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# Kalman Filtering of Accelerometer and Electromyography (EMG) Data in Pathological Tremor Sensing System

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*Abstract*— **Currently there is a lack of objective clinical diagnosis and classification of tremor is difficult when it is subtle. Thus in previous work, a sensing system has been developed to quantify pathological tremor in human upper limb. In this paper, a Kalman filter algorithm to fuse information from accelerometers and surface electromyography is proposed. As the ground truth, an optical motion tracking system will be utilized. Then two sensor fusion algorithms based on Kalman filter are formulated to estimate the joint angle of the limb from the reading of accelerometers and surface EMG. Initial results using tremor data from two Parkinson's disease patients show promising future in this sensor fusion. The sensing system and the algorithms proposed are useful for actively compensating the tremor and helping the clinicians in tremor diagnostics.**

## I. INTRODUCTION

Tremor is the most common movement disorder [1], defined as the involuntary rhythmic or semi rhythmic body part oscillation resulting from alternating simultaneous antagonistic muscle group contractions. People suffering from excessive tremor bear heavy economic and social costs. Moreover, upper limb tremor cause difficulties in performing simple activities of daily living like buttoning, inserting a key into a keyhole, writing, etc., leading to social embarrassment and sometimes isolation.

The recent advancement in the research of assistive technology gives tremor suppression alternatives to medication and surgery. Current examples include DRIFTS [2] and Micron [3]. Our approach employs the same active compensation approach employed in DRIFTS and Micron. The proposed active tremor suppression method is depicted in Fig. 1. The spatial (accelerometer) and neuromuscular (sEMG) information from the sensing module contain tremor and intended motion, so a filtering algorithm is applied to separate such movements. Then, the corresponding muscle can be actuated in anti-phase to the tremor signal using functional electrical stimulation (FES). The long term goal of the project is to implement a wearable tremor suppression orthosis for the upper limb.

A sensing system has been developed to acquire tremor data from the upper limb [4], with the goal of determining superior tremor information and subsequent development of a tremor mathematical model suitable for engineering manipulation. The sensing system and sensor fusion algorithms will help clinicians in tremor diagnosis as currently, there is a lack of objective automatic methods for the recognition and classification of different types of tremor [5].

In the system developed, the two main sensing modalities are sEMG and ACC. Both sensor modalities are self-contained sensors thus suitable for wearable application. These two sensors are very different in their nature: sEMG gives neuromuscular information while ACC presents kinematics knowledge (acceleration). The information from both sensors will be fused together to obtain a better estimate of the joint angle of the limb. To validate the sensor fusion method, the joint angle data from the Vicon MX optical motion tracking system will serve as the ground truth.

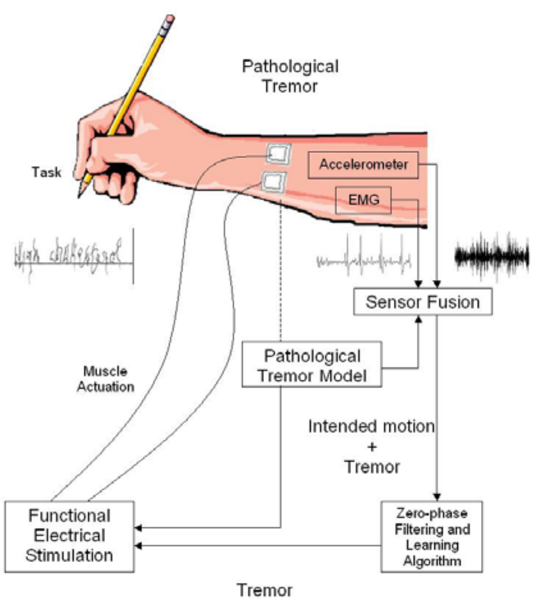


Fig. 1 Active tremor compensation using wearable orthosis

Each sensor measuring the same phenomenon independently has its own strengths and weaknesses. With sensor fusion, it is expected that the limitations can be overcome, thus providing more accurate estimation about the observed phenomenon. This concept has been used in navigation systems in which INS (Inertial Navigation

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System, accelerometers, gyroscopes, etc) and GPS (Global Positioning System) are fused together. The fusion of these two modalities will be able to compensate the weaknesses of each sensor.

One of the most common sensor fusion methods is the Kalman filter and so far, few literature exists for fusing data from different domains (e.g. both GPS and INS contains kinematics information). In clinical settings, both accelerometers (ACCs) and surface electromyography (sEMG) have been used to gain more understanding about pathological tremors. ACC and sEMG signals have been used for differentiation of pathological tremors statistically [6], using data mining techniques [7], and to identify functional activity [8]. This paper will focus on the Kalman filter algorithm to fuse the information from the sensors to estimate the joint angle of the upper limb. Section II will discuss briefly about the sensing system implemented. The Kalman filtering algorithm for the sensor fusion is developed in Section III. Lastly, some results will be presented at Section IV.

## II. SENSING SYSTEM DEVELOPMENT

Data is collected from the subjects' upper limb. Seven channels of bipolar EMG are attached to the upper limb to record elbow flexion-extension, wrist flexion-extension, index finger extension and abduction, and thumb abduction. The 10 mm diameter electrode used is made of Ag/AgCl. Inter-electrode distance is about 35-40 mm for bigger muscles and 25-30 mm for the smaller ones. In placing the electrode, the guidelines from [9] are closely followed.

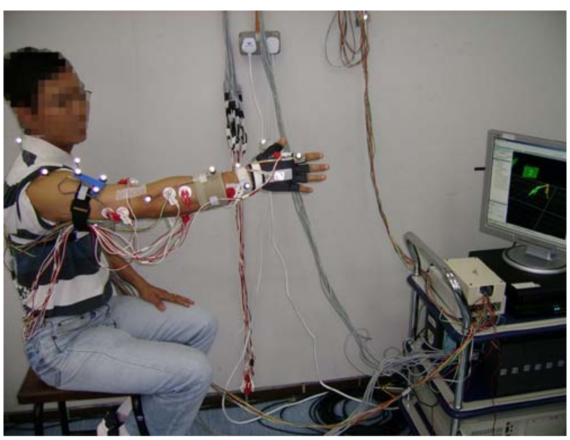

Fig. 2. The whole setup for the sensing system developed

The amplifier and A/D system utilized is from Biopac Systems Inc. The detection mode employed is differential mode. The cutoff frequencies are 10 Hz for the high pass filter and 500 Hz for the low pass filter. Gain is set to 2000 and sampling rate is 2000 Hz.

Accelerometers are located in 5 places on the upper limb: upper arm, lower arm, dorsum of hand, first metacarpal of index finger, and thumb. An analog accelerometer solution, developed by Dimension Engineering, is used. This board incorporates the 3-axis MEMS accelerometer by Analog Devices Inc (ADXL330) which has a minimum measurement range of $\pm 3g$. This board also provides integrated operational amplifier buffers and onboard voltage regulator. Data is sampled at 150 Hz.

For the optical motion tracking system, 4 Vicon MX3+ cameras, each fitted with a 6 mm C-mount lens are used. The upper limb Plug-in-Gait (PiG) model is furnished by Vicon to provide the user with useful kinematics information (joint angle) of the upper limb. Here we will concentrate on the model for one arm only. The upper limb model presented provides seven degrees of freedoms (DOF) for one arm: 3 DOF at shoulder, 2 DOF at the elbow, and 2 DOF at the wrist. Sampling rate is 50 Hz.

With collaboration from local hospitals, both control subjects and patients with tremor are recruited to perform standard clinical tests such as resting, hands outstretched, finger to nose, Archimedes spiral drawing, and so on.

## III. FORMULATION OF THE KALMAN FILTER

### A. Sensor fusion

Kalman filter is a frequently used method for sensor fusion. Thus, a Kalman filter algorithm is developed to show the feasibility of sensor fusion (ACC and EMG signal) to estimate the upper limb joint angle. A Kalman filter combines all available measurement data, plus prior system and measuring devices knowledge to produce an estimate of the desired variables where the error is minimized statistically. The basic assumptions of a Kalman filter are the system is a linear model in which system and measurement noise are white and Gaussian. The state estimation cycle comprises the state and measurement prediction (time update) and state update (measurement update).

### B. Preprocessing of data

In this paper, we only analyze the hand tremor from a Parkinson's disease (PD) patient and specifically only the tremor at resting is considered. For the initial stage of the project, all the processing applied to the signals are done offline. Real time implementation of the algorithm will be done in the future, but is outside the scope of this paper. Subsequently, the algorithms developed in this paper are meant only for pure tremor signal without intended motion/general trend overriding it. It basically assumes that the motion from the subject has been passed through a zero phase filtering algorithm which can separate the tremulous part from the intended motion or any slow moving trend.

The zero-phase aspect of the filtering is crucial here. If the signal's phase is changed and the filtered signal is used for cancellation, then we are not canceling the actual tremor seen by the sensing process. Currently the zero-phase filtering research is in progress [10] and as a temporary replacement, a built-in function which implements zero-phase filter from MATLAB is used to remove the intended motion, which generally has very low frequency (less than 1 Hz).

As mentioned in section I, the optical tracking system serves as a ground truth, thus the result of our algorithms will be compared with the reading from this system. And because the sampling rate of the optical system is the lowest among all, the data from ACC and sEMG system is downsampled to match the sampling frequency of the optical motion tracking system. It does not matter whether the downsampling is done before or after the filtering.

Hence, the ACC signal is passed through a zero phase high pass filter to remove the intended motion. The filter employed is a 3rd order Butterworth filter with 1 Hz cutoff frequency. A zero phase low pass filter (4th order Butterworth with 15 Hz cutoff frequency) is subsequently applied to remove the unwanted noise in the ACC signal. This cutoff is chosen as pathological tremor never exceeds this bandwidth. The ACC signal used for the sensor fusion is still in its raw format (voltage). No calibration has been done to determine the bias and scale factor.

The joint angle signal from Vicon MX is also passed through the same high pass and low pass filters used for the ACC signal.

The RMS of the sEMG signal will be used instead of the raw data as it reflects the kinematics clearer. Furthermore, RMS is also preferable compared to the linear envelope (full wave rectification followed by low pass filter) because it gives the physical meaning of the sEMG signal power. The RMS value is specified over 100 samples of data. Finally, since the motion in one axis (e.g. flexion-extension) involves two muscles, two RMS sEMG signals should be used. To combine both signals, the extensor's signal is subtracted from the flexor's signal.

For all the tests done by the subjects, the time taken is at most 24 seconds.

It is known that there is an electromechanical delay between the sEMG and kinematics signals. This delay must be known prior to the sensor fusion regardless in real time or offline implementation. At this stage, the delay is determined by using cross correlation between the signals. The cross correlation function between two signals $x(k)$ and $y(k)$ with $N$ elements is defined by

$$R_{xy}(m) = \begin{cases} \dfrac{1}{N}\displaystyle\sum_{n=0}^{N-m-1} x_{n+m}y_n & m \geq 0 \\ \dfrac{1}{N}R_{yx(-m)} & m < 0. \end{cases} \quad (1)$$

The value of m which gives the maximum value, is the delay between x and y (positive m means $x(k)$ is leading $y(k)$).

These are all the preprocessing done before applying the Kalman filter. There will be two implementations of Kalman filter developed in the next section.

### C. First implementation of Kalman filter

The first implementation of Kalman filter for sensor fusion between the sEMG and ACC signals utilizes the fact that tremor is approximately rhythmic and roughly sinusoidal [11]. Thus, the process model can use sinusoidal signal whilst the sEMG and ACC measurements will serve as the corrector.

Suppose that the (tremulous) joint angle profile for wrist (flexion-extension) follows a sinusoidal curve; and along with its derivative (angular velocity) are defined as the states of the system ($x(k) = [\theta(k) \;\; \dot{\theta}(k)]'$):

$$\begin{aligned} \theta(k) &= A_T \sin(2\pi f_T k T_s) \\ \dot{\theta}(k) &= A_T 2\pi f_T T_s \cos(2\pi f_T k T_s) \end{aligned} \quad (2)$$

where $A_T$ and $f_T$ is the tremor amplitude and frequency, $T_s$ is the sampling time. The tremor amplitude and frequency can be known by obtaining some data from the patient beforehand. It is known that tremor characteristics do not change much over time. To get the dynamic plant equation, trigonometric addition formula is employed:

$$\begin{aligned} \theta(k+1) &= A_T \sin(2\pi f_T (k+1) T_s) \\ &= A_T \sin(2\pi f_T k T_s)\cos(2\pi f_T T_s) \\ &\quad + \cos(2\pi f_T k T_s)\sin(2\pi f_T T_s) \\ &= \theta(k)\cos(2\pi f_T T_s) + \frac{\dot{\theta}(k)}{2\pi f_T T_s}\sin(2\pi f_T T_s). \end{aligned} \quad (3)$$

Similarly

$$\dot{\theta}(k+1) = \dot{\theta}(k)\cos(2\pi f_T T_s) + \frac{\ddot{\theta}(k)}{2\pi f_T T_s}\sin(2\pi f_T T_s). \quad (4)$$

Notice that

$$\begin{aligned} \ddot{\theta}(k) &= -A_T (2\pi f_T T_s)^2 \sin(2\pi f_T k T_s) \\ &= -(2\pi f_T T_s)^2 \theta(k). \end{aligned} \quad (5)$$

Hence,

$$\dot{\theta}(k+1) = \dot{\theta}(k)\cos(2\pi f_T T_s) - 2\pi f_T T_s \theta(k)\sin(2\pi f_T T_s). \quad (6)$$

Therefore, the dynamic plant equation for sinusoidal model is

$$\begin{aligned} \begin{bmatrix} \theta(k+1) \\ \dot{\theta}(k+1) \end{bmatrix} &= x(k+1) \\ &= \begin{bmatrix} \cos(2\pi f_T T_s) & \dfrac{\sin(2\pi f_T T_s)}{2\pi f_T T_s} \\ -2\pi f_T T_s \sin(2\pi f_T T_s) & \cos(2\pi f_T T_s) \end{bmatrix} x(k) + v(k), \end{aligned} \quad (7)$$

where $v(k)$ is zero mean white Gaussian noise with $Q(k)$ as its covariance matrix:

$$E[v(k)v(k)'] = Q(k) = \begin{bmatrix} \sigma_\theta^{\,2} & \sigma_\theta \sigma_{\dot{\theta}} \\ \sigma_\theta \sigma_{\dot{\theta}} & \sigma_{\dot{\theta}}^{\,2} \end{bmatrix} \quad (8)$$

For the measurement model, a relationship between the joint angle and sensor readings from sEMG and ACC has to be defined. Existing literature that discusses the relationship between joint angle and EMG is rare. Most literature talks about EMG-force relationship. However, there is no consensus and there are still a lot of discussions going on this field [12]. By using neural network, it has been shown that EMG signals contain information about the arm kinematics, but the RMS error for joint angle estimation is between $8^0$ and $20^0$ [13]. Different neural networks have been explored in the same line and the result is better in one plane only [14].

The relationship between joint angle and ACC reading are well defined, although it is nonlinear. The acceleration measured consists of 4 components, the inertial acceleration of the link, $a_{CG}$, the centripetal acceleration, $a_C$, the tangential acceleration, $a_T$, and the gravitational acceleration, $g$.

$$\begin{aligned} a(k) &= a_{CG}(k) + a_C(k) + a_T(k) + R_{\theta(k)}g \\ &= a_{CG}(k) + \omega(k) \times \left(\omega(k) \times P_a\right) + \alpha(k) \times P_a + R_{\theta(k)}g \end{aligned} \tag{9}$$

For the 3-axis accelerometer implemented in the system, (9) contains 3 nonlinear equations. By approximating the angular velocity and acceleration using backward difference method, there will be 3 unknowns in 3 equations. Thus, it is feasible to solve it theoretically using numerical method such as Levenberg-Marquardt algorithm. However, it is noted that the equations involve trigonometric function ($R_{\theta(k)}$) and will cause singularity problem. Quaternions is another way to represent the direction cosine matrix without transcendental function, but the numerical method still cannot find the solution due to local minima problem. This may be caused by the minimal constraints we have in (9).

Even if the centripetal acceleration component is neglected (angular velocity is assumed to be comparably small than other components), the numerical method still cannot find a good approximation. The approximated equation is:

$$\begin{aligned} a_x(k) &= \ddot{\theta}_y(k)r_z - \ddot{\theta}_z(k)r_y - (\theta_x(k)\theta_y(k) + \theta_z(k))g \\ a_y(k) &= \ddot{\theta}_z(k)r_x - \ddot{\theta}_x(k)r_z - (\theta_y(k)\theta_z(k) - \theta_x(k))g \\ a_z(k) &= \ddot{\theta}_x(k)r_y - \ddot{\theta}_y(k)r_x - g \end{aligned} \tag{10}$$

Despite the seemingly difficulties to relate joint angle with EMG and ACC data, there is one way to overcome it by exploiting the periodic motion assumption. Since shape of all the signals from each sensor are quite similar (because of its periodicity), it is reasonable to try a simple first order polynomial for the relationship. Thus, linear regression will be applied to a slice of data to determine the coefficients of the polynomial. In linear regression, a first order relationship between the input and output can be modeled as in the equation below

$$\begin{gathered} [y_1\ y_2 \dots y_n]' = \begin{bmatrix} 1 \\ x_1\ x_2 \dots x_n \end{bmatrix}' \begin{bmatrix} \beta_0\ \beta_1 \end{bmatrix}' + \begin{bmatrix} \varepsilon_1\ \varepsilon_2 \dots \varepsilon_n \end{bmatrix}' \\ \mathbf{y} = \mathbf{X}\mathbf{b} + \mathbf{e} \end{gathered} \tag{11}$$

where $\mathbf{y}$ is either the EMG or ACC data, $\mathbf{X}$ contains the joint angle data, $\mathbf{e}$ is the error, and $\mathbf{b}$ is the coefficient vector which can be estimated using

$$\mathbf{b} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y} \tag{12}$$

Therefore, the measurement for this system is

$$z(k) = \begin{bmatrix} EMG(k) \\ ACC(k) \end{bmatrix} = \begin{bmatrix} c_{EMG}(1) & 0 \\ c_{ACC}(1) & 0 \end{bmatrix} \begin{bmatrix} \theta(k) \\ \dot{\theta}(k) \end{bmatrix} + \begin{bmatrix} c_{EMG}(2) \\ c_{ACC}(2) \end{bmatrix} + w(k) \tag{13}$$

where $w(k)$ is also zero mean white Gaussian noise with $R(k)$ as its covariance matrix. . It is assumed that the noise from EMG and ACC are independent of each other.

$$E[w(k)w(k)'] = R(k) = \begin{bmatrix} \sigma_{EMG}^2 & 0 \\ 0 & \sigma_{ACC}^2 \end{bmatrix} \tag{14}$$

The noise covariance matrix for measurement model is obtained by calculating the variance of the signal during stationary motion. It is assumed that the noise from EMG and ACC are Gaussian and they are independent of one another.

The initial value of the state and error covariance matrix is all chosen to be zeros.

### *D. Second implementation of Kalman filter.*

In the first implementation of Kalman filter to fuse the sEMG and ACC information, a sinusoidal model is used as its process model and first order polynomial for its measurement model. The next implementation will utilize the fact that sEMG data arrives earlier than the kinematics (ACC) data due to electromechanical delay. The sEMG information, thus, serves as a predictor in this implementation of Kalman filter. Then, the ACC data is used as a corrector to the predicted value from the sEMG process model. The state considered in this implementation is the joint angle only and the model to relate both sEMG and ACC to joint angle is a first order polynomial as implemented in previous implementation.

Since this is a one dimension problem (state is joint angle only) and assuming the noise of EMG and ACC reading is Gaussian and white noise, we can obtain the Kalman filter gain and the estimate of the joint angle, given the two readings from sEMG and ACC is

$$\hat{\theta}(t) = \theta_{EMG}(t) + \frac{\sigma_{EMG}^2}{\sigma_{EMG}^2 + \sigma_{ACC}^2}(\theta_{ACC}(t) - \theta_{EMG}(t)) \tag{15}$$

Using relevant slice of data to establish the coefficients for the polynomial relating sEMG and ACC to joint angle and the measurement covariance matrix as defined in (13), the estimated joint angle is calculated.

## IV. Results and Discussions

With everything defined, Kalman filter can be applied to the sEMG and ACC signals. The signals chosen are measured from two PD patients at resting position. The joint angle observed is the flexion-extension of the arm. sEMG data are taken from wrist flexor (flexor carpi ulnaris) and wrist extensor (extensor carpi radialis); ACC from the arm. The preprocessing of data is applied as described in previous section.

To observe the Kalman filter performance in estimating the joint angle, the estimated angle is subtracted from the actual angle measured by optical tracking system. The result is labeled as ‘error’ signal in the plots (See Fig. 3 for first patient). The variance of the subject’s actual joint angle will be compared to the error. Another way to see the performance is to compare the power spectrum of the actual joint angle and the error (see Fig. 4 for first patient). A very distinct peak is noted in the power spectrum, which shows the tremor frequency. The power of the peak will also be compared. Finally, the RMS error between the actual and estimated joint angle is calculated. The results are tabulated in Table 1.

Fig. 3 and Fig. 4 show the results for the first PD patient using the first implementation of Kalman filter. The next two figures show the respective results of the second implementation. The subsequent four figures are the results of a PD patient with a more severe condition than the first patient.

The results for two PD patients clearly illustrate successful exploitation of the Kalman filtering algorithms to fuse the information from accelerometer and sEMG data. The first implementation shows that indeed, tremor can be modeled as an approximately sinusoidal movement. The second implementation confirms that the sEMG signals can act as a predictor for the joint angle whilst the accelerometer signal, which comes in later, able to use as the corrector of the estimate by the sEMG signal.

In this paper, it is assumed that the profiles of both sEMG and kinematics data are the similar due to the periodicity of tremor. The dependency on this assumption is shown in Fig. 9 where the accelerometer reading is not smooth. This is probably due to its placement on the upper limb as the reading from the optical motion tracking system does not show the same artifact. The estimated joint angle follows the accelerometry profile and the artifact will also creep in. In future, the relationships between joint angle and both sEMG and ACC data will receive further investigation and more patients recruited to verify and validate our sensor fusion algorithm.

TABLE I
PERFORMANCE OF SENSOR FUSION OF ACC AND SEMG DATA OF THE FIRST PD PATIENT (TOP) AND THE SECOND (BOTTOM)

| PD1 | Variance | | Error | Power spectrum | |
|---|---|---|---|---|---|
| Method | Actual | Error | RMSE | Actual | Error |
| First | 0.1045 | 0.0175 | 0.1185 | 7.315 | 0.1199 |
| Second | 0.1045 | 0.0145 | 0.1202 | 7.315 | 0.3075 |

| PD2 | Variance | | Error | Power spectrum | |
|---|---|---|---|---|---|
| Method | Actual | Error | RMSE | Actual | Error |
| First | 7.39 | 0.4219 | 0.6494 | 1591.6 | 22.2239 |
| Second | 7.39 | 0.8976 | 0.9475 | 1591.6 | 24.84 |

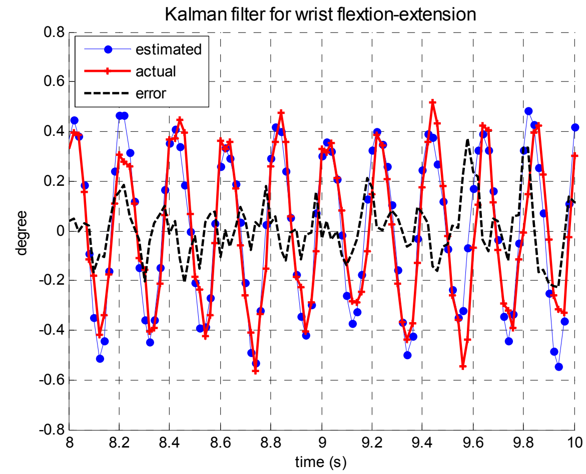


Fig. 3. Estimated joint angle from first implementation of Kalman filter of the first PD patient at resting position for 2 seconds.

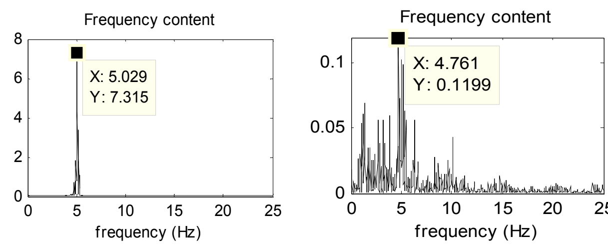


Fig. 4. Power spectral densities of the joint angle (left) and the joint angle after subtracted by the estimated one (right).

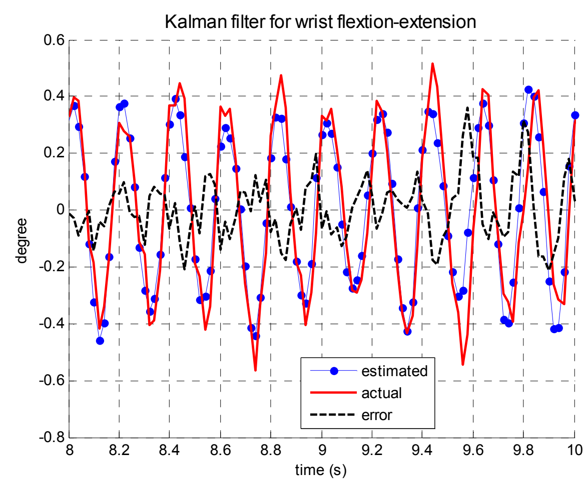


Fig. 5. Estimated angle from second implementation of Kalman filter of the first PD patient at resting position for 2 seconds.

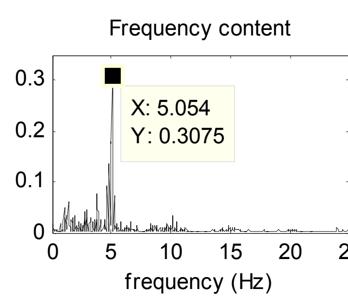


Fig. 6. Power spectral densities of the joint angle after subtracted by the estimated one.

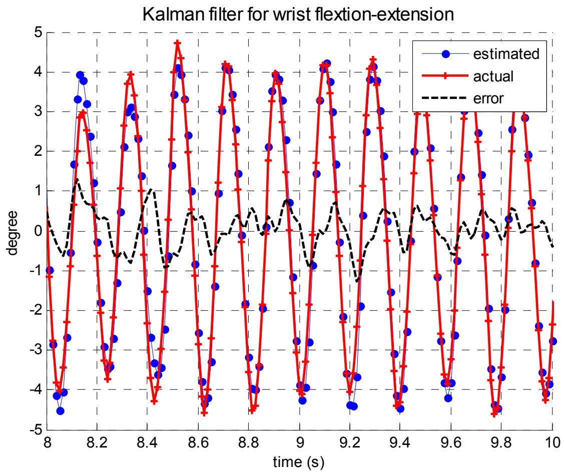


Fig. 7. Estimated angle from first implementation of Kalman filter of the second PD patient at resting position for 2 seconds.

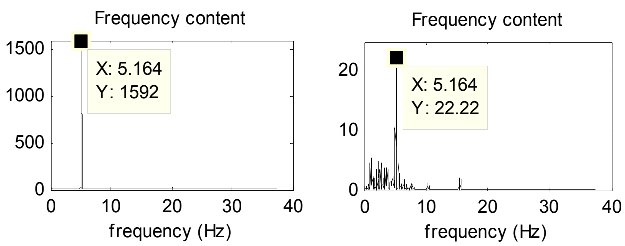


Fig. 8. Power spectral densities of the joint angle (left) and the joint angle after subtracted by the estimated one (right).

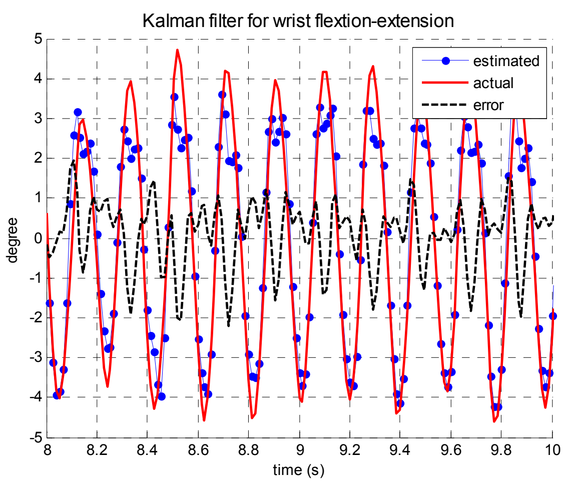


Fig. 9. Estimated angle from first implementation of Kalman filter of the second PD patient at resting position for 2 seconds.

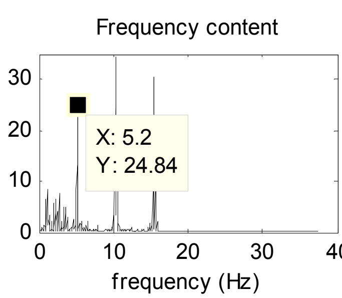


Fig. 10. Power spectral densities of the joint angle after subtracted by the estimated one.

## V. CONCLUSION

An initial attempt to fuse the data from accelerometer (spatial) and sEMG (electrophysiological – neuromuscular) has been successfully carried out based on Kalman filtering algorithm. The initial results achieved show a promising future and further investigations will be carried out to discover the best sensor fusion approach for these two very different sensor modalities. This algorithm can be useful for active tremor compensation and also for making clinical diagnosis of tremor more robust and objective.

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