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A radial basis function neural network adaptive controller to drive a powered lower limb knee joint orthosis

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This paper deals with the rehabilitation purposes using an active orthosis driven by an adaptive neural controller based on a radial basis function neural network (RBFNN). Two essential conditions are required in our study: ensuring the wearer safety and the good trajectory tracking. We consider for our experiments the same movements often recommended by the doctor during therapy sessions. In this context, it is possible to add some trivial prior knowledge as the dynamic model structure and all dynamical identified parts. The unknown or the uncertainty part of the inertia term of the knee-shank-orthosis system is identified online using an adaptive term. All other uncertainties or unknown dynamics are identified online by the RBFNN. The Lyapunov approach has been used to derive adaptation laws of the neural parameters and the inertia term. These adaptation laws ensure the stability of the system composed of the exoskeleton and its wearer. The wearer can be completely inactive or applying either a resistive or an assistive effort. Experimental results have been conducted on a real exoskeleton that is used for rehabilitation reasons. Based on these results we conclude with the effectiveness of the proposed approach.

1. Introduction

Exoskeletons are increasingly developed in the literature and are designed to solve several problems that may be encountered by humans [1–3]. In fact, every person is not immune to an accident or a pathology causing him a partial/total impairment of its movement. He can become paraplegic for example [4–6]. Exoskeletons can be used to reduce the degree of dependence with regard to this kind of situations. They are also used in the field of rehabilitation of lower and/or upper limbs. Out deficiencies that can happen to human, exoskeletons can be used to improve comfort and assist him in its various daily tasks (gardening, carry heavy loads, climb stairs, walk longer, etc.). An exoskeleton may concern a single part of the body (arm, knee, pelvis, etc.) or it may concern several parts of the body at the same time (both feet with the pelvis for instance). Exoskeletons have been considered for several purposes and we summarize here some of them. The Tokyo University of Agriculture and Technology has designed an exoskeleton to assist its wearer to realize farming work that is considered as tough. In the context of military applications, Hercule has been developed in the goal to improve the performances of soldiers. Moreover, one can find in references [7–9] a good state of the art on exoskeletons and their applications.

Generally, it is not possible to establish an accurate dynamic model that takes account of dynamic changes related to the wearer's desired movements. Indeed, the wearer can be completely inactive or apply either an assistive or a resistive torque. On the other hand, the exoskeleton can be used for rehabilitation of a class of humans, which have different morphologies and haven't the same behavior. In the goal of considering these situations, adaptive controllers represent one of several solutions widely studied in literature [10–12]. Training techniques like neural networks are ones of those considered in designing of these adaptive controllers [13,14]. In the work proposed previously in [15] using Multi Layer Perceptron Neural Networks (MLPNN), we have considered the system as a black box. Consequently, the MLPNN inputs are composed

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of joint position, joint velocity and joint acceleration. In the goal to reduce the control complexity, we have ignored the acceleration from the MLPNN inputs considering the possibility to reconstruct it implicitly. On the other hand, the convergence study concerns only the joint position and the case of a priori knowledge has not been discussed. Concerning the new proposed approach in this paper, which is of grey box type, it allows to separate inertia dynamics from the other dynamics as frictions, gravity, etc. The used neural network is of RBFNN type and no linearization is needed to get adaptation laws and the measure of the acceleration is not needed. The stability study of the system in closed loop concerns both the joint position and the joint velocity. In addition, the proposed controller algorithm makes it possible to introduce any prior knowledge. In [16], a RBFNN and composite learning is used to propose a precise position control of tubular linear motors. Uncertainties such as friction and other electro-magnetic phenomena are approximated using a RBFNN, which is trained online using a learning law based on Lyapunov approach. Compared to other approaches in literature, this approximation method uses a composite adaptation law based on a model prediction error and the tracking error. Generally, if there is some prior knowledge relative to the system dynamics, classical adaptive approaches can be used adding a robustness part that takes into account any other unmodelled dynamic. Adaptive techniques offer the possibility of adaptation to any changes that can happen during the use of the system. For instance, one can cite servo systems [17], inferential sensors [18], networks [19], etc. In the neural connectionist techniques, controllers can have fixed or adaptive parameters. For fixed parameters neural networks [20], a robustness term is often considered in order to take account of dynamic changes. Whereas in adaptive parameters neural networks, we use adaptation laws that can, for instance, be derived from the system's overall stability study [21]. The advantage of neural networks is the possibility of incorporating some prior knowledge about the system to be controlled. Indeed, the dynamic model structure of robotic systems is generally known, which allows us to associate to neural networks, adaptive control approaches that have proven efficient. Also, we can consider any prior identified part about the dynamic model and add it without any problem into the controller scheme. The neural network by its characteristic of universal approximation has to identify other non-identified dynamics only and that can change while executing movements. By this manner, any undesirable behavior is avoided and the adaptation step is very little and we can simply neglect it because it has no effect on the wearer of the orthosis, which necessitate a high security.

In literature of artificial learning tools, it has been proven that both MLPNN and RBFNN can approximate any unknown nonlinear function [22–24]. These connectionist tools have widely been used in the area of nonlinear control systems [11,25]. Unlike a MLPNN that has the characteristic to learn globally, a RBFNN has the property to learn locally and for this reason it can have a very faster convergence. In the case of systems having a reduced number of entries, RBFNNs are better suited for the approximation procedure [26]. In [27] other advantages of the RBFNN compared to the MLPNN, as its rapid convergence for instance, are also given.

In this paper, we consider the problem of controlling an orthosis intended to the knee joint rehabilitation. Our solution for this problem is based on RBFNN with only the knowledge of the structure of the dynamic model of the system. It is also possible to include in the proposed controller, a nominal model representing all other knowledge on the system. This can be done without affecting the stability of the closed loop system. This article is an extension of the simulation work published in [28].

The paper is organized as follows: Section 2 presents the knee-shank-orthosis system modeling, its structure and the dynamics to be approximated by the RBFNN. Section 3 explains the neural approximation principle and the activation functions. In Section 4, we give an analysis that can be useful for any work of identification of dynamic parameters of the system. However, our approach does not require identification results. In Section 5, the proposed RBFNN controller and the stability analysis of the closed loop system are detailed. Section 6 deals with the experimental results and their analysis. Finally we conclude in Section 7.

Fig. 1. EICoSI (Exoskeleton Intelligently Communicating and Sensitive to Intention) of LISSI laboratory worn by a healthy subject.

2. Active orthosis system

A person wearing the orthosis in a sitting position with the shank freely moving around the knee joint represents the considered system for our experimentations. The orthosis is composed of two jointed segments, upper and lower. The actuator and the mechanical part are placed on the upper part of the orthosis. The torque generated by the orthosis permits to realize flexion/extension movements of the lower part composed by the shank of the wearer and the lower part of the orthosis. For security reason, the knee joint is constrained by a range of motion between 0° and 135°. In Fig. 1, we present a wearer of the orthosis in standing position.

2.1. Electrical part

The joint of the orthosis is actuated by a brushless DC motor (BLDC). A power supply and an adequate electrical system are used to provide the regulation for the current in the motor. A mechanical transmission is used to increase the orthosis applied torque. Fig. 2 shows the schematic diagram of the used electromechanical system.

According to regulation system characteristics of the BLDC motor and as the time constant of the electrical system is unimportant compared to the mechanical time constant [29], we can write the following equation:

$$\tau = \beta_m u \tag{1}$$

where u is the electrical current of the BLDC motor, τ is the applied torque and β_m is a positive constant.