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DESIGN OF SMART ROBOT FOR WRIST REHABILITATION

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Abstract- Generally, the rehabilitation process needs a physical interactions between patients and therapists. Based on the principles governing such human-human interactions (HHI), the design of rehabilitation robots received several attempts in order to abstract the HHI in human-robot interaction (HRI). To achieve this goal, the rehabilitation robot should be smart and provides a useful and comprehensive platform to track the patient status. In this paper, a biofeedback-based high fidelity smart robot for wrist rehabilitation is designed. This robot is intended for repetitive exercises without therapist intervention. Hold the two sets of wrist movement: flexion/extension and radial/ulnar derivation. Distinguished by its compact mechanism design, the developed wrist rehabilitation robot (HRR) offers high stiffness with a total absence of any friction and backlash. Based on EMG signal, the smart robot can understand the patient pain degree. Two features extractions are used to estimate the pain level. A fuzzy logic controller is implemented in the LabVIEW-based human-machine interface (HMI) to determine the desired angle and velocity in real time. Parameters and results of each exercise can be stored and operated later in analysis and evolution of patient progress.

Index terms*: fuzzy controller; EMG signal; smart robot; HMI; features extraction; physical human-robot interaction.*

I. INTRODUCTION

Recently, there has been a knowing interest in the development of robotic applications for rehabilitation purposes [22] [37]. In particular, the development of upper-limb [13], hand exoskeleton [14] and wrist [17] [48] rehabilitation robotic system was oriented to stroked patients.

In recent years, EMG based interfaces have received increased attention due to their several applications. Indeed, the development of EMG biofeedback signal is increasing rapidly, whether in the acquisition structure, either in processing or usages. In order to solve the limitation problems of the traditional EMG-based systems such as the large size and the required wired connections, a compact size preamplifier and wireless EMG measurement system are developed [4]. To perform the EMG acquisition, many types of electrodes are tested [25]. In addition to EMG bio signal, a muscle stiffness is measured and used in the grip force estimation of a powered prosthetic hand [6]. EMG signal can be considered as an information source, a neural information was extracted either for upper-limb prostheses control [18], whatsoever for detection and diagnosis of neuromuscular diseases [30]. Indeed, a task discrimination from myoelectric activity [19] can be applied in rehabilitation cases and neural prostheses.

EMG-based control laws have been developed. From teleoperation systems [21] to prosthesis systems control [9] and through robot manipulator grasping tasks [8], EMG-based control laws have various applications. The EMG signal is used to pattern recognition [43] for hand control [11] and powered upper limb myoelectric prostheses [15]. Moreover, a two channel EMG pattern recognition system was proposed to classify individual and combined finger movements for prosthetic hand control [42]. For hand motion identification, bend sensors are used with a multichannel surface EMG [16].

EMG signals are non-stationary characteristics which always depends on the subject [45]. Several parameters can have an impact on the EMG signals such as muscle fatigue [2] and force [30]. After EMG acquisition, the complex bio-signal will be processed for interpretation using the developed feature methods. Feature extraction is a processing technique used to transform raw EMG data into a feature vector. In the literature, EMG features can be decomposed into several groups which are: time domain, frequency domain or spectral domain, and time-scale or time-frequency domain (TFD) [37]. The most conventional feature methods can be summarized in fives methods: the waveform length (WL), the root mean square (RMS), the maximum fractal length (MFL), the detrended fluctuation analysis (DFA) and the HFD which are fractal time-series algorithms. For both clinical and engineering applications, the RMS [36] and WL [40] are the most popular EMG feature methods.

Previous studies have reported the development of EMG-based rehabilitation systems [3] [5] [20], a rehabilitation system control the hand musculature is presented in [3]. This system is dedicated to people with partially lost movements ability. Based on EMG signal, the system can understand the subject volition and help it to perform the desired hand task. However, this system cannot be effective only in case where patient is already in the therapy advanced stage, i.e, able to provide some muscle power. Based on signals measured from the hemiplegic side, a hand functions task training robotic system was developed for the stroke rehabilitation [5]. For more friendly rehabilitation therapy, an arm strength training machine with electromyography control system is realized [20].

Several offers were made to develop robotic solutions for wrist rehabilitation [10], [24], [26], [32], [47]. A parallel 3DOF MR-compatible wrist robot with compliant actuation was developed and controlled [24]. Based on EMG signal, a simultaneous and proportional control of 2D wrist movements was proposed [26]. For wrist muscular rehabilitation, a computer controlled rotational MR-brake has been controlled to perform the prono-supination wrist movement [47]. For more comfort, the development of robotic devises for rehabilitation have been focused to home-based rehabilitation [10]. The rehabilitation robotic systems have the potential to offer intensive rehabilitation systematically for a longer period [32] without a therapist expertise requirement. Thanks to this smart systems, the rehabilitation exercises can be done and the patient can be treated even without the presence of the therapist.

In this paper, a mechanical structure of writ rehabilitation robot is designed including the different components and operating field. A fuzzy logic controller is developed and implemented ensuring a perfect human-robot interaction. In contrast to the conventional rehabilitations systems which always require the therapist assistance, this developed system is dedicated for home rehabilitation. Indeed, the biofeedback-based high-fidelity rehabilitation system can understand the subject pain and interact with it. Based on high-friendly HMI, our work offers a perfect platform for training and evaluation for both patient and therapist.

The rest of paper is organized as follow. Section 2 presents the mechatronic design. Section 3 demonstrates the bio-signal measurement and processing in two subsections, one to describe the instrumentations and bio-signal acquisition and the second to discuss the features extractions chosen in signal processing. Method and experimental results are detailed in the final section including several parts. First part illustrates the system overview going from initialization to end of training exercise. The second subsection presents the fuzzy logic-based control design used for position and velocity control. The data storage system is described in the third subsection. The HMI managing the rehabilitation process is presented in fourth subsection. In the last subsection, the experimental results are discussed.

II. MECATRONIC DESIGN

The mechanical structure is designed with well-studied characteristics. For more comfort rehabilitation, the device should be design with low friction and zero backlash. Moreover, the device must have high stiffness for home-rehabilitation applications. Based on related literature, the anatomical wrist constraints [46] and wrist range of motion must be respected. Figure 1 and figure 2 show the limits of the two fundamental wrist movements.

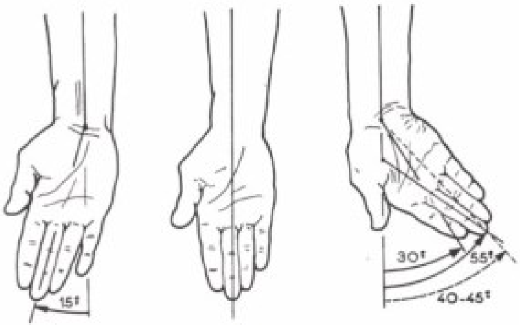


Figure 1. Wrist abduction-adduction

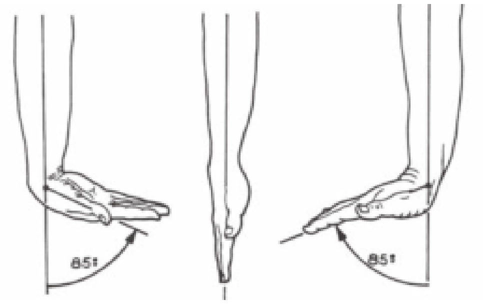


Figure 2. Wrist flexion-extension

Figure 3 shows the 3D mechanical structure designed using Autocad software. The model contains five main blocks. Each block is described with its elementary components in table1.
With a flexible structure transformation, the mechanical structure performs the two fundamental wrist movements. The current state, presented in figure 4, ensures the abduction-adduction movement. Removing the higher front arc support in the block "D", the subject can rotate the block "C" to switch the other wrist movement providing the flexion-extension movement (see figure 5).

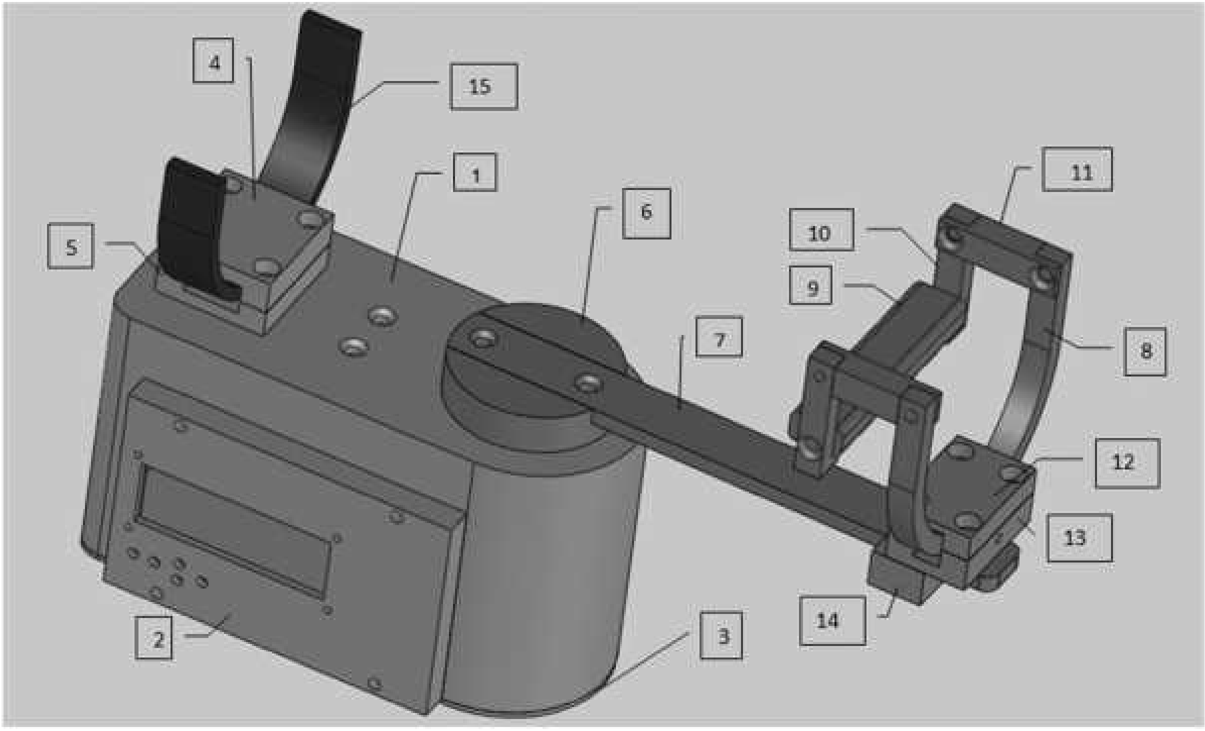


Figure 3. Mechanical design CAD model

Table 1. Mechanical components

Block	Article number	Piece name	Metal	Quantity
Block A	1	Box	ALU AU4G	1
	2	LCD box	Steel C45	1
	3	Box cover	Steel C45	1
	4	Higher back arc support	Steel C45	1
	5	Lower back arc support	Steel C45	1
Block B	6	Drive disk	Steel C45	1

Block	Article number	Piece name	Metal	Quantity
	7	Sliding bar	Steel C45	1
Block C	8	Forward arc	Steel C45	1
	9	Handhold	Steel C45	1
	10	Handhold support in L	Steel C45	2
	11	Handhold support	Steel C45	2
Block D	12	Higher front arc support	Steel C45	1
	13	Intermediate front arc support	Steel C45	1
	14	Lower front arc support	Steel C45	1
Block E	15	Back arc	Steel C45	1

The sliding bar (piece 7) is attached to drive disk (piece 6) assembling the block "B" while the drive disk is fixed to HS805BB servomotor axes. The servomotor allows patient to perform the wrist joint exercise without therapist interaction. The operating field of the servo is 180° when a given pulse signal ranging from 600µsec to 2400µsec as shown in figure 6.

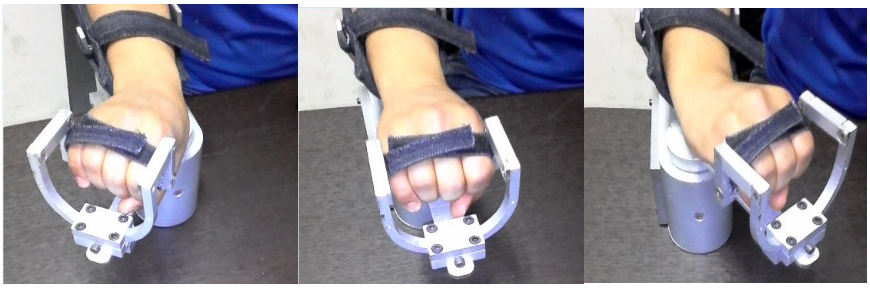


Figure 4. Ulnar-Radial derivation: Ulnar (1) Rest (2) Radial (3)

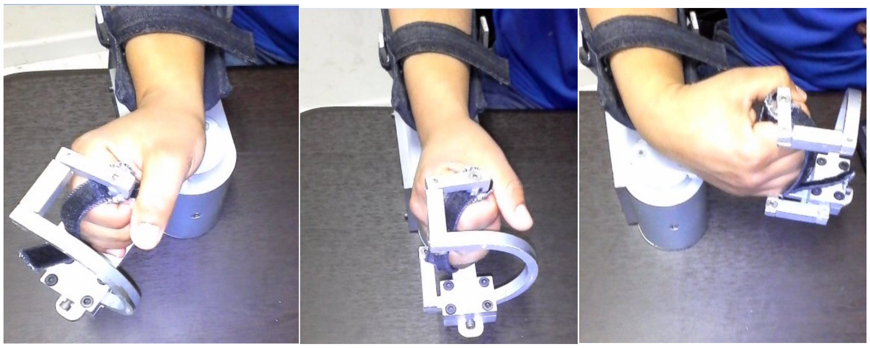


Figure 5. Flexion-Extension derivation: Flexion (1) Rest (2) Extension (3)

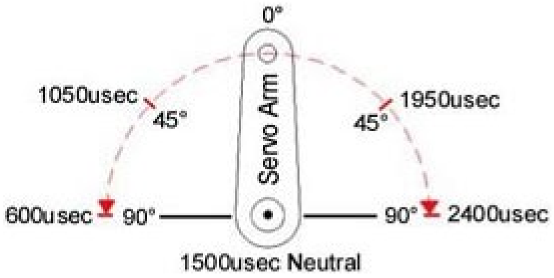


Figure 6. Operating field of HS805BB servomotor

By respecting the motion range in each exercise describing in figure 1 and figure 2, we define the angle limits that the patient should not exceed. These angles are implemented in the LabVIEW block diagram according to the selected exercise. Arduino mega 2560 board is used as a hardware interface between the computer and the servomotor.

III. EMG ACQUISITION AND PROCESSING

1. Instrumentation and signal acquisition

Myoelectric signal is an electrical potential generated by the muscles. Generally, EMG signals have been measured by two methods. The first is an invasive method using a needle electrode sensor, this method is not recommended in our case owing to need of more clinical skills, moreover, and the needle electrodes can cause pain for the patient. The second is a non-invasive method using a surface electrode sensor. This method can be easily applied and still give important information for use in several applications [28] [49].

In this paper, we control the rehabilitation process from multi-channel surface electromyography (SEMG) signal during dynamic contraction. The selection of the muscles, as well as the placement of the electrodes, were based on the related literature [23] [27] for the wrist flexion-extension and radian-ulnar derivation. Indeed, the related muscles for the wrist flexion-extension are the Flexor Carpi Radialis (FCR) and Extensor Carpi Ulnaris (ECU) muscles, the related muscle for the Radian-Ulnar derivation is only the ECU muscle. Every muscle is selected depending on the desired exercise.

Firstly, SEMG signals from patient are acquired using e-health shield for Arduino and Raspberry Pi for biometric and biomedical application. The e-Health Sensor Shield allows Arduino and Raspberry Pi users to perform biometric and medical applications using ten sensors which contains the muscle/electromyography sensor (EMG). This platform has a small form factor and full integrated. In fact, the EMG sensor will measure the filtered and rectified electrical activity of a muscle. Using the centered potentiometer in the shield, the EMG gain is adjusted to 1000.

This sensor use disposable pre-gelled electrodes. Resolution of the acquisition system ADC is 12 bits. Myoelectric signals are detected by placing three electrodes. Two of them for measurement with a distance equal to 3 cm [1] and the third act as a reference electrode placed at the proximal end of the elbow.

2. Feature extraction

In order to optimize the quality of the received signal, we design a Butterworth band pass filter of range of 20– 400 Hz and a notch filter of 50 Hz to remove the power line noise in the LabVIEW block diagram. Sampling frequency of the acquisition system is set at 1000 Hz [31]. This filter is designed based on digital filter design module for LabVIEW.

Tacking account of the very complex natures of the biomedical signals, feature extraction is very important issue in EMG signal processing. The main goal of this technique is to extract the useful information which is hidden in SEMG signal. In addition, the feature extraction focuses to remove the unwanted EMG parts and interferences [44]. The library of 37 EMG feature extraction methods are proposed in review and theory [12]. In our case, the feature extraction is mainly used to analyze the EMG data to extract the useful information for pain detection and estimation. Based on the related library [12], we focused on time domain features. In fact, time domain (TD) features are extracted directly from raw EMG time series and do not need any additional transformation. Then, these features are usually quick and easy implemented.

At this stage, we selected two time domain features extractions. The first feature is selected to pain onset detection. Based on the related literature, we chose one of the most popular used as an onset detection, called mean absolute value (MAV) [38] [36]. This feature, similar to integrated EMG, can be called also with another names like: average rectified value (ARV), integral of absolute value (IAV), averaged absolute value (AAV). As mentioned in its name, it is the average of absolute value of the EMG signal amplitude in a given segment defined as follow

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|X_i| \qquad (1)$$

After pain onset detection, we need to estimate the pain level. To achieve this goal, we add another feature extraction method called Simple Square Integral (SSI). The SSI feature (called also Integral Square) uses a power of the EMG signal as a feature [12] [41]. This feature use the summation of square values of the EMG signal amplitude to define the energy index. This index considered as a degree of the pain level computed as follow

$$SSI = \sum_{i=1}^{N}|X_i^2| \qquad (2)$$

The pain onset and degree are estimated in real time during the rehabilitation exercise. These time domain features are used as the inputs to the fuzzy logic system.

IV. METHOD AND EXPERIMENTAL RESULTS

1. System overview

In this subsection, we present the LabVIEW-based human machine interface (HMI) which allows patient/therapist to control and supervise the rehabilitation process. The HMI allows patient to lunch the rehabilitation process. The control law and Arduino input output management are implemented in the block diagram. The exercise results are stored in the database connected to the HMI. The overview of the designed system is depicted in figure 7.

The global system consists of three parts, where first step deals with robot control with regular velocity going from the repos position of wrist to random derivation. This step is considered as initialization part and therefore it will run only once. The second step takes care of bio signal acquisition and processing. Third step performs the desired velocity and position by means of fuzzy logic system. The final step is filled by data storage and reporting, after each rehabilitation exercise, the defined parameters is uploaded in the database and displayed in the user interface.

2. Control design : fuzzy logic control

Here in this part a fuzzy logic system is used for controlling the human wrist joint velocity during the rehabilitation exercise. The two time domain parameters, mean absolute value and Simple Square Integral obtained from raw SEMG signals are fed as the input to the fuzzy logic system while the desired velocity is taken as the outputs of system. The block level diagram of fuzzy logic system is shown in figure 8.

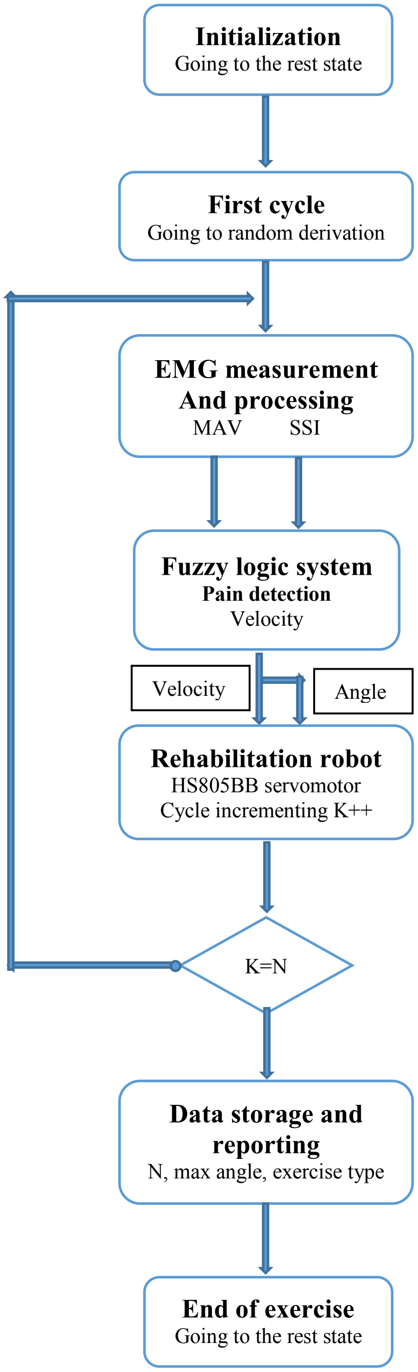


Figure 7. Diagram of developed system

Using the LabVIEW PID and Fuzzy Logic Toolkit, a fuzzy system is designed in order to estimate the pain level and control the rehabilitation robot. For both input and output, we use triangular shapes as the membership function. In addition, center of area method is used for deffuzzification. Since EMG is a bio-signal which always depends on the subject and it is also sensitive to measurement conditions and electrode placement. Therefore, the EMG obtained from any subject should be normalized by mapping the time domain parameters [29].

Figure 8. Block level diagram of fuzzy logic system

The equation for mapping is given by the formula (3) and implemented in sub virtual instrument (sub VI) presented in figure 9.

$$Y_N = \frac{(Y_{Nmax} - Y_{Nmin})(Y - Y_{min})}{(Y_{max} - Y_{min})} + Y_{min} \tag{3}$$

Where $[Y_{min},Y_{max}]$ is the range of the input parameters Y before mapping, $[Y_{Nmin}, Y_{Nmax}]]$ is the output range of the normalized parameter Y_N. The normalized time domain parameters are ranging from 0 to 10.

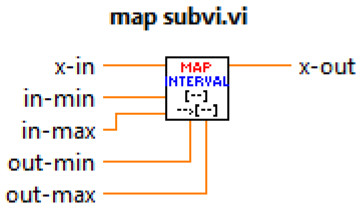


Figure 9. Designed sub VI for EMG normalization

In this paper, triangular shapes membership functions are used for both inputs and outputs. A center of area method, also called the Center of Gravity (CoG) method, is used for defuzzification. Therefore, the fuzzy logic controller uses the following equation to calculate the geometric center of this area.

$$CoA = \frac{\int_{X_{min}}^{X_{max}} f(x) * x \, dx}{\int_{X_{min}}^{X_{max}} f(x) \, dx} \qquad (4)$$

Where CoA is the center of area, x is the value of the linguistic variable, and xmin and xmax represent the range of the linguistic variable.

For the MAV time domain parameters, five membership functions are designed and are named as follow: very low, low, medium, high and very high. Moreover, three membership functions are reserved for the SSI time domain input and are named low, medium and high. Otherwise, four membership functions are reserved for velocity output named null, very low, low and regular. Figure 10 shows the membership functions of inputs and output.

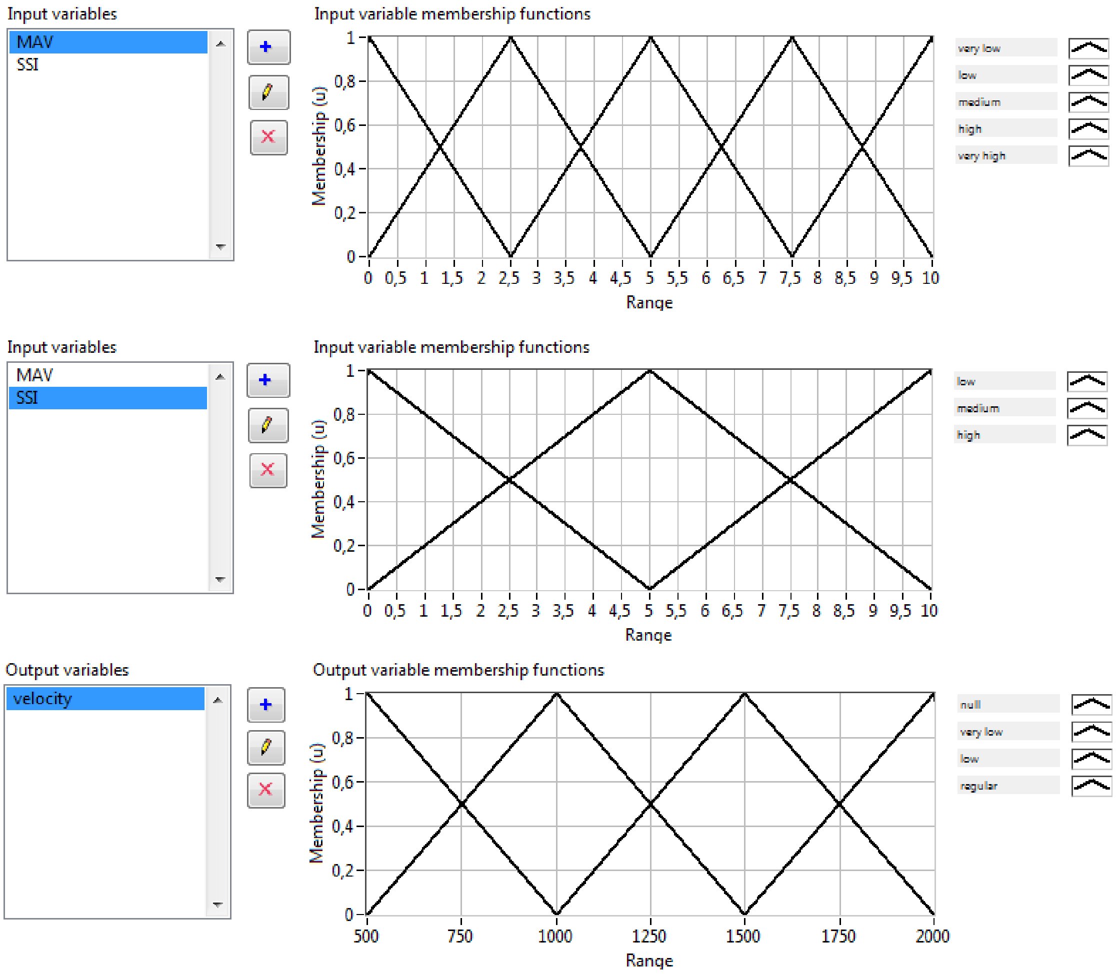


Figure 10. Membership function of (1) MAV (2) SSI (3) velocity

Fifteen if then rules will be implemented to control the rehabilitation exercise. Table 2 shows this rules.

Table 2. Rules base for fuzzy logic

Rules No.	SSI	MAV	Velocity
1	Low	Very low	Regular
2	Low	Low	Regular
3	Low	Medium	Regular
4	Low	High	Low
5	Low	Very high	Low
6	Medium	Very low	Regular
7	Medium	low	Regular
8	Medium	Medium	Low
9	Medium	High	Low
10	Medium	Very high	Very low
11	High	Very low	Regular
12	High	low	Low
13	High	Medium	Low
14	High	High	Very low
15	High	Very high	Null

Noting that the velocity is given as input to the case structure for controlling the direction. In fact, the direction of wrist movement will be inversed if the velocity is null.

3. Data storage and reporting

Database is frequently used in recent rehabilitation systems [34] [33]. However, the majority of existing rehabilitation robotic systems cannot entirely collect the monitoring parameters for analysis. In this section, an integrated monitoring and database system for rehabilitation process based on virtual instrument technology is proposed. Using the database connectivity toolkit, multi-parameters real time collection of rehabilitation exercise is made including the attained wrist angles limit for both derivations, number of cycles, date and type of exercise. Moreover, this toolkit is used to access the database to search historical records of every parameter and therefore allows the therapist to assess the progress of rehabilitation process. Figure 11 describes the relational database.

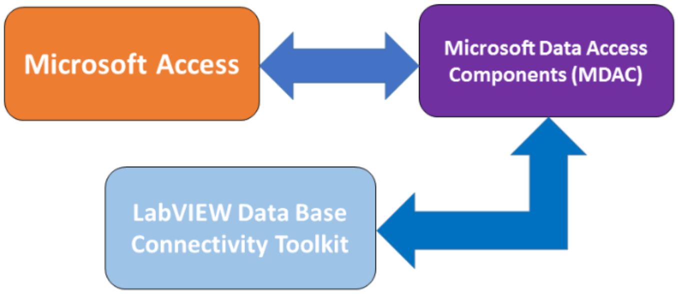
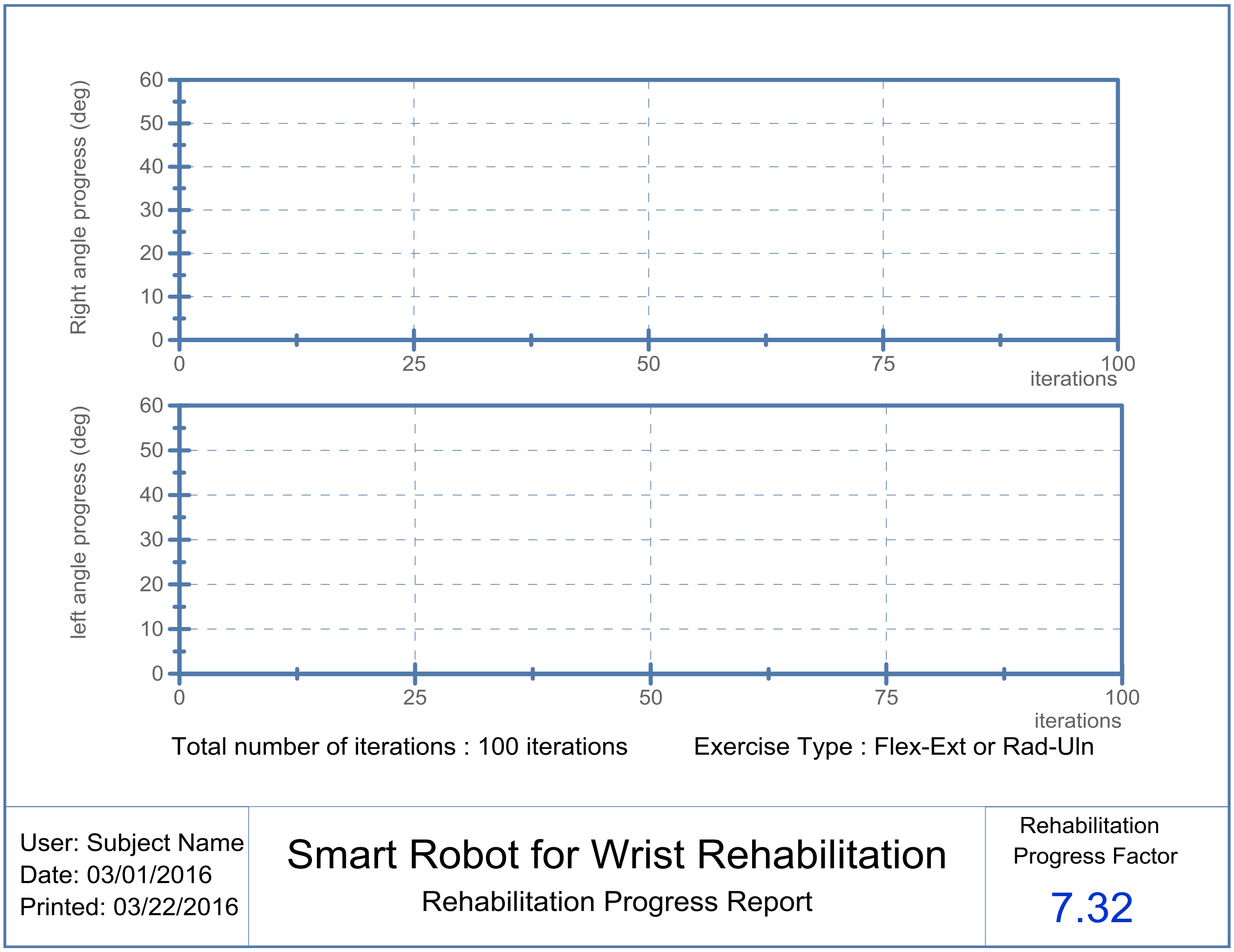


Figure 11. Relational Database

The first step involves the creation of blank database using Microsoft access. Once the related database is designed, the main use of SQL Query Language is to store, remove and retrieve data. The database toolkit allows developer to eliminate or simplify writing SQL queries. However, for the therapist use, additional actions are required such as add new subject, research and select existing subject. Which may distressing the non-expert user. In response to this challenge, based on datafinder technology included in the LabVIEW DataFinder Toolkit, the therapist can perform Internet-like searches across all stored data and selects the desired subject for applying the appropriate exercise.

Once the rehabilitation parameters are stored at each exercise, the results should be reported in a way easily illustrates the rehabilitation progress. As opposed to the entire data stored in the database, reporting focuses on visualization and exchangeability of final results during the rehabilitation process. Although the developed software provides a perfect interface to visualize the real time results but it is not designed for reporting the final results. In addition, the open source Microsoft access database is vague and difficult to interpret by the therapist. In response to these constraints, a custom report template has been designed to update with new results. Using Diadem data management software, a report template was interactively created that includes graphs of right and left angle progress, total number of iterations, subject name, exercise type, beginning date of rehabilitation process and printing date. Moreover, a factor of rehabilitation progress has been estimated and displayed in this template as described by figure 12.



Total number of iterations : 100 iterations

Exercise Type : Flex-Ext or Rad-Uln

User: Subject Name
Date: 03/01/2016
Printed: 03/22/2016

Smart Robot for Wrist Rehabilitation
Rehabilitation Progress Report

Rehabilitation Progress Factor
7.32

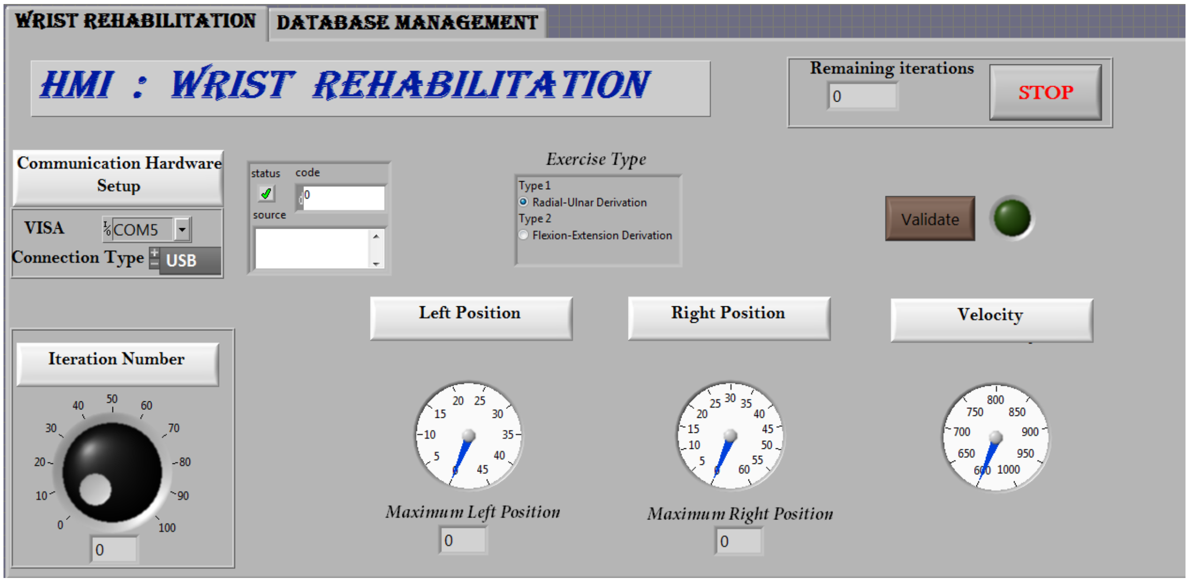
Figure 12. Custom flexible and automated report templates using DIAdem data management software

4. LabVIEW-based Human-Machine Interface (HMI)

Human-Machine Interface (HMI) is highly recommended in robotics fields and many human-machine interfaces has been developed to control robotic systems [35] and rehabilitation devices [39]. In rehabilitation field, the HMI should offer a simplicity of rehabilitation process for both patient and therapist without any expertise requirement.

In this section, a high-friendly HMI is designed to manage the overall rehabilitation process. Composed by two screens, this HMI allows users (subject or therapist) to control in real time the rehabilitation exercise and evaluate the rehabilitation progress by reporting the stored results.

The first screen, named wrist rehabilitation, is designed to real-time human-robot interaction. This page allows user to control the rehabilitation parameters such as exercise type and iterations number. In addition, the hardware communication must be set such as serial port selection and connection type. The user should validate the desired parameters by pressing the button named "validate". Once the input parameters are accepted, a led indicator changes to green to indicate the start of the exercise. Moreover, the display portion contains also the real time left and right derivation and velocity, computed maximum left and right position, remaining iteration and error hardware communication code (if exist). The first screen, before and after validation, is illustrated in figure 13 and figure 14 consecutively.



Remaining iterations 0

status ✓ code 0 source

VISA COM5

Connection Type USB

Type 1 ● Radial-Ulnar Derivation

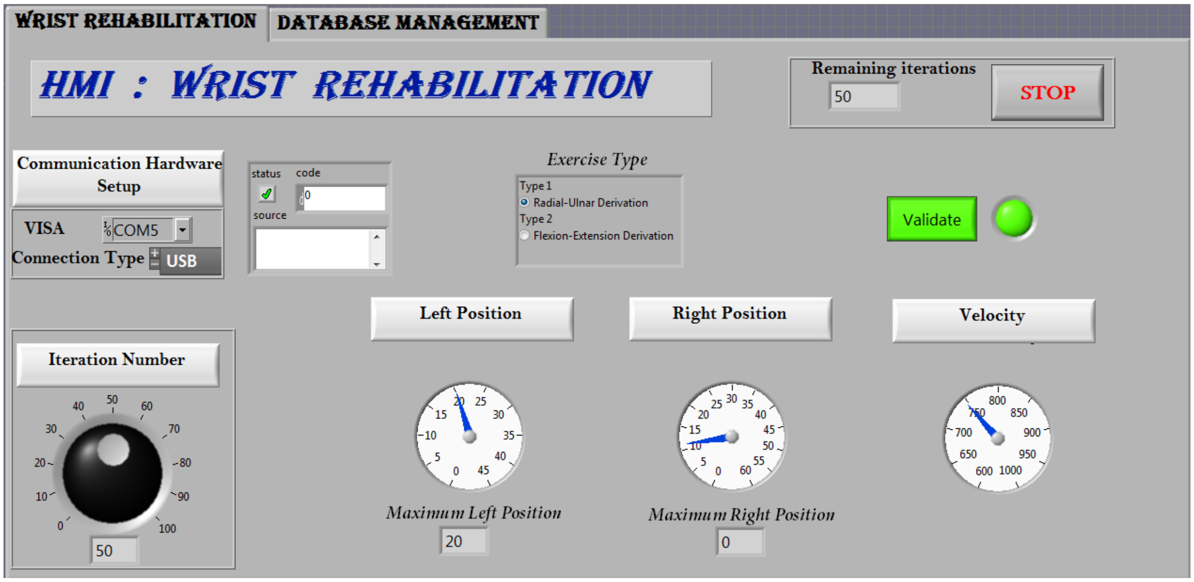
Type 2 ○ Flexion-Extension Derivation

Iteration Number 0

Maximum Left Position 0

Maximum Right Position 0

Figure 13. First screen before validation



Remaining iterations 50

status ✓ code 0 source

VISA COM5

Connection Type USB

Type 1 ● Radial-Ulnar Derivation

Type 2 ○ Flexion-Extension Derivation

Iteration Number 50

Maximum Left Position 20

Maximum Right Position 0

Figure 14. First screen after validation

In the same HMI, the second screen illustrates the storage data and reporting. As shown in “Fig. 15”, this screen contains four portions. All of these portions include text box to enter the subject name. In addition, button control was also included to apply the desired action according to the name subject already seized. The first portion is designed to add new subject and submit it in the connected microsoft access database. Also, informations concerning connection and patient are displayed in the same portion as well as the error code (if any). The columns information is marked to prove the desired parameters such as iteration number, exercise type and angle of left and right derivation. When the user chooses the database and selected it via “create data link” located in the tools bar, a path control is displayed to save the data link file (.udl) and selected it via the path control named connection information. After each exercise, the user can save results in the database. In fact, a maximum left and right position are determined and displayed in the second portion. As usual, the submit button is necessary to save all parameters and results including exercise date and type and number of cycles. The two previous portions are provided for all uses. However, the therapist uses require additional options such as finding subject. Calling data finder technology, the therapist abstract his subject research by typing the subject name. The research result is presented by led indicator. This led change to green if the subject name exists in the database tables. The remaining screen is reserved to report data and results as described in the previous section. Just by a simple click, the user can generate his report after typing the subject name. As described in the third portion, the subject name should be find in the database before report generation. Indeed, an additional algorithm was lunched to estimate the rehabilitation progress factor. This factor is scaled between 0 and 10. Based on the stored results from the database, the factor is affected according to the maximum left and right angle achieved during the rehabilitation process. In fact, subject have a factor around to 10 is healthy. As conclusion, the evolution of this factor shows the efficacy of the developed method.

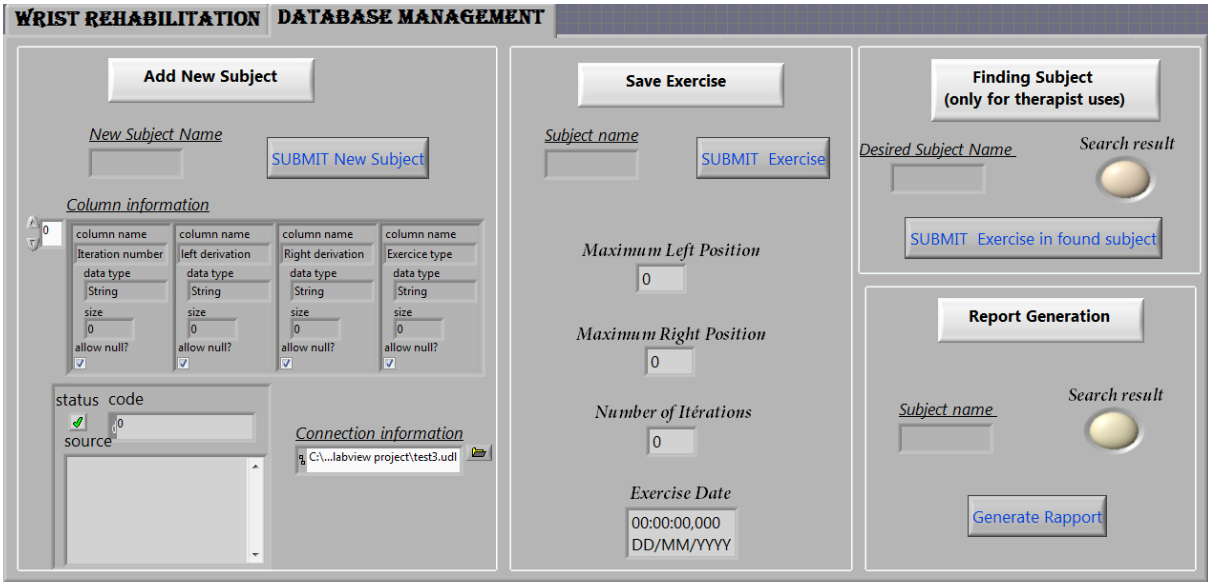


Figure 15. Second screen for data storage and reporting

5. Experimental results

In the beginning, the required modules and toolkits for LabVIEW have been installed. The different results are stored based on LabVIEW data base toolkit. NI Diadem software and DataFinder toolkit are used to create the custom report template and to research subject within the database, respectively. Communication between computer and Arduino board is ensured through a software package called LIFA (LabVIEW Interface For Arduino).

Second step of experimental platform setup consists of hardware installation. According to the desired exercise, the SEMG electrodes should be placed as shown in figure 16.

The remaining step consists of LabVIEW-based HMI parameters configuration. As shown in figure 17 and figure 18, the mechanical structure is fixed to perform an ulnar-radial derivation. According to this configuration, the exercise type radio button must be fixed at ulnar-radial derivation. Therefore, the related angle limits are imposed in the motor control respecting the anatomical structure of this derivation.

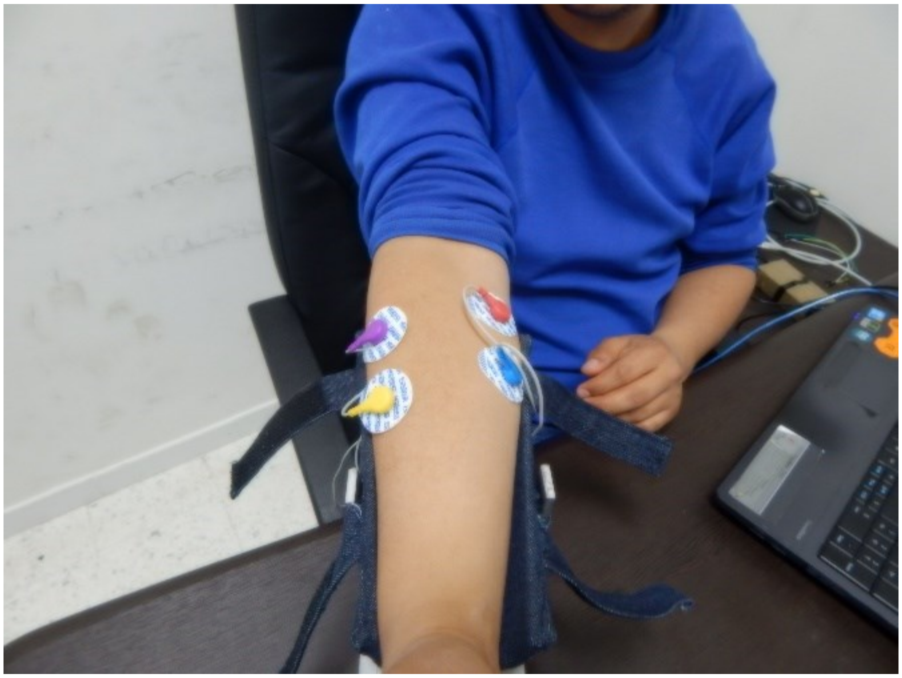


Figure 16. SEMG electrodes placed in the FCR and ECU muscles

Figure 17. Radial derivation

Figure 18. Ulnar derivation

Preliminary results of clinical tests have demonstrated the benefits of the robotic rehabilitation. For both therapist and subject, this smart system offers a perfect platform for repetitive tasks training. Moreover, this system provides a useful feedback for interpreting the rehabilitation state and progress.

V. CONCLUSIONS

In this paper, design and development of a robot-aided therapy are proposed. High friendly human machine interface is designed to perform the human-robot interaction without IT expertise. Database interface is performed to store the rehabilitation exercise results. A report generation option is offered to evaluate the rehabilitation progress with high indicator progress factor. For both patient and therapist, our work offers a perfect platform for training and evaluation. Preliminary clinical results showed efficacy not only in treatment process but also in the progression time improvement.

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