NEUROLAB: A MULTIMODAL NETWORKED EXOSKELETON FOR NEUROMOTOR AND BIOMECHANICAL RESEARCH

A. F. Ruiz, E. Rocon, F. Brunetti, L. Bueno, J. C. Moreno and J. L. Pons
Bioengineering Group, Instituto de Automatica Industrial, Ctra. Campo Real km 0.200, Madrid, Spain
afruiz@iai.csic.es

Keywords: Biorobotics, Biomechanical Devices, Exoskeletons, Health Monitoring Devices.

Abstract: NeuroLab refers to an experimental platform designed to enhance studies in human movement and neuro-motor control. The platform comprises a robotic exoskeleton and some other stand-alone devices. All of these components have communication capabilities integrated in hardware and can work cooperatively taking advantage of a networked architecture. A set of experiments have been conducted with NeuroLab. The objective of the trials was to use mechanical perturbations to identify the viscous-elastic properties in human elbow joint and to correlate such mechanical impedance with the electromyographic information of muscles associated to the joint, during a postural task and in a rest position. In each condition, a pseudo-random torque perturbation was applied directly to the arm and to the forearm by mean of an upper limb powered exoskeleton. The angular kinematics (velocity and position), kinetics (torque) and the muscular activation patterns (EMG) in the two main muscles (biceps and triceps brachii) intervening in the elbow flexion-extension movement were recorded.

1 INTRODUCTION

Human movement and neuro-motor control is a very complex research field due mainly to the complexity of the involved mechanisms and the difficult access to the components of the overall system. Due to these reasons, the research community tries to exploit all kinds of valid information (EMG, EEG, kinetics and kinematics) relating to movement planning and execution in order to understand this complex system and to develop new aids in the medical robotics field.

One common and generally-accepted approach to understanding and modelling the human motor system is to monitor and analyse movement-related data during different motor task. A common approach to understand the dynamics of the motor control system is to independently manipulate the mechanical conditions of each joint while acquiring the biomechanical signals and the generated bio-potentials while the human motor system adapts to those new applied conditions.

In this scenario, a set of tools attached to the human body is required. In NeuroLab, there are independent devices that communicate with each other, based on a Personal Area Network (PAN) concept. Each device has a specific function and helps to address the overall goal of the platform. The NeuroLab integrates several devices in a global architecture. The main goals of NeuroLab are:

1. Study of human movement in subjects with motor disorders such as pathological tremor or spasticity. The information provided by the platform during the execution of specific motor tasks can be used as a tool to diagnose and assess motor disorders, (Rocon et al., 2007).
2. Study of neuro-adaptative strategies for learning and training of specific motor patterns through the application of selected force-fields to the upper limb. This application could potentially be of considerable impact in patients suffering of cerebral injuries, (Krebs et al., 1998).
3. Validation of neurophysiological models of human motor control in upper and lower limbs. This will help to gain a better understanding of the integration of the sensory information and the under-

lying mechanisms for generation of motor commands.

4. Study of human body behaviour under external loads. The load application is the basis for several technical aids to compensate functional disability.
5. Exploration of new communication channels in human-robot interfaces. This is potentially feasible through the use of EMG and EEG information to control wearable robots, (Rosen et al., 2001), (Pfurtscheller et al., 2002).
6. Assessment and quantification of human upper limb parameters, e.g. mechanical impedance. These parameters are considered important for understanding of the control mechanisms of the human joints, the generation of control signals, the execution of movements and the adaptation under changing conditions.

This paper aims at describing the design and the development of a platform to enhance research in several fields. The next section presents each device concept of the NeuroLab system. Next, a set of experiments which are being conducted with such platform in order to model the human motor control at the upper limb will be described. The experimental methods and preliminary results are presented in section 3. Finally, the section 4 discusses future work with NeuroLab.

2 PLATFORM DESCRIPTION

The platform (see figure 1), is composed of modules and devices that provide several capabilities: an upper limb robotic exoskeleton, an EMG module, a Biomechanical Monitoring module, and an EEG module. It can further be expanded with other peripherals. A software platform is defined to manage the system, e.g. setup the experiments and acquire data. Safety and reliability were priority considerations in the development.

The powered exoskeleton and the devices can communicate with each other using a CAN-based network and specific protocols. Each element of the platform provides several services which can be requested by other devices. There are therefore different primitives in the upper layers of the protocol, for instance to retrieve the data acquired by a module or to control a joint of the exoskeleton.

The robotic device is an upper limb exoskeleton which allows the mechanical conditions of each limb joint to be manipulated independently, (Ruiz et al., 2006). The networked platform enables combined

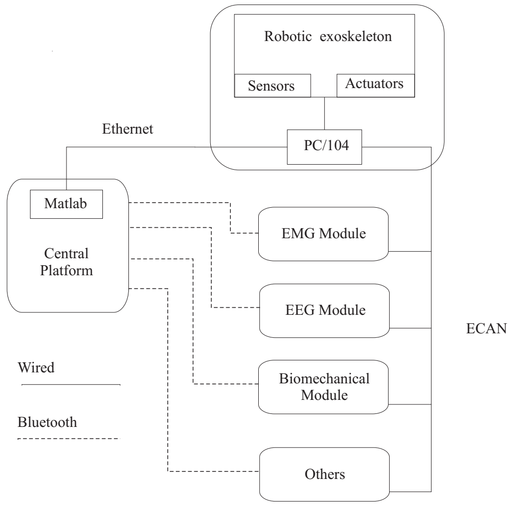

Figure 1: Layout of the NeuroLab system. Different modules can connect to a base station using Bluetooth. At the same time, all the modules are part of the wearable-robot network, called BioNET.

measurement of biomechanical variables (kinematics and kinetics variables) and biopotentials, such as electromyography (EMG) and electroencephalography (EEG).

2.1 Robotic Exoskeleton

The upper limb robotic exoskeleton in NeuroLab spans the human elbow and wrist joints, (Rocon et al., 2007). The sensors (gyroscopes, potentiometers and force sensors) measure the biomechanics of the arm. Using this data, limb movements, motor tasks and several postures can be assessed under different mechanical conditions.

Maxon Motor EC 45 Flat continuous current have been selected as actuation device, which is a very light, small DC motor without brushes that adapts to orthotic applications. In order to match the speed and the torque of the DC motor to the application requirements, a gearbox was necessary for the system. This was done via a harmonic drive. In particular, the drive selected for the application was the HDF-014-100-2A. The actuator system configured in this way can apply a maximum torque of 8 N.m.

The exoskeleton is controlled following an impedance control strategy which includes a position feedback loop. The goal of the controller is to modify the apparent Human–Robot impedance.

NeuroLab has a real-time target computer system (xPC Target) to control the exoskeleton. Control is implemented using the MatLab Real-Time suite by

Figure 2: Upper limb robotic exoskeleton. The device spans the human elbow and wrist joints.

MathWorks, Inc. This environment provides mathematical libraries making it easy to implement control strategies. The algorithm can be coded in C-language and compiled in an executable application.

2.2 EMG Module

Measurements supplied by electromyography (EMG) provide a valuable information regarding physiology and muscle activation patterns. This information describes the forces that will be generated by the muscles and the timing patterns of the motor commands. It can be also used to assess the response of the human motor system to external dynamic conditions or perturbations.

The EMG module allows for acquisition of data on four muscle groups. Since the EMG signal is very small ($50\mu V$- $5mV$), it may be affected by interference from other biological and environmental noise sources, e.g. movement artifacts, electric noise and muscle noise among others, (DeLuca, 1997). In order to minimise the effects of noise, the EMG module amplifies and filters the raw EMG signals before they are digitalized.

Additionally, a battery is used to power the EMG acquisition module in order to reduce 50 Hz harmonics (power-line noise). In the light of international safety regulations regarding electronic devices connected to human beings, several topics were addressed in connection with electric isolation of the EMG module. In particular, galvanic isolation using a wide-band, unity-gain isolation amplifier was implemented in the EMG Module.

2.3 Biomechanical Monitoring Module

This module uses inertial sensors to acquire kinematic and kinetic information on the system. This was the first smart module developed, so further details are given. The modular approach of NeuroLab enables the use of the different devices in many different applications.

The Biomechanical monitoring comprises the following logical components:

- *The controller.* This uses a TMS320F2812 DSP Texas Instrument, which is powerful enough to run all the signal processing algorithms. The clock frequency is up to 150 MHz. The DSP includes several communication interfaces.
- *The Sensor Set.* Two inertial sensors can be connected to the controller using a SPI interface. Each sensor consists of a set of three gyroscopes, three accelerometers and three orthogonally-mounted magnetometers (see figure 3).
- *The Data Logging block.* An ATMega32 microcontroller is used to manage a SD card. The microcontroller implements a FAT16 file system. Using basic commands, the controller can store the data of the sensors in a non-volatile memory.
- *Communication block.* The communication block includes four different communication interfaces for networks. The first is the SPI, which is embedded in the DSP and is used to communicate with the sensors and the data logger. The second block comprises a Bluetooth module for wireless communication with a base station for real-time monitoring. The third interface is a CAN port provided by the DSP. It can be attached to the NeuroLab BioNET using simple CAN drivers. The last interface is an USB port for data transfer and real-time monitoring. The Biomechanical Monitoring Module can be connected to the central platform (Figure 1) using Bluetooth or USB.
- *Power supply.* This is based on an Ion-Lithium battery with a capacity of 900 mAh. The module uses the USB connection to charge this battery.

2.4 EEG Monitoring Module

EEG can be used to study movement planning and to control wearable robots, (Wolpaw et al., 2002). The development of portable EEG module for research purposes is not a trivial task. Noisy environments and movement artifacts affect the quality of the EEG signals. Moreover, EEG signal processing techniques are usually complex and require a powerful platform

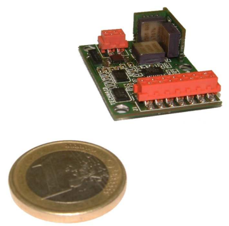

Figure 3: Inertial sensor that include 3 gyroscopes, 3 accelerometers and 3 magnetometers.

to execute these algorithms. Even relatively simple algorithms can require a powerful platform as usually the EEG is acquired using arrays with more than 10 electrodes.

Early developments of EEG Monitoring Module have been based on a PC/104 computer platform. A special amplification board was designed following the safety requirements for devices directly connected to the human body. This board is aimed to amplify 16 channels with variable gain amplifiers and a bandwidth that spans from 0.1 to 80 Hz. The board also has a notch filter centered on 50 Hz to compensate for 50 Hz line noise. This board is connected to the PC/104 through a data acquisition board. The acquisition of the EEG is aimed to use a 512 Hz frequency, minimizing distortion due to acquisition. The CAN connectivity is achieved through the use of an external CAN board attached to the PC/104 platform.

The EEG monitoring module can provide EEG logging through the use of a hard drive connected to the PC/104 board. Other services of the module comprises the identification of patterns related to the movement planning and imagination to be used as a control signal to the robot. This module also uses the xPC target platform (from MatLab, Inc.) used to control the robotic exoskeleton. This software platform was chosen due to the mathematical tools already implemented and for its flexibility.

2.5 BioNET

The purpose of NeuroLab is to integrate several different devices in order to study Human-Robot interaction (both cognitive and physical) and the human neuromotor system using non-invasive techniques. In view of the wide range of profiles and applications of the system, a distributed modular approach was selected to implement the proposed concepts.

A network of smart devices was identified as the optimum solution to achieve the goal. The network is called BioNET and is CAN-based. The work package includes the development of several network protocols including service discovery, synchronisation, and priority management mechanisms among others. A table describing the device, its services and its parameters, is stored in the device itself. This concept is similar to TEDS, used in IEEE P1451.3.

Current research efforts are aimed to develop the monitoring and rehabilitation profiles for the network.

3 EXPERIMENTAL METHODS

Many studies have approximated the dynamic behaviour of human body segments such as upper and lower limbs and their joints as a mechanical impedance, (Hogan, 1984), (Dolan et al., 1993), (Tsuji et al., 1995), (Zhang and Rymer, 1997). The mechanical impedance in this context can be defined as the dynamic relation between small force and position variations.

Using the platform described, NeuroLab, a set of experiments are being conducted to estimate the properties of the human elbow joint impedance and to determine viscoelasticity–EMG relationships. This is supported for the fact that the EMG information can be also used to assess the response of the human motor system to external dynamic conditions or perturbations. In literature, several studies have used electromyography in biomechanical analysis and human joint torque estimation, (Clancy and Hogan, 1997).

To start with experiments on this topic, a system for measuring arm impedance is required. Thus, the robotic exoskeleton is set up as a mechanical measurement system to get reference measurements for correlation with EMG–signals. The robotic device applies torque perturbations to the subject's arm. Sensors of robotic device deliver the necessary data to compute the mechanical impedance.

The human arm and their articulations could be modelled as a mechanical impedance in terms of inertia (I), viscosity (B) and elastic stiffness (K), using a linear second order model (Equation 1), (Dolan et al., 1993).

The parameters in the model that represent the dynamic behaviour of the human neuromusculoskeletal system are non-linear and vary highly depending on factors such as torque bias and posture, (Kearney and Hunter, 1990). Therefore, experiments that fit the data to an impedance of a second-order linear-model must specify an operating point. The operating point consists of constant posture, constant force, and non-fatiguing contractions over a particular task. The ensemble of linear models estimated over a range of operating conditions may be thought of as defining a quasistatic model of arm dynamics and can be defined by the following linear equation:

$$F(t) = I\frac{\partial^2 X(t)}{\partial^2 t} + B(\delta)\frac{\partial X(t)}{\partial t} + K(\delta)X(t) \quad (1)$$

where F(t) and X(t) represent the force and the displacement, respectively, and δ defines the operating point of the system.

According to Equation 1, inertial component remain constant and viscous and stiffness components (B and K) are functions.

3.1 Protocol

Four healthy subjects participated in the experiments. Subjects were instrumented with surface EMG electrodes according to the SENIAM recommendations, (http://www.seniam.org). Two muscles agonist-antagonist involved in the elbow joint movement were measured: the flexor (biceps brachii) and extensor (triceps brachii long head) muscles.

Subjects wore a robotic exoskeleton on its right arm allowing elbow flexion and extension in the vertical plane. Shaft joint on the device was aligned with subject elbow joint, and the device was attached to its upper arm and forearm. The elbow was flexed making an angle of 90 degrees.

The trials consisted of an intentional postural task. In each trial a pseudo-random torque perturbation was applied directly to arm and forearm by the upper limb powered exoskeleton.

The duration of each trial was 10 seconds. The subject was asked to maintain the position while the mechanical perturbation was applied. Three repetitions were chosen for each experimental session and the signals were sampled at 1 kHz for biomechanical variables (kinetics and kinematics) and for the electromyographic signals (sEMG).

3.2 Data Analysis

Kinematics and kinetics data were filtered using a 4^{th} order Butterworth low-pass filter with a cut-off frequency of 10 Hz.

The toolbox *System Identification Toolbox* of Matlab have been used to accomplish the modelling process. In particular, the function *armax* was used to fits the parameters of the linear second-order model to the structure of ARMAX (*Auto-Regressive Moving Average with eXogenous inputs*), based on a prediction error method.

Surface EMG signals were rectified (full-wave) and the envelope of the signals extracted using a low-pass filter with a cut-off frequency of 10 Hz. A 5^{th} order Butterworth filter for this purpose was adopted.

The RMS (*Root Mean Square*) value was used as index to quantify amplitude of EMG signals as defined by Equation 2. In the correlation procedure, the RMS value was the considered variable.

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} \quad (2)$$

where x_i is value voltage in i^{th} sample, n is number of samples in segment.

The RMS value represent the root square of the mean power of the EMG signal for a specific time period.

The linear equation that relates EMG amplitude and the variation of angular position to the variation in the generated torque by the joint might be modelled as Equation 3.

$$\Delta T = I \cdot \Delta\ddot{\theta} + B(\hat{s}_e, \hat{s}_f) \cdot \Delta\dot{\theta} + K(\hat{s}_e, \hat{s}_f) \cdot \Delta\theta \quad (3)$$

where $\hat{s}_e$ and $\hat{s}_f$ are the amplitude estimation of EMG signals for muscles flexor and extensor, respectively. $\Delta\theta$ is the variation in angular position and ΔT is the variation of torque generated by the joint.

3.3 Results

Figure 4 represents the estimated parameters of mechanical impedance and its mean and standard deviation for one subject. Each sample of x-axis in figure represents a trial, in order to evaluate the repeatability. Each trial magnitude was the mean of estimated values of a set of two-second windows of the recorded data.

Several quantitative information have been reported in literature mechanical impedance of human elbow joint, (Zhang and Rymer, 1997). The parameters obtained in the experiments carried out are similar to those values.

Correlating EMG–signals with the computed mechanical impedance can be considered as a function of EMG-activity, according to Equation 3. Currently, this functional relation has being found out.

4 CONCLUSIONS AND FUTURE WORKS

NeuroLab is based on an upper limb robotic exoskeleton with which specific force profiles can be applied. It establish a real multimodal interaction between the user and the powered exoskeleton through a set of

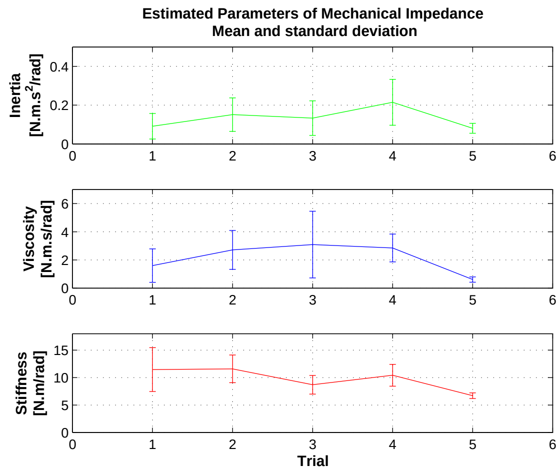

Figure 4: Mean and standard deviation of estimated parameters, for inertia (top), viscosity (middle) and stiffness (bottom).

smart devices. With the networked platform, several different experiments can be configured to explore the human neuromotor system and to study the human movement.

In the platform, there are independent devices that communicate with each other, based on a Personal Area Network (PAN) concept. Each device has a specific function and helps to address the overall goal of the platform.

The system can be used in a wide range of applications. The results obtained with NeuroLab provide valuable information for robotics, modelling of the human motor system, rehabilitation programs in health care, training programs and biomechanics.

Lately, several studies are being conducted with NeuroLab. The experiments presented in the paper aim to estimate the properties of the human elbow joint impedance and to obtain the viscoelasticity–EMG relationships. System identification is achieved by perturbation analysis, using an external perturbation application that produces changes in the dynamics of system and EMG patterns.

The presented method to estimate the mechanical impedance of the human arm is suitable to be used in a clinical setting, e.g., with people with stroke undergoing robotic rehabilitation for a paralyzed arm, (Palazzolo et al., 2007).

Future work includes a quantitative analysis, processing and correlation of the acquired signals (bioelectric and biomechanical signals), based in Equation 3. Currently the EEG Monitoring Module is being validated and integrated in the system presented.

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