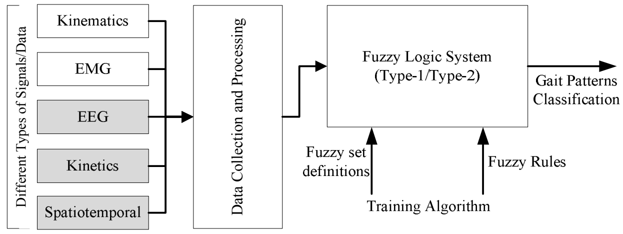

Fig. 1. General framework for classification of gait patterns of ACL-R subjects using adaptive fuzzy logic system

Fig. 2. Wireless motion sensor unit command module and USB receiver from KinetiSense (ClevMed. Inc.)

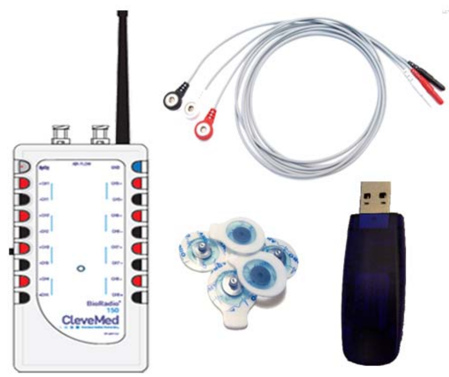

Fig. 3. EMG electrodes with wireless BioRadio and USB receiver from ClevMed. Inc.

on one of the legs (operated leg for ACL-R subjects and any leg randomly selected for healthy subjects) of each subject. The standard guidelines were followed for skin preparation and placements of sensors and electrodes on identified positions [22, 23]. The data from these two hardware components were wirelessly transferred to the workstation using their respective software (KinetiSense and BioCapture). A custom software was developed in MATLAB 7.0 for further processing. The kinematics (angular rate and linear acceleration) and EMG measurements are generally contaminated with various noises so filtering was applied to de-noise these signals. The motion data were filtered using 6th order Butterworth band-pass filter (0.3-3) before computing the orientations.

Moreover, in order to minimize any placement error of each motion sensor, measurements for zero-referencing were obtained prior to starting the experiment when the subjects

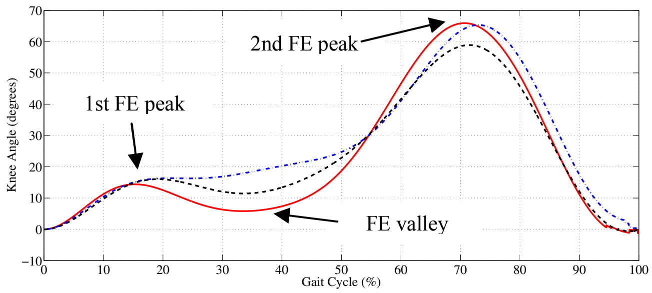

Fig.4. Knee flexion/extension variation in the subjects at km/h - Mean angle values of a healthy subject (——) average, subject ~11 months after surgery ( ); subject 2 months after surgery ( ) - · - ·

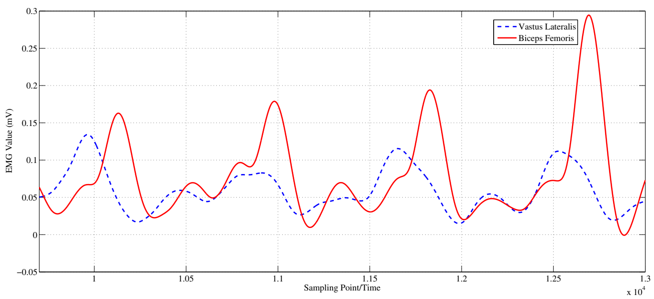

Fig. 5. Characteristics for vastus lateralis (- - -) and biceps femoris (___) muscles in the ACL-R leg of a subject 1 year after surgery during walking for multiple gait cycles

were standing in an upright position and these measurements were then subtracted from each angular rate during the experiment. Trapezoidal integration was applied to the angular rates from motion sensors in order to compute the knee flexion/extension. Similarly, the raw EMG signals from all muscles were band-pass filtered (20-400 Hz) using 4th order Butterworth filter and then rectified. The linear envelopes were generated by using a 4th order low-pass Butterworth filter (Fig. 5). Thus, kinematics and EMG data for 10 gait cycles per trial per subject (240 samples) were selected for further analysis and feature extraction.

C. Feature Extraction and Selection

The selection of features for designing the fuzzy logic system (FLS) was based on number of criteria: the kinematics and EMG parameters studied in the previous literature and differences were found in ACL-R and healthy subjects, data collected during this study, number of rules to be generated and the classification performance of the designed FLS [3, 4, 24, 25]. Initially, six features (three kinematics and three EMG) were extracted from the processed data for each gait cycle of the subjects (Table I). Alterations have been reported in these features for ACL-R subjects even several months after surgery. Different combinations of these extracted features were tested as input to design the FLS. Based on the classification performance and optimum number of rules generated, four features (1st FE peak, FE valley, 2nd FE peak and ratio of activation of the normalized VL and BF muscles during LR) were selected as input. The output of the FLS was classification of gait patterns as normal/healthy, average or poor provided by physiotherapists and physiatrists.

TABLE I
FEATURES EXTRACTED AND ASSESSED AS INPUT PARAMETERS

Type	Feature
Kinematics	Maximum knee flexion during the stance phase (1st FE peak)
	Minimum knee flexion during mid stance (FE valley)
	Maximum knee flexion during the swing phase (2nd FE peak)
EMG	Ratio of activation of the normalized vastus lateralis and biceps femoris muscles during load response (LR) phase
	Activation timing patterns of vastus lateralis
	Activation timing patterns of biceps femoris

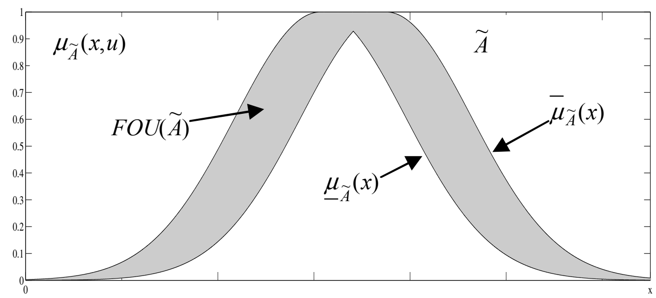

Fig. 6. An example interval type-2 fuzzy set ($\tilde{A}$) - type-2 Gaussian membership function with uncertain mean, FOU, upper and lower MFs

D. Interval Type-2 Fuzzy Logic System

Type-2 FL has the potential to deal with the high level of uncertainties which are present in a system such as linguistic and measurement uncertainties [21]. Type-2 FLS employs the type-2 fuzzy set (Fig. 6) which are characterized by the concept of footprint of uncertainty (FOU), and upper and lower membership functions (MFs). Type-2 fuzzy sets are three dimensional where this extra dimension lets uncertainty to be handled. The interval type-2 FLS uses interval type-2 fuzzy set where all values in the third dimension are equal to 1 which makes the computation much simpler as compared to a general type-2 FLS. An interval type-2 fuzzy set ($\tilde{A}$) is defined by a type-2 membership function $\mu_{\tilde{A}}(x,u)$ i.e.

$$\tilde{A} = \{((x,u),\mu_{\tilde{A}}(x,u)) \mid \forall_x \in X, \forall_u \in J_x \subseteq [0,1]\} \qquad (1)$$

where $0 \le \mu_{\tilde{A}}(x,u) \le 1$, x and u are the primary and secondary membership variables, J_x is the primary membership function of x and all secondary grades are equal to 1. The FOU of the type-2 fuzzy set is given by (2):

$$FOU(\tilde{A}) = \bigcup_{\forall_x \in X} (\underline{\mu}_{\tilde{A}}(x), \overline{\mu}_{\tilde{A}}(x)) \qquad (2)$$

Fig. 7 depicts an interval type-2 fuzzy logic classifier for detecting the gait patterns of healthy and ACL-R subjects based on [21]. The important details related to this study are described here. Further information about each component of type-2 FLS can be found in [21]. In this study, Gaussian MFs have been used to describe antecedents and consequent. A Gaussian primary MF with uncertain mean is expressed as (3) for *kth* antecedent.

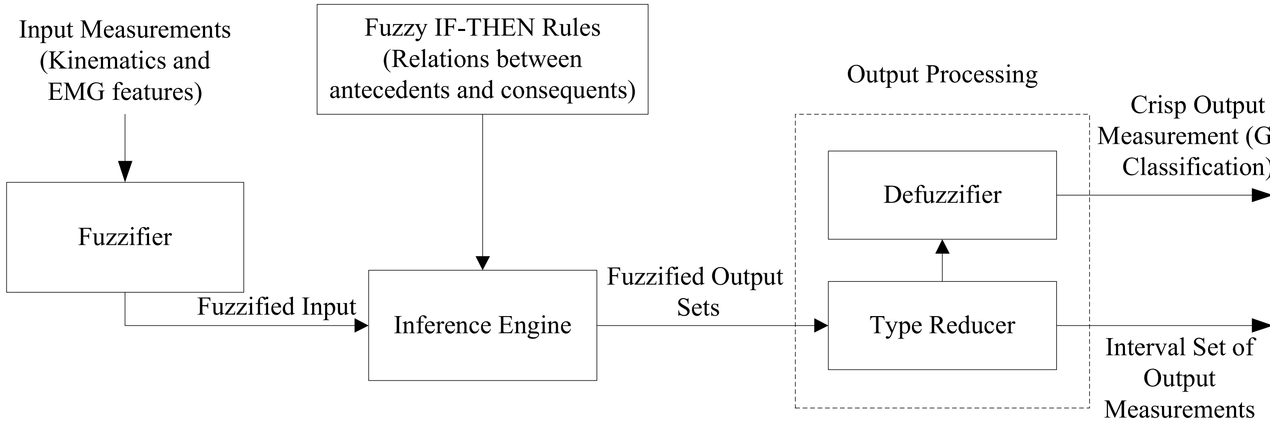

Fig. 7. Type-2 fuzzy logic based framework to build the gait patterns' classification model

$$\mu_k(x_k) = \exp\left[-\frac{1}{2}\left(\frac{x_k - m_k}{\sigma_k}\right)^2\right], \quad m_k \in [m_{k1}, m_{k2}] \qquad (3)$$

The upper $\bar{\mu}_k(x_k)$ and lower $\underline{\mu}_k(x_k)$ MFs can be computed as follows:

$$\bar{\mu}_k(x_k) = \begin{cases} G(m_{k1}, \sigma_k; x_k) & x_k < m_{k1} \\ 1 & m_{k1} \le x_k \le m_{k2} \\ G(m_{k2}, \sigma_k; x_k) & x_k > m_{k2} \end{cases} \qquad (4)$$

$$\underline{\mu}_k(x_k) = \begin{cases} G(m_{k2}, \sigma_k; x_k) & x_k \le \frac{m_{k1} + m_{k2}}{2} \\ G(m_{k1}, \sigma_k; x_k) & x_k > \frac{m_{k1} + m_{k2}}{2} \end{cases} \qquad (5)$$

$$G(m_{k1}, \sigma_{k1}; x_k) = \exp\left[-\frac{1}{2}\left(\frac{x_k - m_{k1}}{\sigma_{k1}}\right)^2\right] \qquad (6)$$

Both singleton and non-singleton fuzzification methods were employed and tested in this study. Singleton fuzzification method assumes the measurements which activate the FLS to be certain and noise free while non-singleton considers the measurements to be uncertain. The result of the singleton fuzzification is a single value where the MF has a value of 1. In case of non-singleton fuzzification, a fuzzy membership function is used for fuzzification where the fuzzy membership function is centered at the measurement value. Based on the noise characteristics (stationary/non-stationary), the non-singleton fuzzification can be performed using either type-1 and type-2 fuzzy sets. The output of the type-2 FLS is computed in two steps such that output type-2 fuzzy set is first type-reduced and then defuzzified. There are type-reduction/defuzzification methods available. In this study, height defuzzifier (7) and modified height defuzzifier (8) were used and compared in order to evaluate the effect of considering the input spread on the output.

$$y_h(x) = \frac{\sum_{l=1}^{M} \bar{y}^l \mu_{B^l}(\bar{y}^l)}{\sum_{l=1}^{M} \mu_{B^l}(\bar{y}^l)} \qquad (7)$$

$$y_h(x) = \frac{\sum_{l=1}^{M} \bar{y}^l \mu_{B^l}(\bar{y}^l) / \delta^l}{\sum_{l=1}^{M} \mu_{B^l}(\bar{y}^l) / \delta^l} \qquad (8)$$

where $\bar{y}^l$ is the point having maximum membership in the *lth* output set, and its membership grade in the *lth* output set is $\mu_{B^l}(\bar{y}^l)$ and δ^l is measure of the spread of the *lth* consequent set.

E. Designing the Classification System

A flow chart of steps involved in designing the FL based classification system for ACL-R gait patterns is shown in Fig. 8. The details of these steps are given below:

1) Initialize the System: In order to initialize the type-2 FLS, definitions (types of MFs and their parameters) were determined for antecedents, consequents and inputs. The proposed FLS consisted of four antecedents (1st FE peak, FE valley, 2nd FE peak and ratio of activation of the normalized VL and BF muscles during LR) and one output (class for gait patterns). The numerical data collected during experiments were used to obtain definitions of antecedents, while the consequent were determined based on the recommendations from physiotherapists and physiatrists for corresponding input. In this context the antecedents and consequent were considered to be type-2 Gaussian with uncertain mean and the input membership functions was type-1 Gaussian for non-singleton inputs. After defining the types of the membership functions, the antecedents' intervals were divided into suitable number of fuzzy sets. In this study, three fuzzy sets were assumed for kinematics features (1st FE peak, FE valley and 2nd FE peak) and two fuzzy sets were used for EMG feature (ratio of activation of the normalized VL and BF muscles during LR) as depicted in Fig. 9 to Fig. 12. In order to initially overlap the fuzzy sets, the tails of each fuzzy set lie at the mean (μ) of adjacent fuzzy sets. This overlap exploits the power of fuzzy logic to help in dealing with subjects who fall between intervals of two fuzzy sets intervals.

The initialization of the parameters (mean, standard deviation etc.) of antecedents' membership functions was done as follows; Let *p* be the number of different antecedent's membership functions and assume that the historical data are available from *n* subjects such that there are *m* different measurements (data from *m* gait cycles) for each antecedent. Table II represents a sample structure of the corresponding input dataset for *FE valley* antecedent for 5 gait cycles (GC) of 5 subjects with mean μ and standard deviation σ. The actual input dataset was a 24x10 matrix (i.e. 10 gait cycles per trial per subject). Based on an input structure for each antecedent *i=1..p* with *F* fuzzy sets for *n* subjects, following parameters were computed [21]:

$$M_{1i} = \min(\mu_{1i}, \mu_{2i}, ..., \mu_{ni}) \tag{9}$$

$$M_{2i} = \max(\mu_{1i}, \mu_{2i}, ..., \mu_{ni}) \tag{10}$$

$$M_{i} = mean(\mu_{1i}, \mu_{2i}, ..., \mu_{ni}) \tag{11}$$

$$S_{i} = std(\mu_{1i}, \mu_{2i}, ..., \mu_{ni}) \tag{12}$$

$$R_{1i} = \min(\sigma_{1i}, \sigma_{2i}, ..., \sigma_{ni}) \tag{13}$$

$$R_{2i} = \max(\sigma_{1i}, \sigma_{2i}, ..., \sigma_{ni}) \tag{14}$$

$$R_{i} = mean(\sigma_{1i}, \sigma_{2i}, ..., \sigma_{ni}) \tag{15}$$

$$T_{i} = (M_{2i} - M_{1i})/(F-1) \tag{16}$$

where M_{1i} and M_{2i} define the width of *ith* type-2 antecedent MFs. For all fuzzy sets *j=1..F*, uncertain means U_{j1} and U_{j2} and standard deviations were defined as follows:

$$U_{j1} = M_{1i} + (j-1)T_i - \alpha_i R_i \tag{17}$$

$$U_{j2} = M_{2i} + (j-1)T_i - \alpha_i R_i \tag{18}$$

$$\sigma_j = \beta R_i \tag{19}$$

where α and β are real constants which were adjusted to encounter the uncertainty around means of MFs and to cover the whole universe of discourse, respectively. For this study the values of α and β were between 0.5 to 0.6 for different antecedents. The MFs for consequent were defined based on the judgments of physiotherapists and physiatrists about the gait patterns of each subject. A scale of a range 0 through 10 was used to take their input and later mapped to three MFs as *Poor*, *Average* and *Normal/Healthy* to represent the current status of the gait for each subject. The MFs for consequents were generated using the same approach as described for antecedent MFs.

Two types of input membership functions were initialized. In the case of singleton inputs the mean value of each input membership function was the corresponding mean of the

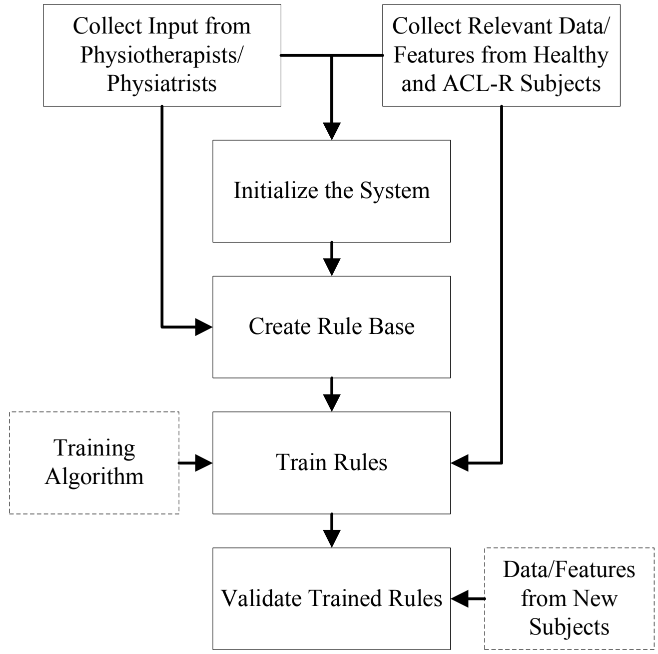

Fig. 8. Interaction of various components of FLS to produce a gait patterns classification system for ACL-R subjects

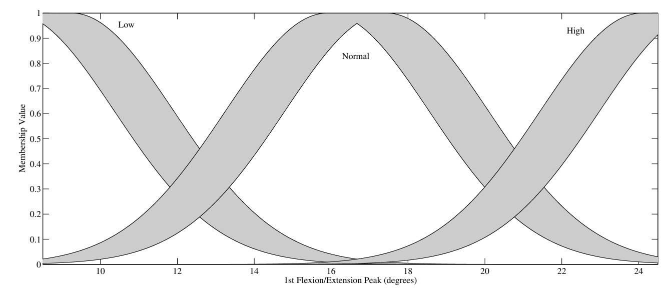

Fig. 9. Type-2 Gaussian membership functions for 1st flexion/extension peak during a gait cycle

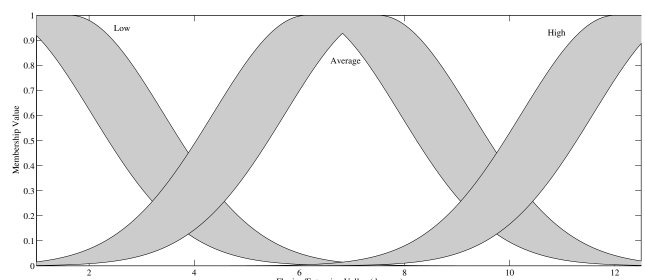

Fig. 10. Type-2 Gaussian membership functions for flexion/extension valley during a gait cycle

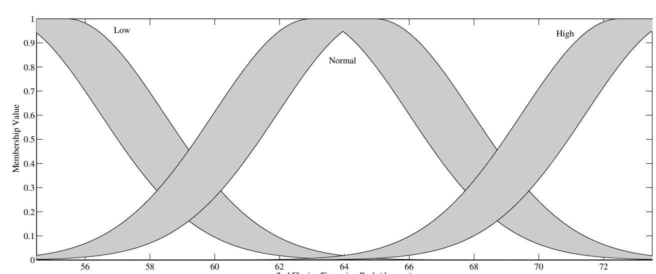

Fig. 11. Type-2 Gaussian membership functions for 2nd flexion/extension peak during a gait cycle

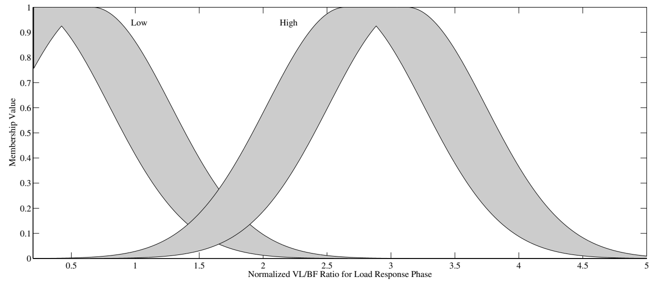

Fig. 12. Type-2 Gaussian membership functions for normalized ratio between vastus lateralis and biceps femoris muscles during load response phase of a gait cycle

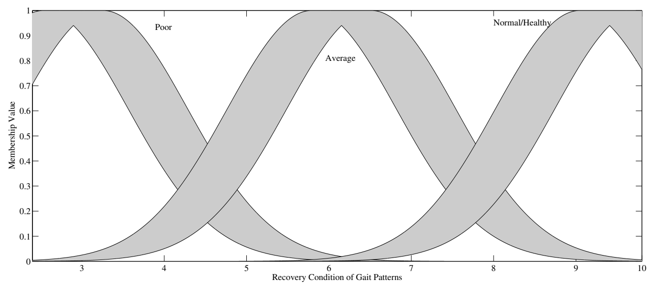

Fig. 13. Type-2 Gaussian membership functions for recovery condition of gait patterns on a scale of 1-10

various gait cycles as computed in Table II, e.g. μ_i represents the mean of the *ith* input membership function and the standard deviation (σ_i) of each input membership function is the corresponding standard deviation of the various gait cycles as computed in Table II. For non-singleton inputs, the structure of the dataset was similar to Table II with a little difference that now the various measures were represented by type-1 Gaussian MFs. The mean and standard deviation value of each input membership function were the average of means and standard deviation of various measures for a particular subject, respectively.

2) Create Rule Base: The rules were formulated by employing all possible combinations of antecedent fuzzy sets. A total of 54 (3×3×3×2) rules were generated based on four antecedents. The consequent of each rule was decided based on the feedback from physiotherapists and physiatrists. An example rule for status of gait pattern appears as follow:

R_1**:** *IF 1st FE Peak is Normal AND FE Valley is Low AND 2nd FE Peak is Normal and VL/BF Ratio is High THEN Gait Pattern's Status is Healthy*

In general, an *lth* rule can be written as:

R_l**:** *IF 1st FE Peak is* $\widetilde{A}_i$ *AND FE Valley is* $\widetilde{B}_j$ *AND 2nd FE Peak is* $\widetilde{C}_k$ *and VL/BF Ratio is* $\widetilde{D}_r$ *THEN Gait Pattern's Status is* $\widetilde{G}_{ijkr}$ $(1 \le i,j,k \le 3,\ 1 \le r \le 2)$

where $\widetilde{A}_i$, $\widetilde{B}_j$, $\widetilde{C}_k$ and $\widetilde{D}_r$ are the fuzzy sets of respective antecedents and $\widetilde{G}_{ijkr}$ represents the corresponding fuzzy set from consequent.

TABLE II
SAMPLE INPUT STRUCTURE FOR FE VALLEY ANTECEDENT

Subject	GC_1	GC_2	GC_3	GC_4	GC_5	μ	σ
1	1.99	1.95	2.53	1.32	1.82	1.92	0.43
2	4.90	5.80	5.45	4.73	6.64	5.50	0.77
3	5.39	4.37	5.44	4.17	4.21	4.72	0.64
4	9.60	10.86	11.09	10.24	9.52	10.26	0.71
5	8.46	8.91	8.34	8.08	8.24	8.41	0.31

3) Train Rules and Validate Trained Rules: The rules were trained in order to improve their accuracy in classifying the gait patterns. The parameters of various membership functions were modified by propagating the inputs through FLS based on computed error and steepest descent approach [21]. The data recorded from healthy and ACL-R subjects were used as training dataset. This dataset contained the input-output pair where the inputs were kinematics and EMG measurements for each subject and the output was the classification of gait patterns provided by the physiotherapists and physiatrist. The structure of the dataset was similar to Table II. For singleton input system, the mean (μi) of multiple measurements for each feature was used as the input or output measurement for a particular feature i of a subject. For non-singleton input system, μi was used as the mean of type-1 Gaussian membership function and the standard deviation of the measurements (σi) was used as the standard deviation of the non-singleton input type-1 Gaussian membership function. The validation of the system was done by using the Leave-One-Out Cross Validation (LOOCV) method. This method was suitable for the small sample size used in this study. In LOOCV method, the FLS was trained on N-1 samples from the dataset as described above and one sample was left as the validation sample. This process was repeated N times and the overall classification accuracies and error measurements were computed for fuzzy logic systems based on singleton and non-singleton inputs.

III. RESULTS AND DISCUSSION

Four types of fuzzy logic systems namely type-1 non-singleton interval type-2 (NSFLS type-2), singleton type-2 (SFLS type-2), non-singleton type-1 (NSFLS type-1) and singleton type-1 (SFLS type-1) were designed and their performances were compared. The inference system was Mamadani type for all FL systems with product implication and *t*-norm fuzzy operations. For interval type-2 FL systems, two different type-reduction/defuzzification methods namely height reduction and modified height reduction were used and classification results were compared. For type-1 FL systems, the defuzzification process was the height method. After designing the systems, a dataset of size 24×10 was used for training (step size = 0.01) and testing (using LOOCV method) each FLS. Table III shows a comparison of overall classification accuracy for gait patterns of healthy and ACL-R subjects using type-1 and type-2 (using height reduction method) FL systems before and after training. The percentage of change in accuracy is shown in Fig. 14 and the average of mean square error (MSE) is depicted in Fig. 15 for all FL systems. Table III shows that the performances of all FL systems were more or less similar before training. But after training, the classification accuracy values have been sufficiently improved for three FL systems (NSFLS type-2, SFLS type-2 and NSFLS type-1) while for SFLS type-1 classification performance was slightly reduced (0.053%). The classification accuracy values for three (NSFLS type-2, SFLS type-2 and NSFLS type-1) FL systems were found higher (with maximum value of approximately 86% for SFLS type-2) as compared to SFLS type-1 system because these three types of FL systems can handle the stationary noise in measurements and noise in training/testing data. Fig. 15 depicts that both type-2 systems have performed better than type-1 systems which indicates that type-2 FLS handles uncertainty better than type-1 FLS and the outputs produced by type-2 FLS were much closer to the actual outputs.

A comparison of height defuzzification and modified height defuzzification method was also performed for type-2 FL systems. Fig. 16 depicts that the modified height defuzzification performed superior than height defuzzification method while detecting the gait patterns of healthy and ACL-R subjects. The modified height defuzzification method considers the spread of consequent membership function which provides the contribution of a particular fuzzified input to the corresponding consequent and thus uncertainty in the inputs can be better handled. In order further test the classification performance, the area under curve (AUC) parameter was also computed for modified height reduction type-2 NSFLS and SFLS by performing receiver operating characteristic (ROC) analysis. Due to multi-class problem, a pair-wise comparison (one class vs. all other classes) was carried out using *perfcurve* function available in MATLAB. The AUC values for 'Healthy', 'Average' and 'Poor' classes were found as 0.926, 0.886 and 0.830 for modified height reduction type-2 NSFLS, respectively. For modified height reduction type-2 SFLS, the AUC values for 'Healthy', 'Average' and 'Poor' classes were found as 0.919, 0.911 and 0.850, respectively. These results indicate that modified height defuzzification should be preferred over height defuzzification methods due to its better classification performance. Both systems were able to identify the gait patterns of normal subjects more accurately as compared to ACL-R subjects.

There are multiple sources of uncertainty and impreciseness in gait analysis data including noise in sensors' measurements, intra- and inter-subject variability (stride-to-stride, subject-to-subject variations in the same group), nature of EMG signals etc. These uncertainties should be handled while designing and activating (using) the FLS. Type-2 fuzzy logic provides a better mechanism in terms of FOUs to deal with uncertainties at different levels in a system. During initialization phase, type-2 MFs can be defined to represent the noise in the data and while tuning, these MFs can be adjusted based on the noise/uncertainties in the training data by using non-singleton fuzzification technique. During activation phase (actual usage

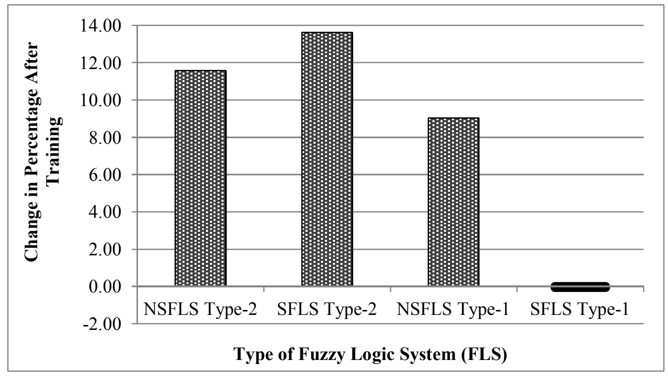

Fig. 14. Comparison of percentage of change in overall classification accuracy before and after training for all FL systems

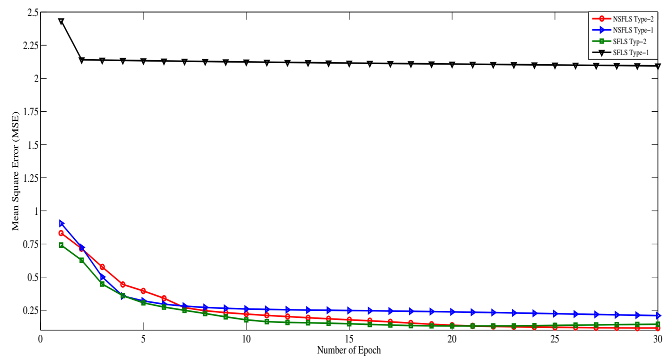

Fig. 15. Average mean square error (MSE) for type-1 and type-2 FL systems for during training phase

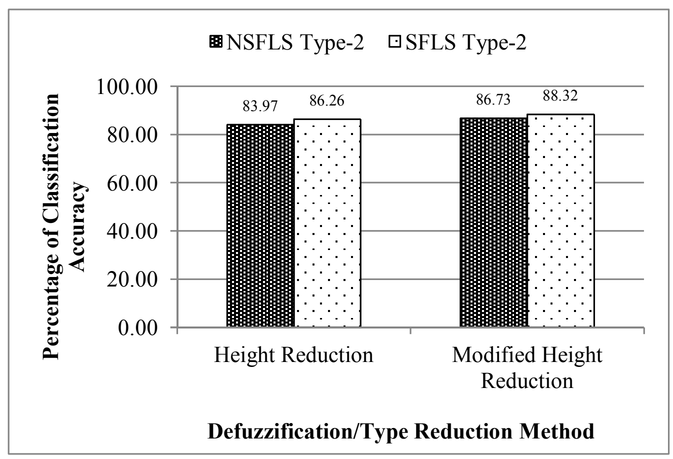

Fig. 16. Comparison of percentages of overall classification accuracy for gait patterns using different defuzzification/type reduction methods for type-1 non-singleton type-2 and singleton type-2 FL systems after training

TABLE III
COMPARISON OF OVERALL CLASSIFICATION ACCURACY FOR GAIT PATTERNS OF HEALTHY AND ACL-R SUBJECTS USING DIFFERENT FL SYSTEMS

Type of FLS	**Accuracy Before Training (%)**	**Accuracy After Training (%)**
NSFLS Type-2	72.38	83.97
SFLS Type-2	72.63	86.26
NSFLS Type-1	74.04	83.09
SFLS Type-1	73.48	73.42

of the FLS), type-1 or type-2 non-singleton fuzzification (e.g. type-1 or type-2 Gaussian MFs) can be applied to the noisy input data in order to handle the uncertainty in the measurements.

The selection of appropriate antecedents and corresponding number of fuzzy sets are crucial factors which affect the classification performance of the FLS. The maximum accuracy (88.32%) achieved for modified height reduction type-2 SFLS suggests that further investigations are required for selecting the most distinguishing features between healthy and ACL-R subjects at different stages of recovery in order to improve the classification accuracy. However, increasing the number of antecedents or fuzzy sets would require defining more rules in the rule base and consequently requiring more time for training. A possible solution is to use the rule reduction/optimization techniques after generating the rules based on all combinations of fuzzy sets for antecedents. Moreover, in order to define accurate MFs for antecedents/consequents, a large sample of subjects (healthy and ACL-R) would be beneficial.

IV. Conclusion and Future Work

An interval type-2 fuzzy logic system was presented for modeling the uncertainty in the gait data and classifying the gait patterns of healthy and ACL-R subjects at different stages of recovery. Based on the selected kinematics and EMG input parameters, type-2 fuzzy logic system performed superior as compare to type-1 fuzzy logic system for recognizing the gait patterns. The maximum overall classification accuracy (88.32%) was achieved for type-2 SFLS with modified height defuzzifier by using LOOCV method which shows that an adaptive gait patterns' classification system with good accuracy can be developed for healthy and ACL-R subjects by using type-2 FL. Further investigations will be done about choosing the appropriate input features and increasing the number of fuzzy sets for antecedents and consequent. Moreover, data will be collected from additional subjects for designing a robust classification system.

References

[1] E. S. Gardinier, K. Manal, T. S. Buchanan, and L. Snyder-Mackler, "Gait and neuromuscular asymmetries after acute anterior cruciate ligament rupture," *Med Sci Sports Exerc*, vol. 44, pp. 1490-6, 2012.

[2] A. D. Georgoulis, A. Papadonikolakis, C. D. Papageorgiou, A. Mitsou, and N. Stergiou, "Three-dimensional tibiofemoral kinematics of the anterior cruciate ligament-deficient and reconstructed knee during walking," *Am J Sports Med*, vol. 31, pp. 75-9, 2003.

[3] D. L. Shi, Y. B. Wang, and Z. S. Ai, "Effect of anterior cruciate ligament reconstruction on biomechanical features of knee in level walking: A meta-analysis," *Chin Med J (Engl)*, vol. 123, pp. 3137-42, 2010.

[4] B. Gao and N. N. Zheng, "Alterations in three-dimensional joint kinematics of anterior cruciate ligament-deficient and -reconstructed knees during walking," *Clinical Biomechanics*, vol. 25, pp. 222-229, 2010.

[5] R. Papannagari, T. J. Gill, L. E. Defrate, J. M. Moses, A. J. Petruska, and G. Li, "In vivo kinematics of the knee after anterior cruciate ligament reconstruction: A clinical and functional evaluation," *Am J Sports Med*, vol. 34, pp. 2006-12, 2006.

[6] H. Asano, T. Muneta, H. Ikeda, K. Yagishita, Y. Kurihara, and I. Sekiya, "Arthroscopic evaluation of the articular cartilage after anterior cruciate ligament reconstruction: A short-term prospective study of 105 patients," *Arthroscopy*, vol. 20, pp. 474-81, 2004.

[7] F. M. Chang, A. J. Seidl, K. Muthusamy, A. K. Meininger, and J. J. Carollo, "Effectiveness of instrumented gait analysis in children with cerebral palsy--comparison of outcomes," *J Pediatr Orthop*, vol. 26, pp. 612-6, 2006.

[8] R. Baker, "Gait analysis methods in rehabilitation," *J Neuroeng Rehabil*, vol. 3, pp. 4, 2006.

[9] D. A. Fuller, M. A. Keenan, A. Esquenazi, J. Whyte, N. H. Mayer, and R. Fidler-Sheppard, "The impact of instrumented gait analysis on surgical planning: Treatment of spastic equinovarus deformity of the foot and ankle," *Foot Ankle Int*, vol. 23, pp. 738-43, 2002.

[10] M. Lewek, K. Rudolph, M. Axe, and L. Snyder-Mackler, "The effect of insufficient quadriceps strength on gait after anterior cruciate ligament reconstruction," *Clin Biomech (Bristol, Avon)*, vol. 17, pp. 56-63, 2002.

[11] R. Thomee, Y. Kaplan, J. Kvist, G. Myklebust, M. A. Risberg, D. Theisen, E. Tsepis, S. Werner, B. Wondrasch, and E. Witvrouw, "Muscle strength and hop performance criteria prior to return to sports after acl reconstruction," *Knee Surg Sports Traumatol Arthrosc*, vol. 19, pp. 1798-805, 2011.

[12] A. L. Bryant, J. Kelly, and E. Hohmann, "Neuromuscular adaptations and correlates of knee functionality following acl reconstruction," *J Orthop Res*, vol. 26, pp. 126-35, 2008.

[13] J. Baumeister, K. Reinecke, and M. Weiss, "Changed cortical activity after anterior cruciate ligament reconstruction in a joint position paradigm: An eeg study," *Scand J Med Sci Sports*, vol. 18, pp. 473-84, 2008.

[14] R. Begg and J. Kamruzzaman, "A machine learning approach for automated recognition of movement patterns using basic, kinetic and kinematic gait data," *J Biomech*, vol. 38, pp. 401-8, 2005.

[15] M. A. Hanson, H. C. Powell, A. T. Barth, J. Lach, and M. Brandt-Pearce, "Neural network gait classification for on-body inertial sensors," presented at Sixth International Workshop on Wearable and Implantable Body Sensor Networks. BSN 2009., Berkeley, CA, 2009.

[16] H. Y. Lau, K. Y. Tong, and H. Zhu, "Support vector machine for classification of walking conditions using miniature kinematic sensors," *Med Biol Eng Comput*, vol. 46, pp. 563-73, 2008.

[17] A. Yardimci, "Fuzzy logic based gait classification for hemiplegic patients," in *Advances in intelligent data analysis vii se - 31*, *Lecture notes in computer science*, M. R. Berthold, J. Shawe-Taylor, and N. D. LavraÄ, Springer Berlin Heidelberg DA, 2007, pp. 344-354.

[18] C. O. Moraiti, N. Stergiou, S. Ristanis, H. S. Vasiliadis, K. Patras, C. Lee, and A. D. Georgoulis, "The effect of anterior cruciate ligament reconstruction on stride-to-stride variability," *Arthroscopy*, vol. 25, pp. 742-9, 2009.

[19] M. D. Lewek, J. Scholz, K. S. Rudolph, and L. Snyder-Mackler, "Stride-to-stride variability of knee motion in patients with knee osteoarthritis," *Gait Posture*, vol. 23, pp. 505-11, 2006.

[20] D. A. Winter and H. J. Yack, "Emg profiles during normal human walking: Stride-to-stride and inter-subject variability," *Electroencephalogr Clin Neurophysiol*, vol. 67, pp. 402-11, 1987.

[21] J. M. Mendel, *Uncertain rule-based fuzzy logic systems: Introduction and new directions*: Prentice Hall PTR, 2001.

[22] H. Lau and K. Tong, "The reliability of using accelerometer and gyroscope for gait event identification on persons with dropped foot," *Gait Posture*, vol. 27, pp. 248-57, 2008.

[23] H. J. Hermens, B. Freriks, C. Disselhorst-Klug, and G. Rau, "Development of recommendations for semg sensors and sensor placement procedures," *J Electromyogr Kinesiol*, vol. 10, pp. 361-74, 2000.

[24] J. M. Hart, B. Pietrosimone, J. Hertel, and C. D. Ingersoll, "Quadriceps activation following knee injuries: A systematic review," *J Athl Train*, vol. 45, pp. 87-97, 2010.

[25] G. Leporace, L. A. Batista, G. R. Pereira, G. Zeitoune, T. Oliveira, T. Luciano, M. Zeitoune, L. Metsavaht, and J. Nadal, "Comparison of quadriceps and hamstrings activation ratio between healthy and anterior cruciate ligament reconstructed subjects," presented at Biosignals and Biorobotics Conference (BRC), 2013 ISSNIP, Rio de Janerio, 2013.