Wrist torque estimation during simultaneous and continuously changing movements: surface vs. untargeted intramuscular EMG

Ernest N. Kamavuako,1 Erik J. Scheme,2 and Kevin B. Englehart2
1Center for Sensory-Motor Interaction, Department of Health Science and Technology, Aalborg University, Aalborg, Denmark; and 2Institute of Biomedical Engineering, Department of Electrical and Computer Engineering, University of New Brunswick, Fredericton, New Brunswick, Canada

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Kamavuako EN, Scheme EJ, Englehart KB, Wrist torque estimation during simultaneous and continuously changing movements: surface vs. untargeted intramuscular EMG. J Neurophysiol 109: 2658–2665, 2013. First published March 20, 2013; doi:10.1152/jn.00086.2013.—In this paper, the predictive capability of surface and untargeted intramuscular electromyography (EMG) was compared with respect to wrist-joint torque to quantify which type of measurement better represents joint torque during multiple degrees-of-freedom (DoF) movements for possible application in prosthetic control. Ten able-bodied subjects participated in the study. Surface and intramuscular EMG was recorded concurrently from the right forearm. The subjects were instructed to track continuous contraction profiles using single and combined DoF in two trials. The association between torque and EMG was assessed using an artificial neural network. Results showed a significant difference between the two types of EMG (P < 0.007) for all performance metrics: coefficient of determination (R²), Pearson correlation coefficient (PCC), and root mean square error (RMSE). The performance of surface EMG (R² = 0.93 ± 0.03; PCC = 0.98 ± 0.01; RMSE = 8.7 ± 2.1%) was found to be superior compared with intramuscular EMG (R² = 0.80 ± 0.07; PCC = 0.93 ± 0.03; RMSE = 14.5 ± 2.9%). The higher values of PCC compared with R² indicate that both methods are able to track the torque profile well but have some trouble (particularly intramuscular EMG) in estimating the exact amplitude. The possible cause for the difference, thus the low performance of intramuscular EMG, may be attributed to the very high selectivity of the recordings used in this study.

simultaneous movement; intramuscular EMG; surface electromyography; dynamic movement; torque and force estimation

THE ABILITY OF THE CENTRAL NERVOUS SYSTEM (CNS) TO CONTROL joint movements is so remarkable that no human-made machine has been able to approach its performance. At the level of the peripheral nervous system, coordination of movement requires neural drive sent from the CNS, which activates associated muscles (De Luca et al. 1982). Muscles, on the other hand, contain systems that provide feedback to the CNS about the state (e.g., muscle tension) of the movement. Proprioceptive sensors at the joint also contribute information about joint position and torque to the overall feedback to the CNS. Consequently, the CNS is able to modulate the descending neural drive to the muscles to regulate the desired net joint torque. The CNS achieves this by recruiting different motor units and muscles that together, act on a single joint (Henneman 1957). This is a well-defined, closed-loop system that remains one of the most critical yet unresolved components of motor control (de Rugy et al. 2012).

To date, several attempts have been made to model this complex system and estimate joint torque, while relying, however, only on the open-loop part of recording muscle activities and joint torque. Among different methods for estimating joint torque from muscle activities using electromyography (EMG) are those models that aim at simulating the real physiological processes of the coupling between excitation and contraction (Buchanan et al. 2004) and the mechanical application of muscle tension to generate torques (Tsianos et al. 2012). Other techniques are based mainly on the associations between measured muscle activities and joint movement (Castellini et al. 2009; Seifert and Fuglevand 2002). Recently, an approach was proposed that defines a virtual representation of muscle biomechanics that reconstructs limb torque when combined with EMG recordings (de Rugy et al. 2012). To achieve certain fidelity-of-torque estimation, the relationship between EMG and joint torque has been assumed to be either linear (Hoozemans and Van Dieën 2005; Inman et al. 1952) or nonlinear (Herzog et al. 1998; Liu et al. 1999). Several studies have also compared the difference in performance between linear and nonlinear models during a single movement (Kamavuako et al. 2009, 2012b) and simultaneous degrees of freedom (DoF) (Jiang et al. 2009). So far, linear and nonlinear methods have shown comparable performance during single movement tasks (Kamavuako et al. 2012b); however, for estimating torque in several DoF, nonlinear estimators have shown greater performance (Jiang et al. 2009). The electrical activity generated by muscles can be recorded on the surface of the skin (surface EMG), on the surface of the muscle fascia (epimysial EMG), or from inside of the muscle (intramuscular EMG). Surface EMG is noninvasive and is usually chosen when studying the behavior of the muscle as a whole, as it measures the superimposed waveforms of the underlying EMG. With advances in electrode design, not only temporal patterns can be studied, but also, it is possible to investigate motor unit (MU) action potential (AP) propagation (Merletti et al. 2003), estimate the MU conduction velocity (Farina et al. 2000; Farina and Merletti 2004), locate the innervation zones (Masuda et al. 1985), investigate MU recruitment (Farina et al. 2002; Gazzoni et al. 2001), or decompose the signals into constituent APs (Holobar and Zazula 2004). MU investigation with surface EMG often requires a very low activation level of the muscle or very low force.

From the kinetics point of view, there is extensive literature [for reviews, see Disselhorst-Klug et al. (2009) and Stauden-
mann et al. (2010)] that models the EMG-torque relationship based on surface EMG, making it attractive for many applications, e.g., controlling a prosthetic device. The amplitude of the surface EMG signal may be used to determine the speed or strength of activation of a prosthesis (e.g., DMC Plus; Ottobock, Minneapolis, MN). Intramuscular EMG is being investigated as a potential replacement for surface EMG in advanced devices that require simultaneous or more targeted control of movements (Farrell and Weir 2008; Hargrove et al. 2007; Kamavuako et al. 2009, 2012a), because intramuscular EMG signals are less affected by crosstalk and may provide more selective recordings. Intramuscular EMG also has the potential advantage of avoiding variation experienced in surface EMG due to changes in skin-electrode impedance or electrode shift in a socket. So far, intramuscular recordings have been used to study the physiology and pathology of the MU, because it contains more spatially resolved information compared with surface EMG (DeLuca et al. 1982; Freund et al. 1975). With intramuscular recordings, one can study MU recruitment and firing pattern (with higher force then surface EMG), both of which give information on CNS motor control and its disturbances (Trontelj et al. 2005). The relationship between intramuscular EMG and muscle force has been demonstrated in a few studies (Inman et al. 1952; Kamavuako et al. 2009; Onishi et al. 2000). Moreover, it has been shown that during single movements, features of selective intramuscular recordings correlate with the grasping force to a similar degree as features of the surface EMG recordings. Nevertheless, to our best knowledge, the predictive capability of surface and intramuscular EMG has not been compared with respect to torque, and it is unknown which type of measurement better represents joint torque during multi-DoF movements. This is important to investigate, both from the physiological modeling point of view and to determine if untargeted intramuscular EMG is applicable in the same way as surface EMG incontinuously changing signals that mimic real applications with varying joint torque level.

Torque estimation in two DoF has been investigated (Jiang et al. 2009; Nielsen et al. 2011) from surface EMG, but only one study has demonstrated the ability of targeted intramuscular EMG to predict torque in two DoF (Kamavuako et al. 2012a). Contrary to that study, here, we use untargeted intramuscular EMG for the following reasons: 1) to evaluate the performance with respect to targeted intramuscular EMG (Kamavuako et al. 2012a), as it has been shown to have similar performance for multiclass pattern recognition (Farrel and Weir 2008) and 2) to allow a direct comparison with untargeted surface EMG. Furthermore, application of targeted intramuscular EMG requires the identification of specific muscle sites, which may be difficult with amputee subjects. Therefore, the aim of this study was to compare the use of surface and untargeted intramuscular EMG for estimation of wrist-joint torque during simultaneous and continuously changing movements.

METHODS

Subjects. The experiments were conducted on 10 able-bodied subjects (six men/four women; age range: 23–26 yr). The procedures were in accordance with the Declaration of Helsinki and approved by the Danish Local Ethical Committee (approval no. N-20080045). Subjects provided their written, informed consent prior to the experimental procedures. The subjects had no history of upper-extremity or other musculoskeletal disorders.

Experimental procedures. EMG and torque signals were collected during simultaneous, isometric, but continuously varying contractions, corresponding to two wrist DoF. The experiment was carried out in two trials with a 5-min rest in between. Each trial included six combinations of tasks, separated by 2 min of rest to minimize the effect of fatigue. The performed tasks were categorized into individual and combined (simultaneous) DoF to test the ability to estimate isolated torque and torque in two simultaneous DoF. The selected DoF were wrist flexion/extension (DoF1) and wrist supination/pronation (DoF2). The following six tasks were chosen: wrist flexion/extension, supination/pronation, simultaneous flexion + pronation/extension + supination. We chose to use only the two DoF, because no commercially available prosthetic device is currently capable of ulnar and radial deviation. All tasks were dynamically varying, following a sinusoidal profile lasting 30 s at maximum amplitudes of 3 Nm and 2 Nm for men and women, respectively. Torque level was limited to 2 Nm for female subjects, because concerns were raised during pilot testing about the combined movements being uncomfortable for higher torque levels. On the contrary, 2 Nm was too easy for most male subjects, thus 3 Nm was adopted to allow similar EMG activation for female subjects. The first and last 3 s of each profile consisted of a rest period. Sinusoidal profiles were used to elicit dynamic contractions, requiring constant changes in the torque (and EMG intensity) level of the performed task. The subjects were seated in a chair with their right arm placed in an arm rest, while the left arm was left relaxed on the table (Fig. 1). Subjects were asked to track one profile or two simultaneous profiles, depending on whether it was a single DoF or two simultaneous DoF, as shown in Fig. 2. The order of the tasks was randomized, and subjects received visual feedback as to how closely they tracked the profiles. The subjects were given sufficient time for training and to become familiar with the profiles. The frequency of the profiles was 0.5 Hz.

Data collection. A custom-made hand support, incorporating a commercially available dynamometer (Gamma FT-130-10; ATI In-
Intramuscular EMG was recorded using six bipolar wire electrodes, inserted to reside underneath of each surface EMG electrode pair, providing an equidistant distribution around the forearm. Intramuscular wire electrodes were made of Teflon-coated stainless steel (A-M Systems, Carlsborg, WA; diameter 50 μm) and were inserted into each muscle with a sterile, 25-gauge hypodermic needle. The insulated wires were cut to expose only the cross section at the tip, providing high selectivity, with typically up to 14 MUs at 10–12% maximum voluntary contraction (Kamavuako et al. 2009; Negro et al. 2009). The needle was inserted to a depth of 10–15 mm below the muscle fascia and then removed to leave the wire electrodes inside of the muscle. To compare with previous studies on force estimation (Kamavuako et al. 2012a, b), we chose to expose only the end of the wires, thus yielding high selectivity. All signals were anti-alias filtered and amplified (AnEMG12; OT Bioeletronica, Torino, Italy), analog-to-digital converted on 16 bits (NI-DAQ USB-6259), and sampled at 10 kHz. A reference electrode was placed around the wrist, starting a few centimeters lateral to the ulnar exposure at the point of the largest circumference.

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Signal processing. Intramuscular and surface EMG signals were band-pass filtered digitally (fourth order Butterworth filter) between 100 and 3,000 Hz and 20 and 500 Hz, respectively. Features were extracted from overlapping (by 50 ms) signal intervals of 200 ms duration. The same time intervals were used for computing the average torque. The following five features were extracted from the EMG signals, since it has been shown previously that a combination of five time-domain features provides the highest estimation accuracy: waveform length (WL), mean absolute value (MAV), zero crossing (ZC), slope sign changes (SSC), and Willison amplitude (WAMP) (Hudgins et al. 1993; Kamavuako et al. 2012b). WL contains amplitude and frequency information about the activation of the muscle. MAV is an estimate of the SD of the signal. ZC measures the number of times the signal crosses zero and is related to the frequency content. SSC measures the number of times the sign changes in the slope of the signal. WAMP estimates the number of active MUs, which is an indicator of the level of muscle contraction.

Torque estimation. The ability to estimate torque from the extracted intramuscular EMG features was quantified using the two-dimensional (2-D) measure of data variability, coefficient of determination (R²; Eq. 1), as proposed previously (d’Avella et al. 2006; Jiang et al. 2009), and will be referred to as 2-D correlation coefficient throughout the manuscript.

\[
R^2 = 1 - \frac{\sum_{i=1}^{2} \sum_{t=0}^{N} (\hat{f}_i(t) - f_i(t))^2}{\sum_{i=1}^{2} \sum_{t=0}^{N} (f_i(t) - \bar{f}_i)^2}
\]

where \(i = 1, 2\) is the two DoF, \(N\) is the number of data points, \(f_i(t)\) is the \(i\)th DoF and \(\hat{f}_i(t)\) its corresponding estimate, and \(\bar{f}_i\) (\(t\)) is the temporal average of \(f_i(t)\). The 2-D Pearson correlation coefficient (PCC) and the root mean square error (RMSE) were also used to determine further whether the source of error was related to the shape or the scaling of the amplitude. RMSE was expressed as the percentage of maximum torque produced by the subject. The association between the features and torque was investigated using an artificial neural network (ANN) model. The network consisted of a two-layer, feed-forward network with one hidden layer of a varying number of neurons, with a tangent sigmoid function, and one output layer with linear function. Up to 10 neurons were tested in the hidden layer to optimize the per-subject performance. The network used a back-training approach, based on the Levenberg-Marquardt algorithm, and had two output neurons (corresponding to the two DoF) that provided the estimated torque. All of the features were used as inputs to the ANN. Data for each trial and subject were divided into four blocks for a fourfold cross-validation procedure. Each fold comprised assigning a one-half trial as testing data and the remaining one and one-half trials as training data. For each training/test block combination, the ANN was trained 10 times, selecting the network parameters corresponding to the highest R² during training for use during testing. Thirty percent of the training data was used for validation during training of the network to avoid over-fitting. This was repeated for each of the four combinations of test/training blocks, and the mean R², PCC, and RMSE were calculated for the test datasets across the four combinations. Both single and combined DoF were used for training, as they have been shown to provide the best performance (Kamavuako 2012a; Nielsen et al. 2011). For the remainder of the manuscript, performance will refer to the performance of the ANN.

Statistical analysis. As performance parameters violated the normality assumption, the nonparametric Kruskal-Wallis test was used to compare the performance of intramuscular with surface EMG. \(P < 0.05\) was considered significant. Results are reported as mean ± SD.

RESULTS

From the ensemble average across subjects, the performance of both EMG types depended on the number of neurons in the ANN. The optimal number of neurons was seven and eight for surface EMG and intramuscular EMG, respectively. These settings resulted in similar performance as when using a number of neurons optimized for each subject. For all of the parameters, intramuscular EMG performed worse than surface EMG (\(P < 0.007\)), as shown in Fig. 3.

Figure 3 shows higher values of PCC with respect to R², which might indicate that the source of error is more related to the amplitude (under/overshoot) than the shape. For both surface and intramuscular EMG, the regression \((ax + b)\) between estimated and measured torque has a slope \(a\) statistically different from 45° (\(P > 0.1\)), with the offset \(b\) significantly different from 0 (\(P < 0.005\)). It appears that the estimation of DoF2 (supination/pronation) is the most difficult, especially for the intramuscular EMG, as shown by the scatter plots in Fig. 4 for one subject. This is confirmed by looking at the R² of each DoF. In the case of surface EMG, R² for DoF1 and DoF2 was 0.97 ± 0.03 for DoF1, whereas only 0.79 ± 0.09 for DoF2.

Table 1 provides the results obtained for each subject, and Figs. 5 and 6 show examples of the best and worst scenarios,
where there is overshoot and undershoot in the estimation of torque from DoF2. Figures 5 and 6 are concatenations of the one-half trials used for testing during the fourfold validation. Figure 7 shows an example of a full trial during simultaneous activation of both DoF. It can be seen that ulnar and radial deviation (DoF3) is always, at least partially, active during combinations, despite subjects having been given a familiarization period to minimize its activation. A combination of both EMG types as inputs to the ANN was tested, but the results were similar to those of surface EMG alone.

DISCUSSION

The ability of surface and untargeted intramuscular EMG to estimate wrist-joint torque was investigated in this study, and the results showed a significant difference between the two types of EMG. The performance of surface EMG was superior compared with intramuscular EMG. The mean $R^2$ across subjects was 0.93 for surface EMG, which is similar to performances reported in some studies (Laursen et al. 1998; Nielsen et al. 2011) and superior compared with others (Jiang et al. 2009), in terms of simultaneous DoF estimation in the upper limb. Particularly, the DoF that involves supination and pronation of the wrist has been considered difficult to estimate, contributing to the low global performance, both from kinetics (Jiang et al. 2009; Nielsen et al. 2011) and kinematics (Muceli and Farina 2012) studies. However, in the present study, when looking at per-DoF performance, supination/pronation performed very well, with $R^2 > 0.92$. This might suggest two things. First, the performance is likely to depend on the way subjects performed the task, especially in previous studies using unnatural combinations of three DoF, making it difficult for the subjects to elicit the contraction properly. Although it appeared that subjects naturally included DoF3 during simultaneous movements, they were asked to minimize its activation, and the ANN was trained without DoF3. Consequently, incorporating a third DoF would have an impact on the performance of the ANN. Second, it could be associated with the fact that the ANN model was optimized in this study in terms of number of neurons. The performance may also be increased with further optimization of the model, such as using optimal...
Table 1. Results obtained for all of the subjects (S) in terms of 2-D $R^2$, 2-D PCC, and RMSE.

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<th>Surface EMG</th>
<th>Intramuscular EMG</th>
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2-D, 2-dimensional; R2, coefficient of determination; PCC, Pearson correlation coefficient; RMSE, root mean square error; EMG, electromyography. RMSE is expressed as percentage of the maximum allowed torque.

Combinations of additional features, as studied recently for one DoF (Kamavuako et al. 2013). However, the performance of the untargeted intramuscular EMG (mean $R^2$ = 0.80) was lower than reported previously (mean $R^2$ = 0.88) using targeted intramuscular EMG, where electrodes were placed in the prime movers of the studied DoF (Kamavuako et al. 2012a). Contrary to surface EMG, DoF2 (supination/pronation) yielded lower performance when using intramuscular EMG, with $R^2 < 0.80$, whereas Kamavuako et al. (2012a) reported performance $>0.94$ for supination and pronation. This may be related to the superficial placement of the wire electrodes in this study. The prime mover muscles of DoF2 are located deeper in the forearm; thus the performance will strongly depend on the amount of information recorded from these prime movers. Conversely, the prime movers of DoF1 are superficial and contribute significantly to the recorded surface EMG signals.

The PCC assesses the linear relationship between two variables, without taking into account the scales and therefore, does not differentiate between dependent and independent variables. Thus PCC captures how well two variables change together over time (in the present case). Figure 3 shows that the values obtained for PCC are much higher for both signal types compared with $R^2$. This might indicate that the decrease in $R^2$ is mostly related to the magnitudes of the estimated torque; e.g., intramuscular EMG has higher RMSE compared with surface EMG. Thus PCC can be an indication of the torque estimate capturing the envelope of the neural drive, also referred to as the common drive (De Luca et al. 1982), to different muscles during execution of the tasks. It has been shown that oscillations recorded on the primary motor cortex during voluntary movements are correlated with the electrical activity produced on the surface of the muscles (Nagao and Farina 2011), which can be assumed to be well captured by the EMG in this study, whereas its contributing magnitude/muscle cannot be estimated entirely. This can be attributed to the variability in discharge times of APs; when elicited torque is $<10\%$ of the maximum voluntary torque, studies indicate that MU recruitment and muscle properties of typical muscle are tuned to limit the influence of synaptic noise on force steadiness (Dideriksen et al. 2012). However, the torque applied in this study was $>10\%$. Consequently, forward modeling of the EMG torque relationship is less able to cope with the variability, which is more pronounced for intramuscular than surface EMG. Therefore, intramuscular EMG likely requires either a longer window during data analysis (Kamavuako et al. 2009) to better match the low-frequency content of the torque output or larger recording surfaces (achievable by exposing more of the wire electrode). Furthermore, the CNS controls the torque generated by a muscle through size-governed recruitment (Henneman 1957) and modulation of the discharge rate of the motor neuron pool (Milner-Brown et al. 1973; Person and Kudina 1972). This can be captured with indwelling (intramuscular) electrodes if the entire muscle is sampled, but in this study, the selectivity of the electrodes did not provide high spatial sampling; thus electrodes with a larger pick-up area may do better. On the other hand, surface EMG is the product of superimposed MU actions, low-pass filtered by the volume conductor (Pozzo et al. 2003) and captured with a larger area so that the variability is less pronounced (due to the low-pass effect of the volume conductor), and more MUs contribute to the global information. In both cases, 100\% accurate estimation is not possible at the chosen torque level, due to the physiological assumption that the neural control signals are corrupted by noise, whose variance increases with the size of the control signal (Harris and Wolpert 1998). Nevertheless, variability in the performance between subjects implies additional contributing factors: 1) the ability of subjects to perform each task consistently and 2) the variability introduced by the
measurement system. These two factors play a role in how well we can model the EMG-torque relationship.

The results obtained in this study may indicate that the greater selectivity (electrodes cut at the tip) of intramuscular EMG with respect to surface EMG and its superficial placement may be a disadvantage, since the signal may provide local rather than global information. Nevertheless, it has been shown that surface EMG and intramuscular EMG performed equally for classification of hand movements (Farrel and Weir 2008; Hargrove et al. 2007). Furthermore, Farrel and Weir (2008) showed no significant difference between targeted and untargeted intramuscular EMG-based classification of movements. The task of torque estimation, however, is more complex, as it is a continuous problem. Despite that a couple of studies have now compared the performance of surface vs. intramuscular EMG with pattern recognition, they do not deal with the actual usability of both EMG types. For example, Hargrove et al. (2010) found a poor correlation between classification error and usability in a virtual clothespin task. Thus with the positive results obtained in this study using continuously changing signals, future studies should involve a usability test, such as Fitt’s law test, which has been validated recently for EMG control (Scheme and Englehart 2012) and is used in many applications, such as robot-assisted surgery (Chien et al. 2010), motor imagery in Huntington’s disease (McLennan et al. 2000), and motor planning (Harris and Wolpert 1998).

Conclusion. In this study, the performance of untargeted intramuscular and surface EMG was compared in terms of $R^2$, PCC, and RMSE. For all performance metrics, the results showed higher performance of surface-based over intramuscular-based wrist-joint torque estimation, which may be attributed to the very high selectivity of the recordings used in this study. With the level of accuracy obtained here, there is indication that intramuscular EMG may be used to drive a prosthetic device. This study, however, provides only an experimental assessment, per-subject basis, on how force can be estimated in two DoF. The training modality used in this study is a theoretical expression on how the model might work in practice and should be tested in real prosthetic applications.

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GRANTS

Support for this study was provided by a grant from the Danish Agency for Science, Technology and Innovation (Council for Independent Research/Technology and Production Sciences, Grant Number 10-080813, to E. N. Fig. 6. Example of force estimation for worst performance using (A) surface EMG and (B) intramuscular EMG. The solid, gray line represents the measured force, and the dark, dashed line represents the estimated force. The $y$-axis is given in an arbitrary unit (1 trace is offset for visualization). Note that the plot is not a full recording from a single trial but rather, a concatenation of 1/2 trials that acted as testing folds during the 4-fold validation test.

Fig. 7. A representation of a complete recording from 1 trial during simultaneous activation of both DoF. It can be seen that ulnar and radial deviation (DoF3) was also activated unintentionally, although minimally. This appeared to be due to the wrist biomechanics, as we observed during this study that ulnar and radial deviation was always involved when combining wrist flexion/extension and supination/pronation.
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