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Active Motor Control for an Upper Extremity Exoskeleton

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An active control system for a five degree of freedom (5-DOF) upper limb robotic exoskeleton was developed to fill in the need for an accessible and cost-effective rehabilitation system. Since physical therapy sessions are labor intensive, it aims to be a tool in augmenting the capacity of local rehabilitation centers in catering more patients. Many different control systems were already done on similar devices but the challenges remain in adapting to the limits of the mechanical design of the exoskeleton it is implemented on and availability of local electronic components. Arduino Microcontroller was used as the embedded platform in the implementation of the control system. Using Myoware electromyography (EMG) sensor, signals were measure from biceps and triceps for elbow flexion and extension; deltoids and teres major for shoulder abduction and adduction. The rectified signal was further smoothened thru running average. Experimental results showed that baseline EMG and activation level of the target muscle groups were different from each other, thus different threshold levels were established. An adaptive algorithm using pulse width modulation (PWM) was also implemented in varying the supplied power depending on the applied load on the arm. Stall conditions via the current sensor was monitored and used as positive feedback. The system was successful in interpreting intent to move and translating it to motor movement.

Keywords: biofeedback, electromyography control, Rehabilitation Robotics, powered exoskeleton.

1. INTRODUCTION

Stroke is the second leading cause of death among top five diseases with the greatest burden based on disability-adjusted life-years[1]. As the fertility rate decreases the percentage of the local population of Senior Citizens in the Philippines continue to increase from just 5.3% (2.5M) during the 1980s, 7.8% (8M) currently in 2016 to a projected 13.8% (19.6M) in 2040[2], with it also comes the increase in demand for rehabilitation services and facilities. Since senior citizens usually rely on insufficient pension and 16% or 1M of them live below the poverty line, there really is a need for cheaper medical care.

Recovery of daily activities can be achieved through rehabilitation, specifically repetitive movements which are normally assisted by physical therapists. Rehabilitation Robotics aims to augment and provide cheaper alternative means of treatment to patients[3]. This also opens up a lot of possibilities like improved patient monitoring thru biofeedback, customized therapy routine, and gamification of therapy which motivates the patient to pursue treatment[4]. Robots are also vital force multipliers in augmenting limited resources than sole conventional methods thus making medical services more accessible to the public.

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Meta-analysis done on studies involving several commercialized therapeutic robots like MIT-MANUS, ARM (Assisted Rehabilitation and Measurement) Guide, MIME (Mirror-Image Motion Enabler), In-Motion Shoulder Elbow Robot and the BiManu-Track revealed a positive effect of robot-assisted therapy on motor recovery when compared to traditional therapy revealing a potential in rehabilitation robotics[5]. It also showed the possibility that if the robot is made as safe as possible, multiple units can be monitored by a single therapist thus becoming a force multiplier.

Recent challenges on rehabilitation robotics are ensuring smooth motor actuations from biofeedback trigger and at the same time quantitatively gauge the progress of the rehabilitation. Most exoskeletons use neural networks to classify EMG signals and coordinate different motors simultaneously. This high-level machine intelligence requires complicated circuitry that adds to the development cost of equipment. The goal of this research is to develop a cost-effective control system using readily available components and a simpler algorithm that can be implemented in microcontroller.

2. CONTROL SYSTEM OF ROBOTIC EXOSKELETONS

Classic control systems of exoskeletons are either passive and/or active. Most therapeutic exoskeletons provide assistance-as-needed in the active mode, which pushes the subject to make an effort. This in turn will make patient recovery faster because he will not primarily depend on the robot's power to move himself[6]. A basic robotic control system employs a feedback mechanism but is often combined to a feed-forward mechanism to anticipate the effects of the exoskeleton design i.e. weight and dynamic forces (Fig. 1). Another important feature of a rehabilitation exoskeleton is transparency wherein it must not hinder the intended movement the patient. Its importance is furthermore emphasized when there is a need to actively record the actual effort done by the patient. Since this cannot be completely eliminated, algorithms have been proposed to compensate for this condition[7].

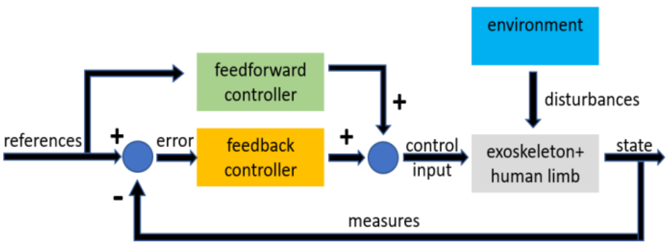

Figure 1. General control scheme. A feedback control calculates error from current state, and a feedforward control containing desired values are combined as a single control to trigger actuators. Environment acts like a disturbance affecting performance of the exoskeleton[7].

3. MATERIALS AND METHODS

A 5-DOF upper limb exoskeleton was used as the platform for the control system implementation. The Microcontroller board used was the Arduino MEGA 2560 powered by the 16 MHz High performance low-power Atmel 2560 microcontroller[8]. The software used was C-based Arduino IDE while the EMG sensor used was the Myoware Muscle Sensor (Fig. 2). that is directly interfaceable to a microcontroller. This sensor will measure the filtered and rectified electrical activity of a muscle, outputting voltage proportional to EMG input[9].

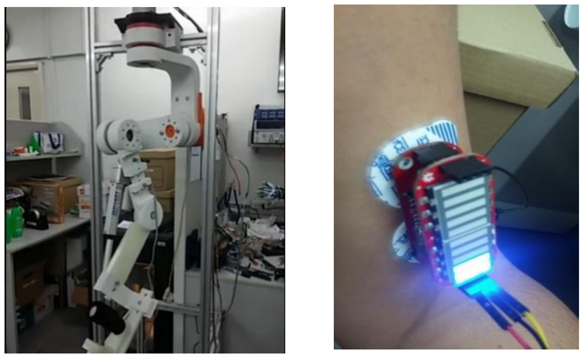

Figure 2. Agapay 5 -DOF Exoskeleton (Left) Myoware Sensor (Right)

Using Myoware EMG Sensor, 1000 samples in a minimum 100 ms single period was taken as suggested by Delsys as the minimum samples for EMG processing[10]. Running Average Algorithm was used for simpler filtering of the signal. Improper selection of sampling quantity can lead to issues in representation and processing of the original signal. Too few and error will be large, to many and delays will be long.

$$SMA = \frac{p_M + p_{M-1} + \cdots + p_{M-(n-1)}}{n} = \frac{1}{n}\sum_{i=0}^{n-1} p_{M-i}$$

Equation 1. Simple Moving Average [11]

Resting EMG was initially recorded by minimum 15 quick controlled bursts. Two standard deviations from the average burst peaks will be used as the minimum threshold for muscle onset detection[12].

To implement active control, PWM signals to the abduction motor needs to vary depending on current load[13]. Smaller pulse width will result to lower voltage hence lower supplied power, then a wider pulse width will result to a higher voltage hence higher supplied power. Setting the pulse width at minimum will not be enough to lift a load, but setting it at maximum will rotate the arm too fast especially in unloaded condition. Amount of increment was determined as well as boost factor to expedite PWM increase when needed to minimize duration of stall condition.

Maximum PWM determination was based on the highest PWM value that will be capable of continuous abduction of the arm, meaning no stall condition from zero to 90 degrees with a 3 kg load. Arm weight is usually defined as 5% of the total body weight[14]. The average Filipino Weight is 60kg hence the typical arm weight of a Filipino is 3 kg[15].

To trigger active control, stall current condition must be detected. When the motor stop rotating due to stall condition, back-EMF goes to zero, dramatically increasing the drawn current. The amount of current increase during stall current will be determined with varying voltages. This will be used to determine the condition when the PWM needs to be increased.

Minimum PWM determination will be based on the lowest PWM value that will result to the slowest possible continuous abduction of the arm, meaning no stall condition from zero not 90 degrees without a load. At least 24 trials was done at this level then stall condition will be induced by manually resisting arm rotation.

4. RESULTS AND DISCUSSION

Separate threshold measurement was taken for biceps, triceps, deltoid and teres major. Table 1 shows the measurements for deltoid which is necessary for shoulder abduction. A total of 367 data points was collected in this experiment (Fig. 3), comprising of resting controlled burst. Standard deviation of resting condition and the 17 peaks was taken to define maximum and minimum limits.

After computing for mean and SD of the two conditions, it was determined that the threshold for deltoid activation is at approximately 30%. In case a higher sensitivity is needed, threshold value must not be lower than 2SD of resting EMG or approximately 8% .

Stall current measurement experiment was rated at 5 A for easier implementation of stall condition. At 5 A minimum PWM was also determined to be 115. After 24 trials, it was discovered that stall condition is approximately 22% more than the operating current. It was also revealed that the measured current at 5 A has an error of +/- 2.35% based on a standard deviation of 0.122. Given this scenario, stall condition will be identified when operating current increases by at least 3%.

When stall current is detected to be at least 3% more than operating current (Fig. 4), PWM was increased by a minimum of 10% to maximum of 20% depending on how large the present operating current is. The larger the operating current, the larger the PWM increase will be. Maximum PWM was also determined at 250 resulting to a current of 12 A during lifting a 3 kg load. 5 trials each were done in varying load conditions from zero to 3 kg with 0.5 kg increment

Table 1. deltoid SD and limits

	Resting	Activation
Average	6.69	39.68
1SD	0.35	5.08
2SD	0.70	10.16
Minimum	7.39	
Threshold		29.52

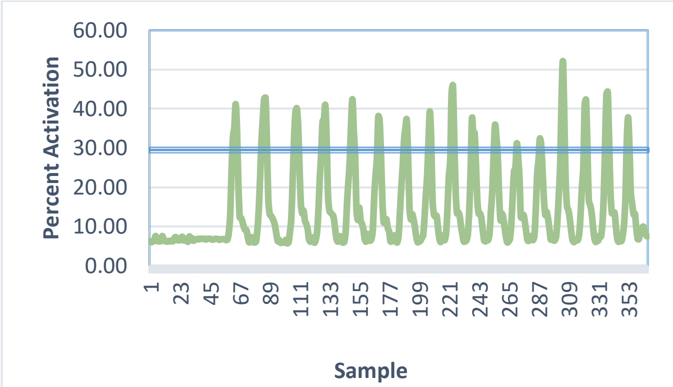

Figure 3. deltoid EMG recording (green) of rest and controlled burst. Activation threshold (red) set at 30%

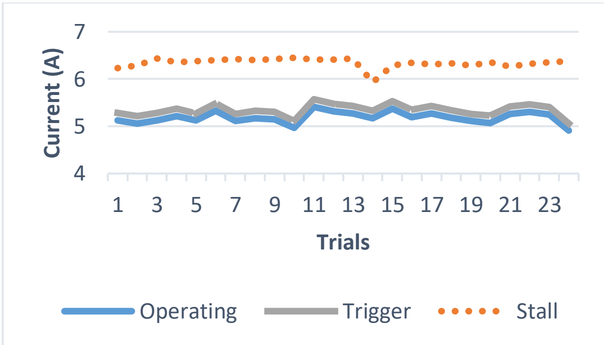

Figure 4. Stall condition characteristics at 5 A operating current

To further improve rotation, a boost parameter was also introduced to further increase the PWM increment during stall condition thereby decreasing rotation time (Fig. 5). Boost parameter is triggered when instantaneous stall current reaches 10% more than the operating current. On the average, the boost parameter further made the rotation 13%. faster

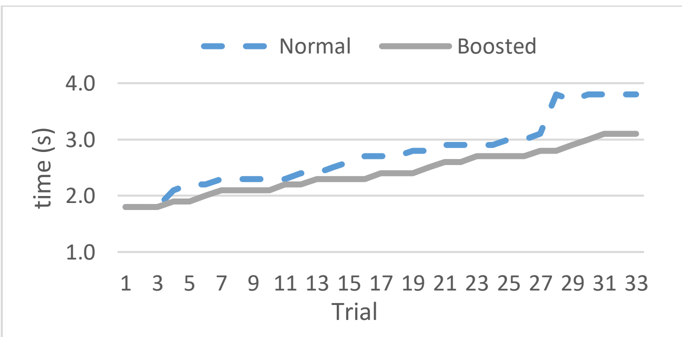

Figure 5. normal vs boosted rotation time of shoulder abduction from zero to 90 Degrees

6. CONCLUSIONS AND FUTURE DIRECTIVES

The results from the experiments conducted prove that the objectives have been met. Feedback parameters EMG reading, angle position and stall current obtained from the sensors have provided the necessary signals to control the system. The EMG readings have successfully detected the presence of intent and effort. Experimental results proved that upon reaching a certain threshold of effort, the system will only assist as needed in completing the motion. The system was also able to actively adapt to varying load by automatically increasing the power supplied to the motors during stall conditions.

Additional research on EMG data processing particularly on the mean frequency shift due to effects of fatigue can be beneficial in properly identifying EMG-based torque. The threshold values used in the study is limited to the design experiments conducted for the study. More accurate sensors are recommended to be used particularly the use of absolute sensors for position sensing. The implementation of the control system through the use of the powered exoskeleton is just limited to two active joints among the 5–DOF of the exoskeleton. Additional degrees of freedom can be added to allow the system to accommodate compound movements, as required by occupational therapy rehabilitation exercises.

More EMG samples particularly from actual stroke patients should be taken in order to give a better understanding of its characteristics compared from a normal healthy subject. Clinical testing of the system can provide the critical information to further improve the system.

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