Pathological Sit-To-Stand Predictive Models for Control of a Rehabilitation Robotic Device

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Abstract—**The aim of the work presented in this paper is to realize the model for the control of a robotic interface for equilibrium assistance during sit-to-stand transfer.**

Interactive robotic devices designed as human-centered robotics, can give more comfortable and more efficient solutions than traditional technical devices. One supposes the need of a virtual model of the pathology. This model, called observer, aims at being used in the smoothing control part of this assisting device. A useful property of this observer should be a postural prediction ability.

This article presents a study of different neural solutions : a Neural Predictive Observer (NPO) and a Reduced Neural Predictive Observer (RNPO). Records used for the learning have been done from healthy people that stand up normally and quickly. Some tests will also be done in patients with cerebellar syndrome disease.

The presented experimental results show the good accuracy of these approaches whatever the speed of the movement.

I. Introduction

This work concerns the control of robotic devices interacting with patients during rehabilitation training.

The interaction between the assisting device and the patient can be considered as a control loop (cf. fig. 1). In this case, the *patient* is assimilated to an unknown system and the robot to an actuator regulating disorders. The stabilization is obtained comparing the patient's state with a physiological trajectory generation [1]. Our aim is to improve the human-robot interaction. Some classical approach to improve a control is to include a predictive observer in the control loop.

This article will focus on the design of predictive models for STS trajectories in joints space of both diseased and healthy subjects. The different models will have different input vectors (i) but they always return computed joint trajectory ($q*$) (cf. fig. 1).

The particular device studied is a robot [2] helping for STS (cf. fig 2). Composed of two degrees of freedom independent handles on an active mobile platform, this robot can interact with a person during the STS motion and also all along the gait.

The kind of control we wanted to evaluate on this device concerns only the sagittal movements that is the reason why we will reduce the Sit-To-Stand (STS) modelization to a 2 dimensional problem (fig. 6). We suppose that the lateral motion is reduced by the handles grasping.

The STS transfer (fig. 7) is a complex motion that combines the sensori-motor action with a fine regulation all along the process. Diseases that affect this movement are very often pathologies concerning the regulation which is usually considered as the cerebellum role.

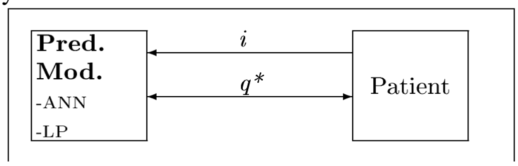

Fig. 1: Control System Overview

One of the main problems that must be solved to implement a model based controller depicted in fig. 1 is that there is not any suitable model for healthy and/or cerebellar disease movement. Focused on STS trajectories, models presented in this article are used inside the assistive device control during an STS transfer for diseased subjects. An Artificial Neural Network (ANN) based modeling are used, the structure of which has been designed as an intermediate solution between complex models developed in neuroscience \cite{manto}, \cite{albus}, \cite{schweig} and simplistic solutions often used in robot control \cite{kuo}, \cite{zmp}. As a result, the proposed models will be studied for the following properties :

- Generalization : the model performs equally for normal speed STS as for fast one.
- Specialization : the solution must be able to fit an individual disease expression.
- Disease ability : the best solution will be tested on diseased trajectory.

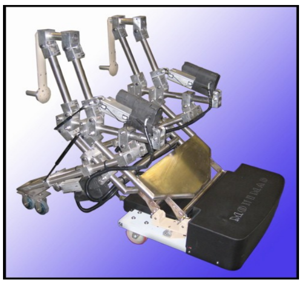

Fig. 2: MONIMAD

II. Method

A. Artificial Neural Networks

i. Description

ANN are commonly used in literature dedicated to problems involving some behaviours that are not polynomials and must be learned. This software structure (fig. 3) is composed of many artificial neurons. It is organized in layers. The first layer is directly connected with the inputs of the system, the last layer represents the outputs of this structure and the layers between are called hidden layers.

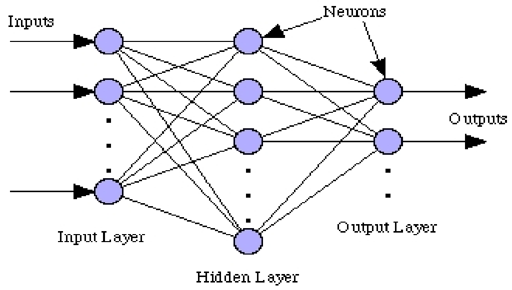

Fig. 3: Neural Network Structure

The artificial neuron is a computer implementation of the neuron behaviour. Indeed a neuron is an integrator of signals, and the result is an activation of the neuron
which is transmitted on the axon. The artificial one (fig.\ref{fig:AN}) is composed of weighted inputs(w), an integrator which is a sum ($\sum$) and finally an
activation function (\textit{f}) computing the output ($axon$).

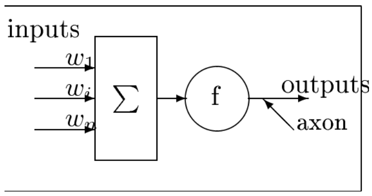

Fig. 4: One Artificial Neuron

ii. Non-linearity

One of the motivations of this choice is the ability of this method to work through some kind of non-linearity. Simple examples of non-linearity are movement discontinuities : when a person pulls up a foot, or when he or she falls. Other kinds of discontinuities are singularities in the kinematics model. These singularities can be found in some particular configurations. Therefore, it is important to choose a method that deals with these problems.

In a classical mechanical approach, the trajectories of a system are considered as polynomial functions. It is often considered as a good approximation. ANN are able to generate non-polynomial solutions. It could be interesting to see if this property can be an asset for the solution accuracy.

iii. Learning

The flexibility is defined as a system ability to solve particular problems without changing its structure. In the proposed solutions, flexibility is one of the most
important things that leads to the choice of learning based approach. As it is mentioned
in the introduction part, a particularity of the gait and STS diseases, is that they
require a solution adapted to each person. ANN seems to be the best way to achieve
this goal.
In the studied cases, the activation functions will be hyperbolic tangent f.
The approach in the edge of neuroscience and robotics motivates the choice of a classical learning approach in ANN domain based on back-propagation \cite{leven}, \cite{nn}.
This learning method is also based on the relation :

$$g=\sum w_{s,i}\cdot g_i \qquad \text{\{eq:NN\}}$$

where g is a vector of precedent layer outputs (g_i) and w_i are the weights of the links and i is the number of the current layer. The weights learning (w_i) is based on a gradient back-propagation expressed as the expression (\ref{eq:grad}):

$$w_{s+1,i}=w_{s,i}-\alpha\cdot LG_s \qquad \text{\label\{eq:grad\}}$$

with s as learning step, α as learning rate and LG_s as local gradient.
Local gradient is computed with the back-propagation algorithm and the computation basis in each step k is a cost function gradient expressed for each output. The back propagation learning tries to minimize the Neural Network (NN) objective function (*fc*). This function (*fc*) is a simple Root Mean Square Error (RMSE) between the desired trajectory ($\dot{q}$) and the NN outputs (q).

iv. Motivation

According to the literature, an ANN is able to fit the considered problem of prediction. But there are few works dealing with the ANN dimensions. In this lack of information case, problems like overfitting can occur. Indeed the work presented in \cite{agnn} describes a method to generate Functional Electrical Stimulation(FES) patterns but the obtained structure is not studied. So the understanding of how and why the ANN solves the problem is very difficult in this case. That's the reason why this paper puts the stress on the results accuracy and in the description of the ANN.

B. Neural Predictive Observer

As noticed in figure 5, the only difference between inputs and outputs is the time reference. Indeed the outputs are angular forward values of the inputs. For the learning process the database is a set of angular values of one kind of STS: normal and fast. Those initial values are used in the initial process which is the learning of the neural network represented on figure 5 with a dashed line.

The NPO can be represented as in figure 5, q(k) is a vector composed of the three angular values (ankle, hip and knee values) at instant k and boxes named d are delay functions.

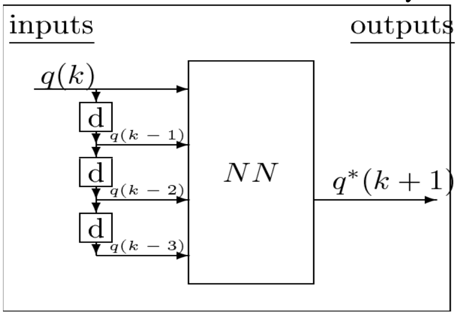

Fig. 5: NPO Structure

The NN inputs size is q(k) size multiplied by sliding window size : 3xBW (Backward Window is a scalar value defining the time sliding window size). For each input in one STS trajectory learning, only 3 new values are given. Others values are obtained from the last inputs with d. This NN provides in each step the three angular values in forward time : q*(k+1).

So, the angular values prediction is used in the postural state evaluation.

C.Linear Predictor (LP)

As we know, there is no predictive approach for human STS movement. So we describe a Linear Predictor (LP) in order to have a comparison point. This LP is a simple linear extrapolation. The aim of a linear extrapolation is to define the two parameters of the line, a and b in relation (\ref{eq:line}):

$$y_k = a.k + b \qquad \text{\label{eq:line}}$$

This is obtained with a pseudo-inverse (noted with symbol $^+$) of the last parameters of the BW as shown in expressions (\ref{eq:LP}):

$$\left\{ \begin{array}{c} u_k = [k\ 1]^T \\ D_k = [u_{k-BW} \dots u_k] \\ Y_k = [y_{k-BW}\ \dots\ y_k] \\ D_k^+ = D_k^T \cdot (D_k \cdot D_k^T)^{-1} \\ AB = Y_k \cdot D_k^+ = [a\ b] \\ y_{k+1} = AB \cdot u_{k+1} \end{array} \right\} \qquad \text{\label{eq:LP}}$$

D.Conclusion

As far as we know the three models presented here have not already been presented in the control of assistive devices for the STS movement. We also chose these modelling approaches to show different ways that can be used in model-based control. A good trajectory generator is able to define a joint trajectory set that is similar to the real action and in this case we can look at the next trajectory values to choose the best control action. In one way the trajectory generator is the ideal predictive system. We then define two kinds of predictors, one neural based and another which is a simple linear extrapolation.

According to our control solution in figure \ref{fig:ConDesc}, we can see that the model outputs will go in a ZMP box. This box represents dynamical computing to obtain the position of the Zero Moment Point (ZMP) well described by \cite{sardain}. The ZMP* box describes the desired ZMP coordinate (X value in our 2 dimensional mechanical model presented in figure 6) for the patient which should be right in the middle of the sustentation polygon. TrajRob* is a box representing physiological trajectory investigated in [1]. In this control scheme, each defined model can give an asset for our control structure because of its predictive ability. We can define two main reasons why a predictive approach is an improvement in our control.

The first reason is a conceptual one : in a falling movement or another dangerous movement, having information the earliest in advance gives the most time to let the robot react in order to help the patient. A second reason is a technical one : all mechanical devices can be considered as a low pass filter, so having good predictive information reduces the latencies in its control.

III. Application

A.Biomechanical model

Since handles are grasped, we reduce the motion to a 2 dimension one. The subject movement is equivalent to a three rotations plane robot \cite{zajac}, the main reason for this simplification is that it is supposed that the feet are not moving during the STS.

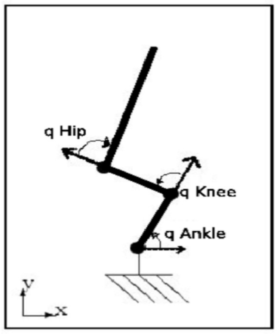

Fig. 6: A Three Link Model

In this condition, it can be considered that the feet are considered sealed with the ground. All the more, ankle joints can be reduced to a one rotation joint, in the same way the hip and the knees are both reduced to a rotation joint. Finally the system can be considered as three rotations plane robot.

From the 3-bar mechanism (fig. 6), the dynamical model is determined according to classical equations (eq.\ref{eq:MDD}), *q(t)* represents the vector (3X1) of the 3 angular values, *H(q)* is the 3X3 mass matrix , $h(q, \dot{q})$ is the vector (3X1) of Coriolis and rotation effects and *C(q(t))* is a vector of gravity terms.

$$\begin{gathered} H(q)\ddot{q}+h(q,\dot{q})+C(q(t))=\tau+J^T\lambda \\ q_{min}\leqslant q\leqslant q_{max} \\ q(t_0)=q0,\ q(t_F)=q_F \\ \dot{q}(t_0)=\dot{q0},\dot{q}(t_F)=0 \end{gathered} \quad ()$$

As far as it is not a redundant system, there is no need of Lagrangian coefficient :

$$J^T\lambda=0$$

B.Data acquisition

Fig. 7: Sit-To-Stand Movement

Records (fig. 7) on healthy persons are performed with goniometers placed on ankle, knee and hip of the right leg. Statistical informations concerning the goniometers are presented in table \ref{tab:StatGonio}, where SD is the Standard Deviation and Max represents the maximum error. The persons were asked to stand-up normally with arms crossed on their chest. They were also asked to stand-up as quickly as they can.

units	*SD* rad x 10^(-2) [rel.(%)]	*Max* rad x 10^(-2) [rel.(%)]
hip	0.32 [1.17]	0.54 [1.96]
knee	0.18 [0.16]	0.50 [0.45]
ankle	0.20 [0.09]	0.01 [0.23]

Table 1: Goniometers Statistical Information

Concerning the diseased people, records have been taken with a motion capture system developed by Motion Analysis. This system gives the position of some points. So a geometrical model is used to reconstruct the angular values. This reconstruction can cause some discontinuities, so we have to be aware of those problems in the results interpretation.

C.Generalization

In this paper, it is considered that if the observer keeps a good accuracy in normal speed and in fast speed, then it is able to keep it all along the speeds between those two extrema. It has been decided to look at the speed of the movements as a proof of generalization of this approach.

D.Specialization

In this paper, it is considered that if the observer doesn't keep a good accuracy between two persons STS, the model show a good specialization ability. Using NPO or NTG should be interesting only if this method may be specialized for one person and if it can have a good accuracy in all the situations used.

E.Learning process

For these tests, learning for NPO is done with all the data from one person at one given speed from which 2 verticalisation are withdrawn one for validation and the other for evaluation. The database is composed of movements from one person in normal speed (9 records) and in fast speed (11 records).

For NTG, learning database is composed of only one STS motion, because we try to be similar with the KUZE, the method that we used for comparison.

First, the results will be studied in the same speed field of data. Then, a cross test will be performed in order to know if a network which learns a normal (resp. fast) STS trajectory can observe a fast (resp. normal) movement.

Indeed this solution should be able to identify an STS for every speed.

IV. Results

A.Generalization

This section puts the light on a comparison between LP, NPO in the generalization point of view. In this paper, a method is considered with ability to generalization when it can keep a comparable accuracy when it is tested on another speed database. Figure \ref{fig:ResPredRapid2Lent} presents outputs of NPO learned on fast speed applied to normal speed data, it is interesting to notice the similarities between NPO outputs and real values whereas the learning is done on another speed database. LP is also performing good results in the different speed databases.

units	LP rad (%)	NPO rad (%)
Normal	0.0001(0.0041)	0.0037 (0.159)
Fast	0.0001(0.0041)	0.0030 (0.128)
Fast to Slow	0.0001(0.0041)	0.0024 (0.099)
Slow to Fast	0.0001(0.0041)	0.0021(0.0859)

Table 2: RMSE and MAE of the best NN for two speed

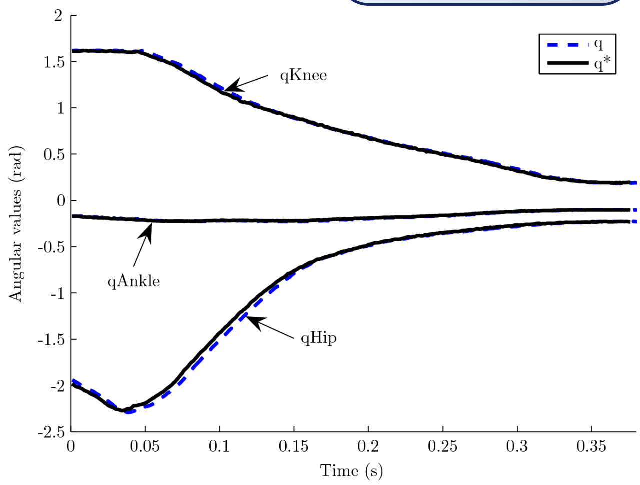

Fig. 8: Real angular trajectories and neural network output for a normal STS

B.Specialization

In order to show the specialization of this approach the best NPO learned with data of person A has been evaluated on four STS records of person B. As presented in table \ref{tab:res4}, it can be noticed that the RMSE are ten times higher than the learned one. It is very interesting because we can say that the NPO solution has learned only one person's STS behavior with good accuracy. The NPO is looking for a solution defining a virtual model of this person.

The general definition of LP doesn't allow any specialization. As far as it is defined as a minimum error straight line that fit the precedent values. So there is no defined parameter that concerns individual motion expression.

	1	***2***	***3***	***4***
NPO	0.0383	0.0299	0.0282	0.0177
LP	0.0001	0.0001	0.0001	0.0001

Table 3: Results on STS trajectories of other person

C.Minimum Inputs

LP seems seems to be the best solution concerning our problem but if we take a look on ANN properties, we know that ANN have parsimony ability, property that can be used to improve NPO in inputs number point of view. This improvement is done with a partial autofeed approach called Reduced Neural Predictive Observer (RNPO). A complete autofeed with a predictive system will take all the outputs as new inputs for the next result. A partial one will take only some outputs. In our case, we made the autofeed with q_{Knee} and q_{Ankle}.

q_{Hip} is already given from the database. It can be noticed that the number of inputs decrease and the results presented in table \ref{tab:resNPODiab} stay with a good accuracy. This accuracy is also shown in figure \ref{fig:Diabolo2in}.

units	***NPO*** rad (%)	***RNPO*** *rad (%)*
Normal	0.0037 (0.159)	0,0090 (0.387)

Table 4: RMSE Comparison between NPO and RNPO

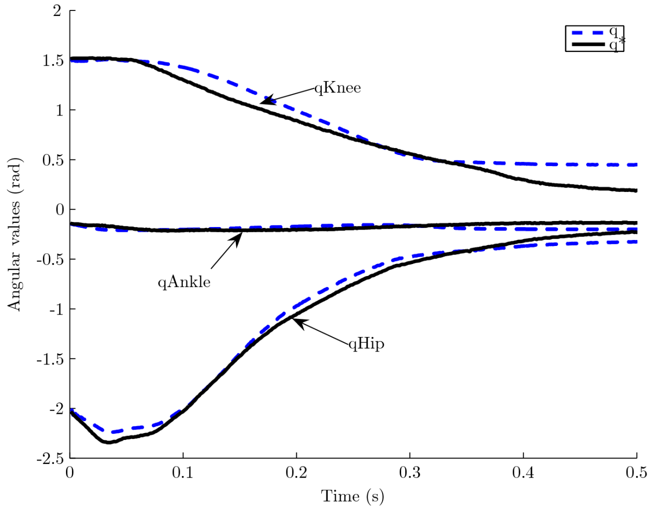

Fig. 9: Real angular trajectories and neural network output with RNPO

D.Disease Ability

In our point of view the best neural based solution is the NPO. Because of its accuracy, specialization and ability in data reduction, we decided to evaluate this neural structure on diseased patients. In table \ref{tab:res6} and in figure \ref{fig:NPOPat4}, we can notice that this structure is suitable for diseased motion. It is remarkable to see that LP also gives very good results on this pathological trajectory.

	Patient 1	***Patient 2***
NPO	0.0023	0.0025
LP	0.0001	0.0001

Table 5: RMSE Results for NPO and LP with patient 1 and 2

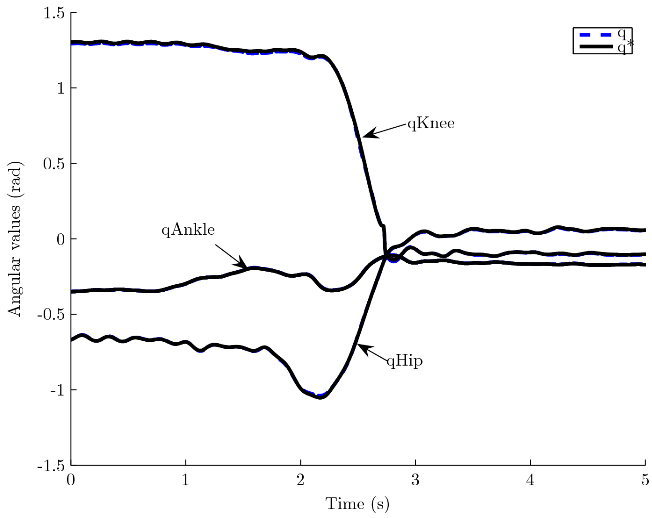

Fig. 10: Real angular trajectories and neural network output for cerebellar patient 2

V. Conclusion

In this paper, we present predictive modelization methods . First, we demonstrate that a neural approach can fit this kind of problem.
In addition, we studied 2 different prediction approaches: neural and linear. Specialization and reduction properties excepted, the LP seems to be the best approach for the frequency used (100Hz), with as an asset the fact that we don't need any data to define this prediction model. As far as we consider that we want this structure to be used in rehabilitation devices, we need an approach that is a representation of the pathology, because the model also aims at being used as an evaluation system. According to this critical property the NPO is usefull as a model based control of rehabilitation robotics. All the more,
we show in this paper that ANN parsimony abilities can be used to reduce the number of inputs. That means we can develop some strategies with a minimum number of inputs which is for the moment one angular value. Indeed, the smallest sensor number we take on the subjects gives the simplest and the most applicable process in real applications.
Those are the main reason why we will continue with the Neural Based Approach. Following this realistic approach, we can notice that many learning results obtained are done with less than ten STS transfers and need only a few minutes to be computed (10-20mn).
This is another positive argument to consider that a neural based approach is realistic to be used in the control of an assistive device.
We evaluate these different methods in a fixed frequency. We will study the sensibility of this parameter in our different methods.
We develop some neural based solutions to predict human motion, the future work will deal with the application of these model in a complete assistive control that identify posture and interact with the patient to help them.

VI. References

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