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Influence of advanced electromyogram (EMG) amplitude processors on EMG-to-torque estimation during constant-posture, force-varying contractions

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Abstract

Numerous studies have investigated the relationship between surface EMG and torque exerted about a joint. Most studies have used conventional EMG amplitude (EMGamp) processing, such as rectification followed by low pass filtering, to pre-process the EMG before relating it to torque. Recently, advanced EMGamp processors that incorporate signal whitening and multiple-channel combination have been shown to significantly improve EMGamp processing. In this study, we compared the performance of EMGamp-torque estimators with and without these advanced EMGamp processors. Fifteen subjects produced constant-posture, nonfatiguing, force-varying contractions about the elbow while torque and biceps/triceps EMG were recorded. EMGamp was related to torque using a linear FIR model. Both whitening and multiple-channel combination reduced EMG-torque errors and their combination provided an additive benefit. Using a 15th-order linear FIR model, EMG-torque errors with a four-channel, whitened processor averaged 7.3% of maximum voluntary contraction (or 78% of variance accounted for). By comparison, the equivalent single-channel, unwhitened (conventional) processor produced an average error of 9.9% of maximum voluntary contraction (variance accounted for of 55%). In addition, the study describes the occurrence of spurious peaks in estimated torque when the torque model is created from data with a sampling rate well above the bandwidth of the torque. This problem occurs when the torque data are sampled at the same rate as the EMG data. The problem is corrected by decimating the EMGamp prior to relating it to joint torque, in our case to an effective sampling rate of 40.96 Hz.

Keywords

EMG; EMG amplitude; Torque; EMG-torque model; Optimal sampling rate

1. Introduction

It has long been desired to relate the surface electromyogram (EMG) to the *tensions* produced by *individual* muscles (Inman et al., 1952). This relation would provide a noninvasive tool for musculoskeletal assessment in various applications, including clinical biomechanics, prosthetics control and ergonomics assessment. However, direct mechanical verification of the

estimated individual muscle tensions is not presently possible in situ, the surface EMG is dominated by the activity of superficial muscle fibers, and EMG recordings from the skin surface overlying one muscle are contaminated by crosstalk arising from adjacent muscles. Although a less specific measure, EMG-based estimates of *total torque about a joint* can alleviate these short-comings and still provide valuable information about the musculoskeletal system. First, net torque about a joint can be easily and accurately measured in a calibration apparatus. Second, synergistic activation of muscle groups can render the superficial muscle activity sufficient to identify total joint torque, even if the individual torque contributions of underlying muscles can not be discriminated. Third, certain crosstalk contributions are automatically accounted for in the total joint torque estimate — even if they cannot be attributed to individual muscle tension contributions (c.f., Clancy, 1991).

Hence, noninvasive musculoskeletal research has often utilized EMG-torque models (e.g., Gottlieb and Agarwal, 1971; Thelen et al., 1994). A classic paradigm for relating the EMG waveform to joint torque has emerged (Fig. 1). One or more EMG electrode recordings are made from agonist and antagonist muscle groups, and EMG amplitude (EMGamp) estimates are computed for each muscle group. EMGamp represents the degree of neural input to the muscle groups. A model relationship is then constructed that relates agonist-antagonist EMGamp's to total joint torque. Prior studies, as well as this study, fundamentally assume that EMGamp can be identified from the “raw” EMG waveform and that joint torque is an identifiable function of the EMGamp's. Although individual torque contributions appear as internal states of the model (see Fig. 1), only total joint torque contributes to the estimation error. Hence, the internal torques need not, and are not, verified or used. Both linear (Gottlieb and Agarwal, 1971; Thelen et al., 1994) and non-linear (Hof and Van den Berg, 1981; Wyss and Pollack, 1984; Zuniga and Simons, 1969) dynamical models have been used to relate EMGamp to torque. In addition, modern estimation techniques routinely model agonist-antagonist activity, since antagonist muscle activity accompanies agonist contraction (An et al., 1983; Solomonow et al., 1986); as well as optimize some or all of the system identification stage to individual experimental subjects.

While the system identification models have received a great deal of attention, advances in EMGamp processing have seen little incorporation into EMG-torque estimation. Most EMG-torque techniques still use conventional rectify and low pass filter processing of the raw EMG. State of the art EMGamp estimation incorporates signal whitening and multiple channel combination (see Clancy et al., 2002, for a review). Combined, these two techniques improved the signal to noise ratio of EMGamp estimation 187%, compared to conventional EMGamp processing, during constant-posture, constant-force, non-fatiguing contractions (Clancy and Hogan, 1995). During quasi-isotonic contractions about the elbow, these techniques reduced the EMG-torque error by one third (Clancy and Hogan, 1997). The advanced EMG processing techniques have also shown improvements during dynamic contractions. Subjects used real-time EMGamp feedback to track a 0.25 Hz bandwidth random target during constant-posture force-varying contractions. Compared to conventional EMGamp processors, the advanced processors reduced tracking error approximately half-way to the error achieved using direct force feedback (Clancy and Farry, 2000). Preliminary EMG-torque modeling has also been conducted with these dynamic data (Clancy et al., 2001). Initial results suggest that the advanced EMGamp processors lead to reduced EMG-torque error; however, the system identification stage exhibited a large proportion of “non-convergent” trials, i.e. recordings that did not produce usable EMG-torque models.

In this report, we re-examined the dynamic EMG-torque modeling of Clancy et al. (2001). Based on the results of prior studies, we hypothesized that the inclusion of whitening and multiple-channel combination in amplitude estimation would each decrease the error in EMG-torque modeling, and that their simultaneous use would reduce error further. We also

hypothesized that the issue of “non-convergent” trials was not a fundamental limitation to utilizing the advanced EMG processors in EMG-torque processing, but rather was a correctable artifact of our prior system identification method.

2. Methods

2.1. Apparatus and experimental methods

The experimental apparatus and methods have been described and pictured in detail elsewhere (Clancy, 1999; Clancy and Farry, 2000). Briefly, after securing written informed consent, subjects were strapped into the seat of a Biodex exercise machine (Biodex Medical Systems, Inc., Shirley, NY). A subject's right arm was positioned in the plane parallel to the floor, with the shoulder abducted 90°, the forearm oriented in the parasagittal plane, the wrist fully supinated and the elbow flexed 90°. The wrist was rigidly attached to the Biodex dynamometer with a cuff at the styloid process. This constant posture was utilized for all experimental trials.

The skin above the investigated muscles was cleaned with an alcohol wipe and four EMG electrode-amplifiers (Liberty Technology model MYO115, Hopkinton, MA) were placed over each of the biceps and triceps muscles, midway between the elbow and the midpoint of the upper arm, centered on the muscle midline. This placement attempted to avoid the innervation region (at the muscles' midpoints) as well as the muscles' tendons. The two contacts (4 mm diameter, stainless steel, separated 15 mm center-to-center) of each electrode-amplifier were oriented along the muscle's long axis. Adjacent electrode-amplifier centers were spaced 1.75 cm apart, transversely across the arm. The ground electrode was applied over the acromion process. Each electrode-amplifier had a gain of 725, a common mode rejection ratio of 90 dB at 60 Hz, and a second-order 10–2000 Hz bandpass filter. Each electrode-amplifier output was electrically isolated, amplified, and low pass filtered (fourth-order filter at 2000 Hz). This wide bandwidth for surface EMG has been shown previously to be advantageous when signal whitening is applied (Clancy and Hogan, 1994; Clancy and Farry, 2000). Recordings with the two contacts of each electrode-amplifier shorted gave a measure of equipment noise, which averaged $2.1 \pm 1.7\%$ of the root mean square EMG at 50% maximum voluntary contraction (MVC). The EMG and dynamometer signals were sampled at 4096 Hz using a 16-bit A/D converter (Computer Boards model CIO-DAS1600/16, Mansfield, MA).

Fifteen healthy subjects (eight male, seven female; aged 23–65 years) each completed one experiment. Subjects initially performed two 2 s MVCs each in flexion and extension, the averages of which were used as the subject's MVCs for the experiment. Next, they performed a 0% MVC (rest contraction) and separate flexion and extension 50% MVCs for five seconds, utilizing force feedback on a computer screen. These contractions were used to calibrate the advanced EMGamp processors (Clancy and Farry, 2000). The subjects then performed dynamic (constant-posture, force-varying) target tracking contractions. A computer screen displayed one of either their elbow joint torque (the dynamometer signal) or the algebraic difference between real-time biceps and triceps EMGamp, as a biofeedback signal. The EMGamp difference provided a biofeedback signal that was similar in character to the torque feedback, albeit with increased variance. The distinct biofeedback signals were not necessary for this EMG-torque study, but were utilized for a companion study conducted with these same experimental trials (Clancy and Farry, 2000). For this EMG-torque work, each biofeedback signal produced a torque profile with similar bandwidth and amplitude characteristics, thus, the post hoc EMG-to-torque analysis did not distinguish between them.

The computer screen also displayed a “target” which traversed back and forth across the screen in a random fashion. Subjects were instructed to follow this target as best as possible. Precise tracking performance was not required for a successful experiment. In fact, the purpose of the target was to ensure that subjects would produce a torque signal whose frequency content

spanned the frequency range of interest (0–2 Hz). The random profile followed a (continuous-valued) uniform random distribution with a bandwidth of either 0.25 Hz (slow tracking) or 1 Hz (fast tracking), over a range spanning 50% MVC extension to 50% MVC flexion. Subjects took a few minutes (followed by a 3 minute rest) to become familiar with the tracking task as none had any prior experience. Subjects then completed 15 slow tracking trials (three sets of five) and 15 fast tracking trials (three sets of five), each of 30 s duration. Each set used each of the five biofeedback signals, with the order of presentation randomized within each set. The subject's arm was removed from the wrist cuff between all recording trials to allow 2–3 minutes of rest to avoid fatigue.

2.2. Data analysis

All data analysis was performed off-line using MATLAB (The Mathworks, Natick, MA). Four different EMGamp processors were contrasted. In each case, an EMGamp estimate was produced separately for the biceps and triceps muscle groups (refer to Fig. 1). For all processors, the EMG data were high-pass filtered at 15 Hz using a zero-phase, 10th-order, FIR filter; detection was performed with an absolute value operation; and the smoothing stage was omitted, since smoothing was incorporated within the ensuing analysis step. Processor 1 was the “conventional” single-channel, unwhitened processor (i.e., the digitally high-pass filtered, rectified signal). For each muscle group, an electrode located centrally on the muscle was selected. Processor 2 was a single-channel, whitened processor (utilizing the same electrode channels as Processor 1). Prior to rectification, each channel was whitened using the adaptive whitening technique of Clancy and Farry (2000), implemented in a stand-alone MATLAB toolbox (Clancy, 2004). Processor 3 was a four-channel, unwhitened processor. After rectification, the four EMG signals from a muscle group were normalized in magnitude and ensemble averaged. Processor 4 was a four-channel, whitened processor. Each channel was adaptively whitened prior to rectification, and then normalized and ensemble averaged.

Because the raw EMG were sampled at 4096 Hz, the EMGamp estimates were also produced at 4096 Hz. The flexion (biceps) and extension (triceps) EMGamp's formed the inputs to a system identification model in which elbow joint torque was the output. The torque output, however, has signal power over a *much* lower band of frequencies than raw EMG. Therefore, the EMGamp's could be decimated prior to the ensuing system identification. Various integer-valued downsampling rates from 1–900 were evaluated. In each case, the amplitude estimates were first low pass filtered with a cut-off frequency equal to half the new sampling rate (8th-order Butterworth filter applied in the forward, then the backward time directions to achieve zero phase). Note that decimation must occur *after* an EMG amplitude estimate has been formed since high-pass filtering, whitening, rectification and channel combination utilize the full bandwidth of the raw EMG signal.

The decimated flexion [$F(k)$, where k is the downsampled discrete-time sample index] and extension [$E(k)$] EMGamp's were related to torque [$T(k)$] via the dynamic, linear, FIR (a.k.a., moving average) model (Ljung, 1999)

$$T(k) = -e_1 E(k-1) - e_2 E(k-2) - \dots - e_{nb} E(k-nb) + f_1 F(k-1) + f_2 F(k-2) + \dots + f_{nb} F(k-nb), \quad (1)$$

where the e_i are extensor model coefficients, the f_i are flexor model coefficients and nb is the model order. A train-test evaluation paradigm was utilized in which the model coefficients were fit to the data from a training trial and then used to “predict” the torque from a distinct test trial. Prediction referred to passing the EMGamp's from the test trial through the EMGamp-torque model calibrated in the training trial to predict the joint torque recorded during the test trial. An error signal was formed as the difference between the predicted and actual test trial torque. For training, optimal fit coefficients were determined from the overdetermined system

of Eq. 1 via linear least squares (Ljung, 1999). For testing, the 15 trials at a given tracking speed were organized as three sets of five contractions. Within a set, fit coefficients were trained to one trial, then tested on the four remaining trials. Thus, for a given processor-decimation combination, a total of 180 error signals were available (15 subjects $\times$ 3 sets per subject $\times$ 1 training trial per set $\times$ 4 test trials per training trial). One second of data from the beginning and end of each error signal was removed (trimmed), since these data were corrupted by the startup transients of the various processing filters.

EMG-torque error was investigated with two metrics. All errors were normalized to twice the torque at 50% flexion MVC, denoted $\%MVC_F$. First, the mean absolute error (MAE) was computed for each trial. Second, the percent variance accounted for (%VAF), defined as (Kearney, et al., 1997):

$$\% VAF = 100 \cdot \left(1 - \frac{\sum_{k=1}^N [Error(k)]^2}{\sum_{k=1}^N T^2(k)} \right), \quad (2)$$

[where N is the sample duration of the trimmed error sequence, $Error(k)$] was computed for each trial. Statistical comparisons (performed using SAS, SAS Institute, Cary, NC) were made using the MAE results only, since the %VAF results were derived from the same error signals. MAE data were analyzed separately for each speed for model orders 1–20 (responses stabilized thereafter). The natural logarithm of the natural logarithm of each MAE value was used as the response value, since this transformation succeeded in removing the substantial right skewness in the data. To account for the correlation across model order, a multivariate mixed linear model was fit to the data, comprised of a fixed effect due to the EMG processor and random effects due to the subject, subject-EMG processor interaction, training set, training set-EMG processor interaction and test set. The model response was a 20-dimensional vector consisting of $\ln(\ln(MAE))$ at models orders 1–20.

3. Results

3.1. Decimation

In the absence of decimation (i.e., when the downsampling factor equaled one), some of the prediction torque sequences exhibited a few large spikes — errors that were *several orders of magnitude* above the test torque, but lasting only a few samples in duration. Although the spikes occurred infrequently, their magnitude caused the overall MAE (and %VAF) to be unrealistic. This error is what caused trials to be considered “non-convergent” in our prior EMG-torque work (Clancy et al., 2001).

On closer inspection during this study, we were able to establish that the errors were related to the sampling rate. Even at the fast tracking bandwidth, 99.9% of the power in the joint torque signal occurred below 4 Hz. Our raw EMG sampling rate of 4096 Hz represents (un-aliased) power out to 2048 Hz. When the system identification model of Eq. 1 determines the fit coefficients, it has no signal above 4 Hz which it can use to calibrate a model — but noise will exist above this frequency. When decimation was omitted, our system identification method was producing models with unrealistically high gain at frequencies above 4 Hz (e.g., gains 100,000 times the passband gain). Thus, a small amount of noise power at frequencies above 4 Hz in a test trial caused a noise spike in the predicted torque. Although the occurrence was infrequent, the result was disastrous.

Ljung (1999) describes this problem of spurious model performance when the system identification model is grossly oversampled. Our solution to this problem was to decimate *after* forming the EMG amplitude estimate. As we progressively lowered the effective

EMGamp sampling rate, the spikes reduced both in occurrence rate and magnitude. Decimating by a factor of 100 (effective EMGamp sampling rate of 40.96 Hz) extinguished all spikes. Decimating with rates above 100 eliminated all spikes, but decreased EMGamp-torque performance. This excessive decimating clearly discarded signal bandwidth. The optimal sampling rate of 40.96 Hz is approximately 10 times the highest signal frequency, which is precisely the “rule-of-thumb” rate recommended by Ljung (1999). In addition, this rate still captured all of the signal power. This optimal decimation factor of 100 was used in all further analyses and results.

3.2. Comparison of EMGamp processors

In general, each EMGamp-torque processor captured much of the dynamics exhibited in the actual torque (Fig. 2). For all EMG-torque processors (Fig. 3, Fig. 4), a progressive increase in performance resulted as model order was increased up to about 10–15th order. Little or no additional improvement occurred above a model order of 15–20. The median results were substantively better than the mean results, suggesting that a few large errors overly influenced the distribution of errors. For the fast tracking speed trials, the best EMG-torque model (multiple-channel, whitened EMGamp; system identification order greater than 15) produced an average error of 7.3% MVC_F with a % VAF of 78%. Similar results were found for the slow tracking speed data (Fig. 4).

For the fast tracking speed, multivariate statistical tests indicated highly significant differences due to the subject-EMG processor interaction (Wilk's Lambda $F = 2.27$, 840 and 1397.8 degrees of freedom, $p < 0.0001$). However, interaction plots and the size of the sums of squares (one or more orders of magnitude lower than those for EMG processor) indicated a multivariate test for EMG processor was valid. This test indicated highly significant differences as well (Wilk's Lambda $F = 3.58$, 60 and 69.454 degrees of freedom, $p < 0.0001$). Follow-up pairwise contrasts for EMG processor (with Holmes stepdown Bonferroni adjustment) found all EMG processor combinations to be significantly different (each $p < 0.0174$). To identify which model orders exhibited differences in EMG processors, univariate comparisons were conducted for each model order using Tukey pairwise comparisons (Bonferroni adjusted to an overall confidence level of 0.95). For twelfth-order models and above, significant differences consistently resulted when comparing the following processor combinations: single-channel unwhitened to multiple-channel unwhitened, single-channel unwhitened to multiple-channel whitened, and single-channel whitened to multiple-channel whitened. Comparison of single-channel unwhitened to multiple-channel whitened was highly significant in every multivariate and univariate test. For the slow tracking speed, substantially similar results were found, except that the follow-up pairwise contrasts for EMG processors was significant for all EMG processor combinations *except* when comparing single-channel whitened to multiple-channel whitened ($p = 0.19$).

4. Discussion

4.1. EMG-torque estimation

The objective of this research was to investigate the incorporation of recent advances in EMGamp processors into EMG-torque estimation algorithms. It was anticipated that higher fidelity (i.e., lower noise) EMGamp processing would reduce the errors in EMG-torque prediction. Indeed, our results show that both whitening and multiple-channel combination of the EMG — methods previously shown to improve EMGamp estimates — lead to reduced EMG-torque prediction errors. Even lower errors result when the two techniques are used in combination. Using 15th-order and higher linear FIR models, EMG-torque errors with a four-channel, whitened processor produced an average error of 7.3% MVC (% VAF of 78%) at the fast tracking speed. By comparison, the equivalent single-channel, unwhitened (conventional)

processor produced an average error of 9.9% MVC (% VAF of 55%). In addition, our work highlights the oversampling problem that occurs when EMG data (typical bandwidth from 20–500 Hz) are simultaneously sampled with torque data (typical bandwidth < 5–10 Hz). In these cases, it is common to sample all data at the highest required rate. Thus, the torque data are grossly oversampled. In this circumstance, the EMGamp-torque model transfer function produces spurious gains at frequencies above the typical band of torque data. This issue was resolved by decimating after EMG amplitude estimation, to a rate of 40.96 Hz — a rate that is approximately ten times the highest torque frequency, as recommended by Ljung (1999).

4.2. Study limitations

Our primary interest was the influence of different EMGamp processors on EMG-torque prediction performance. As such, we limited our study in several manners so we could isolate the effect of EMGamp without the complexity of less restrictive EMG-torque models. One would expect that the benefits shown here of improved EMGamp processors would transfer to many other EMG-torque modeling problems. Indeed, it now seems justified to progressively release these restrictions and validate these benefits in more general applications. First, our experimental design consisted of constant-posture nonfatiguing contractions about the elbow, while most “real-life” contractions are more fully dynamic. Second, the mechanical model for the elbow treated the joint as a simple hinge, with only one agonist (biceps) and one antagonist (triceps) muscle group. These assumptions simplified the system identification to a two-input (flexion, extension EMGamp), one-output (torque) system. In actuality, each muscle acts in a unique manner and other muscles (e.g., brachialis, brachioradialis) contribute to torque about the joint. However, crosstalk and the limited spatial resolution of conventional surface EMG constrain the ability to monitor closely spaced muscles, or even distinct compartments within a muscle group. Contributions of muscles that act synergistically with the biceps/triceps are accounted for in the model. However, muscles that do not act synergistically with the biceps/triceps see their contributions contribute to the system identification error. Third, we limited our EMGamp-torque model to a linear FIR form. Linear IIR forms (c.f., Gottlieb and Agarwal, 1971) often require lower model orders. Nonlinear models can potentially capture additional subtle behavior in an EMG-torque relationship such as the electromechanical delay between action potential activation and muscle fiber contraction, and any systematic differences in the EMG-torque relation between concentric and eccentric contractions. Fourth, the contraction bandwidth was limited to a 1 Hz tracking target, since subjects were unable to track random targets with wider bandwidths.

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Fig. 1.

EMG-to-torque model. Raw EMG data are acquired from multiple sites over the biceps muscle group, from which one flexion EMG amplitude (EMGamp) estimate [$F(n)$] is produced. Similarly, raw EMG data are acquired from multiple sites over the triceps muscle group to produce an extension EMGamp estimate [$E(n)$]. These EMGamp's are decimated [giving $F(k)$ and $E(k)$] and then applied to a two-input, one-output model to form the joint torque estimate [$T(k)$]. Index n is the discrete-time index at the sampling rate and index k is the discrete-time index at the downsampled rate.

Fig. 2.

Top two plots show raw extension (triceps) and flexion (biceps) EMG signals from one 30-s fast tracking trial. Extension EMG is scaled to MVE_E , the extension EMG amplitude at 100% extension MVC. Flexion EMG is scaled to MVE_F , the flexion EMG amplitude at 100% flexion MVC. Lower plot shows the measured torque as the solid line; the torque predicted from the single-channel, unwhitened EMGamp processor in the dashed line; and the torque predicted from the four-channel, whitened EMGamp processor in the dotted line. All torques are normalized to twice the torque at 50% flexion MVC. Predicted torques use a 25th order model and a decimation factor of 100.

Fig. 3.

Fast tracking speed results. Mean and median values of percent variance accounted for (% VAF) and mean absolute error (MAE) results, as a function of the system identification model order, for each of the four EMGamp processors, using a decimation factor of 100. All errors normalized to twice the torque at 50% flexion MVC. Each value in each plot is the average/median of 180 test recordings. Better EMG-torque performance is indicated by higher % VAF and lower MAE.

Fig. 4. Slow tracking speed results. Mean and median values of percent variance accounted for (% VAF) and mean absolute error (MAE) results, as a function of the system identification model order, for each of the four EMGamp processors, using a decimation factor of 100. All errors normalized to twice the torque at 50% flexion MVC. Each value in each plot is the average/median of 180 test recordings. Better EMG-torque performance is indicated by higher % VAF and lower MAE.