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# Approaches and Learning Phases for a Robotic Adaptive Deambulation Task

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**Abstract**— The elderly part increases each year and their needs on technical aids represent a great challenge for robotics. This article presents a study about a mobility aid system integrating robotics and learning adaptive control. The particularity system depends on using of an auto-adaptive interface that improves the interpretation of the patient driving actions. The experimentation results show the advantage of such an approach for a deambulation task. We present, in this paper, two methods for an adaptive deambulation mode to the person.

**Keywords**— Mobile Robotics, Neural Network, Adaptive Control, Interface Human/Machine, Handicaps, Technical Aids.

## I. INTRODUCTION

According to the French National Institute for Statistics INSEE (Institut National de la Statistique et des Études Économiques)[1][2], the mean lifetime expectation in France is 75.2 years for men and 82.7 years for women. Lifetime increased with 3.5 months in the year 2000. The same trend is observed in many developed countries. Furthermore, according to the "Canadian Review of the Ageing": Autonomy represents a fundamental value that elderly place ahead of life itself [3].

The loss of autonomy is the main syndrom of geriatrics and is responsible for almost half of the total health spendings (the population over 60 years old represents more than half of these spendings). Robotics could allow these old and/or disabled persons to retrieve part of their autonomy, avoiding an undesired and often apprehended hospitalization. This solution has a double benefit : firstly a satisfaction of these people recovering a part of their autonomy, and secondly a substantial reduction of the cost of hospitalization or admission in specialized houses.

Many laboratories working on robotics have already begun to develop and to work on such new applications of the cooperation between human and robot by technical aid. Particularly, in the field of mobile robotics : powered wheelchairs, intelligent sticks and service robots [9][5][6][7][8][4]. Most studies are focused on means to strengthen the movements of these people and on the simplification of the controls (Interface, sensors, automatic processes). Our works are focused on the adaptation of the system to the specific needs of a patient in the aim of keeping the human most actively in the processus. Then, the system must adapt itself to the particularities of the patient and not the opposite. It is important to improve the understanding of the robot to the user's orders, even if these are sidesteps, perturbed, or not completed. Our findings show two sides for this adaptation.

- a "behavior adaptation" side which allows to take the way of the person driving into account.
- a "structural adaptation" (or "biomechanical" side), which takes the physical particularities of the person into account.

The behavior adaptation procedure can be realized using a number of formalisms of adaptive control based on neural networks, fuzzy logics or expert systems. In this article, a study on behavior adaptation based on neural technics for a robotic walker is presented (fig. 1). The benefits of these technics are multiple : they are noise robust. They can be easily integrated in on-board real time process and they are remarkably efficient for learning some non-linear system and/or not determined models like human actions (they are universal approximator [12] and possess the parcimonie property [14][13]).

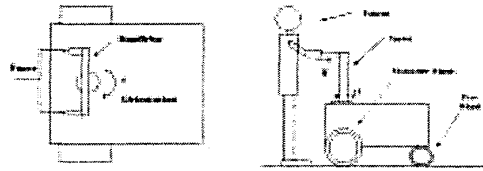


Fig. 1. Principle of Robotic Walker

Waiting the construction end of a robotic walker, we use one realized from a reconfigured mobile robot. A turret, which is able to revolve around a vertical axis and is equipped with an orientation sensor, has been fit to the robot (fig. 1). On this turret, handlebars with a force sensor have been mounted. Only these two information sensors were interpreting the orders. The interest of this approach is the utilization of neural networks which allow, with their generalized properties, the realization of this complex task with a minimal sensor configuration.

This paper is divided in four parts. The first part introduces the control architecture and the neural network used in this application including our proposed learning methods. The second part is about these learning phases of the patient behavior. The third part presents experimental results of the two approaches in the evaluation phase. Finally, in a fourth part, we conclude and discuss possible perspectives of such an approach.

## II. CONTROL ARCHITECTURE

### A. Neural Approach

To learn the driving way of the patient, an adaptive controller named ACANN is used. This architecture is an on-board software kernel which monitors and controls the learning and executive phases. It insures the correct information management and communications between the patient (handicapped and/or old person) and the walker (figure 2).

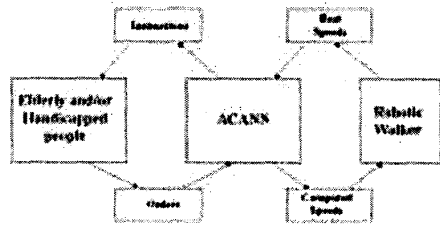


Fig. 2. Neural Control Architecture

ACANN integrates a process based on the multi-layers Perceptron Neural Network. The neural controller can be seen as an auto-adaptive control system based on the minimization of a cost function (gradient back propagation) which use a robot behavior model (figure 2). ACANN uses a modified version of the software Matrix Back Propagation [10][16], which was implemented on the real time operating system named QNX. The learning algorithm of the gradient back propagation trains neural controllers on-line in a non-supervised approach [11] [15].

### B. Learning Protocols

Two different protocols for the adaptation of the walker to the patient have been chosen. The first protocol consists of an instrumented learning, the second, of a non-instrumented learning. The instrumented approach is a learning method in which some informations about the patient and the task are configurable by an external process: parameters, predefined trajectories, measurements. For the non-instrumented approach, no information about the patient is known. The constraints on these two protocols, in order to realize the learning of the deambulatory function, are to ensure user friendly which includes the need of simple and fast learning phases. It is very important to ensure secure and predictable behavior from the first run, in order to maintain confidence between the patient and the robot.

#### B.1 Instrumented Learning Way

To adapt the system to the patient, the controller ACANN must train the neural network first. We are talking about an instrumented learning protocol where

the controller has informations about the patient like his comfort speed in movement or on the desired task. The neural system integrates a representation of the test

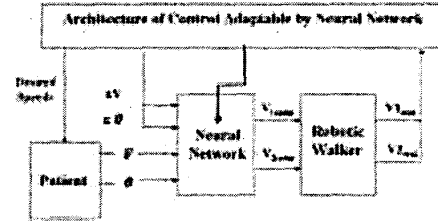


Fig. 3. Instrumented Control Architecture Way

task. It compares operator actions with expected results for a predefined sequence of actions in term of trajectories and/or speed. In this approach, neural adaptation works on the interface function : which is understanding the manner in which the patient gives a waited order (fig. 3). The neural network must calculate the speed of the right and of the left wheel from four measured inputs :

- the force  $F$  measured by the force sensor,
- the rotation angle  $\theta$  measured by the angular sensor,
- the difference  $\varepsilon_v$  between the walker and the patient linear speed,
- the difference  $\varepsilon_\theta$  between the walker and the patient rotation speed.

$$J = \alpha(V_{real} - V_{des})^2 + \beta(\dot{\theta}_{real} - \dot{\theta}_{des})^2$$

Where  $\alpha$  et  $\beta$  are normalization parameters.

The cost function, in which the gradient is used for the learning phase, is the difference between real linear and rotation speeds of the robotic system and linear and rotation speeds of the patient. Learning with back-propagation allows to minimize  $J$  with neural weight updating. For this protocol, the experimentation is for the patient to realize many different actions like "going fast" or "going slowly", "turn fast" or "turn slowly". Actions are achieved several times to refine the neural network weights. In our case, it means predefine continuous actions in which the order sequence is : "stay still", "go slowly and fast", "turn left slowly and fast", "turn right slowly and fast", "stay still". These continuous actions are repeated three times in order to refine the neural network convergence. The learning phase has three same order cycles, it lasts 240 seconds and for 80 seconds a cycle. Experimental results are presented on figure 4. Each main peak corresponds to a new order in the action sequence. One can observe that the cost function, expressed by the error value, decreases faster and faster during the learning. The error decreases in amplitude and the larger of each peak too. Between the first cyclé and the third one, convergence time of the criterion decreases faster and faster, after each new order. The network responds to order immediately with

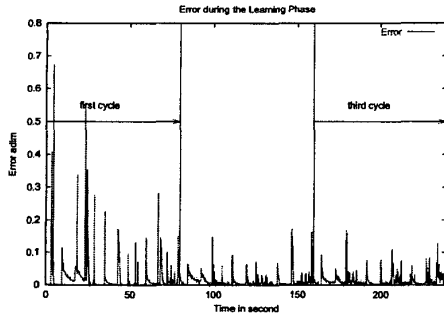


Fig. 4. Evolution of the Cost Function during the Instrumented Learning

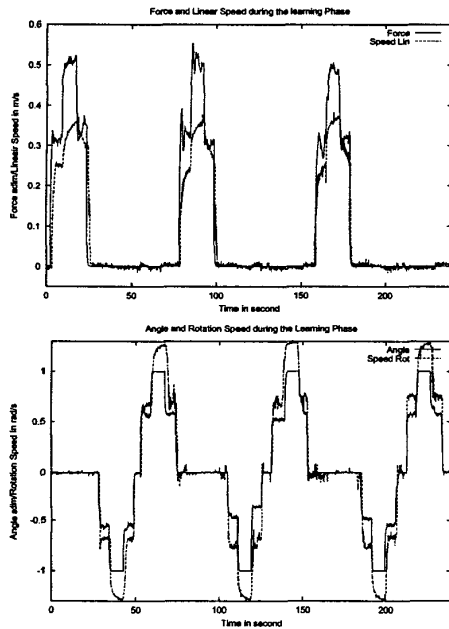


Fig. 5. Inputs and Responses of the Mobile Robot during the Instrumented Learning

minimization of the cost function. For this experiment, the network is composed with 4 neurons in input, 15 neurons on the hidden layer and 2 neurons on output. The maximum speed of the robot is 0,4 m/s. The maximum measured rotation speed is 1,3 rad/s. Each order, corresponding to a specific couple of inputs ( $F$ ,  $\theta$ ), is associated to a measured speed. During the learning, the robotic walker velocities converge to the measured velocities faster and faster (fig. 5). The reaction time between the execution order and the obtention of known speeds decreases significantly between the first and the third cycle.

## B.2 Non-Instrumented Learning Way

In this second approach, ACANN controller doesn't have any information about the patient displacement speeds or about a typical trajectory. The procedure consists for the neural controller in learning the walker function with the only goal to satisfy the actions of the patient. The neural network has been modified to cope with such a lack of informations. The input layer has 2 neurons, the hidden layer 10 neurons and the output layer 2 neurons. Inputs are :

- the force  $F$  measured by the sensor,
- the rotation angle  $\theta$  measured by the sensor.

The unknowledge of the characteristic speeds or on the reference trajectories gives the person high flexibility in the use of the learning robotic system. Such flexibility involves constraints for the learning phase which must be short and secure. Taking these constraints imposes fast convergence of the neural system into account.

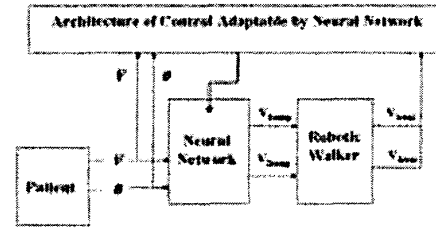


Fig. 6. Non-Instrumented Control Architecture Way

For the non-instrumented approach, the cost function must face up to the lack of informations while maintaining optimal security. So, the function is now:

$$J = \alpha(V_k - V_{k-1})^2 + \beta(\dot{\theta}_k - \dot{\theta}_{k-1})^2 + \mu(F_k - V_k)^2 + \psi(\theta_k - \dot{\theta}_k)^2$$

Where  $\alpha$  and  $\beta$  are constraint parameters.  $\mu$  and  $\psi$  are normalization and target parameters

The modification is realized by introducing a criterion in this function. This criterion includes a part expressing the walker relation, and terms describing the quality relation. The goal is to follow the patient orders. Then the optimization has to minimize fast accelerations and discontinued changes of the sensor measures which describe a no adaptation function. Actually, if the network doesn't identify correctly the couple of inputs sensors with the right couple of velocities, the system responds with a different way to the one desired by the patient. The orders will be changed, or amplified. Then the network outputs will have to be modified. To simplify, if the patient pushes on the handlebar, the force increases. The system goes to have a specific speed. When this speed goes over, it means that the system have a higher speed than the patient and then the force applied on the handlebar decreases. When the force decreases, the system slows down and if the speed is lower to the patient one, the applied force will increase. The system

stabilizes itself when its speed satisfy the patient. For the learning phase, the patient only has to control the walker through a predefined set of landmarks. During the learning phase the patient walked along a free trajectory with turns.

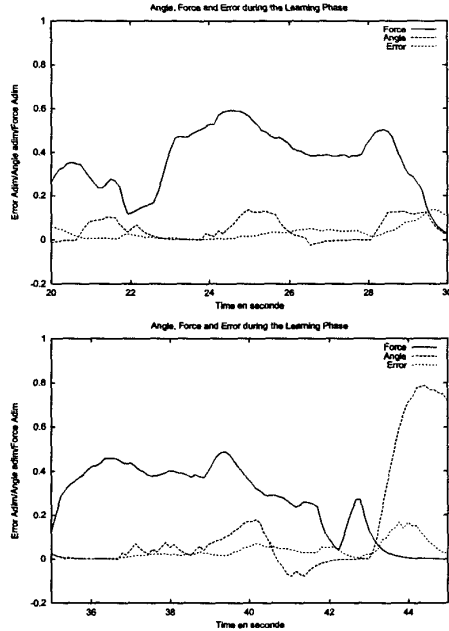


Fig. 7. Evolution of the cost function during the Non-Instrumented Learning: two views of the same order at different times

Figure 7 focus a temporel evolution of the criterion on two different periods during the learning phase. The control architecture tries to reduce the error for each new order. A reduction of the cost function for the same orders can be observed at both different times. The neural network has converge. But with the lack of informations, we can not talk about a right convergence. On the first graphic of the figure 8, the neural controller anticipates the orders. A sudden change of the force value can be observed at time 16 seconds (the force goes from 1 to -0.6). The controller replies a very small speed variation (about 0.4m/s). It is the "no-shake" effect. The duration of the evaluation phase is around 60 seconds. Different sequences can be observed on other both graphics (fig. 8) : 4 advance sequences and 4 rotation sequences at time  $t=15$ ,  $t=32$ ,  $t=45$  and  $t=60$  seconds. The reaction time of the system to the given orders decreases faster and faster. So the neural network has identified a relationship between the robot and the person.

### III. EVALUATION PHASE

The evaluation phase consists on testing the controller after the learning phase for both approaches. It

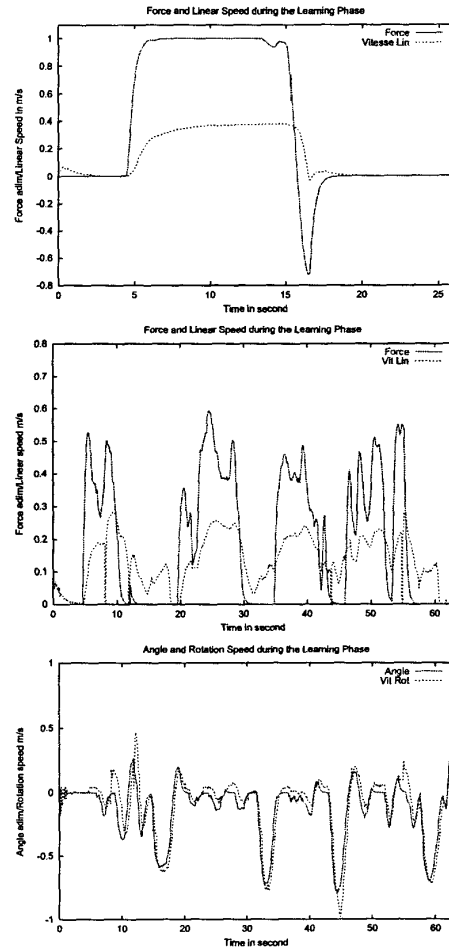


Fig. 8. Inputs of the Neural Network and the Walker Responses during the Non-Instrumented Learning Phase

is done without any modification of the obtained network weights. The patient must drive the walker and crosses landmark on a rectangular trajectory of 1.70 meters length by 2.20 meters large in a constrained environment (displacements are made with reduced leaving area : 50cm for a 60cm at the largest side of the mobile robot). The idea is to impose a constraint on the person to evaluate the pertinence of both methods. This evaluation phase allows to observe the convergence quality with the final configuration of the neural network.

#### A. Instrumented Approach

The network uses the speed difference between the desired and those realized by the system ( $\varepsilon_V$ ,  $\varepsilon_\theta$ ). When the network converges to 0, these two inputs also converge to 0. The inputs are only  $F$  and  $\theta$ . The duration

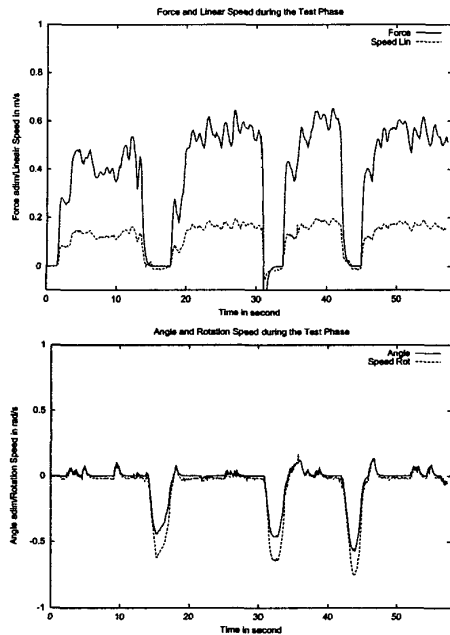


Fig. 9. Inputs of the Neural Network and Walker Responses during the Evaluation Phase

of the evaluation phase is around 60 seconds. Figure 9 shows 4 identical sequences in first graphic and three sequences in the second. These sequences correspond to the given orders and define the trajectory : the advances are the sides and rotations are the right angles of the rectangle. The maximum velocity is 0.2m/s. The maximum rotation speed 0.7rad/s. For each variation of the two robotic system inputs, we obtain similar variation of the moving velocities. Then the function has been correctly identified by the neural controller. The

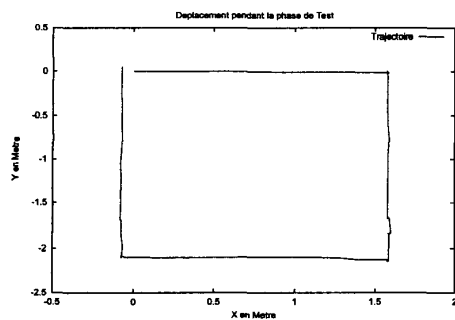


Fig. 10. Displacement Trajectory during the Evaluation Phase

displacement along the rectangle ends with a final static error of 10cm on X axis and 0.5cm on Y axis (fig. 10).

Sliding problems on a very smooth evolution floor and the speed of displacement cause this odometric error.

### B. Non-Instrumented Approach

For this approach, no modification has been made. The controller ACANN has the same architecture as in the learning phase. The duration of the evalua-

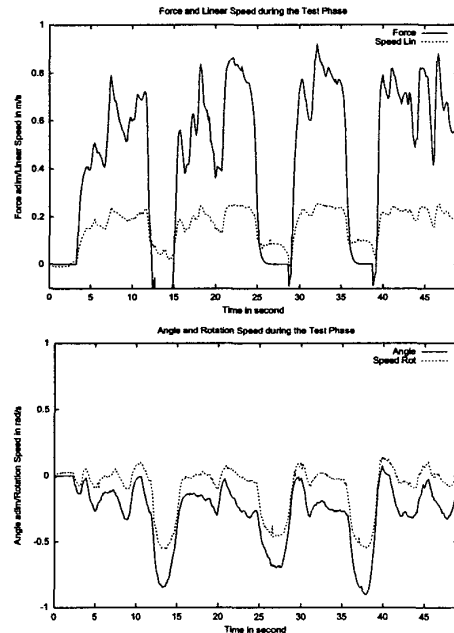


Fig. 11. Inputs of the Neural Network and the Walker Responses during the Non-Instrumented Evaluation Phase

tion phase is around 50 seconds. Different sequences can be observed (fig. 9) : 4 advance sequences and 3 rotation sequences at time  $t=13$ ,  $t=26$  and  $t=37$  seconds. Maximum linear speed is 0.25m/s and maximum rotation speed 0.8rad/s (fig. 11). These speeds are slightly higher than those obtained with the instrumented method (fig. 8). The static final error after the displacement is negligible (around the millimeter). The position error and the linear speed error along the trajectory are very small. Maximal position error is 3cm and maximal linear speed error is 4cm/s (fig. 12).

## IV. CONCLUSION

As a result of these experiences we can conclude that correct results were obtained with both methods. With accurate measurements on the patient, the instrumented method enables to modify the force/speed relation as well as angle/speed relation. This allows to compensate for any weakness of the user. The main benefit resides in the knowledge of the neural controller convergence. This method enables to validate learning before tests. If a correct learning path is chosen, the non-instrumented

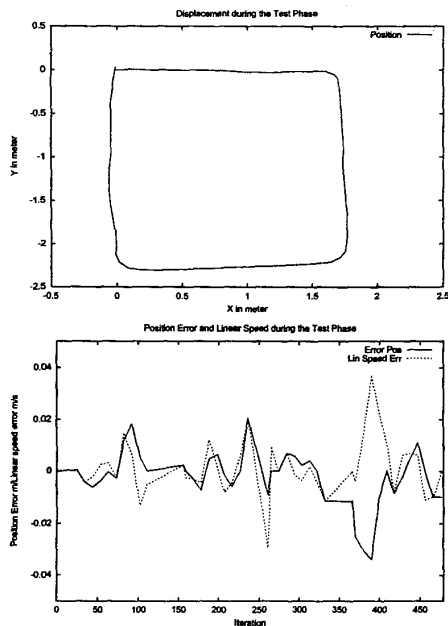


Fig. 12. Displacement Trajectory and Position Error with Linear Velocity Error during the Evaluation Phase

method results in better learning adaptability. Such efficient path should explore the configuration phases as the whole of the robot system. This method gives also a greater adaptability to the behavioral aspects thus allowing easy modifications of the Patient/Walker relation. An hybrid approach could eliminate the difficulties encountered in both methods. It is now important to improve efficiently by performance analysis on the chosen user group. With this correct results, the methods are actually experimented with medical team on handicapped and/or old persons to validate the medical side. A better interface for the adaptation is going to be realized for knowing handicap compensation.

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