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Fusion of Electromyographic Signals with Proprioceptive Sensor Data in Myoelectric Pattern Recognition for Control of Active Transfemoral Leg Prostheses

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Abstract—**This paper presents a myoelectric knee joint angle estimation algorithm for control of active transfemoral prostheses, based on feature extraction and pattern classification. The feature extraction stage uses a combination of time domain and frequency domain methods (entropy of myoelectric signals and cepstral coefficients, respectively). Additionally, the methods are fused with data from proprioceptive sensors (gyroscopes), from which angular rate information is extracted using a Kalman filter. The algorithm uses a Levenberg-Marquardt neural network for estimating the intended knee joint angle. The proposed method is demonstrated in a normal volunteer, and the results are compared with pattern classification methods based solely on electromyographic data. The use of surface electromyographic signals and additional information related to proprioception improves the knee joint angle estimation precision and reduces estimation artifacts.**

Keywords - Electromyographic signals, proprioceptive sensors, entropy, cepstral coefficients, Kalman filter, transfemoral prostheses.

I. INTRODUCTION

ELECTRONIC knees can be designed for providing different levels of damping during swing, and for adjusting to different walking speeds, assuming they have the appropriate sensors and control algorithms for estimating the knee joint angle and the walking speed. With the appropriate control algorithm, it is possible to program the prosthesis to allow the knee to flex and extend while bearing a subject's weight (stance flexion). This feature of normal walking is not possible with conventional prostheses.

Electronic knees use some form of computational intelligence to control the resistive torque about the knee. Several research groups have been involved in designing prototype knee controllers. Grimes *et al.* [1] developed an echo control scheme for gait control, in which a modified knee trajectory from the sound leg is played back on the contralateral side. Popovic *et al.* [2] presented a battery-powered active knee joint actuated by DC motors, together with a finite state knee controller that utilizes robust position tracking control algorithm for gait control. A small number of companies have also developed electronic knee for clinical uses. For example, the Otto Bock C-leg [3] provides adjustable resistance for flexion and extension in swing through onboard intelligence and a special software package.

Processing of surface electromyographic (SEMG) signals may be used in actively powered myoelectric prostheses for extracting command signals from muscle in the residual limb [4]. We recently proposed two different algorithms for estimating the intended knee joint angle from SEMG signals measured on opposing muscles of the upper-leg [5],[6]. The first method uses the auto-regressive model for feature extraction and a Levenberg-Marquardt (LM) multi-layer perceptron neural network for pattern classification [5]. The second method uses time-domain and frequency-domain SEMG feature extraction (amplitude histogram and AR model, respectively), self-organizing maps for feature projection, and a LM neural classifier [6].

For the development of an active leg prosthesis that also possesses ankle and foot axes, it is necessary to use other sources of information besides the SEMG signal (e.g. proprioceptive data). This could improve the precision of the prosthesis during movements of knee flexion and extension. Data fusion applied to myoelectric signals and proprioceptive sensors is capable of providing reliable myoelectric control [7].

The level of activity of muscles, either in isometric or isotonic contraction in dynamic limb motion, is the most important process to be recognized in myoelectric control. The combination of time domain features that represent the term of energy in the SEMG signal, with frequency domain features that show the muscle's level of activation, provides good classification precision, is computationally efficient, and is more robust to electrode displacement [8].

This paper proposes an algorithm for estimation of intended knee joint angle from SEMG signals and proprioceptive sensor data, for the control of active transfemoral leg prostheses (Fig. 1). Two channels of SEMG

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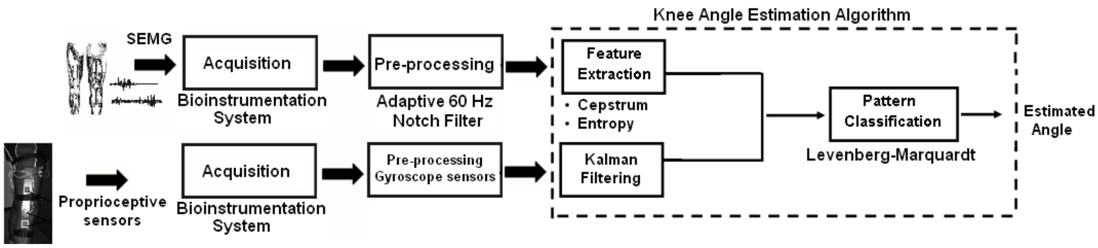

Fig. 1: Block diagram of the proposed knee angle estimation algorithm.

signals are simultaneously acquired from bipolar pairs of electrodes placed on different muscles. The angular rate information from two gyroscope sensors placed on the upper and lower legs is also measured. The entropy and the cepstral coefficients associated with the SEMG signals are calculated, and a Kalman filter is used to estimate the knee's angular rate. The intended knee joint angle is estimated from this set of features using a Levenberg-Marquardt multi-layer perceptron neural network. The proposed method is demonstrated in a normal volunteer, and the results are compared with our previous knee joint angle estimation methods, which were based solely on classification of electromyographic data.

I. METHODOLOGY

A. Data Collection

A specifically-designed microcontrolled bioinstrumentation system was constructed [9] as part of the project of an active transfemoral prosthesis [10]. The system implements up to four channels of front-end amplifiers for SEMG signal acquisition, and a channel connected to an electrogoniometer, for measuring the knee joint angle. In this work, two channels, connected to gyroscope sensors that provide knee angular rate information, were added to the system. Two channels of amplified SEMG signal, the angular displacement signal and the data from the gyroscope sensors are analogically multiplexed and sampled using a 13-bit analog-to-digital converter, which is electrically isolated from the microcontroller and the power supply using an optocoupler and a DC-DC converter. The sampling rate was 1043.45 Hz per channel. Analog filters are used to limit the SEMG signal to the 20–500 Hz frequency range. The microcontrolled system implements a digital real-time adaptive notch filter, which maintains a running estimate of the 60 Hz power line interference [9]. The data is transferred to a personal computer through a serial interface.

For a preliminary evaluation of the myoelectric algorithm, the following experimental protocol was designed. Two pairs of 10-mm Ag/AgCl surface electrodes were placed in bipolar configuration over a pair of antagonist muscles (rectus femoris and semitendinosus muscle) of a healthy subject (Fig. 2a and 2b). These muscles correspond to the flexion and extension movements of the knee joint, respectively. The distance between the centers of the electrodes of each pair was 3–5 cm. The reference electrodes were placed over the lateralis and medialis epicondyles bones. An electrogoniometer was placed and strapped over the external side of the leg, and the gyroscope sensors were placed over the upper and lower legs, respectively (Fig. 2c). The difference between the signals measured by the gyroscopes reflects the angular rate of the knee joint.

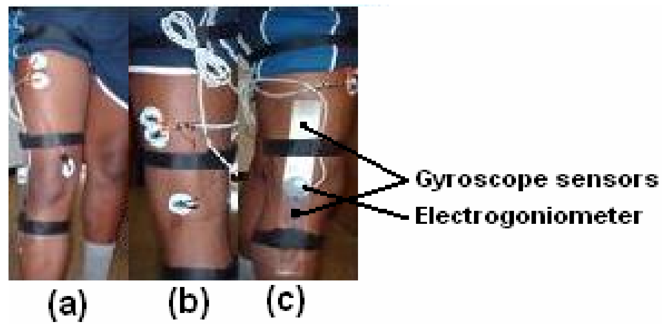

Fig. 2: Placement of SEMG electrodes (a,b), electrogoniometer and gyroscope sensors (c).

Figure 3 presents an example of SEMG signals and proprioceptive sensor data (electrogoniometer and gyroscope sensors), which were simultaneously-acquired while the subject was walking in a constant direction and at a constant pace, for 15 seconds.

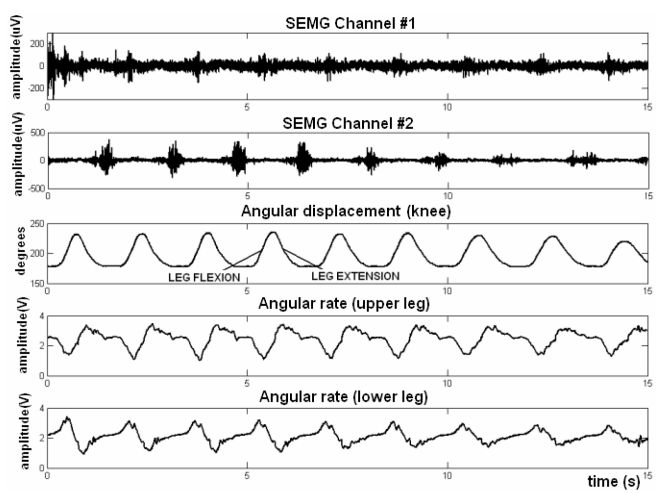

Fig. 3: Representative set of simultaneously-acquired SEMG signals (rectus femoris and semitendinosus muscles), electrogoniometer angle (knee), and gyroscope measurements (upper and lower legs).

B. Feature Extraction

In this work, cepstral analysis is used for frequency-domain SEMG signature discrimination. The cepstrum of a signal is defined as the inverse Fourier transform of the logarithm of the squared magnitude of the Fourier transform of a signal, as follows:

$$c(n) = \frac{1}{N} \sum_{k=0}^{N-1} \log\left(\left|X(k)\right|^2\right) e^{j2\pi kn/N}. \quad (1)$$

If all transfer function poles are inside the unit circle, the logarithmic transfer function can be represented as a Laurent expansion [11]. From (1), it is possible to derive the following recursive relation:

$$c_1 = -a_1$$
$$c_i = -a_i - \sum_{n=1}^{i-1} \left(1 - \frac{n}{i}\right) a_n c_{i-n}, \quad 1 < i \leq P. \quad (2)$$

Using (2), the first P cepstral coefficients (c_k) can be obtained from the Pth order coefficients (a_k) of the autoregressive (AR) signal model. Even though the cepstral coefficients are derived directly from the AR coefficients, they do not contain exactly the same information, because the recursive operation changes the distribution of the features nonlinearly [11]. The cepstral coefficients were obtained using a sixth-order AR model and (2). The cepstral coefficients obtained from each of the two SEMG channels form a feature vector for the pattern classification process.

The entropy of each SEMG channel is calculated and used as a time-domain feature vector [12]. We focus on the difference in entropy between stationary SEMG in a relaxated state and in movement. Assuming that electromyographic signals can be approximated by a normal distribution process with zero mean, the entropy of the distribution is

$$H(\sigma_i) = \frac{1}{2} \log_2(2\pi e \sigma_i^2)$$
$$\sigma_i^2 = \frac{1}{N-1} \sum_{n=1}^{N} x_i(n)^2, \quad (3)$$

where σ_i^2 represents the variance estimated from the signal measured from each electrode, and $x_i(n)$ is a vector containing N EMG samples from the i-th electrode [12]. For each SEMG channel, the calculated entropy is concatenated with the cepstral feature vector. This combination provides robustness in weak SEMG signals.

In addition, angular rate information from the gyroscopes is used to increase angle estimation precision and reduce estimation artifacts. Feature extraction is performed using a Kalman filter. The goal of Kalman filters is the estimation of nonstationary signals buried in noise, by minimizing the mean squared error (i.e., recursive least squares for stochastic models). The estimated signal (e.g., angular rate) is modeled using a state-space formulation, describing its dynamical behavior [13], according to the following linear stochastic model:

$$x(k) = x(k-1) + n(k)$$
$$y(k) = x(k) + v(k), \quad (4)$$

where, in this work, $x(k)$ is the joint angular rate; $n(k)$ is noise modeling the evolution of the joint angular velocity between two sampling intervals; $y(k)$ is the measured angular rate, obtained from subtracting the angular rate values measured on the upper and lower legs, respectively; and $v(k)$ is the measurement noise. It is assumed that $n(k)$ and $v(k)$ have zero mean, uncorrelated Gaussian distributions, with variances q^2 and r^2, respectively. When applying the Kalman filter to this model, one obtains $\hat{x}(k/k)$ as an optimal estimate of $x(k)$, in the least-squares sense. It can be shown that, for this specific problem, this filter is equivalent to a unity-gain, low-pass, first-order filter, with time-varying cutt-off frequency. This cutt-off frequency is computed considering noise variances q^2 and r^2, as well as the error variance associated to $\hat{x}(k/k)$ [13]. The value of $\hat{x}(k/k)$ is an optimal estimate of the mean of the knee joint angular rate at sampling step k. At each time instant k, the angular rate estimate $\hat{x}(k/k)$, along with the SEMG cepstral and entropy coefficients, are used as input to the neural classifier, discussed next.

C. Pattern Classification

This stage attempts to estimate the intended knee joint angle from the SEMG feature vector and the angular rate estimate. This is implemented using a Levenberg-Marquardt multi-layer perceptron neural network [14]. Similarly to the quasi-Newton methods, the Levenberg-Marquardt algorithm was designed to approach second-order training speed without computing the Hessian matrix. The key step in the LM algorithm is the computation of the Jacobian matrix, which can be computed through standard backpropagation techniques [14], which are much less complex than computing the Hessian matrix. Although the computational requirements of the LM algorithm become much higher after each iteration, this is fully compensated by its higher efficiency, especially when high precision is required.

Network training and testing were performed in Matlab (The MathWorks, Inc., Natick, MA, USA). For each SEMG channel, the proposed algorithm was implemented such that the feature extraction process (cepstral analysis and entropy) was performed for 200 samples (192 ms) windows, using a sliding window approach. Similarly, for each new pair of gyroscope sensor samples, an updated Kalman filter angular rate estimate was calculated. This results in a 15-coefficient feature vector (6 cepstral coefficients and 1 entropy coefficient per SEMG channel, plus 1 angular rate coefficient) per sample interval. This information is transferred to a three-layer LM neural network, with 15 nodes in the input layer, 6 nodes in the hidden layer, and 1 node in the output layer, which represents the estimated knee joint angle. The network architecture and size was empirically chosen. The true displacement angle measured with the electrogoniometer is used as training reference.

Training and testing were performed using two different set of signals obtained from the same subject, with a 20-minute rest interval between acquisitions. Each signal was 15-second long (15640 samples per data channel).

III. Results and Discussion

The results in Fig. 4 demonstrate the performance of the proposed algorithm in a representative 15-second experiment, compared with two knee angle estimation methods based solely on electromyographic data [5],[6]. The correlation between estimated and electrogoniometer-measured knee joint angles was 0.87 for the proposed method, and 0.62 and 0.81 for methods [5] and [6], respectively, in this example. The results obtained with methods [5] and [6] presented significant artifacts, which may be interpreted by the leg prosthesis as false positives, depending of their duration. These errors peaks may be due to noise in the SEMG feature space. The use of proprioceptive data considerably improved upon those methods with respect to this issue.

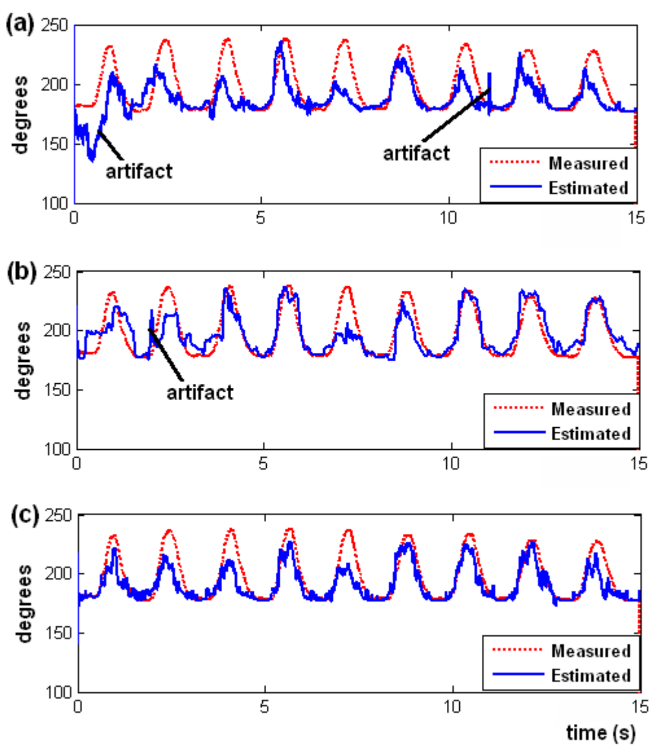

Fig. 4: Measured and estimated knee angle displacements: (a) algorithm from ref. [5]; (b) algorithm from ref. [6]; (c) proposed algorithm.

The processing time for these 15-second long signals were 1.5 seconds for method [5], 41 seconds for method [6], and 2.3 seconds for the proposed method. These were measured on a 1.6 Ghz AMD Sempron CPU, and refer to the testing stage only. The proposed method is 20 times faster than method [6], and is computationally equivalent to method [5], but provides considerably better results and robustness. These results shows that the algorithm may potentially be used in real-time on the leg prosthesis.

IV. Conclusion

This paper introduced a knee angle estimation algorithm for control of active transfemoral leg prostheses. The proposed algorithm implements data fusion of SEMG signals and proprioceptive sensor information, which improves the angle estimation precision when compared with algorithms based solely on SEMG data. The concepts used in this algorithm may be useful in the development of a control algorithm for active leg prostheses, in which signals from many different sensors may be fused and used in the conception of a movement predictive model. Future experiments will include a multi-subject evaluation, and tests under variable conditions of moving direction and speed.

V. Acknowledgment

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