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HMM-Fuzzy Model for Recognition of Gait Changes due to Trip-related Falls

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Abstract— **This paper reports the use of HMM-based fuzzy rules generation for identifying the differences in gait between people with tendencies to fall and healthy people. This work is built on the work reported earlier by the authors where fuzzy rules were successfully applied in gait pattern recognition. This paper reports the hybridization of HMM with fuzzy logic for improving the recognition accuracy.**

Gait features were extracted from Minimum foot clearance (MFC) data that was collected during continuous walking on a treadmill from 20 elderly subjects, 10 healthy and 10 with reported balance problem and history of falls. The input feature space was divided into a number of groups based on HMM generated log-likelihood values, and consequently each group was applied to construct a new fuzzy rule. Gradient descent method was used to optimize the parameters of the generated rules. These were then applied to recognize differences in the gait in subjects with trip-related falls history. The model's performance was evaluated using a cross-validation protocol applied on the training and testing data. The HMM-Fuzzy model outperformed the Fuzzy-based gait recognition as reflected both in the receiver operating characteristics (ROC) results as well as absolute percentage accuracy.

I. Introduction

Research involving the gait of the ageing is of concern due to the high incidence of falls related injuries suffered by the senior citizens. Different measures are being studied including features relating to basic time distance data, kinematics and kinetic data [1]. These findings suggest deterioration in the balance control mechanisms of the locomotor system with age. Falling behavior in older adults has been shown to change gait characteristics. Falls in older adults has been identified as a major concern for public health and cost the community $billions/annum.

Reduced toe clearance during the swing phase of the gait cycle can result in the inability in avoiding obstacles and obstructions during movement. The minimum foot/toe clearance (MFC), defined as the minimum vertical distance between the lowest point under the shoe and the walking surface, (see Fig. 1) is particularly critical. This is due to its very low magnitude i.e., the foot comes very close to the ground (~1cm), and also at this time the foot moves with a very high horizontal velocity (4.6 m/s) [1]. One way of reducing falls-risk is to identify potential fallers from their modified gait characteristics, so that intervention could be implemented to improve their gait function. A model is therefore necessary that would associate MFC information with falls-risk individuals so that MFC features could be utilized to diagnose potential falls-prone individuals.

Due to the large intra-subject variation in gait, the task of identifying gait features that map the potential fall-risks is complex. One possible solution to this is to develop non-linear models with the help of fuzzy logic to map a relationship between MFC features and different categories i.e., falls-prone and healthy individuals with no-falls history. This could potentially lead to many applications as gait diagnostics including, early identification of at-risk gait.

In recent years, fuzzy inference model have emerged as a powerful tool for solving such classification problems. Previous work in the application of fuzzy rules to classify gait types include, grouping children based on ambulatory function and gait measurements [2], classifying normal and ankle arthrodesis gait patterns [3].

In the previous work reported by the authors [4], successful use of fuzzy logic to classify healthy and falls-risk gait has been demonstrated. Fuzzy rules were generated from the training dataset using subtractive clustering. This paper reports the use of Hidden Markov Model (HMM) to partition the input space and formulate the set of fuzzy rules following the hybrid method described in [5]. The fuzzy rule parameters are fine-tuned for the given data sets. Performance of the hybrid HMM based fuzzy model is evaluated using accuracy rates and measures of receiver operating characteristics (ROC) curves. The advantage of HMM-based fuzzy system is the relatively smaller number of rules required for relating the MFC gait features with the respective gait types.

II. Materials and Methods:

A. *Participants:*

Ten healthy older adults (H) and 10 older adults with balance impairments (I) volunteered to participate in the gait data collection. All the participants were > 65 years old and were volunteers from the local community and senior citizen clubs. All subjects undertook informed-consent procedures approved by the Victoria University Human Research Ethics Committee. The subjects had no known injuries or

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abnormalities that would affect their normal gait.

B. Extraction of Gait Features:

Data collection and gait features extraction can be found in [4], however, a brief overview of the procedure is given below. Foot clearance data sets were collected during steady state self-selected walking on a treadmill using the PEAK MOTUS 2D (Peak Technologies Inc, USA) motion analysis system. Two reflective markers were attached to each subject's left shoe representing the 5th metatarsal head and the great toe. Each subject completed between 10 to 20 minutes of normal walking at a self-selected comfortable walking speed. The marker positions were automatically digitized for the entire walking task and raw data were digitally filtered using optimal cut-off frequency, which used a Butterworth filter with cut-off frequencies ranging from 4 to 8Hz. The marker positions and shoe dimensions were used to predict the position on the shoe traveling closest to the ground at the time when minimum foot clearance (MFC) occurs using a 2D geometric model of the foot [11]. MFC was calculated by subtracting ground reference from the minimum vertical coordinate during the swing phase (see Fig. 1).

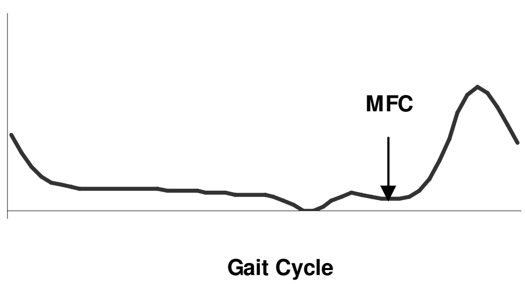


Figure 1: Foot clearance over the swing phase showing the MFC event [4]

Features describing major statistical characteristics of MFC distributions were extracted and these included altogether nine features: mean, median (Q2), min, max, 25th quartile (Q1), 75th quartile (Q3), standard deviation (SD), skewness and kurtosis [4].

III. HMM BASED FUZZY RULE EXTRACTION:

A. Input space partition:

The aim of the HMM is to identify the log-likelihood between the sequence of MFC belonging to different individuals. The inputs to the HMM are the sequence of feature values for an individual. The parameters of the HMM were initialized randomly and then optimized using Baum-Welch expectation maximization algorithm [6] for describing the training dataset by the HMM.

The resultant trained HMM produces log-likelihood values for each of the data sequences. For '*n*' number of data sequences, a total of '*n*' log-likelihood values are obtained. The range of log-likelihoods is split into equal-sized bins/buckets as suggested in [5]. Thus, each bin/bucket would contain a number of log-likelihood values. The algorithm for bucketing is given below [5]:

```
bucket_size= θ;
startRange= minimum of the likelihood values;
endRange= maximum of the likelihood values;
i=startRange;
j=1;
while (i<=endRange)
        bucket[j].start=i;
        bucket[j].end=i+bucket_size;
        bucket[j].data = find (dataLikelihood ≥ i and
                        dataLikelihood > i+bucket_size)
        i=i+bucket_size;
while end
```

Algorithm-1. The pseudo-code to split range of log-likelihood into buckets/bins.

The buckets are arranged in the range of log-likelihood values from minimum to maximum. Initially single fuzzy rule was generated for the entire space. Bucketed log-likelihood values were then used as the basis for extracting the fuzzy rules from the dataset which we describe in section 3C.

B. Fuzzy output generation

There are various options to compute the output for the fuzzy rules. This paper reports the use of Takagi-Sugeno-Kang [7] model to calculate the output for the respective part of the fuzzy rules.

There are number of options of the membership function for the antecedent part of the fuzzy rule. This paper reports the use of the model used in [5] and hence the membership function used here is Gaussian or Normal distribution. For each of the input feature (attribute), a membership function needs to be created. For this aim, initially, for a single fuzzy rule, the mean, μ_{mn} and the standard deviation, σ_{mn} were obtained for the entire input data. Then, for the n^{th} input feature, the membership function is:

$$M_{mn}(i_n) = e^{-\frac{1}{2}\left(\frac{i_n-\mu_{mn}}{\sigma_{mn}}\right)^2}$$
(1)

where, M_{mn} = membership function for the rule *m* and data feature *n*

i_n = n'th input feature in the input space

C. Fuzzy rule extraction: Top down tree approach

This approach initially generates a single fuzzy rule covering the entire training dataset. Outputs are obtained for the training input dataset using the generated fuzzy rule and the cost function is the mean square error (MSE). The MSE being less than a threshold level 'ξ', is the criterion for the input space to be divided into two parts with the help of bucketed log-likelihood values. If there are '*n*' number of buckets, then the first rule is generated for the data containing in the buckets ‘1’ to ‘n/2’ and the second rule is generated to cover the data containing in the buckets ‘(n/2+1)’ to ‘n’. Then MSE value for training dataset is obtained using the obtained fuzzy rules. If the MSE value is $\leq \xi$, the process of rule generation is stopped. If MSE value is greater than the ξ and more rules can be generated and the process is continued to further divide the input space.

After generating the rules, parameters of the rules are optimized using gradient descent method. The optimization requires the minimization of the MSE over the training dataset. Two set of parameters are required to be optimized: the antecedent (non-linear) parameter and the consequent (linear) parameter. This process is similar to the technique described in [9].

IV. Evaluation and Performance Metric:

The input data consists of nine features representing the individual gait patterns and belonging to two classes: healthy and balance impaired (fallers).

To generalize the performance of the model a five fold cross validation test was adopted. For this purpose, the dataset was divided into subsets such that each subset consisted of two healthy and two fallers' data. Four subsets were used to extract fuzzy_rules. The parameters obtained after training were saved, and the remaining data subset were tested using these parameters. Results of five fold cross-validation tests were used to obtain an average result for the measure of accuracy.

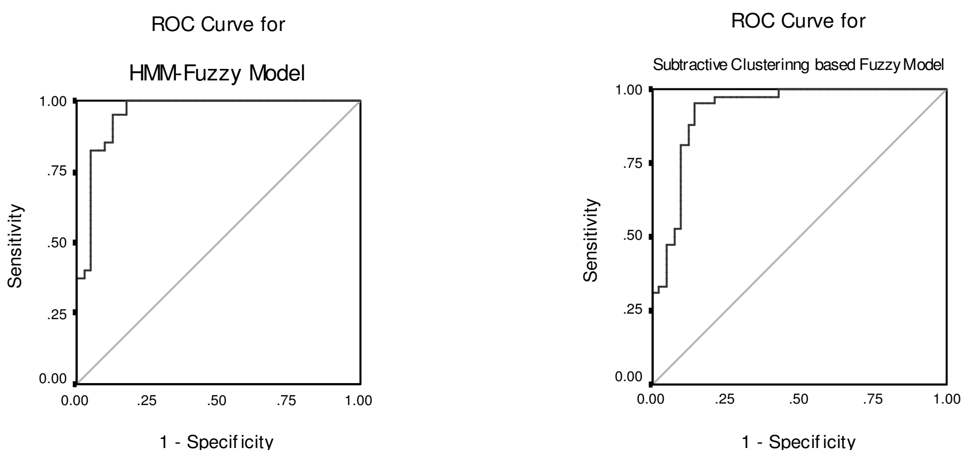
Classification outcomes were plotted (see Figure 2) to obtain the receiver operating characteristics (ROC) curves. ROC plots have been used in many investigations [4][8] to gauge the predictive ability of a classifier over a wide range of threshold values.

A. *Results:*

Table 1 illustrates overall test results for the cross validation scheme. From this table, it is observed that the overall accuracy is greater than 91% for a relatively less number of fuzzy rules. The high accuracy offered by the HMM-Fuzzy model is also observable in the ROC plot, where the ROC area is >0.95. ROC area is a better indicator of the performance of the classifier as it accounts for threshold variation from the default (0). The HMM-Fuzzy model provided a better ROC area and also improved sensitivity and specificity results with 2 fuzzy rules(see Figure 2(a) and

Table 1. Experimental result for the cross validation of HMM-based fuzzy logic and Subtractive clustering based Fuzzy logic

	HMM-Fuzzy Model	Subtractive clustering based Fuzzy Model
Accuracy	91.3%	89.3%
Sensitivity	0.884	0.87
Specificity	0.95	0.92
ROC area	0.954	0.93
Number of Rules	2	15 to 18



(a) (b)

Figure 2: (a) ROC curve for HMM-Fuzzy Hybrid model (b) ROC curve for Subtractive clustering based Fuzzy model[4]

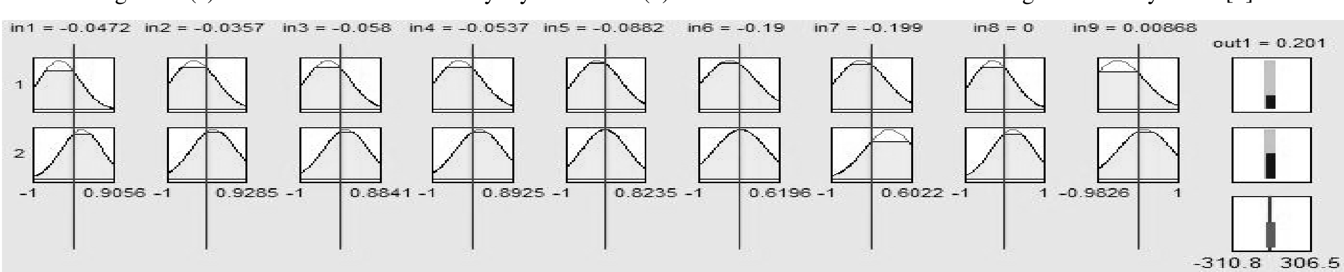


Figure 3: Fuzzy rules generated by HMM based input space partitioning

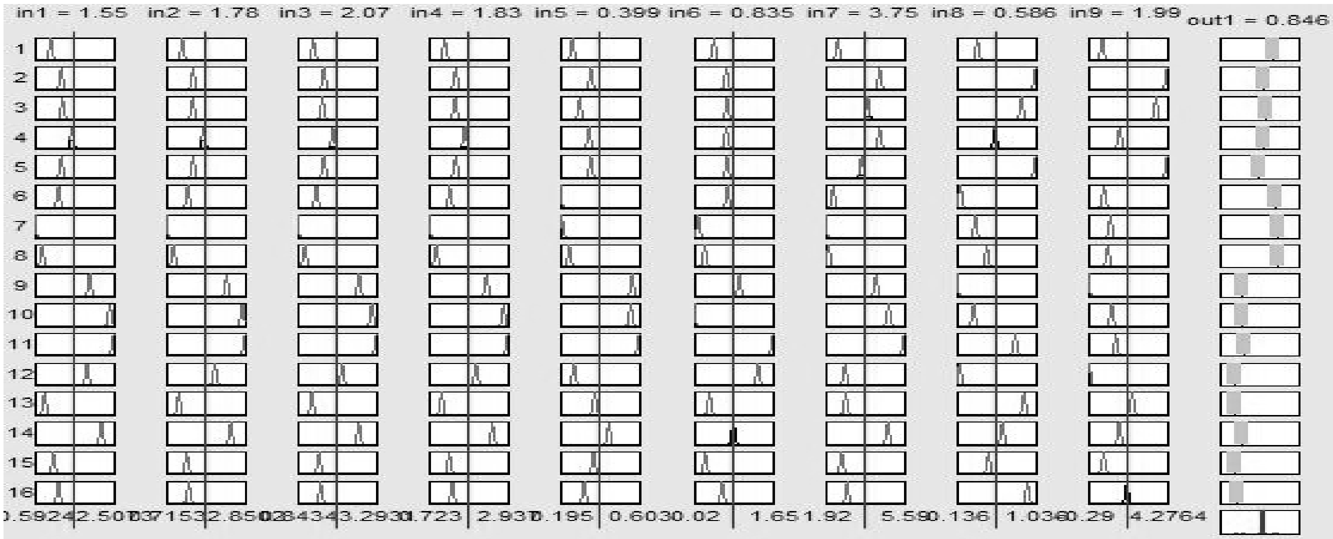


Figure 4: Fuzzy rules generated by subtractive clustering based input space partitioning

2(b)). Figure 3 shows an example plot of a set of fuzzy rules for one of the cross validated dataset. Figure 4 illustrates extracted fuzzy rules for the same dataset using subtractive clustering applied in [4].

V. DISCUSSION

This research has demonstrated that HMM-based fuzzy rule extraction technique followed by gradient descent method, is effectively able to identify the gait patterns of older adults' gait with balancing difficulties. This hybrid technique clearly outperforms the other fuzzy rule extraction used in [4]. Moreover, the HMM based fuzzy rule requires a significantly fewer number of rules than that was used in [4].

This system has reduced complexity and simultaneously improves the classification accuracy. This is attributable to the HMM's efficiency in identifying similarities in the gait data sequences leading to improved partition in the input space. Outputs presented in Figures 3 & 4 demonstrate this.. Furthermore, while partitioning the input space using HMM, the similarities among the feature attributes are identified by HMM in terms of fluctuations in magnitude. This leads to improved fuzzy rules to classify the differences in the gait of the two classes.

To determine the efficacy of the HMM based fuzzy rule finding method proposed in this paper, it is important to compare with the standard rule finding methods such as subtractive clustering [4]. From the comparison, it is evident that standard techniques consider the individual input features to be independent of each other and, this may generate extra rules making the overall system complex. The increased number of rules without taking into consideration the interdependencies among the input variables does not always lead to a more effective model. The experimental results presented in this research support this.

The work reported in this paper has demonstrated that hybridization of the strengths of HMM with Fuzzy logic has the potential to achieve a better performance when applied to the task of discriminating such as the gait patterns of healthy and people with falling tendencies. The work reported also demonstrates that the use of minimum foot/toe clearance (MFC) as a gait pattern diagnostics for identifying people with tendencies to fall is very encouraging. It is recommended that further research with increased sample size and various types of pathologies should be conducted to lead to helping the elderly in our society.

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