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Smart Mechatronic Elbow Brace using EMG Sensors

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ABSTRACT

Majority of injuries are involved in damages of elbow and the recovery therapy period may take up to 12-24 months in health care centres. Therefore, it is needed to supply a smart mechatronic brace for patients who cannot come to health care centres, can exercise their rehabilitation at home. This project designs and tests a smart mechatronic brace for home rehabilitation of elbow injured patients. The device is run by electromyography (EMG) sensors. Data from EMG sensors is processed, filtered, smoothed, and converted into pulse width modulation (PWM) to run the DC motor. The system is controlled by adaptive linear quadratic Gaussian (LQG) and Kalman filter (KF). The DC motor can track well the human motion with the error less than 5%. The system is relatively simple, reliable, safe, low cost and high accuracy.

Keywords: Biomechatronic, electromyography, biceps brachiii, triceps Branchii, linear quadratic gaussian, kalman filter, pulth width modulation.

1. INTRODUCTION

Majority of injuries are involved in damages of human activity and more than half of them are on the upper limbs or the elbow injuries [1]. Due to the complexity of human neuromuscular system, the post-operative recovery period may take 12-24 months. In order to avoid stiffness of joints and muscular contractures as well as to undergo therapy at health care centre, it is needed to design an active mechatronic brace for patients, who can exercise therapy at home. Therefore, this project develops a home-based rehabilitation brace for the elbow injured patients with low cost, safety and high accuracy based on EMG signals.

A novel EMG driven state space model for estimation of continuous joint movements is presented in [2]. The model is applied for modified hill and used Kalman filter to estimate the update state space parameters. However, the EMG sensors are used only with BB and therefore, the device performance is with low accuracy and needed long calibration. The tracking accuracy of this device is of 90.5%. An update hill type model for motion estimation based on EMG signals from both BB and TB is referred in [3]. The model is tested for moderate speeds and used artificial intelligent algorithm of neuro-fuzzy modification. This system is complicated since it uses additional ElectroEncephaloGraphy (EEG) sensors and provides an accuracy level of 92%.

For estimation of upper limb joint movement angle, [4] uses also surface EMG signals. But this method requires 4 electrodes and needs long calibration period. The controller algorithm is used with back propagation neural network (BPNN) and gets an accuracy level of 93%.

A recent project in [5] to estimate elbow joint angles using nonlinear autoregressive network with exogenous input (NARX) is also used with EMG signals from BB and TB. The probability of the NARX prediction is at 95%. There is no information of calibration length and the accuracy level.

A new research on role of muscles as real-time data for estimation of upper limb motion using extreme learning machine and neural network is proposed in [6]. This algorithm provides faster learning time and calibration. However, the device is required signals from 7 different muscles. The calculation algorithm is complicated and the accuracy level reaches to 92%.

A device for estimation of elbow flexion force during isometric muscle contraction from MechanoMyoGraphy (MMG) and EMG is referred in [7]. This model is tested only on isometric contraction and electrodes are placed only on BB. The controller is used with artificial neural network for both MMG and EMG signals. The accuracy of this method is of 93%.

A project on hierarchical projection regression for online estimation of elbow joint angle is referred in [8]. This system is hierarchically projected regression algorithm of EMG signals but only on BB. Therefore, the errors are high and the accuracy is attained at 91.6%.

A project for joint motion EMG estimation based on dynamic control is presented in [9]. The authors use mathematical mapping model for both BB and TB in a joint angle range from 0-900. The accuracy of this method reaches 95%. However, the calibration is slow and the calculation process is complicated.

In this research, we assume that the EMG BB and TB signals can be used to indicate the elbow movement. They are random variables with independent Gaussian noises, which can be well handled by KF. Further, adaptive LQG is a very powerful tool for online generating the optimal control action from KF estimation. Similarly, to model predictive control (MPC), adaptive LQG algorithm can be online included with input/output constraints and provides faster and smoother response than conventional control systems. Researches for handling stochastic random variables and online optimal control generation are referred to in [10-17].

Thus, this project develops a relatively simpler and safer mechanical design and provides better control algorithm from adaptive LQG and KF, which should be able to control the motor tracking as high precise but not too complicated. The target of this project is to provide a low-cost device (less than $1000), light weight (less than 3 kg), and high tracking accuracy (higher than 95%).

2. DESIGN HARDWARE

The mechanical design covers three considerations which are as follows:

- Adjustability for different elbow parameters and ability to use the device on both arms without any reconstruction;
- Ability to track joint motions in all motion ranges from 0° to 150°;
- High safe, reliable and comfortable.

People have different anthropometric parameters and the hardware has to be regulated to fit 95 percentiles of population according to the data in [9] shown in Table 1.

Table 1. 95 percentiles of human anthropometric data

Parameter	**Male**	**Female**
Upper arm length (m)	0.389	0.358
Lower arm + hand length (m)	0.517	0.458
Lower arm + hand mass (kg)	2.29	1.74
Distance for the lower arm + hand center of mass from distal (%)	0.318	
Elbow breadth (cm)	8.2	7.4

Under the safety requirement of elbow injured patients, the brace must be able to hold and fix in a serial position from 0° to 150° in the range of motion (ROM). During certain trainings, the patient can use some part of ROM. In our device, a hinge is designed with 17 holes and mechanical stoppers are pins placed into these holes. Therefore, the rotation in each step is equal to 9°.

3. SOFTWARE DESIGN

The EMG BB and TB are achieved at a sampling rate of 500 Hz on the sensing recorder system and data is stored in PC for Matlab processing. The raw EMG data is filtered by a high pass filter 2nd order Butterworth to cut off low frequency signal less than 2Hz and then, by a low pass filter to cut off the high frequency of more than 200 Hz. The filtered EMG data is then sent to calibration routine to identify the maximum and minimum muscle contraction from BB and TB. As per recommendation in [7] and [9], the process is recorded the maximum voluntary contraction (MVC) as 1) to reach the maximum TB and hold it for 5 seconds; 2) to reach the maximum BB and hold it for 5 seconds; 3) then, give a rest for 20 seconds. The flow chart of data flowing and processing is shown in Figure 1.

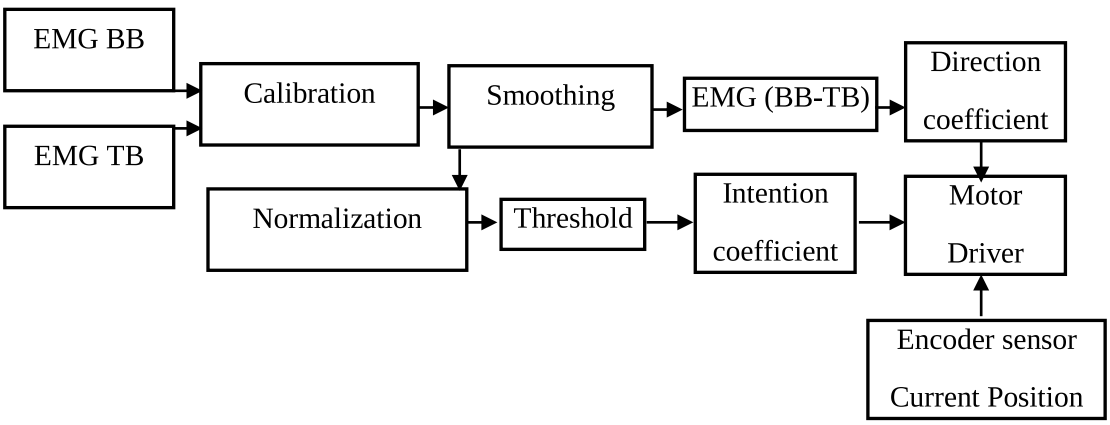

Figure 1. Data processing flowchart

Since the EMG signals are still contained uncertainties and noises, it is needed further to smooth by moving average filter: $Mooving\ average = (EMG(N))_i = \frac{\sum_{i=1}^{N} EMG_i}{N}$, where $(EMG(N))_i$ – value after moving average; EMG_i – EMG signal; and N – number of samples. In our smoothing, N is chosen as 100. EMG signals now are ready for normalization.

The purpose of normalization is to convert the different absolute MVC values from different users to be normalized from 0-1 or 0-100%. $Force = \frac{(EMG\ Activity - MIN(EMG\ Activity))}{(MAX(EMG\ Activity) - MIN(EMG\ Activity))}$, where: $EMG\ Activity$ – current EMG signal; $MAX(EMG\ Activity)$ and $MIN(EMG\ Activity)$ – values obtained in calibration; $Force$ – normalized signal. For example, one user has maximal contraction of 1500 μV, minimal of 200 μV, and during the normal exercise reaches 950 μV, the normalized signal will be (950-200)/(1500-200), equal to 0.58 or 58%.

In order to detect the human action direction and intention, a threshold at 20% of MVC is selected.

Hence, $abs\big(EMG(BICEPS) - EMG(TRICEPS)\big) > 0.2\ \boldsymbol{muscle\ active}$, and $abs\big(EMG(BICEPS) - EMG(TRICEPS)\big) < 0.2\ \boldsymbol{muscle\ inactive}$. Signals from human action direction and intention are now sent to adaptive LQG and KF to run the DC motors.

In adaptive LQR problem, we must determine the feedback matrix gain K of the optimal control vector $u(t) = -Kx(t)$, so that to minimize the quadratic performance index or the objective function of $J = \int_0^\infty (x'Qx + u'Ru)dt$, where Q and R are positive square matrices. We consider the use of KF to reconstruct the uncertain state variables: $\begin{cases} x_{k+1} = Ax_k + Bu_k + Gw_1 \\ y_k = Cx_k + Du_k + w_2 \end{cases}$, where w_1 and w_2 are independent Gaussian random variables with covariance matrix V_1 and V_2 respectively; x_k is the sum of BB and TB; A, B, C, D and G are system matrices; w_1 and w_2 are process noise; y_k is the current position measured output from encoder sensor; u_k is the optimal DC voltage input determined from the feedback matrix gain K: $u(t) = -Kx(t)$. The optimal DC voltage input u_k is then converted into PWM.

KF produces the optimal estimate $\hat{x}_k$ from the current state x_k, that is covariance of the state error e = $\hat{x}_k - x_k$ minimized. The solution of the steady state KF is a state estimator of: $\hat{x}_{k+1} = A\hat{x}_k + L(y_k - C\hat{x}_k)$. The required gain matrix L can be obtained by solving an Algebraic Ricatti Equation: $A\Sigma + \Sigma A^T - \Sigma C^T V_2^{-1} C\Sigma + V_1 = 0$. Then, $L = \Sigma C V_2^{-1}$. The optimal LQG controller is then, $\begin{cases} u_k = Kx_k \\ \hat{x}_{k+1} = A\hat{x}_k + Bu_k + L(y_k - C\hat{x}_k) \end{cases}$.

The complete adaptive LQG and KF block diagram are shown in Figure 2. The motor controller is designed to convert the input DC voltage to PWM signal. In this project, the motor driver of L298 dual full bridge driver is selected. The driver can be able to control two DC motors with maximum current up to 5A and DC voltage up to 50V.

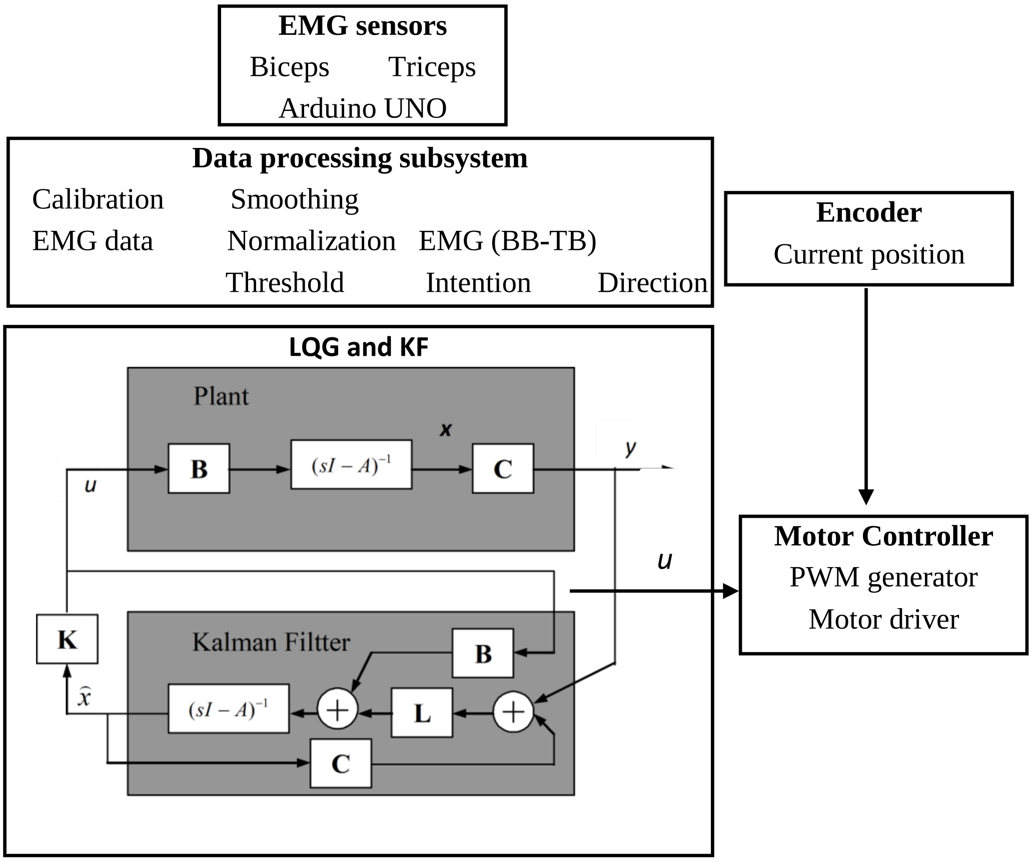

Figure 2. Adaptive LQG and KF flowchart

4. EXPERIMENTAL WORK

A prototype of the above design is fabricated and tested with two EMG sensors for BB and TB, two DC motors, two quadrature encoders, and one Arduino UNO microcontroller ATmega328P as shown in Figure 3.

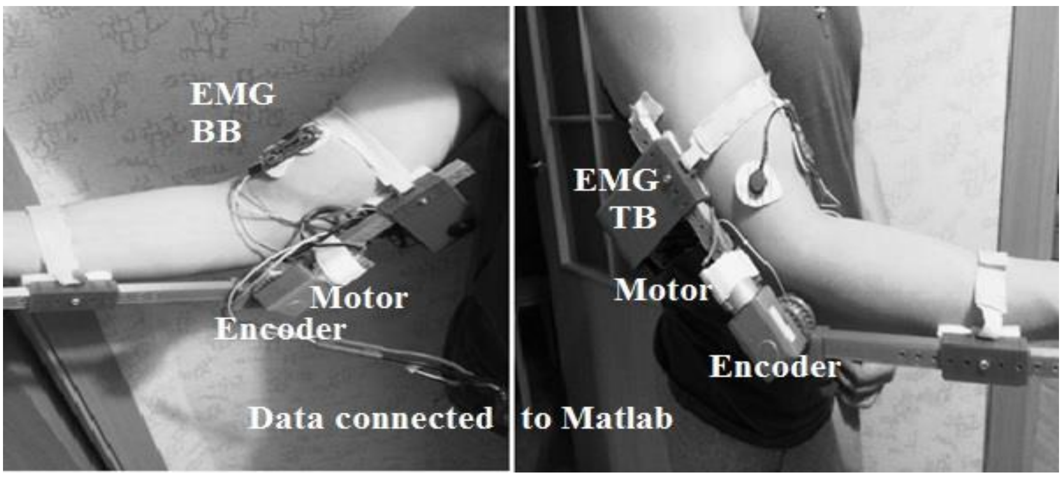

Figure 3 Prototype device and real test

Two EMG sensors are placed on BB and TB muscle. One encoder sensor is placed on the elbow joint to identify the real human movement and another encoder sensor is place on the DC motor to measure the motor rotation. Raw signal data from BB and TB is processed on microcontroller ATmega 328 and upload/download to a PC via 16 MHz USB. Data is filtered, smothered, and processed in Matlab 2017B as mentioned in Section 3 of software design. After KF filtering and moving average smoothing, the filtered and smoothed signals of BB and TB are shown in Figure 4.

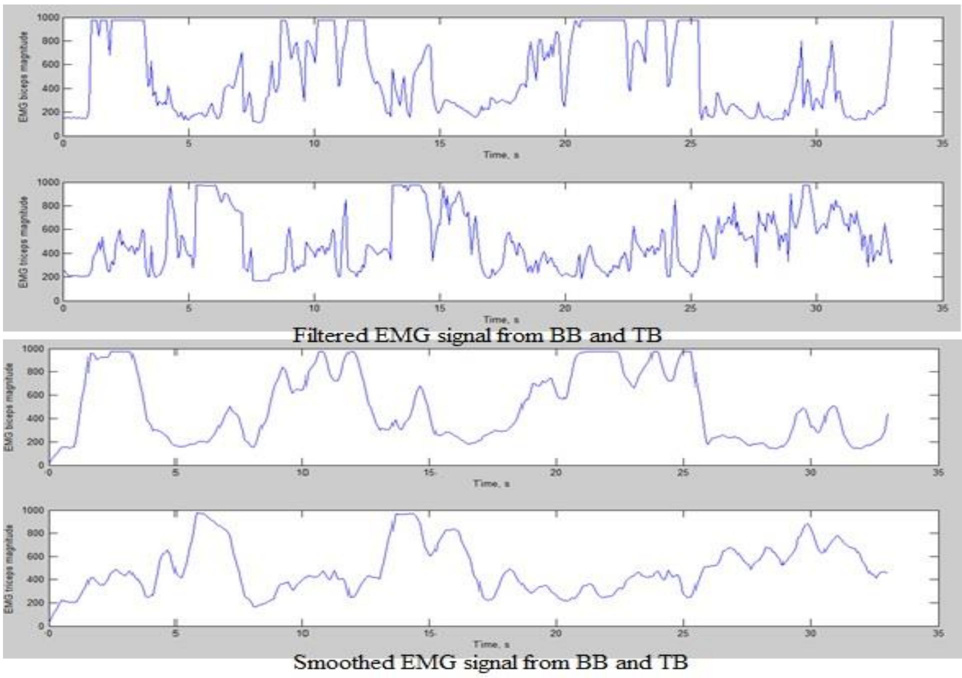

Figure 4. Filtered and smoothed EMG signals from BB and TB

From different BB and TB magnitudes, signals are now normalized for a unique range from 0-1 for everyone. The combination sum of (BB-TB) is now to pass through a threshold of 0.2 MVC to determine the human motion and direction. Results of normalized EMG signals and the motion detection conversion are shown in Figure 5.

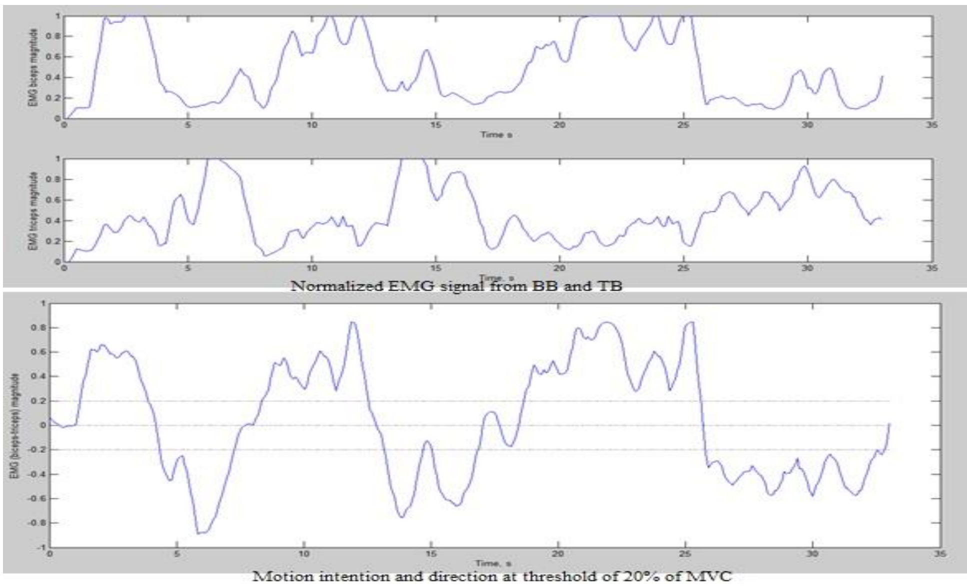

Figure 5. Normalized EMG and motion detection conversion

Finally, the motion intention and direction movement are converted into PWM to run the DC motors with adaptive LQG-KF feedback controller. Figure 6 shows the output PWM conversion signal and the comparison of the real human movement vs the motor rotation.

At starting point, a little delay of approximately 1s, the motors start tracking the human motion. In our experiments, the human exercises three free elbow rotation angles of 540, 810 and 1220 recorded by elbow encoder sensor. The motor can track well the human movement with the maximum error of 6.9º at the maximum rotation angle of 122º or the system accuracy reaches to more than 95%.

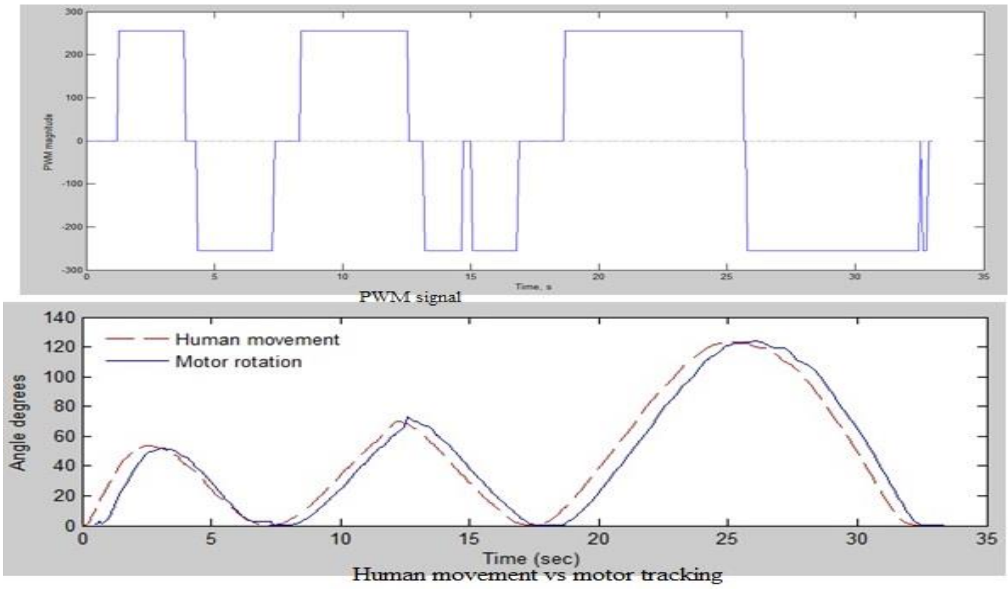

Figure 6. Human movement vs motor tracking

5. CONCLUSION

Experimental results show that the EMG with both BB and TB can provide a really better performance than the use of only BB. Since the EMG data is very noisy stochastic, KF can help to estimate the optimal values from Gaussian random variables by ´minimizing the covariance errors. Adaptive LQG algorithm can be applied directly from KF to provide online the optimal solution to control the DC motor. The motor can track well the human movement with the error less than 5%. The system is relatively simple, reliable, safe, low cost and high accuracy. In the future, some integration of advanced wireless communication networks can be installed into the current brace for exchanging data, monitoring and controlling it from remote distanced. Part of our experiment in YouTube is on: https://www.youtube.com/watch?v=rsxIwoitJhc.

CONFLICT OF INTERESTS

The authors would like to confirm that there is no conflict of interests associated with this publication and there is no financial fund for this work that can affect the research outcomes

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