Proceedings of the 2010 3rd IEEE RAS & EMBS
International Conference on Biomedical Robotics and Biomechatronics,
The University of Tokyo, Tokyo, Japan, September 26-29, 2010

Neuro-fuzzy Compliance Control for Rehabilitation Robotics

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Abstract— **This paper presents a methodology for the design of a real-time neuro-fuzzy controller for the robotic rehabilitation of patients with upper-limb dysfunction due to neurological diseases. The approach utilizes a fuzzy-logic schema to introduce compliance into the human-robot interaction, and to allow the emulation of a wide variety of therapy techniques. It also allows for the fine-tuning of system dynamics using linguistic variables. The rule base for the system is trained using a fuzzy clustering algorithm and applied to experimental data gathered during traditional therapy sessions. The compliance rule base is combined with a hybrid neuro-fuzzy compensator to automatically tune the dynamics of the system on-line. The control algorithm is implemented as a platform-independent solution to facilitate the rehabilitation of patients using multiple manipulator configurations. Preliminary experimentation has shown promising results indicating that the proposed methodology can accurately replicate the desired compliance profiles in real-time.**

I. Introduction

THE human-in-the-loop nature of rehabilitation robotics requires a fundamentally non-traditional approach to the design and development of manipulator control systems, which emphasizes the interaction between the patient and the manipulator system. This human-centred design methodology is an ideally suitable ground for the application of soft-computing approaches including fuzzy c-means (FCM) clustering and neuro-fuzzy control. To this end, a real-time compliance control strategy has been developed to evaluate the effectiveness of a neuro-fuzzy approach to the challenges inherent to rehabilitation therapy.

The primary design challenge in rehabilitation robotics is the replication of the complex movements associated with traditional physiotherapy, which involve resistive and/or assistive forces applied at specific times. Traditionally, a hybrid force-position controller would be required to regulate the interaction forces while precisely monitoring and controlling the position and velocity of the limb movement. Since during the rehabilitation therapy the patient is also a part of the dynamic system, traditional control schemes are difficult to develop based on the system model. Current research efforts in the field of rehabilitation robotics have, therefore, centred on the development of systems that offer goal-oriented movement tasks coupled with the therapist prescribed levels of assistance and compliance.

Manuscript received June 30, 2010.

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An approach that has been proposed by some researchers to overcome the difficulties associated with the application of traditional force control to rehabilitation robotics is the use of fuzzy logic [1,2,3]. Fuzzy logic control has the advantage of being able to provide rule-based force control while compensating for nonlinearity and parameter uncertainty. This feature enables the system designers to create a model of the prescribed interaction between the robot and the patient based on the therapist's qualitative description of the desired behaviour of the coupled system. However, the traditional approach to the generation of the rule base for fuzzy rehabilitation systems creates a fundamental reliance on the expert knowledge of the therapy professionals. Given the complexity of traditional therapy tasks, this dependency on an accurate understanding of the dynamics of the interaction has meant that the fuzzy based rehabilitation systems are normally only able to perform very simple trajectory profiles.

One such controller was developed using a conventional fuzzy logic system with triangular membership functions for position control [1]. For force control, the work uses a conventional linear PI controller with a fuzzy rule base acting as PI tuner. This approach was used to compensate for the nonlinear dynamics of the robot and the human subject. To provide trajectory tracking for a wearable pneumatic rehabilitation device, a fuzzy PID controller was proposed by Wu et al. [3]. The fuzzy system performed better than a conventional PID controller during trials with a healthy patient.

The application of neuro-fuzzy control to rehabilitation robotics has been very limited. Hybrid neuro-fuzzy systems combine fuzzy rules with neural networks to enable the fuzzy system to tune its performance [4]. To compensate for non-linear system elements, the 3 d.o.f exoskeletal system proposed by Kiguchi et al. made use of a neuro-fuzzy schema [5]. The system was used to overcome design challenges inherent in EMG signal acquisition. In order to adapt the system parameters responsible for the human-robot interaction to different patients, an adaptive impedance controller was proposed by Xu and Song [6]. The system uses a dynamic fuzzy neural-network to alter the impedance parameters of the system on-line based on an estimation of the impaired limb's impedance. Preliminary simulations have shown that the system is more effective than traditional impedance control.

The chief consideration for the design of robotic rehabilitation control systems is the dynamics of the interaction between the robotic system and the patient. The performance of therapy robots is defined not by the ability of the system to accurately follow specific trajectories, but by their ability to provide the desired "feel" at the interaction point [7]. This paper presents a neuro-fuzzy compliance controller that emphasizes flexibility, adaptability, and usability in an attempt to appeal directly to the needs of therapists. The methodology proposed in this paper was developed as a platform-independent, model-based solution. A unique approach to the generation of behavioral rules is utilized which uses the human-patient interaction as a basis for the control behaviour in order to achieve an inherently human-centred design. This approach was taken to give the therapist the flexibility to perform a wide range of both established and emerging therapy techniques, using a variety of manipulator systems.

II. Neuro-fuzzy Compliance Control

In order to create a controller that is able to emulate the behaviour of a therapist as closely as possible, our approach utilizes a fuzzy-logic based inference system. Using a fuzzy approach enables the system to emulate the humanistic dynamics of traditional therapy more effectively than traditional control approaches by making use of model-based variable compliance. In addition, each unique exercise and each patient can take advantage of a unique rule base to better emulate each specific treatment scenario. Therefore, it should be emphasized that the system is not meant to replace the therapist, but to enable the autonomous treatment of patients at home or in the clinic.

A. Data Gathering

There are several considerations that must be paid due diligence during the data gathering stage including: 1) the need for a representative dataset, 2) the specification of appropriate protocols for handling exceptional circumstances, and 3) verification that there are no conflicting relationships contained in the dataset.

The need for a representative dataset is a fundamental requirement for all fuzzy modeling based controllers. The nature of fuzzy logic enables a fuzzy controller to infer appropriate system responses to undefined input values by extrapolating based on the behaviour contained within the system model. It is for this reason that fuzzy logic-based inference systems are widely applied in situations where a humanistic or reasoned approach is appropriate. However, if the universe of discourse defined by the fuzzy input space is too limited in its scope with respect to the input variables passed to the system during its application, the system will not respond properly when the input lies outside of the realm of knowledge. Therefore, in the case of knowledge based systems such as the fuzzy trajectory generator proposed in this paper, a dataset that contains a reasonably complete input space is essential to ensure that the system is able to react to all potential training scenarios in a controlled manner.

The specification of protocols for the proper compensation during exceptional circumstances involves the inclusion of situations within the experimental data that specify the proper system reactions during abnormal conditions. Given the interactive nature of the neuro-fuzzy training system, it is imperative that the system respond gracefully under exceptional circumstances, such as a large patient jerk or spasm to ensure the safety of the patient at all times. During the therapist training sessions used for the generation of the fuzzy rules, therefore, proper responses to unanticipated patient reactions should be recorded.

The confirmation that the therapist dataset does not contain conflicting behaviour is required to ensure that the system response is consistent and well defined. For this reason, it is important to specify a clear and consistent protocol for the therapy action taken during the data gathering stage. For instance, during the training sessions, the therapist must consistently lead the patient along the trajectory while providing consistent assistance. If the patient is allowed to lead, or "push" the therapist along the trajectory, then the interaction will result in two conflicting compliant conditions for the same measured forces. This is also the case if the therapist has allowed the patient to deviate laterally from the specified trajectory, and the resistive force applied by the patient is reduced without the therapist leading the patient back to the proper trajectory. In this case, both low and high force conditions will be measured corresponding to the same deviation from the desired trajectory. If the behaviour expressed by the dataset used to generate the compliance model is clear and consistent, then the ability of the fuzzy system to replicate the prescribed interaction when working with the patient is greatly increased.

B. Compliant Trajectory Generator

The purpose of the trajectory generator module is to generate the end-effector positions necessary to follow the position trajectory specified by the exercise, while providing a force-dependent level of compliance to the human-patient interaction. The fuzzy rule-base, thus, expresses the dynamics of the relationship between changes in the interaction forces measured at the end-effector and the resultant compliant position increment.

In order to provide a basis for the initial selection of the number of clusters c and exponent m, an iterative heuristic algorithm is used [8]. Once the appropriate initial conditions are obtained, the output space of the experimental dataset is clustered using the FCM optimization algorithm. Trapezoidal membership functions are then fitted to the output space based on the generated cluster centres. The output membership functions are then projected onto the input space using the fuzzy line clustering technique, to generate the appropriate input membership functions. To complete the fuzzy inference system, the Takagi–Sugeno–Kang (TSK) inference method is integrated into the system to determine the corresponding crisp outputs for each input set. This unique approach to the generation of fuzzy rules for compliant trajectory generation was proposed in [9] and is shown in Fig. 1 (Block A).

When the current forces between the patient and the robot, F_n, are fed back from the force transducer, they are compared with a corresponding desired interaction force, F_d, as specified by the therapist. The resultant force error, $F_e = (F_d - F_n)$, is then passed into the fuzzy trajectory generator module along with the desired trajectory position for the exercise in the task space. In order to reduce the influence of high-frequency noise inherent in the signal from the force sensor, a moving average of three consecutive measurements is used as a simple low-pass filter.

To reduce the complexity of the fuzzy inference system necessary to generate each compliant increment vector, three separate rule bases are used for each component of the consequent change in the end-effector position. The force errors across all axes are input into the fuzzy consequent layer in order to allow the fuzzy rules to evaluate the state of the system including any coupling between the forces acting along all axes. The control action of the fuzzy system for each rule base can be expressed linguistically as:

IF F_{ex} is B_1^1 **AND** F_{ey} is B_2^1 **AND** F_{ez} is B_3^1 **THEN** ∂pos is D_1
ALSO
… (1)
ALSO
IF F_{ex} is B_1^n **AND** F_{ey} is B_2^n **AND** F_{ez} is B_3^n **THEN** ∂pos is D_n

where n is the number of rules, $B_j^i (i = 1, \ldots, n, j = 1,2,3)$ and $D_k (k = 1, \ldots, n)$ are fuzzy sets over the input and output spaces, $F_e = \{F_{ex}, F_{ey}, F_{ez}\}$, and ∂pos is either ∂x, ∂y or ∂z depending on the rule base. The resultant trajectory point is then added to the desired trajectory position and the additional compensator position to generate the total position command to be passed to the manipulator servo controller. The overall trajectory generation scheme is illustrated in Fig. 1 (Block B).

C. Hybrid Neuro-fuzzy Compensator

The fuzzy rule base representing the compliance behaviour of the therapy action is structured as an outer-loop module to enable the trajectory generator to remain kinematically independent. This original schema addresses both the need for specialized human-centred systems designed for rehabilitation and the high cost of custom robotic manipulators. By enabling the proposed system to be applied to multiple manipulator configurations, the trajectory generator can be packaged as a self-contained software module to facilitate automated rehabilitation therapy using both custom and industrial manipulators with various degrees of freedom. However, in order to ensure that the system is able to replicate the behaviour dictated by the fuzzy rule base regardless of the dynamics of the manipulator, an additional

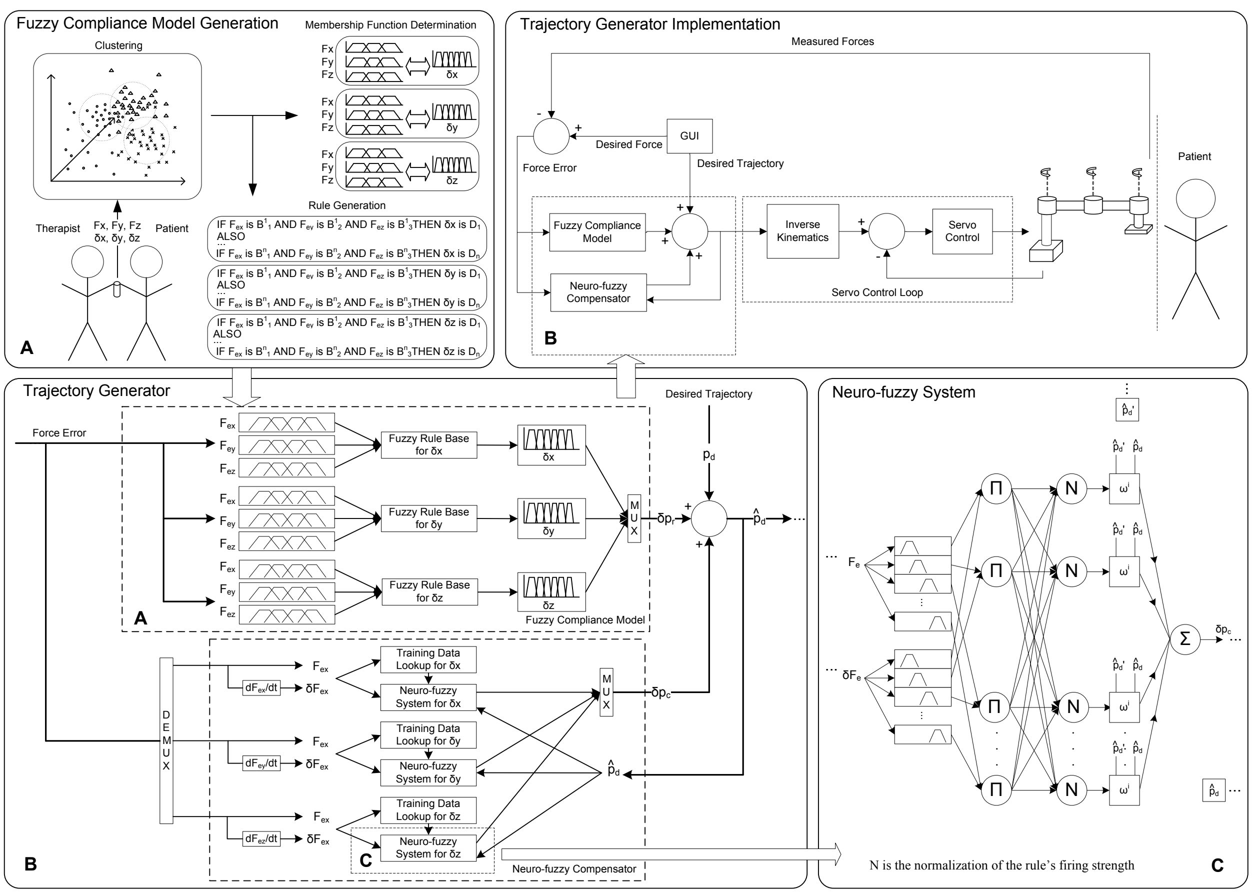

Figure 1: Neuro-fuzzy Compliance Control Methodology

control module was necessary. Several fuzzy impedance compensators have been proposed in the literature for industrial tasks to compensate for situations where the environmental dynamics are unknown and for parameter uncertainty [10,11]. To maintain a computationally-efficient system, a position-based fuzzy compensator was implemented based on the approach taken in [11]. This module provides an additional position correction to the trajectory based on the measured force error.

The task of the fuzzy compensator module is to generate additional position increments based on the interaction force measured at the end-effector in order to compensate for the difference in dynamics between the manipulator and therapist. Three separate inference systems are utilized, one for each position increment component, to allow the dynamic components to be independently tuned. Each module is implemented as a MISO fuzzy system utilizing TSK interpolation.

The antecedent inputs for each system are force and force increment along each respective axis. A rule base with n×m rules is used where n and m are the number of input membership functions for each input, respectively. To simplify the tuning of the resultant systems, constant consequents are used for each rule.

For example, the rules for the *x*-axis component of the fuzzy compensator can be expressed linguistically as:

IF F_{ex} is B_1 **AND** δF_{ex} is D_1 **THEN** ∂x_c is c_1
ALSO
… (2)
ALSO
IF F_{ex} is B_n **AND** δF_{ex} is D_n **THEN** ∂x_c is c_n

where *n* is the number of rules, B_i $(i = 1, \ldots, n)$ and D_i are the i^{th} antecedent fuzzy sets for the three inputs, respectively, and c_i is the consequent constant of the i^{th} rule.

Given the complex nature of the interaction between the patient and the manipulator system, a learning algorithm was integrated into the trajectory generator module in the final stage of development to form the hybrid neuro-fuzzy system shown in Fig. 1 (block B). The neuro-fuzzy algorithm, shown in Fig. 1 (block C), enables the system to autonomously tune the consequent constants in real-time to improve the performance of the system, and to compensate for changes in the manipulator configuration.

In the first stage of the neuro-fuzzy scheme, similar to the traditional fuzzy control methodology, the two crisp input values are assigned to the appropriate fuzzy sets and corresponding linguistic variables based on the trapezoidal antecedent membership functions. In the second stage the activation degree of each rule is calculated. The error signal between the model inferred value $\hat{P}_d$, and the corresponding training value, $\hat{p}_d^{'}$ is then evaluated and integrated into an objective function *E* which expresses the mean quadratic error of the system. The training value based on the experimental data is generated using a lookup table and a linear search algorithm of *O*(n) time. If the value is not found in the table, then the three closest values based on the input vector are averaged to generate an appropriate reference. The error is evaluated as:

$$E = \frac{1}{2}\left[\, \hat{P}_d - \hat{p}_d^{'} \right]^2 \tag{3}$$

where the model inferred value, $\hat{P}_d$, is the overall compliant position generated by the trajectory generator system, and $\hat{p}_d^{'}$ is the corresponding training value. The inferred response to the input vector X is consequently calculated as:

$$\hat{P}_d(X^{'}) = \frac{\sum_{i=1}^{n}\left(\prod_{j=1}^{n} B_j^i\left(x_j^0\right)\right)\omega^i}{\sum_{i=1}^{n}\left(\prod_{j=1}^{n} B_j^i\left(x_j^0\right)\right)} + \delta p_r + p_d \tag{4}$$

where ω^i is the weighted consequent rule conclusion, δp_r is the output from the compliance rule base, p_d is the desired trajectory point, and $B_j^i (i = 1, \ldots, n, j = 1,2,3)$ are the fuzzy sets over the input space. The algorithm utilizes the gradient-decent method to adjust the weight of the rule conclusions as a function of the objective function as:

$$\omega^i(t+1) = \omega^i(t) - \alpha \frac{\partial E}{\partial \omega^i} \tag{5}$$

where α is the learning rate. By calculating the variation of the objective function *E*, in relation to the variation that occurred in ω^i in the anterior instant, the adjustment of each conclusion value can be expressed as:

$$\omega^i(t+1) = \omega^i(t) - \alpha \frac{\left(\hat{P}_d - \hat{p}_d^{'}\right) d^i}{\sum_{i=1}^{n}\left(d^i\right)} \tag{6}$$

where d^i is the contribution of rule *i* to the final neuro-fuzzy inference. The adjustment to the weight of the rule conclusion can thus be interpreted as being proportional to the error between the model inferred value and the experimental value, weighted by the contribution of the rule to the overall crisp output.

III. System Implementation

In the first stage of the implementation of the trajectory generator, a number of experimental datasets were recorded during mock therapy sessions with a (healthy) patient. The data was gathered in order to generate a number of behaviour models using the fuzzy clustering procedure outlined in Section II. The position and force information was recorded using a six d.o.f ATI Mini45 force transducer, in conjunction with an NDI Optotrack® optical motion tracking system. A custom handle mechanism was designed to be mounted on the top of the force transducer interface, to allow the therapist to train the patient in the same orientation as the manipulator end-effector. Various two-dimensional circular and linear trajectories were performed to generate a representative body of data for different therapy actions. Three dimensional position profiles were not tested due to restrictions inherent to the manipulator, though the system is applicable as a 3D trajectory generator. The resultant position profiles were then compared with the ideal minimum-force desired trajectories to yield the corresponding force and position deviation data for clustering.

IV. Experimental Results

A. Preliminary Off-line Implementation

The objective for the application of a learning algorithm to the fuzzy compensator module was to improve the performance of the compliance control system without detrimentally affecting its computational efficiency. In order to first determine if the integration of the fuzzy compensator into a hybrid neuro-fuzzy framework would successfully improve the accuracy of the overall trajectory generator, the compliance rule base was tested with a manually tuned compensator. The neuro-fuzzy algorithm was then applied to the recorded compliant trajectories as an offline simulation. The output from the compliance rule base for each recorded end-effector force set was combined with the generated neuro-fuzzy compensator output to generate an approximation of how the system would have performed had the learning algorithm been present.

A comparison of the compliant positions generated by: a) the fuzzy compliance rule base, b) the compliance rule base combined with the fuzzy compensator to form the fuzzy compliance controller, and c) the neuro-fuzzy compliance controller is shown in Fig. 2a and 2b when applied to a linear trajectory along the manipulator x-axis. The results show that the error between the generated compliant position and the desired compliant position can be reduced by modifying the compensator rule base using a hybrid neural-network. Without the neuro-fuzzy schema, the manually-tuned fuzzy compensator merely adds an additional offset to the output from the compliance rule base as a function of the measured force.

B. Real-time Implementation

To demonstrate the feasibility of a real-time implementation of the proposed hybrid neuro-fuzzy schema, the neuro-fuzzy trajectory generator was implemented as a real-time module on an Epson E2L853 manipulator.

The performance of the neuro-fuzzy compliance controller while leading the patient along an x-axis trajectory is evaluated in Fig. 3a and 3b. The root-mean-squared (RMS) error of the (x,y) components were (14.47, 10.04) for the fuzzy rule base, (25.11, 30.86) with the manually tuned compensator, and (3.81, 5.08) for the neuro-fuzzy controller. The results indicate the ability of the neuro-fuzzy algorithm to better replicate the human-robot interaction, shown in the preliminary testing. According to the results shown in Fig. 3a, the manually-tuned fuzzy compensator actually had a detrimental effect on the performance of the system, in some cases driving the magnitude of the compliant position far higher than the desired position. To determine the influence of multiple compliant trends for the same force profiles, or "branches", the experiment was repeated with a refined reference dataset. The additional results are shown in Fig. 4a and 4b. Though the refined reference dataset did not influence the performance of the y-axis component of the system, the performance of the x-axis component improved slightly. It should be noted that the additional "branches" were not removed from the compliance rule base, which likely influenced the deviation in the compliance trend between 5N and 10N in Fig. 4a. The compliance rule base was not generated using single branch datasets to retain more robust control behaviour. The RMS error of the (x, y) components were (25.67, 15.33) for the fuzzy rule base, whereas for the neuro-fuzzy controller the errors were (5.44, 9.32). These results indicate that the neuro-fuzzy system is able to adapt a generic rule-base to a specific implementation or experiment. The specialization of the system using a general purpose rule base highlights the further potential for development of a library of generic fuzzy rule bases for a variety of diseases or levels of impairment.

V. Conclusion

A hybrid neuro-fuzzy compliance control scheme was proposed as a proper human-centred solution for rehabilitation robotics. The experimental results indicate that a robotic manipulator can replicate therapist behaviour by providing the prescribed level of compliance during a therapy action, though more experimentation is needed. The introduction of learning into the trajectory generator significantly improved the performance of the proposed system. The successful generation of several models of the human-patient interaction while performing a variety of exercises has confirmed the potential for a library of custom therapy rule bases. A modular approach to the rule base specification might provide a means to quickly and effectively alter the system parameters to appeal to a wide variety of exercises and levels of patient motor impairment.

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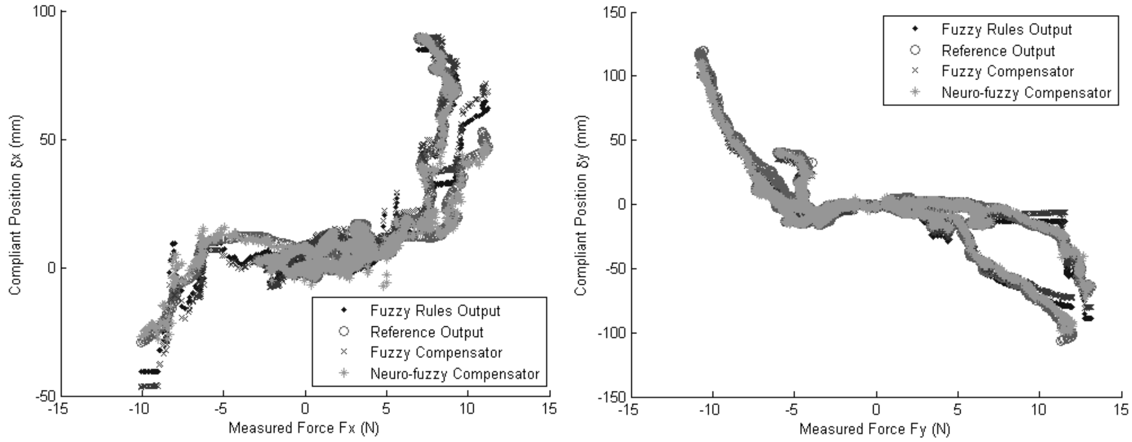

Figure 2: a) Learning Algorithm applied to: X-axis Rule Base, b) Y-axis Rule Base for a Linear X-axis Trajectory

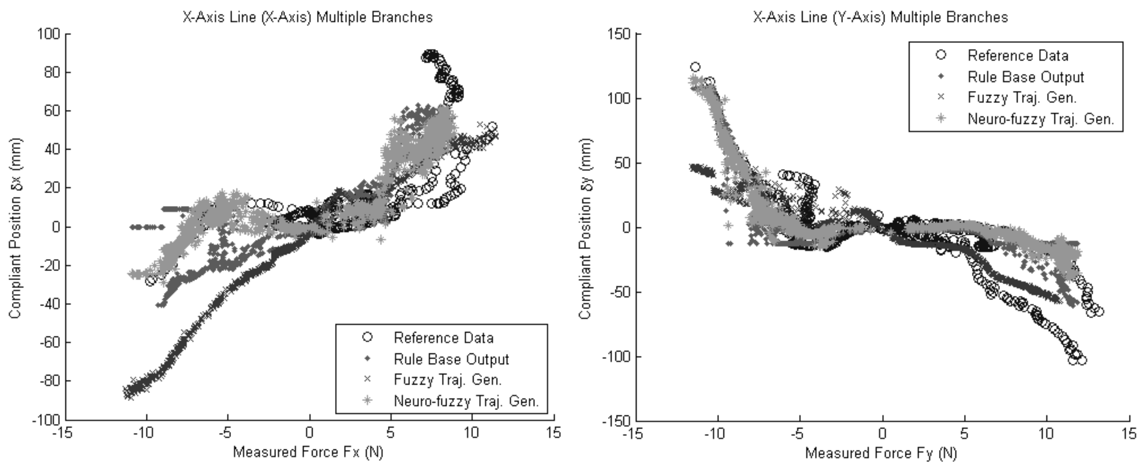

Figure 3: a) X-axis Comparative Results, b) Y-axis Comparative Results using Multiple X-axis Linear Trajectories

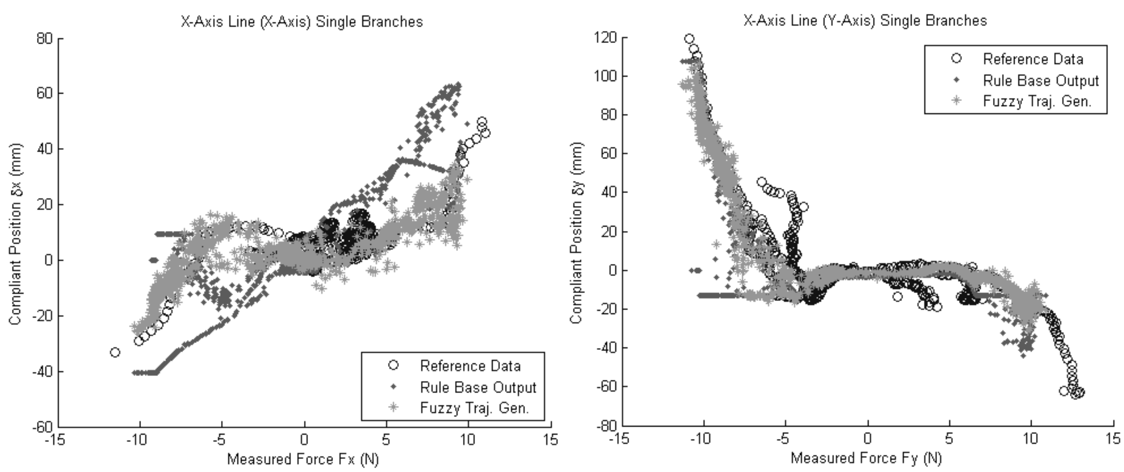

Figure 4: a) X-axis Comparative Results, b) Y-axis Comparative Results using a Single X-axis Linear Trajectory