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A neuro-fuzzy approach to real-time trajectory generation for robotic rehabilitation

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HIGHLIGHTS

- A neuro-fuzzy schema introduces compliance into the human–robot interaction to emulate a wide-variety of exercises.
- Implemented as a manipulator independent solution.
- Preliminary results indicate that the system is able to very closely replicate a generic patient–therapist interaction.

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ABSTRACT

This paper proposes a method for the design of a real-time neuro-fuzzy trajectory generator for the robotic rehabilitation of patients with upper limb dysfunction due to neurological diseases. The primary objective of the methodology is to assist therapists by allowing them to delegate repetitive therapy tasks to a mechatronic system. The trajectory generator is packaged as a platform-independent solution to facilitate the rehabilitation of patients using multiple manipulator configurations. The system 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. This approach also allows for the fine-tuning of patient specific behaviour using linguistic variables. The rule base for the system is trained using a fuzzy clustering algorithm and applied to the 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 robot–patient interaction. Preliminary results indicate that the approach can accurately reproduce a prescribed patient/therapist interaction, validating the proposed approach.

1. Introduction

Though a considerable body of research has been conducted in the field of rehabilitation robotics over the past decades, the commercial viability and widespread use of robotic systems for rehabilitation therapy are still very limited. This lack of large-scale commercially-viable systems has been attributed to several factors, the most significant of which are cost and usability, essentially non-technical issues. It is imperative to the development of a successful robotic rehabilitation system, therefore, to appeal to the needs of physiotherapists. Therapists are ultimately responsible for deciding whether a rehabilitation system is a worthwhile investment of their time and money [1].

The primary objective of the methodology proposed in this paper is to assist therapists by allowing them to delegate repetitive therapy tasks to a mechatronic system that is able to replicate the patient–therapist interaction as closely as possible. This approach aims to mitigate the cost and labour-intensive aspects of neurorehabilitation to improve clinical efficiency and efficacy [2,3].

The system was developed as a platform-independent, model-based solution. This approach was taken to give the therapist the flexibility to perform a wide range of both established and emerging therapy techniques, using a wide variety of manipulator systems. This can also serve to mitigate the costs associated with developing specialized rehabilitation platforms by offering a software framework that is compatible with off-the-shelf industrial manipulators.

The fundamental design challenge for robotic rehabilitation therapy is the replication of the complex movements with resistive and/or assistive forces applied at specific positions associated with traditional physiotherapy. 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 movement. Since during rehabilitation, the patient is also a part of the dynamic system, traditional control parameters are difficult to develop based on the system model and its parameters [4].

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Impedance control, which is well established in the field of rehabilitation robotics [5], allows for variable deviation from a given limb trajectory while keeping the limbs within a predefined range. One of the most prevalent forms of impedance-based force control in rehabilitation robotics is adaptive impedance control [6,7]. In adaptive impedance control, the human represents a component of the control system that influences its behaviour. This enables the control structure to adapt to changes in the reference trajectory initiated by the patient to regulate the interaction forces between the patient and the manipulator system.

Though adaptive impedance control has become the standard method of robotic force control for rehabilitation, there remain some fundamental shortcomings inherent in the approach. The complexity of the traditional control approach dictates that changes in the environmental dynamics require significant tuning and parameter alteration. Once a control system has been tuned to perform a specific exercise with a specific patient, the system parameters must be altered and tuned by an expert if the therapist wishes to change the way the exercise is performed.

An approach to the implementation of force control that is able to inherently overcome the difficulties associated with impedance control is through the use of fuzzy logic [4,8–10]. 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. The control parameters can also be tuned quite easily to modify specific aspects of the interaction.

The traditional approach to the generation of the rule base for fuzzy rehabilitation systems does, however, create 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. To overcome this limitation, our methodology utilizes fuzzy clustering and a hybrid neuro-fuzzy schema to generate a representative model of a wide variety of force–position profiles.

2. Material and methods

In order to create a system that is able to emulate the behaviour of a therapist as closely as possible, our trajectory generator 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.

2.1. Data gathering

The first stage in the generation of a fuzzy model of the patient–therapist interaction is the acquisition of a suitable dataset. 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 modelling 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 responds 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 prescribed.

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 compensation. 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.

2.2. Fuzzy clustering

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.

The first stage in the application of the proposed methodology is to create a representative rule base using clustering. In order to provide a basis for the initial selection of the number of clusters c and exponent m, an iterative heuristic algorithm described in [11] is used. Once the appropriate initial conditions are obtained, the output space of the experimental dataset is clustered using the FCM optimization algorithm. Using the unlabelled data $X = \{x_1, x_2, \dots, x_N\} \subset \mathcal{R}^h$, where N is number of data arrays and h is the dimension of each data array, clustering can be viewed as the assignment of labels c to the arrays in X. The problem of fuzzy clustering is thus expressed as the problem of finding the optimum $(c \times N)$ matrix of membership values $\{u_{ik}\}$, $U = [u_{ik}]$. The FCM