Haptic Rehabilitation Exercises Performance Evaluation Using Automated Inference Systems

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***Abstract*— Stroke has been a major source of disability that strikes humans in different age, causing chronic disability in adults. A common type of this disability is hand stroke which deprives patients from controlling their hands and fingers. Rehabilitation of stroke is usually done by functional Occupational Therapy (OT) in which the patient is trained to perform everyday exercises. On the other hand, haptics and virtual environments research offer the opportunity to improve the traditional methods of therapy. During a certain rehabilitation exercise, at least one therapist has to subjectively monitor the patient's performance in order to assess his/her improvement. This paper aims to introduce an automated Inference System that utilizes haptic data to quantize the patient's performance. For this purpose, two systems were implemented: a Fuzzy Inference System (FIS) and an Adaptive Neuro-Fuzzy Inference System (ANFIS). The two systems were validated with sample input/output datasets. However, when testing them with real subjects' data, they gave irrational evaluations. Re-tracing the whole process has lead us to the conclusion that the CyberForce system is incapable of providing normative data for evaluating the patient performance due to calibration and consistency issues.**

***Index Terms*— Haptics, Occupational therapy, Rehabilitation, Stroke, JTHF, Fuzzy logic, Adaptive neuro-fuzzy inference systems, CyberForce**

I. Introduction

STROKE is the clinical term used for naming the state of a rapidly developing loss of brain function due to disturbance in the blood vessels supplying blood to the brain [1]. If stroke is diagnosed and treated immediately in its early stages, permanent neurological damage and even death can be avoided. Otherwise, chronic disabilities are highly probable and death is also a valid possibility. According to statistics in the United States and Europe, stroke is a major cause of death and the leading cause of chronic disabilities for adults [2]. Post stroke patients, especially after surgery, often suffer from residual hand impairments. There are mainly two methods for rehabilitation of post stroke patients: physiotherapy or occupational therapy. While physiotherapy deals more with motor disorders, occupational therapy may be more general in terms of treating both mental and motor disorders. Occupational therapy aims at improving one's ability to perform daily activities. It usually takes a repetitive manner in doing a set of exercises having gradually increasing difficulty. At least one therapist should supervise the patient while performing a certain test/exercise in order to fine-tune the exercise.

The role of haptics and virtual environments in this field is embodied in providing entertaining (game-like) exercise environments while recording behavioral measurements for quantitatively evaluating the patient's performance. At the MCRLAB, University of Ottawa, we have developed a set of well-established exercises based on the Jebsen Test of Hand Rehabilitation (JTHR) test. The exercises set includes: moving a cup, navigating a maze, arranging blocks, training with a dumbbell and grasping a rubber ball [3]. The purpose of these exercises is to improve important skills like: hand movement, fingers movement, force exertion with fingers and hand, eye-hand coordination, and doing tasks with time deadlines. Furthermore, the use of haptic data glove provides significant information about the hand and fingers movement, and the forces applied while doing the exercise. These information include the global position of the hand (3D coordinates), finger joints angles, exerted forces, collisions with virtual objects, and their temporal derivatives (velocity and acceleration). These data are recorded by the exercise software and forwarded to the therapist for offline evaluation (by analyzing the recorded data) instead of watching the patient directly. Finally, the decision of the therapist will be based on comparing the patient's data to well-person's data.

In this paper, we introduce two inference systems that can assess patient's performance in a certain exercise (here we selected the cup exercise), and give a decision to the patient whether to repeat the same exercise, move on to the next level, or contact the therapist. The first system is a Fuzzy Inference System (FIS) which is then upgraded to an Adaptive Neuro-Fuzzy Inference System (ANFIS) that has some superiority to be explained later. The proposed systems can be used to assist the therapist in analyzing the collected data, which reduces significantly the supervision time of the therapist and reduces the overall cost of the rehabilitation process.

For the sake of simplicity, we implemented the systems for only three fingers (thumb, index and middle) and considered joint angles and fingertips forces, using the cup exercise shown in Figure 1.

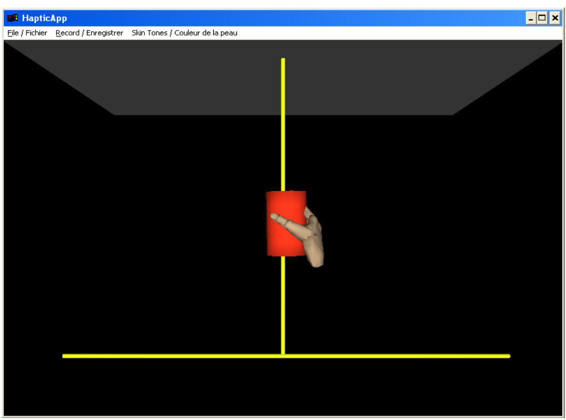

Figure 1: The cup exercise

The remainder of the paper is organized as follows: Section 2 reviews related work and points out our major contribution. In Section 3, a description of the FIS system, its components, and design procedure are introduced. Section 4presents the ANFIS system and its comprising components, in addition to the design methodology. Section 5 presents the performance analysis of the system and provides a comparison of the two systems. Finally, Section 6 summarizes the contents of the paper and provides insight for future work.

II. RELATED WORK

Several studies highlighted the use of haptic technology in brain damage therapy and consequently several systems have been developed to serve that. Haptics based systems for stroke patients are reaching a higher level of maturity. For instance, several researchers have focused on the rehabilitation of upper and lower extremities, such as, the hand motor function in [4-7], the arm [8], and the ankle [9]. They used haptic devices to physically support the patient while doing a certain exercise. However, fewer attempts have been done to develop evaluation tools to quantitatively evaluate the patient performance.

The use of haptic gloves in the field of rehabilitation has recently gained a significant interest. For instance, [10] proposes a low-cost virtual rehabilitation of the hand using the inexpensive P5 game glove and Java 3D simulation. It is found that the P5 glove cannot measure the individual joints of each finger, unlike the CyberGlove. Furthermore, compared with the CyberGlove system, the P5 glove has less accuracy and resolution. The authors in [11] implemented five task-oriented exercises based on well established and common exercises, namely the Jebsen Test of Hand Function (JTHF) and the Box and Block Test (BBT). The five exercises include moving a cup, arranging blocks, navigating a maze, training with a dumbbell, and grasping a rubber ball. Furthermore, key performance measures (metrics) are proposed for each exercise to quantitatively evaluate and judge performance of stroke patients.

The authors in [12] presents a virtual reality-based system that uses the CyberGlove and the Rutgers Master II-ND haptic gloves to train finger range of motion, finger flexion speed, independence of finger motion, and finger strength through specific VR simulation exercises. Burdea and colleagues [13] used the Rutgers Master II glove to perform a set of physical and functional therapy exercises for home use. The data is collected during the exercise and stored on a remote server; to be analyzed by the therapist. The authors did not propose the use of intelligent systems to quantitatively evaluate the patient performance.

In our previous preliminary work [3], we have developed a framework for post-stroke patient therapy. Through performance evaluation, there was enough evidence that the framework can be used for diagnosis to quantitatively measure and evaluate the patient's performance and progress.

Even though haptic devices are not yet mature as rehabilitation equipment [17], data gloves have been a common practice in rehabilitation. The proposed model can be tuned for a data glove with Augmented Reality

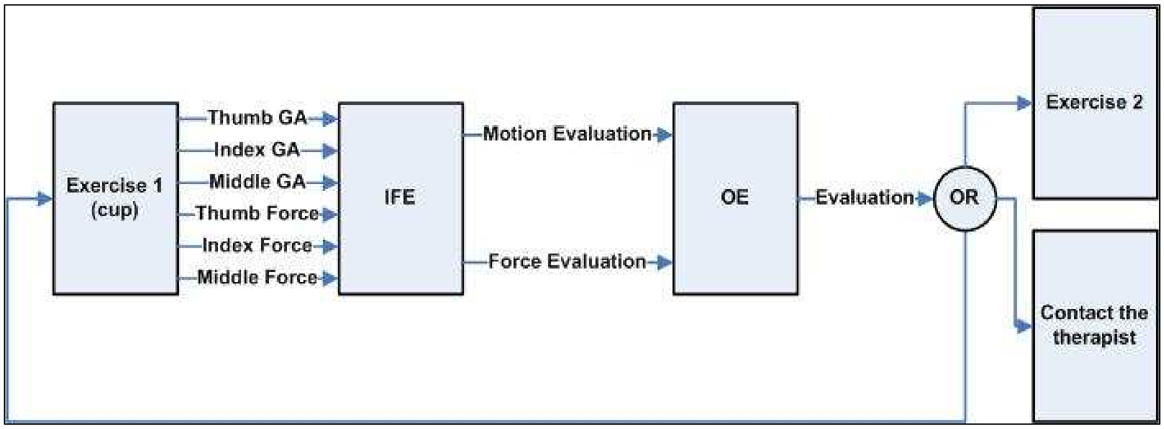

Figure 2: System Overview

(AR) exercises. In AR rehabilitation, subjects see real world scene and manipulate real objects. Moreover, the patient wears haptic gloves that measure the hand/fingers movement and the interaction forces [19]. These measurements form the raw data to our system.

Despite the fact that most of the preceding works have used haptic devices for rehabilitation, none of them has implemented any autonomous decision making system for assessing the patient's performance. However, an interesting work was presented by [14] where an intelligent decision support system based on fuzzy logic is used in hand-eye coordination therapy. The system takes haptic data from previous tests performed by the subject and uses them to make decision about the complexity of the next test to be performed.

Our system employs a two-stage fuzzy inference system for evaluating the performance of a stroke patient in a certain exercise using haptic data from CyberForce system. The system offers high modularity as for providing capability for more parameters to be added as needed. Furthermore, ANFIS system is used to optimize the performance of the fuzzy inference system. The ANFIS system enables tuning the membership functions by training the system to comply with the predetermined input/output data sets.

III. FIS SYSTEM DESCRIPTION

A. Overview

The FIS system comprises four components (Figure 2): the rehabilitation exercise, the CyberForce glove system, and a fuzzy inference system called Individual Feature Evaluator (IFE) which is fed with the collected exercise data and provides evaluation for each feature separately. The fourth component is a fuzzy inference system called Overall Evaluator (OE) that provides the overall evaluation of the patient's performance by combining the motion and force evaluation parameters.

B. IFE

IFE is a Mamdani fuzzy model [15] implemented using MATLAB 7.1. It has six inputs and two outputs as shown in Figure 2. Here are the descriptions of each:

Inputs: The inputs to IFE are: thumb grasping angle, index grasping angle, middle grasping angle, thumb force, index force, and middle force. This means that for each of the three fingers we are taking two inputs: the grasping angle and the force. The finger grasping angle is considered to be the sum of the three finger joints angles indicated by $\theta1$, $\theta2$ and $\theta3$ in Figure 3 except the thumb grasping angle which is the sum of the two joints angles with the metacarpal angle. In other words, the grasping angle is the sum of the averages of the three angles. This means that if we want to derive the middle grasping angle, for example, we get the average of each of the three angles and then add them together. Each of the input forces is also the average of the applied force by each fingertip.

Input membership functions: Given that when the patient is grasping the cup none of the grasping angles could exceed 200 degrees, the universe of discourse for each input variable is selected between zero and 200 degrees. For the forces, it depends on the weight of the cup in the exercise and they are calculated from the displacement of the fingers and stiffness of the cube. Sample input membership functions are shown in Figures 4 -6.

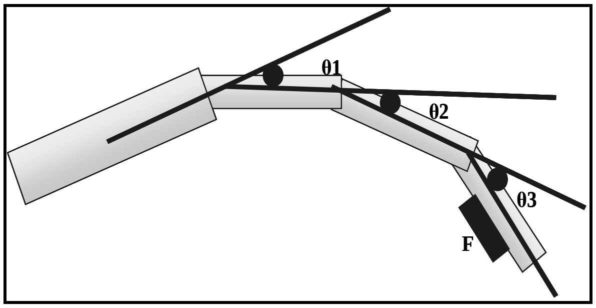

Figure 3: The finger grasping angle is the sum of θ1, θ2 and θ3. The finger force is the force F applied by the fingertip

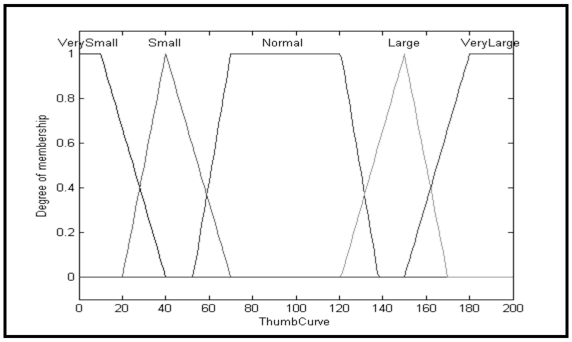

Figure 4: Thumb grasping angle MFs

The definition of the membership functions is initiated by finding the normal range for each input, designing the "normal" membership function, and then designing other membership functions (small, large, weak, etc.) based on the normal one.

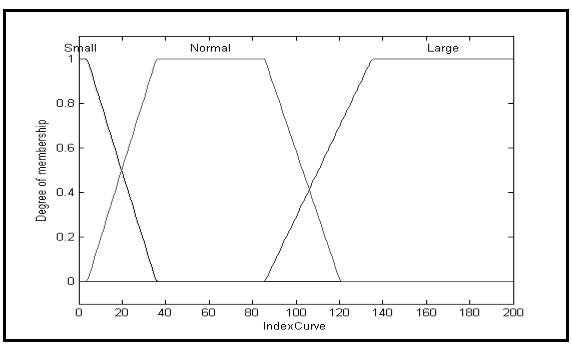

Figure 5: Index grasping angle MFs

We have chosen to use trapezoidal membership functions to indicate that there is a certain range of inputs that is all considered to be normal. Same thing applies for the extremities membership functions. For membership functions lying between the normal range and an extreme we have chosen the triangular membership functions (like in Thumb Grasping angle). However, Bell membership functions could be used instead of trapezoidal ones and Gaussian instead of triangular ones, but they would have induced more computational complexities. We have assigned five membership functions for the thumb grasping angle because a more precise look into the thumb performance is needed since it is the critical finger in the grasping activities.

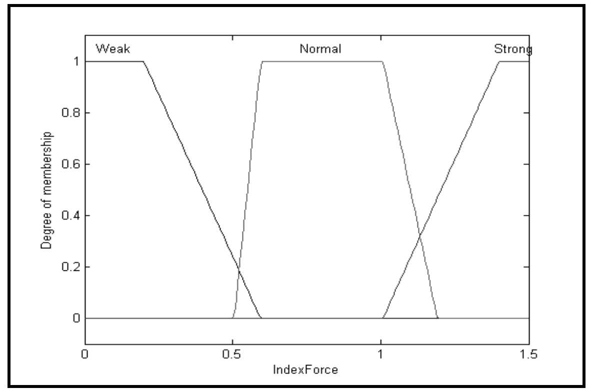

Figure 6: Index force MFs

In order to determine the normal ranges for the input variables, we have utilized the results obtained from four normal persons who performed the exercise. The average, minimum, and maximum values of each input were computed. The range is the interval [min, max]. The measurements taken from the four subjects for each input are shown in Table 1.

Table 1: Statistics of the measured values of the angle

Angle	Min	Avg	Max
Thumb θ1	47.19	57.02	68.07
Thumb θ2	7.52	15.93	24.24
Thumb θ3	6.54	22.98	36.79
Index θ1	0	2.87	8.33
Index θ2	24.24	42.99	62.69
Index θ3	3.45	13.61	23.29
Middle θ1	6.92	11.95	16.8
Middle θ2	57.88	66.99	76.85
Middle θ3	0.6	11.51	17.46

The value of each grasping angle is obtained by adding the values of each of the rows in Table 1 for the corresponding finger. The results are shown in Table 2.

Table 2: Statistics of the obtained grasping angle of each finger

Finger	**Min**	**Avg**	**Max**
Thumb	61.26	95.93	129.1
Index	27.69	59.48	94.33
Middle	65.4	90.45	111.12

The "normal" membership function was designed in a way to give all values in the normal range membership values greater than or equal to 0.75 as illustrated in Figure 7. The design and the ratio are subject to possible changes after incorporating the therapist's feedback. In addition, the slopes on both sides are related to the deviation of the min or max values from the calculated average. For example, in Figure 7 the range is [65.4, 111.12] and the average is 90.45, so the slope on the left has less inclination than the other one because the deviation of the min is 25.05 while the deviation of the max is 20.67. So, these membership functions were manually optimized. Forces are calculated as mentioned earlier.

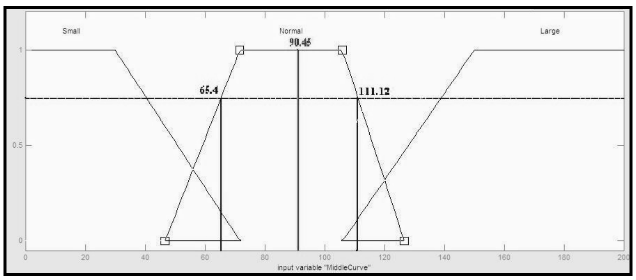

Figure 7: Designing the "normal" MF

<u>Outputs:</u> The outputs of IFE are: movement control evaluation and force control evaluation. As implied by the names, each provides an evaluation (grading) for a certain skill, one for the motion depending on the input finger grasping angles, and the other for the forces depending on the input applied forces.

<u>Output membership functions:</u> The output membership functions have the same design since both of them use a grading scale ranging from 0 to 10. One of them is shown in Figure 8. Grades below 2.5 indicate very weak performance, those between 2 and 4 indicate weak performance, those between 3.5 and 5.5 indicate fair performance, those between 5 and 7 indicate moderate performance, those between 6.5 and 8.5 indicate acceptable performance, and grades above 8 indicate normal performance.

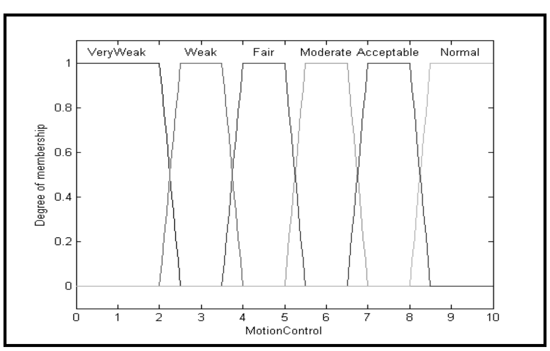

Figure 8: Motion control MFs as output of IFE

<u>Rules:</u> IFE has 72 rules, but since evaluation of each skill can be performed separately, we had 45 rules concerning motion control and 27 rules concerning force control.

The rules for motion control are:

- If Thumb Grasping angle is Very Small (VS), Index Cuve is Small (S) and Middle Grasping angle is Small (S), then Motion Control Evaluation is Very Weak (VW)
- If Thumb Grasping angle is Very Small (VS), Index Cuve is Small (S) and Middle Grasping angle is Normal (N), then Motion Control Evaluation is Weak (W)
- Some of the rules are shown in Figure 9 with the index grasping angle being the x-axis, and the middle grasping angle being the y-axis.

ThumbGrasping angle is S

	S	N	L
S	W	F	W
N	F	M	F
L	W	F	w

ThumbGrasping angle is VS

	S	N	L
S	VW	W	VW
N	W	F	W
L	VW	W	VW

Figure 9: Motion control evaluation rules

It is worth mentioning that the rules are symmetrical with respect to the diagonal in each table. This is because the index and the middle fingers are treated similarly. We notice also the importance of the thumb grasping angle since there was no output above "moderate" if the thumb grasping angle is not in the normal range.

Defining rules for force control evaluation involves more than checking whether the force is in the normal range or not; other factors include potential to exert force, balance of the forces, and control over forces. For example, the case when the thumb force is normal, the index force is weak and the middle force is strong is acceptable assuming that the patient relies more on one of the two fingers to balance the thumb force. Another example is that if all forces are very weak then force evaluation is very weak whereas if all forces are very strong then force evaluation is weak (not very weak) because there is a potential to apply forces but with no control.

C. OE

OE is also a Mamdani fuzzy model implemented using MATLAB 7.1. It has two inputs and one output as shown in Figure 2. This system is responsible for evaluating the overall performance of the patient. The inputs to the system are the outputs of IFE fuzzified in a simple way as shown in Figure 10. Both inputs have the same membership functions design.

The output of this system is the final grade obtained for the patient's performance and consequently the final decision of the system whether to allow the patient to continue to the next level (if the patient's performance was good), repeat the same exercise (if the patient's performance was below average), consult the therapist (if the patient's performance was slightly above average). The rules employed in decision making are summarized in Figure 11 (Bad = B, Average = A, Good = G, Fail = F, Consult the therapist = C, Succeed = S) whereas the output membership functions are shown in Figure 12.

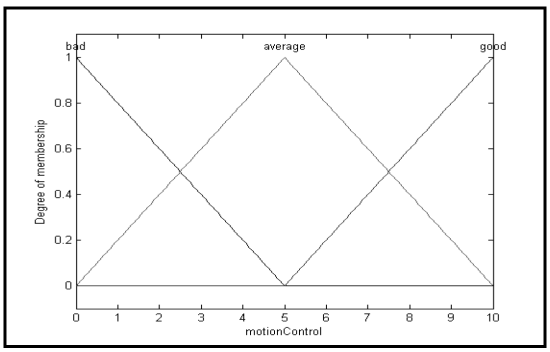

Figure 10: Motion control MFs as input to OE

	B	A	G
B	F	F	F
A	F	C	C
G	F	C	S

Figure 11: Final Grade Evaluation Rules

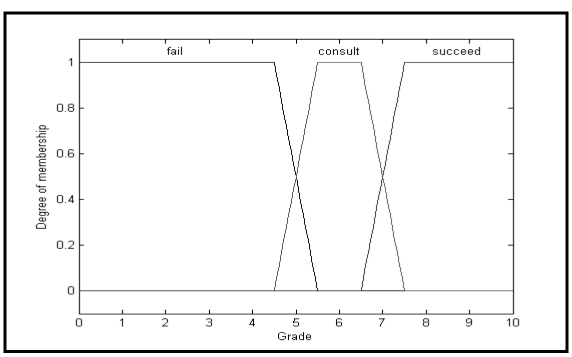

Figure 12: Final Grade MFs

IV. ANFIS SYSTEM DESCRIPTION

An Adaptive Neuro-Fuzzy Inference System is a combination of a neural network and a fuzzy inference system [16]. Among the several types of neuro-fuzzy systems, the hybrid neuro-fuzzy system has parallel neural network architecture. It integrates a neural network and a fuzzy logic system, in an appropriate parallel structure, to work as one synchronous entity.

The ANFIS system exploits learning paradigms similar to those used in neural networks. Then, it maps each functional module of the fuzzy logic system to a particular layer of the neural network (inputs fuzzification, input membership functions, rules, output membership functions, and output). As such, a fuzzy logic inference system can be implemented as a five-layer neural network as shown in Figure 13.

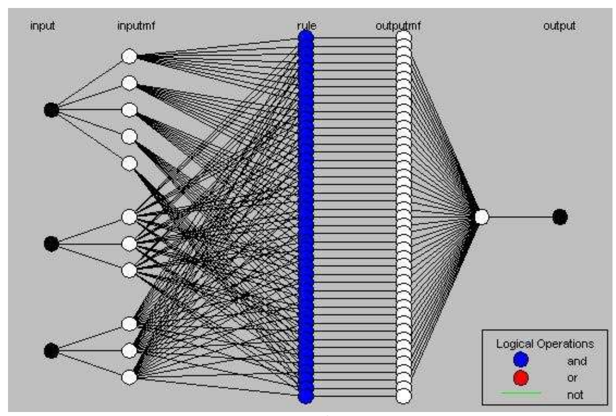

Figure 13: ANFIS Model Structure for Grasping Angle Evaluator

First we have a set of crisp inputs that are fuzzified by mapping them into the input membership functions (could be triangular, trapezoidal, bell, Gaussian, etc.). Then there is a layer that contains one node for each fuzzy if-then rule. Next is a normalization layer that normalizes the firing strength of the fuzzy rules (dividing the firing strength of the rule by the sum of the firing strengths of all the rules). The consequent parts of the fuzzy rules are multiplied by their corresponding firing strengths. The final layer concludes the overall output as the summation of the incoming signals from all the nodes from the previous layer.

The ANFIS system is implemented using MATLAB 7.1. Since ANFIS systems usually offer a possible representation of a multi-input single-output Sugeno type (zeroth or 1st order) system, we had to split the IFE into two ANFIS sub-systems (IFE originally has two outputs). The two ANFIS sub-systems are named: Grasping Angle Evaluator (GAE) and Force Evaluator (FE), as shown in Figure 14. As mentioned earlier, the evaluation of each feature can be assessed separately according to the rules set, so there is no problem with splitting IFE into two ANFIS sub-systems. OE however will be used as-is, and as shown in the second layer in the ANFIS system (Figure 14).

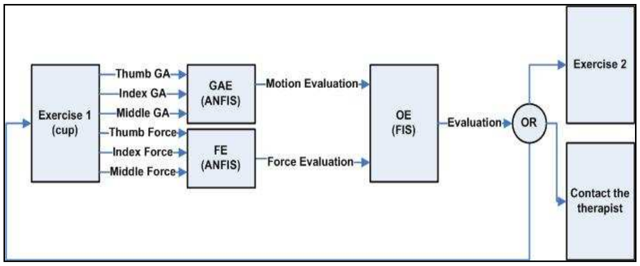

Figure 14: ANFIS System Architecture

The implementation of the GAE sub-system is discussed here (similar description applies to the FE sub-system).

Using MATLAB fuzzy toolbox, we generated a first order (linear) Sugeno type fuzzy inference system with three inputs. For the first input (Thumb Grasping Angle), there are five membership functions. For the second and third inputs, there are three membership functions for each (Index and Middle Grasping Angles) so that it resembles the initial system. MATLAB forces all the rules to have the same weight and all the membership functions to be of the same type, so we chose them to be triangular (after trials with other types and comparing the outputs).

Three datasets were used: the training dataset, the checking dataset and the testing dataset. The training dataset is used to train the system by letting the neural network adapt the fuzzy logic system membership functions so that the output passes through all (in the ideal case) the points of the dataset. The training dataset should be selected carefully so that it covers all the range of possible values (the universe of discourse). A training dataset is been used, consisting of 284 sample vectors, for this purpose. A few sample vectors are shown in Table 3.

The checking dataset is used to validate the system by trying another set of inputs (with known outputs) and checking their output. Furthermore, a set of 284 sample inputs were used for this purpose. Another important reason for using this dataset is determining the training effort needed for the system. Usually, the more epochs the system is trained with, the less the error will be until it reaches a certain point where overfitting starts (the system just starts to memorize the supplied training data). To avoid this, we use checking data and examine the checking error whose value is minimal at the overfitting start point. Hence, the system is best trained at the point prior to overfitting start. The testing data is obviously the data collected from the subjects of the experiment.

Table3: Sample training data and their corresponding output evaluation

Thumb Grasping Angle	Index Grasping Angle	Middle Grasping Angle	Output
24	6	2	1.7
26	12	34	2.3
39	58	34	4.4
30	93	42	3.4
103	57	121	8.2
58	66	150	5.8
49	12	135	3.4
23	0	121	2.3
63	39	134	6.6
88	4	145	4.5
133	6	143	4.0
159	13	135	2.7
142	17	145	3.6
161	18	123	3.4

The system was trained with 200 epochs using the backpropagation optimization technique [18] until the error (measured to training data) reached 0.354. Figure 15 shows the training graph where the y-axis is the error (relative to the output space which is 10) and the x-axis is the epoch number.

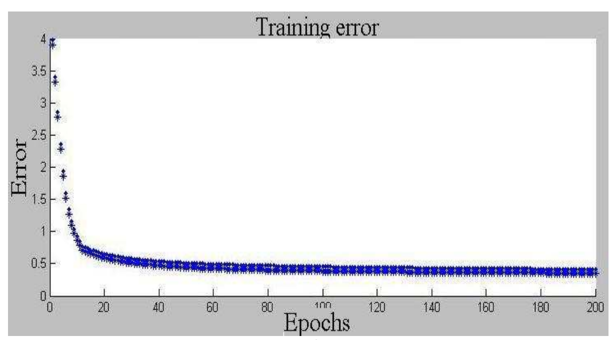

Figure 15: Training of the GAE ANFIS

The training error, as well as the checking error, almost plateaus after 80 epochs (Note that there are two curves in Figure 15). In each epoch, the system tries all the vectors of the training dataset and manipulates the membership functions accordingly.

Although the error can slightly be reduced, this needs a huge number of training epochs. So, we assumed that it plateaus for a value 0.354. Finally, it is worth mentioning that the same procedure was followed in designing the FE ANFIS sub-system.

V. PERFORMANCE ANALYSIS

Performance analysis of each system (FIS based system and the ANFIS based system) is provided in addition to a brief comparison between them.

A. FIS System Performance Analysis

As the system was tested with sample inputs, it showed satisfactory results depending on our knowledge base. A set of experimental inputs and their corresponding outputs are shown in Table 4.

Table 4: Sample data and their corresponding output evaluation

	S1	S2	S3	S4	S5	S6
ThumbGrasping angle	50	80	90	130	140	30
IndexGrasping angle	20	20	60	70	100	60
MiddleGrasping angle	30	100	120	80	20	90
ThumbForce	0.6	1.1	1.5	1.8	2.5	2.7
IndexForce	0.4	0.5	0.3	0.8	1	0.9
MiddleForce	0.3	0.6	0.9	0.8	1.2	0.3
Motion Control Eval	3.76	8.35	8.32	8.48	3.99	5.39
Force Control Eval	1.16	7.12	7.5	9.1	4.69	4.5
Overall Eval	2.95	7.22	7.4	7.85	4.7	5.2

The system is not tested yet with stroke patients. However, when it was tested with another set of healthy subjects, the obtained results were unexpected because they gave unaccepted grades for these well users.

Getting such results has motivated us to recheck the input data obtained from each subject and analyze them manually. Unexpectedly, these data were indeed not in the normal range. This observation has led us to conclude that the CyberForce system is incapable of providing normative data for performance evaluation of the haptic exercise. The data along with the results are shown in Table 5.

Moreover, if the same healthy person performs the same exercise in the same way, a variation of the collected data has been noticed. In other words, CyberForce system can be used to do the exercise but the data that it generates are not satisfactory. This problem may be due to the calibration process of the device or to device errors.

Table5: Results for healty testing subjects

Subject	Thumb Grasping angle	Index Grasping angle	Middle Grasping angle	Motion Control Eval
1	43.67	64.9	69.24	5.89
2	111.06	48.82	76.08	9.14
3	97.61	103.37	134.14	6.2
4	79.35	23.99	22.23	6.35

If we assume that we are getting the normative data from the device, the fuzzy inference system enables not only offline training for patients, but also evaluating their performance and deciding their upcoming tasks. In addition, having two fuzzy inference systems provides much flexibility to the whole system especially if more features need to be evaluated or if some features have to be given more weight than others.

On the other hand, the system has some limitations that need further investigated. First, for now, it incorporates only three fingers and two features for each finger (grasping angle and force). We are planning to incorporate other fingers and other important features as well, such as alignment with the desired track and time taken to perform the exercise. Second, normal ranges were obtained from four 'normal' persons by finding the average, min, and max value for each input. In future, the analysis will rely on a larger number of users and will use standard mathematical norms such as standard deviation or variance because there is no difference for the current system whether min or max values occurred once or several times. Third and most important, the membership functions are manually designed to meet the required results. Only the "normal" membership functions have practical bases to some degree. Nevertheless, membership functions need to be more optimized and this is performed by upgrading the fuzzy system to an Artificial Neuro-Fuzzy Inference System (ANFIS). Using ANFIS, we can provide sample input data with their evaluation (done by a therapist or more for better performance) as training patterns and the ANFIS will automatically modify the membership functions to meet the required result. Training the ANFIS with the appropriate number of training patterns guarantees robustness of the results.

B. ANFIS System Performance Analysis

After training the system, it was able to match closely with the training dataset (as it is supposed to be). This matching is shown in Figure 16. The x-axis

indicates the index/order of the input vector in the dataset, and the y-axis is the output which ranges from 0-10.
In order to validate the correctness of the system we used the 284-vectors checking dataset mentioned previously. The system also matched closely with the supposed outputs, which means that the system was well trained over the universe of discourse of the inputs. Figure 17 shows the plot of the output given by the system (indicated by the red stars) against the predefined output for the checking data (indicated by the blue plus signs).

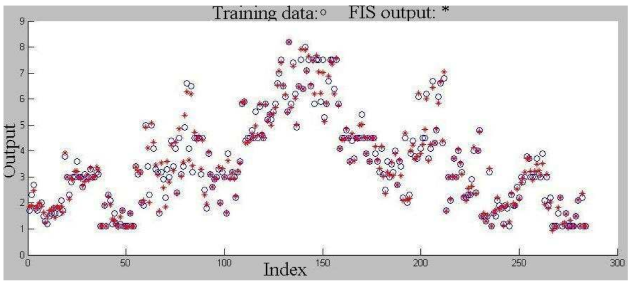

Figure 16: Plotting against training data

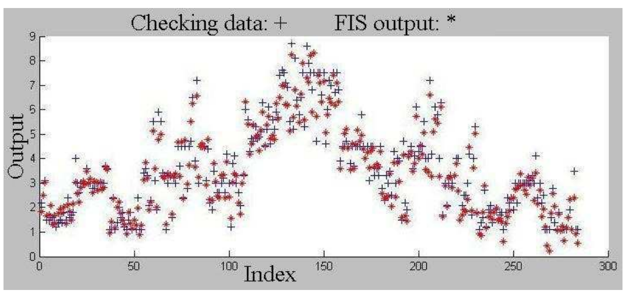

Figure 17: Plotting against checking data

The same data in Table 4 and Table 5 were used as testing data. Therefore, the same testing data is used with both systems (FIS and ANFIS systems) in order to assess the precision of each system, regardless of the input data sets.

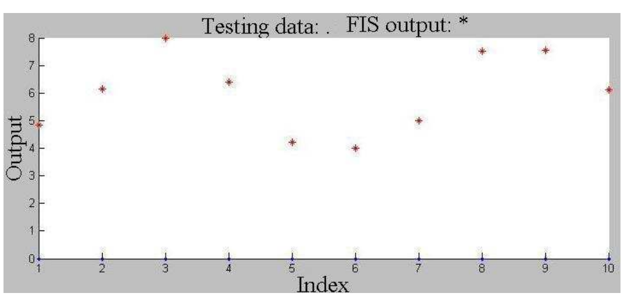

Figure 18: Plotting against testing data

Table 6 summarizes the results by presenting ten evaluations performed by both systems. The table contains evaluations of grasping angles as well as the forces evaluated by the two systems (FIS & ANFIS). Notice that since OE is the same in both systems, it is not presented in this table.

Table6: Results for gasping angles and forces by both systems (FIS and ANFIS)

Subjects	FIS		ANFIS	
	Motion Control Eval	Force Control Eval	GAE	FE
S1	3.76	1.16	4.8	1.3
S2	8.35	7.12	6.1	6.8
S3	8.32	7.5	8	8.3
S4	8.48	9.1	6.4	7.3
S5	3.99	4.6	4.1	4.4
S6	5.39	4.5	3.9	4.1
S7	5.89	4.8	5.3	4.8
S8	9.14	7.9	7.7	7.6
S9	6.2	6.6	7.8	7.2
S10	6.35	5.3	6.3	5.2

The findings obtained by the performance analysis of the FIS system indicated the non-convenience of the data of the device. Therefore, it is expected that even with the ANFIS system some of the subjects (S6, S7, S8, and S9) would fail to pass the exercise. This is what happened for S7 and S10.

C. *FIS vs. ANFIS*

As mentioned earlier, an ANFIS system combines the advantages of both neural networks and fuzzy logic systems. Whereas fuzzy logic systems rely on the expertise of the designer with no need for complex mathematical computations, neural networks have the ability to learn about datasets without being provided with logical rules that govern their analysis. ANFIS systems employ the expertise of the designer and improve it by continuous modification until the largest possible portion of a dataset can fit properly and match with the supposed outputs. Obviously, a combination of both would give the optimum performance.

The first remark in comparing the two systems is the close matching between their results. This indicates that the membership functions of the fuzzy inference system were well tuned to a certain degree (although manually).

The second remark is that the output of the ANFIS system is, generally, lower than that of the FIS system. This is mainly due to the fact that the training dataset outputs was prepared in a way that permits small differences in the inputs to affect the results. In other words, two inputs may produce different results according to their deviation from the average value of the corresponding parameter (which is considered to be the optimal). As the deviation increases, its negative effect on the output increases.

Finally, in most of the cases, the ANFIS system gains more accreditation since it tries to simulate the way of assigning outputs presented in the training data whereas investing the expertise of the designer/therapist.

VI. CONCLUSION

This paper proposed two compound (two-stage) inference systems: The FIS system and the ANFIS system. The FIS system depends solely on the expertise and knowledge of the designer/therapist represented in a set of rules and membership functions. On the other hand, the ANFIS system, in addition to employing the knowledge in the FIS system, makes use of a set of examples (training dataset) that helps it to perform a fine tuning to the preliminary membership functions and thus obtain more precise results. Each of the two systems – with a preference to the ANFIS system - is capable of evaluating a subject's performance in a certain haptic rehabilitation exercise and making decision or recommendation on its behalf. The measurements of the various system parameters are collected by the exercise software from an appropriate haptic device and fed to the system in order to be evaluated. However, two well subjects out of four could not pass the test which indicates the non-convenience of the data obtained from the used device for such work. The architectures of both systems are modular and flexible, so adding parameters or weights for each parameter is such a simple task. Finally, any of the two systems would be a great aid for therapists in rehabilitation tasks if proper devices are used in collaboration with well designed exercises.

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