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Myoelectric Control Algorithms for Leg Prostheses Based on Data Fusion with Proprioceptive Sensors

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***Abstract*— This work describes myoelectric algorithms based on fusion of electromyographic signals and proprioceptive sensor data, for control of active transfemoral prostheses. The algorithms uses feature extraction based a combination of time and frequency domain methods (cepstral coefficients and entropy) and a Levenberg-Marquardt multi-layer perceptron neural network for pattern classification. Angular rate information is extracted from gyroscope sensor data using a Kalman filter. This information is used to correct the estimation of the intended knee joint angle from SEMG signals, which are acquired using two sets of electrodes placed on the upper leg. The results of the proposed algorithms are compared with pattern classification methods based solely on electromyographic data. The concepts used in those algorithms may be useful for the development of control algorithms in which signals from many different sensors are fused and used in the conception of a motion prediction model.**

Keywords – Data fusion, myoelectric algorithms, proprioceptive sensors, entropy, cepstral coefficients, Kalman filter, myoelectric signals.

I. Introduction

The application of multisensor data fusion has found widespread use in diverse areas (industry, commerce, local robot guidance for global military defense etc.) [1]. Data fusion is the continuous process of implementing a model from the domain of the interest, utilizing data from different nature [2]. The purpose of data fusion is to produce an improved model or estimate of a system from a set of independent data sources. The use of range sensory data allows automatically extraction of the information about the sensed environment under different operating conditions, and increases the performance, reliability, data rates and autonomy [3]–[5].

In many real-time applications the desired domain model is the state vector of a dynamic process [6], [7]. The combination of the information from the sensors and subsequent estimation of the state should be done in a coherent manner, such that the uncertainty is reduced. The Kalman filter is a state estimator algorithm widely used for optimally estimating the unknown state of a linear dynamic system from Gaussian distributed noisy observations [8]. The algorithm uses a predefined model of the system to predict the state at the next time step [9].

Processing of surface electromyographic (SEMG) signals may be used in actively powered myoelectric prostheses for extracting command signals from muscle in the residual limb [10]. We recently proposed two different algorithms for estimating the intended knee joint angle from SEMG signals measured on opposing muscles of the upper-leg [6], [11]. The first method uses the auto-regressive model for feature extraction and a Levenberg-Marquardt (LM) multi-layer perceptron neural network for pattern classification [12]. 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. Inaccurate knee joint angle estimation may be observed with those methods, because of the following [13]:

1- high level of amplification due to the low level of the SEMG signals;
2- failures by the broken electrode connections or sudden changes in the electrode-electrolyte interface due to poor contact;
3- motion of the sensor cables;
4- noise caused by the power supplies.

The above makes 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, microelectromechanical gyroscopes and joint motion sensors may be used for measuring the angular velocity of the knee joint. The integration of these data can be used to obtain an estimate of the knee joint angle, which can be used to make small corrections of the neural network coefficients in real-time. 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 [14].

The fusion of SEMG signals with other data is not common in the literature. Silva *et al*. [15] applied data fusion of mechanomyography (MMG) signals for the generation of binary control signals for an electrically powered prosthesis. Lopez *et al*. [16] proposed two strategies for data fusion based in variance weighted average (VWA) and decentralized Kalman filter (DKF), by means of arrangement of redundant potentials, that is, combining the SEMG signals. The muscle contraction amplitude was estimated and transformed to angular reference for the control of the robot joint. The VWA and DKF algorithms demonstrated an efficient performance, and the joint never moved beyond its safety range [16].

This paper proposes two myoelectric algorithms based on data fusion for estimation of intended knee joint angle from SEMG signals and proprioceptive sensor data, for control of active transfemoral leg prostheses. A comparison with pattern classification methods based solely on electromyographic data [6], [11], [17] is presented. The two strategies of myoelectric algorithms based on data fusion use a feature extraction stage where time domain and frequency domain methods are combined. The combination of the term of energy (time domain) of the SEMG signals with the power spectral (frequency domain) provides good classification precision, is computationally efficient, and is more robust to electrode displacement [11]. In addition, angular rates information from the gyroscopes is used to increase the angle estimation. The first strategy uses an additional feature extraction stage from Kalman filters, where the estimated angular rate (from the sensors gyroscopes) and the coefficients obtained by the cepstrum and entropy analyses are fused, and used as the input vectors to the Levenberg-Marquardt neural network, for estimate the knee angle [18]. The second strategy implements the fusion process between the angular rate information and the estimated knee angle obtained from the Levenberg-Marquardt neural network in the Kalman filter's correction process. The filter output is the corrected estimated knee angle from the fusion process. This proposal represents an improvement, based in robustness and artifact reduction with respect to the first proposal.

II. METHODOLOGY

A. Feature Extraction

The cepstrum of a signal is defined as the inverse Fourier transform of the logarithm of the squared magnitude of the Fourier transform of the signal, as follows [19]:

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

If all transfer function poles are inside the unit circle, the logarithmic transfer function can be represented as a Laurent expansion [19]. From (1), it is possible to derive the following recursive relation:

$$\begin{aligned} c_1 &= -a_1 \\ c_i &= -a_i - \sum_{n=1}^{i-1}\left(1-\frac{n}{i}\right)a_n c_{i-n}\,,\ \ 1 < i \le P. \end{aligned} \tag{2}$$

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. Some works have reported that the AR-derived cepstrum feature has better performance than the unprocessed AR feature [19]. 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 [19]. The cepstral coefficients were obtained using a sixth-order AR model and (2).

The entropy of the myoelectric signal is calculated and used as a time-domain feature vector [20]. We focus on the difference in entropy between stationary SEMG in a relaxed state and in motion. Assuming that electromyographic signals can be approximated by a normal distribution process with zero mean, the entropy of the distribution is:

$$\begin{aligned} H(\sigma_i) &= \frac{1}{2}\log_2(2\pi e\sigma_i^2) \\ \sigma_i^2 &= \frac{1}{N-1}\sum_{n=1}^{N}x_i(n)^2, \end{aligned} \tag{3}$$

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 [20]. For each SEMG channel, the calculated entropy is concatenated with the cepstral feature vector. This combination provides robustness in weak SEMG signals.

B. Pattern Classification

Two data fusion strategies for estimating the intended knee joint angle are evaluated: (i) using the SEMG feature vectors and the *estimated* angular rate; or (ii) using only the SEMG feature vectors. This is implemented using a Levenberg-Marquardt multi-layer perceptron neural network [12]. Similarly to the quasi-Newton methods, the Levenberg-Marquardt neural network was designed to approach second-order training speed without computing the Hessian matrix.

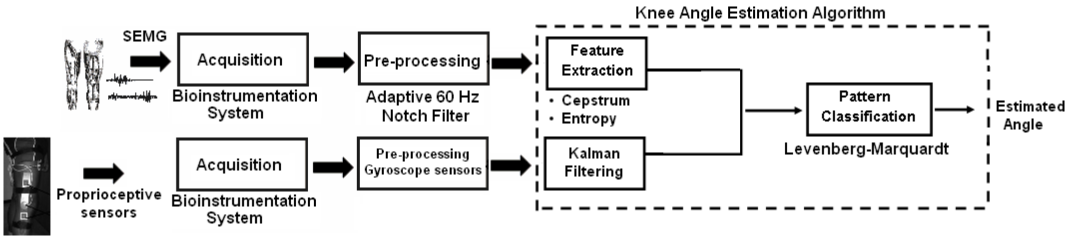

Fig. 1: Block diagram of the proposed knee angle estimation algorithm based on the first data fusion strategy.

The key step in the LM algorithm is the computation of the Jacobian matrix, which can be computed through standard backpropagation techniques [12], 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.

C. First Data Fusion Strategy

Figure 1 presents the block diagram for the proposed knee angle estimation algorithm based on the first data fusion strategy. The use of angular rate information from the gyroscopes improves angle estimation precision and reduces 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 [9], according to the following linear stochastic model:

$$\begin{aligned} x(k) &= x(k-1) + n(k) \\ y(k) &= x(k) + v(k), \end{aligned} \tag{4}$$

where, $x(k)$ 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 cut-off frequency. This cut-off frequency is computed considering noise variances q^2 and r^2, as well as the error variance associated to $\hat{x}(k/k)$ [9]. 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 (Fig. 1).

D. Second Data Fusion Strategy

The second data fusion strategy is presented in Figure 2. In this strategy, the feature vectors obtained from the feature extraction process (section A) are used as input to the LM neural network (section B). The estimated knee joint angle is modeled using a state-space formulation, describing its dynamical behavior [9], according to the following linear stochastic model:

$$\begin{aligned} x(k) &= x(k-1) + T \times u + n(k) \\ y(k) &= x(k) + v(k), \end{aligned} \tag{5}$$

where, $x(k)$ is the corrected estimated knee angle; u is the measured angular rate information at time instant 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 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, for each iteration cycle, the prediction process is expressed according to:

$$\begin{aligned} \hat{x}_{k/k-1} &= \hat{x}_{k-1} + T \times u_k \\ P_{k/k-1} &= P_{k-1} + T^2 \times \sigma_{u_k}^2 + q^2, \end{aligned} \tag{6}$$

and the correction process is expressed as:

$$\begin{aligned} G_k &= \frac{P_{k/k-1}}{(P_{k/k-1} + r^2)} \\ \hat{x}_k &= \hat{x}_{k/k-1} + G_k (y_k - \hat{x}_{k/k-1}) \\ P_k &= (I - G_k) P_{k/k-1}, \end{aligned} \tag{7}$$

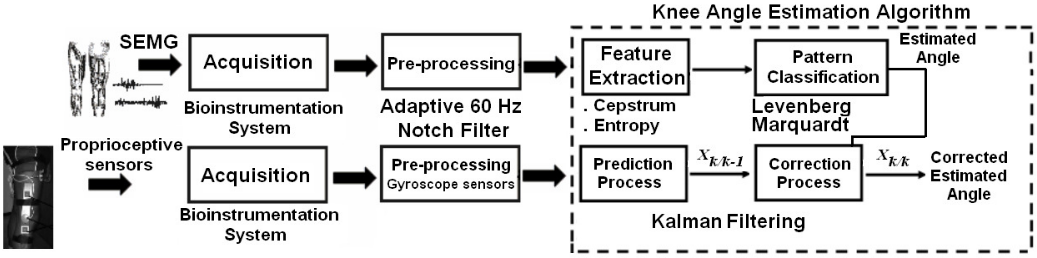

Fig. 2: Block diagram of the proposed knee angle estimation algorithm based on the second data fusion strategy.

where $\sigma_{u_k}^2$ is the variance the measured angular rate information; G_k is the Kalman filter gain; P_k represents the error covariance matrix associated with the estimation process; $\hat{x}(k/k)$ is an optimal estimate of *x(k)* in the least-squares sense. The value of $\hat{x}(k/k)$ is an optimal estimate of the knee joint angle from the fusion process with the angular rate information at each time instant *k*.

E. Data Acquisition

For a preliminary evaluation of the proposed algorithms, a microcontrolled bioinstrumentation system was constructed [7]. Two healthy subjects were studied. Two pairs of 10-mm Ag/AgCl surface electrodes were placed in bipolar configuration over a pair of antagonist muscles (rectus femoris, vastus intermedius – lateralis and semitendinosus muscles) (Fig. 3a and 3b). 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 such that the longitudinal axes of the electrodes were parallel to the longitudinal axes of the muscle. The distance between the centers of the electrodes of each pair was 2–2.5 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. 3c). The difference between the signals measured by the gyroscopes reflects the angular rate of the knee joint.

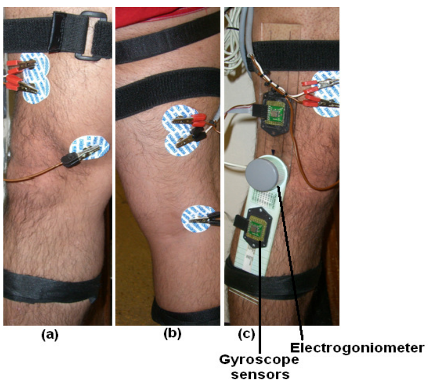

Fig. 3: Placement of SEMG electrodes (a,b), electrogoniometer and gyroscope sensors (c).

The two subjects were studied over the course of five days. Four 15-second measurements were performed on each day, with 5-minute rest periods between measurements. For each measurement, the subject was asked to walk in a particular direction at a constant pace. Some variability in pace was observed between measurements. The first and third measurements from each day were used for training, and the second and fourth measurements were used for testing. Figure 4 presents simultaneously-acquired SEMG and proprioceptive signals from one subject.

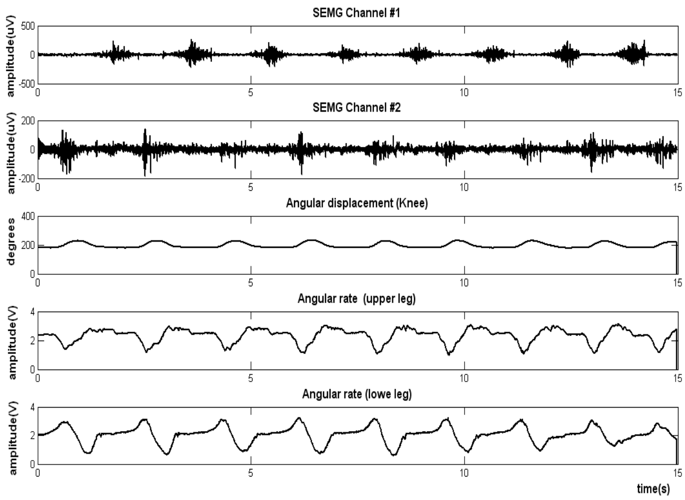

Fig. 4: Representative set of simultaneously-acquired SEMG signals (rectus femoris and semitendinosus muscles), electrogoniometer angle (knee), and gyroscope measurements (upper and lower legs).

III. Results and Discussion

Network training and testing were performed in Matlab (The MathWorks, Inc., Natick, MA, USA). For each SEMG channel, the proposed algorithms were 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, estimates of updated Kalman filter angular rate and knee join angle were calculated for the first and second proposal, respectively. This results in a 15-coefficient feature vector per sample interval, for the first proposal (6 cepstral coefficients and 1 entropy coefficient per SEMG channel, plus 1 angular rate coefficient), and a 14-coefficient feature vector per SEMG channel, for the second proposal (6 cepstral coefficients and 1 entropy coefficient).

For both algorithms the information is transferred to a three-layer LM neural network, with 15 (first proposal) and 14 (second proposal) 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. Figure 5 presents the measured (from the electrogoniometer) and estimated angle displacements for both data fusion algorithms. The absolute difference between measured and estimated angles is also shown.

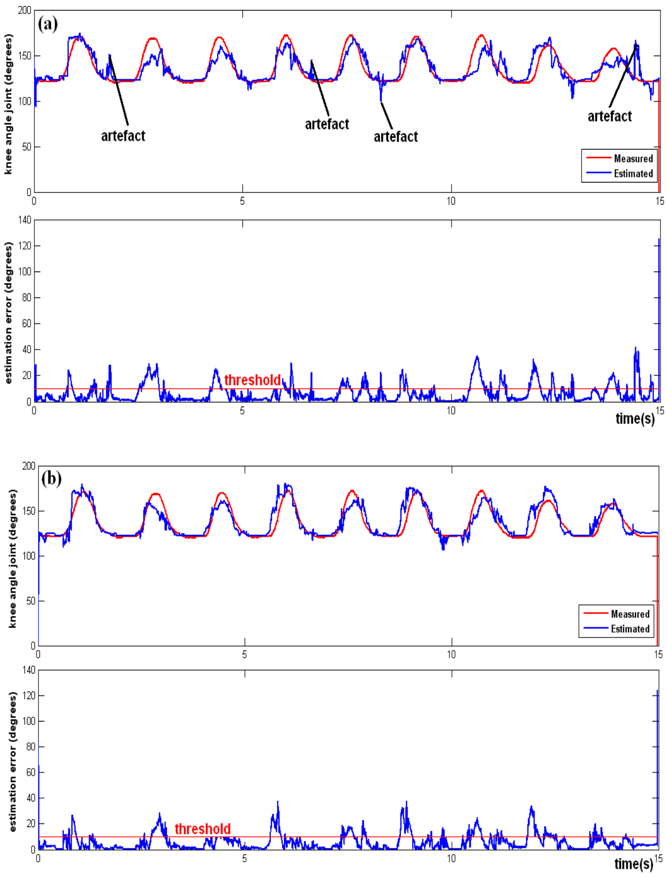

Fig. 5: Measured and estimated knee angle displacements and their absolute difference (estimation error): (a) first strategy; (b) second strategy. The threshold level used for calculating the statistics of the error events (10º) is indicated.

In the presence of movement artifacts on the knee angle estimation, which may be interpreted by the leg prosthesis as false positives (depending of their duration), the second strategy is more robust than the second one. These error peaks may be caused due to noise in the feature space, and by an insufficient number of neurons in the LM network's hidden layer. This problem may be addressed by increasing the number of neurons, by increasing the number of SEMG signals and/or by increasing the sliding window used in the cepstral and entropy analysis. However, these approaches would result in increased computational network complexity and convergence time, and/or would increase the response time of the prosthesis. The addition of other variables associated with leg proprioception (e.g., gyroscope sensors) may improve the precision and reduce artifacts in knee angle estimation, without significantly increasing the computational complexity of the myoelectric algorithm. These section present preliminary results of a comparison between the two proposed algorithms evaluation was performed in off-line mode, using Matlab. At a later stage, they will be embedded in a myoelectric controller. The methods based solely on SEMG signals are:

- Recursive Least Square method–Levenberg Marquardt neural network [6]: uses the autoregressive model for feature extraction and a LM neural network for pattern classification.
- Recursive Least Square+Histogram–Self-Organizing Maps–Levenberg Marquardt neural network [11]: uses a combination of spectral and temporal domain approaches – autoregressive coefficients and signal amplitude histogram for feature extraction, and a feature projection stage with a self-organizing maps and a LM neural network for pattern classification.
- Wavelet Packet Coefficients Energy–Principal Components Analysis–Levenberg Marquardt neural network [17]: uses the energy of wavelet packet transform for feature extraction, principal components analysis for feature projection, and a LM neural network for pattern classification.

For evaluation of performance, the myoelectric algorithms were quantitatively compared using statistic metrics based on the error to signal percentage and the correlation coefficient [11]. Tables I and II present the measured (μ) and standard deviation (σ) for the error to signal percentage and correlation coefficient for the group of test signals from two subjects. The proposed myoelectric algorithms based on data fusion provided lower error to signal percentage and higher correlation than the algorithms based solely on SEMG signals. Figure 6 presents the measured and estimated angle displacement on a qualitative comparison between the proposed algorithms and the methods [6], [11] and [17].

IV. CONLUSION

This work introduced two variants of myoelectric algorithms based on data fusion with the purpose of improving the knee joint angle estimation. The proposed algorithms implement data fusion using Kalman filters, which from a prediction-update formulation process allow obtaining an optimal estimate.

TABLE I
ERROR TO SIGNAL PERCENTAGE, IN % ($\mu \pm \sigma$)

Subjects	**Reference [6]**	**Reference [17]**	**Reference [11]**	**First Data Fusion Strategy**	**Second Data Fusion Strategy**
Subject A	6.73 ± 2.47	8.74 ± 2.08	6.84± 1.68	5.12 ± 0.99	5.73 ± 1.06
Subject B	5.84 ± 2.16	9.20 ± 1.98	5.88 ±1.21	5.21 ± 1.44	5.96 ± 1.69

TABLE II
CORRELATION COEFFICIENT ($\mu \pm \sigma$)

Subjects	**Reference[6]**	**Reference[17]**	**Reference [11]**	**First Data Fusion Strategy**	**Second Data Fusion Strategy**
Subject A	0.78 ± 0.13	0.52 ± 0.19	0.79 ± 0.09	0.88 ± 0.04	0.85 ± 0.03
Subject B	0.79 ± 0.19	0.40 ± 0.21	0.80 ± 0.13	0.84 ± 0.15	0.86 ± 0.05

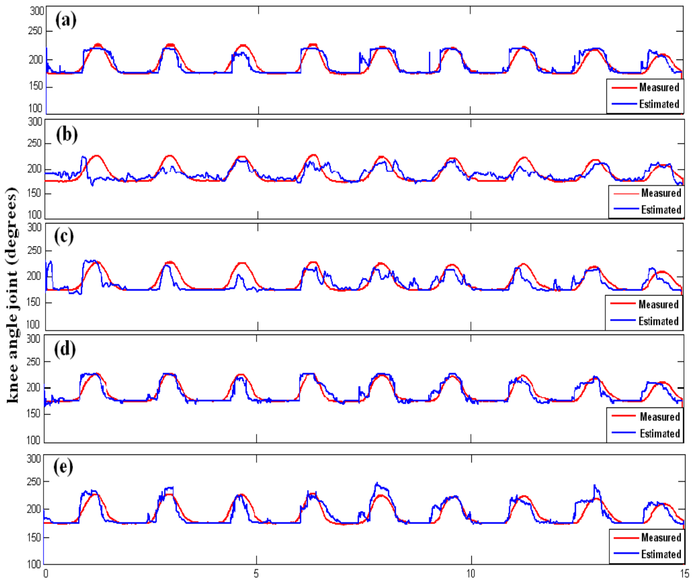

Fig. 6: Measured and estimated knee angle displacements: (a) algorithm from ref. [6]; (b) algorithm from ref. [17]; (c) algorithm from ref. [11]; (d) first algorithm based in data fusion; (e) second algorithm based in data fusion.

It was demonstrated that the fusion of SEMG signals with proprioceptive sensors increases the estimation precision and reduces artifacts in myoelectric algorithms.

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