# Myoelectric algorithm for knee angle estimation using proprioceptive data and a compatibility test

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*Abstract*— **This article presents a method to estimate the knee angle based on data fusion for transfemoral leg prostheses control, using information from two electromyographic signals, two gyroscope sensors and one electrogoniometer channel. This information is processed in three stages: feature extraction using cepstral coefficients and the myoelectric signal entropy; pattern classification using a perceptron neural network and data fusion from a Kalman filter. A compatibility test is introduced based on Mahalanobis distance with the aim to detect possible artifacts to come from the estimated angle at the neural network output. The method was tested in healthy subjects, and the results were compared with another work that was based solely on myoelectric signals. The results showed that the use of additional information related to proprioception improves the precision of the knee joint angle estimation, and reduces artifacts.**

*Keywords- Electromyographic signals; proprioceptive sensors, entropy; cepstral analysis; data fusion; kalman filter*

## I. INTRODUCTION

Multisensor fusion and integration refers to the synergistic combination of sensory data from multiple sensors to provide more reliable and accurate information. The Kalman filter is the best known and most widely applied state estimator algorithm [1]. The algorithm uses a predefined linear model of the system to predict the state at the next time step. Moreover, the algorithm has a component to update for errors in the model using the actual observations of the system. Pattern recognition based algorithms using only surface electromyographic signals (SEMG) may provide a poor accuracy. That arises from factors such as required high level of amplification (due to the low level of the SEMG signals), motion of the sensor cables and/or noise caused by power supplies [2]. These issues make myoelectric control rather sensitive. This motivates the use of other type of sensors on the prosthesis, which may potentially allow parameter adaptation during the use of the prosthesis by the patient. For example, micro-electromechanical gyroscopes sensor may be used for measuring the angular velocity of the knee joint. Fusion of the SEMG signals with proprioceptive sensor data could improve the precision of the prosthesis control during movement and provide a more reliable myoelectric control [3].

Silva et al. [4] applied data fusion of mechanomyography signals. The goal was to implement a practical mechanomyography-based detection system of muscle contractions for prosthesis control. Accuracies of 95% and 86% were achieved in the detection of contraction signals from the wrist extensors and flexors, respectively. Lopez et al. [5] proposed two strategies for data fusion based on variance weighted average and decentralized Kalman filter, by means of an arrangement of redundant potentials, that is, by combining the SEMG signals. The muscle contraction amplitude was estimated and transformed to angular reference for the control of the robot joint. The algorithms demonstrated an efficient performance, and the joint never moved beyond its safety range.

We have proposed different algorithms for estimating the intended knee joint angle based on SEMG signals and data fusion between SEMG signals and proprioceptive sensors, respectively [6], [7]. This paper proposes an algorithm for estimation of intended knee joint angle from SEMG signals and proprioceptive sensor data. The algorithm implements the fusion process between the angular rate information and the estimated knee angle based on a compatibility test, by trough Mahalanobis distance. The variants based on data fusion present improvements (precision and robustness in

presence the artifacts) respect the above algorithms based exclusively on SEMG signals.

## II. METHODOLOGY

### A. Experimental protocol and data collection

Myoelectric signal acquisition was performed using the microcontrolled bioinstrumentation system described by [7]. The experimental protocol was approved by the research ethics committee of the University of Brasília (process no. 079/09, group III). Twelve able-bodied volunteers were studied and provided informed consent in accordance with institutional policy. Two pairs of 10-mm Ag/AgCl surface electrodes were placed in bipolar configuration over a pair of antagonist muscles. These muscles correspond to the flexion and extension movements of the knee joint, respectively. The SEMG electrodes were attached to the skin over the muscle. The distance between the centers of the electrodes from each pair was 2–3 cm. The reference electrodes were placed over the lateralis and medialis epicondyle 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. The difference between the signals measured by the gyroscopes reflects the angular rate of the knee joint. For each measurement, the subject was asked to walk in particular directions at a constant pace. Some variability in pace was observed between measurements. Fig. 1 presents simultaneously-acquired SEMG and proprioceptive signals from a representative subject with duration the 15 seconds.

### B. Feature Extraction

The set of features is obtained from cepstral coefficients extracted from SEMG signals. 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 [8]. If all transfer function poles are inside the unit circle, the logarithmic transfer function can be represented as a Laurent expansion [8]. Hence, the following recursive relations give the cepstral coefficients, obtained from AR coefficients:

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



Figure 1. Data set simultaneously acquired of SEMG signals, electrogoniometer angle and gyroscope measurements.

Using (1), the first $P$ cepstral coefficients ($c_i$, $i = 1, ...,P$) can be obtained from the coefficients ($a_k$) of a $P_{th}$ order auto-regressive 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 [8]. In this work, the cepstral coefficients were obtained using a sixth-order AR model and (1). A second approach for feature extraction is implemented using the entropy of the myoelectric signal, calculated and used as a time-domain feature vector [9]. We focus on the difference in entropy between the stationary SEMG signal in a relaxed state and during motion. Assuming that myoelectric signals can be approximated by a normal distribution process with zero mean, the entropy of the distribution in a $N$-sample time window is computed as:

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

where $\sigma_i^2$ represents the variance estimated from the signal measured from each electrode and $x_i(n)$ is a vector containing $N$ SEMG samples from the $i$-th electrode [9]. For each SEMG channel, the proposed algorithms were implemented using 200 samples (192 ms) sliding windows



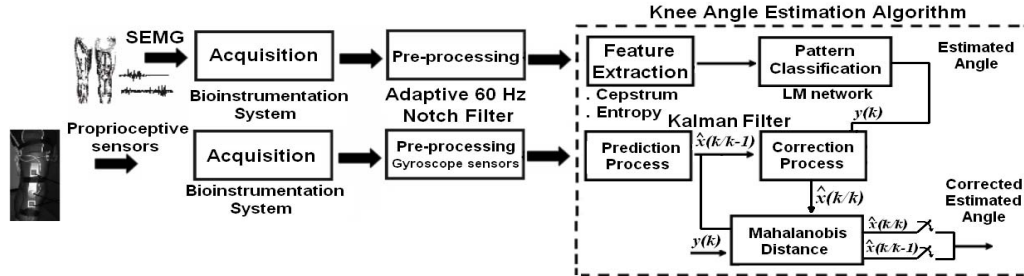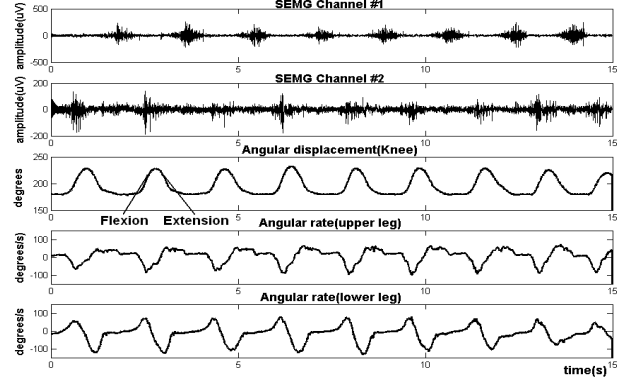Figure 2. Block diagram of the proposed knee angle estimation algorithm based on the data fusion strategy.

for the feature extraction process (cepstral analysis and entropy). This combination provides robustness in weak SEMG signals.

## C. Pattern classification stage

Data fusion strategy for estimating the intended knee joint angle is evaluated using only the SEMG feature vectors. This is implemented through a Levenberg-Marquardt multi-layer perceptron neural network [7]. Similarly to the quasi-Newton methods, the Levenberg-Marquardt neural network 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. The LM network used in algorithm has two layers in its structure, with 14 input nodes in the first layer, six nodes in the second layer (associated with tangential functions), and one node in the output layer (associated with a linear function). This structure was chosen empirically, based on experiments aimed at minimizing the mean squared error (MSE). The node in the output layer represents the estimated knee joint angle. During LM network training, the corresponding angular displacement measurements from the electrogoniometer were used as the target outputs. The same initial weight values were used for all network layers (zero for all neurons). The maximum number of iterations was set to 50, the mean squared error stop criterion was $10^{-10}$ n.u.2, and the initial learning rate was 1.0. These values were empirically chosen, aiming at maximum reduction of the final MSE.

## D. Data fusion strategy

The strategy is based on information fusion in the correction process of a Kalman filter. Also, introduces a compatibility test based on the Mahalanobis distance [7]. The Mahalanobis distance is a useful way of determining similarity of sample sets, as it is not dependent on the scale of the measurements. The Mahalanobis distance is computed between the prediction and correction process of the Kalman filter (Fig. 2). The aim is to detect possible artifacts that come from the estimated angle at the LM neural network output, on each time step of the data fusion process. The estimated knee joint angle is modeled using a state-space formulation, describing its dynamical behavior, according to the following linear stochastic model:

$$x(k) = x(k-1) + T u(k) + n(k)$$
$$y(k) = x(k) + v(k), \tag{3}$$

where $x(k)$ represents the knee angle, $u(k)$ is the measured angular rate acquired with a sampling period $T$, obtained from subtracting the angular rate values measured on the upper and lower legs, respectively, $n(k)$ is noise modeling the evolution of the knee joint angle between two sampling intervals, $y(k)$ is the measured knee joint angle obtained from the LM neural network output, and $v(k)$ is the associated measurement noise. It is assumed that $n(k)$ and $v(k)$ are zero mean, uncorrelated Gaussian distributions, with variances $q^2$ and $r^2$, respectively. In the experiments

realized it was used $q^2 = 4\ deg^2/s^2$ and $r^2 = 10\ deg^2/s^2$. When applying Kalman filter to this model, the prediction process for each iteration cycle is expressed according to:

$$\hat{x}(k/k-1) = \hat{x}(k-1) + T u(k)$$
$$P(k/k-1) = P(k-1) + T^2 \sigma_{uk}^2 + q^2, \tag{4}$$

where $\sigma^2{}_u = 25\ deg^2/s^2$ is the variance of the measured angular rate information $u(k)$, according to datasheet's manufacturing. The algorithm is initialized as $q^2 = 4$, $r^2 = 10$, $\hat{x}(0) = 0$ and $P(0) = 180^{\wedge 2}$. The Mahalanobis distance is calculated between the estimated knee angle from the LM neural network $y(k)$ and the previous estimated knee angle, $\hat{x}(k/k-1)$, based on the following equations:

$$d^2(k) = \frac{(y(k) - \hat{x}(k/k-1))^2}{r^2 + P(k/k-1)} \tag{5}$$

It can be shown that $d^2(k)$ is $\chi_N^2$ distributed. Thus, $y(k)$ and $\hat{x}(k/k-1)$ are said to be statistically compatible if $d^2(k) \leq 3.81$, according to the 95% confidence threshold obtained from the chi-square table. In such a case, $y(k)$ is used to correct $\hat{x}(k/k-1)$, based on the equation:

$$\hat{x}(k/k) = \hat{x}(k/k-1) + G(k)(y(k) - \hat{x}(k/k-1)) \tag{6}$$

If $d^2(k) > 3.81$, the filter uses the predicted values as estimates: $\hat{x}(k) = \hat{x}(k/k-1)$ and $P(k) = P(k|k-1)$, protecting the estimation process from possible angle estimation artifacts at the neural network, originated from SEMG signals. For each new pair of gyroscope sensor samples, estimates of updated Kalman filter knee joint angle were calculated.

## III. RESULTS AND DISCUSSION

A comparative study is presented between SEMG-based myoelectric control algorithms [7], and the proposal. Table I presents the computed Mahalanobis distance between the algorithm proposal based on data fusion and the method based solely on SEMG signals (utilizing various statistic metric [7]). According to the threshold $d_{m1m2} \leq 4.58$ [7], the algorithms present results which were similar in mean. Fig. 3 presents the measure and estimated angle displacements results from a subject in the presence of motion artifacts. The absolute difference between measured and estimated angles is also shown. The threshold level that was used for detecting the error events (10°) is indicated. The straps holding the electrode cables were intentionally left loose during this experiment, which caused motion artifacts in the SEMG signal. The best results in the presence of motion artifacts were obtained for the proposed algorithm, with a false positive detected near to duration the 60 ms. This result is unnoticeable to the leg prosthesis with respect the algorithm using solely SEMG signals that may cause fault operation in the leg movement (false positive detected with duration of 500 ms). The self-organizing maps's features used in the algorithm based on SEMG signals [7] may absorb signal

| Metric | Mahalanobis distance |
|---|---|
| Error-to-signal percentage | 1,53 |
| Correlation coefficient | 1,37 |
| Number of error events | 1,21 |
| Maximum error event amplitude | 1,07 |
| Maximum error event duration | 0,85 |

variations and noise presents in the data's original vector space. However, they do not achieve to reduce motion artifacts. The proposed data fusion based algorithm was more robust than the myoelectric control algorithms using solely SEMG signals (Fig. 3). Addition of more variables of leg proprioception may improve the precision and robustness as well as reduce artifacts in the knee angle estimation. Moreover, it was not significantly increased the computational complexity of the proposed algorithm. However, their implementation involves an additional degree of complexity for obtaining the cepstral coefficients from the AR coefficients, in comparison with the algorithm based on SEMG signals. Considering the robustness aspect in the presence of movement artifacts, the second proposal based on data fusion is recommended.

## IV. CONCLUSION

The proposed 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.

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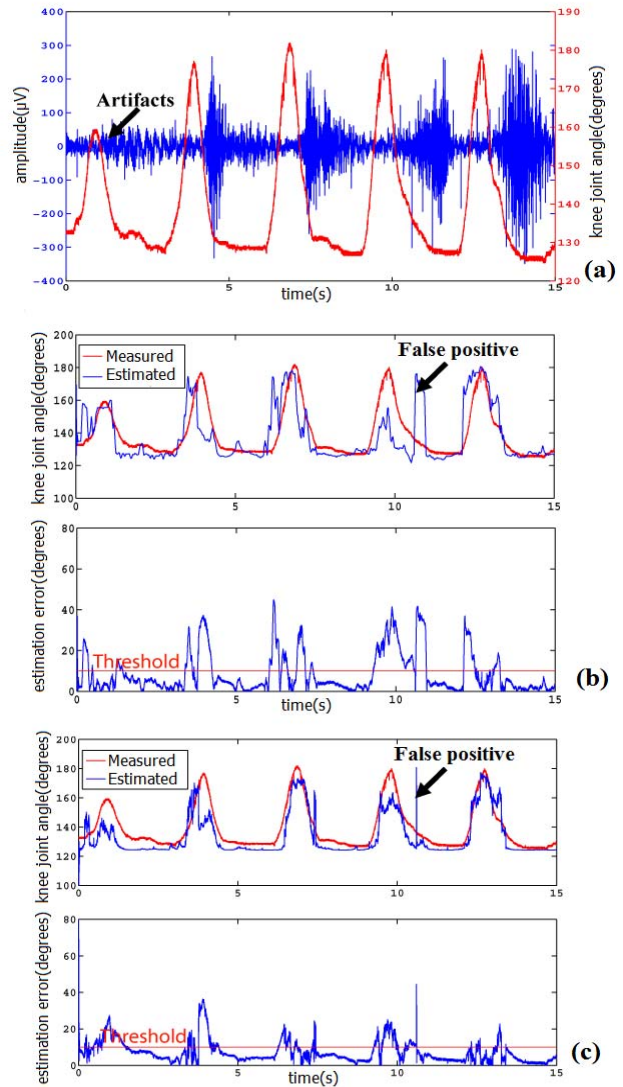


Figure 3. Qualitative comparison between the myoelectric control algorithms: (a) SEMG with motion artifacts, (b) myoelectric algorithm based solely on SEMG, (c) proposed method based on data fusion.

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