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A real-time EMG-driven virtual arm

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Abstract

An EMG-driven virtual arm is being developed in our laboratories for the purposes of studying neuromuscular control of arm movements. The virtual arm incorporates the major muscles spanning the elbow joint and is used to estimate tension developed by individual muscles based on recorded electromyograms (EMGs). It is able to estimate joint moments and the corresponding virtual movements, which are displayed in real-time on a computer screen. In addition, the virtual arm offers artificial control over a variety of physiological and environmental conditions. The virtual arm can be used to examine how the neuromuscular system compensates for the partial or total loss of a muscle's ability to generate force as might result from trauma or pathology. The purpose of this paper is to describe the design objectives, fundamental components and implementation of our real-time, EMG-driven virtual arm.

Keywords: Hill-model; Muscle forces; Muscle coordination; Neural control; Intelligent design

1. Introduction

The human musculoskeletal system is highly redundant. With few exceptions, at any joint there are more muscles than necessary to generate the joint moment and/or joint movement. This poses unique challenges to individuals studying motor control. Namely, how does the nervous system control an over-determined musculoskeletal system to produce smooth, coordinated movement? We are attempting to answer this question, in part, by investigating how individual muscles and/or groups of muscles are activated to produce coordinated elbow movements. To this end, we have developed an EMG-driven virtual arm (VA) to assist in this endeavor. Specifically, we are interested in control of the muscular system during the transition from static arm postures to dynamic movements of the elbow.

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The VA is a mathematical and three-dimensional (3D) graphical representation of a human arm. It is displayed on a computer screen and moves in real-time, in response to electromyographic activity recorded from the arm of a test subject as he performs time varying isometric elbow flexion and extension tasks. EMGs are used to estimate force developed by individual muscles crossing the elbow. These forces, coupled with their respective moment arms are used to calculate the net muscle moment acting at the joint. The net muscle moment estimated from the recorded EMGs is used to drive a kinematic model of the VA. The position of the VA determined from the kinematic model is displayed on a computer screen, providing the subject with visual feedback as he controls the VA via self-modulated changes in EMG. Thus, while the VA is free to move in its virtual environment (i.e., on the computer screen), the arm of the test subject never actually moves during the experiment.

The VA was developed to study the neural control mechanisms involved in the transition from static arm postures to dynamic movements. However, since the VA offers artificial control over a variety of physiological and environmental conditions, it can also be used to examine how the neuromuscular system compensates for the partial or total loss of a muscle's ability to generate force as might result due to trauma or pathology. The purposes of this paper are to describe the design objectives, fundamental components and implementation of our *real-time*, EMG-driven virtual arm.

2. Design objectives

The foremost design objectives of the VA project are twofold. First, it is imperative the subject perceives he is controlling the VA in real-time. Failure of this objective implies that visual feedback received by the subject was for an event that occurred in the past, making control of the VA difficult. Secondly, it is important the musculoskeletal system be modeled realistically so that the kinematic and kinetic behavior of the VA is anatomically and physiologically feasible. These objectives must be satisfied for the VA to respond as would the subject's own arm had it been free to move.

2.1. Design objective #1

The VA must work in real-time. That is, the steps involved in calculating the net muscle moment from the recorded EMGs and updating the computer screen with the new position of the VA must take place in an interval of time near or less than that governed by the flicker fusion frequency. Computer game programmers strive for character movement rates of 25 Hz or faster so that movement between frames appears smooth without noticeable transitions. All calculations must therefore be completed and the computer screen refreshed with the new pose of the VA in less than 40 ms for the semblance of real-time, smooth, life-like motion. Thus, for the purposes of the VA project, "real-time" is defined as updating the computer screen with the new position of the VA at a rate faster than 25 Hz (i.e., less than 40 ms). This objective has been verified by including a time-stamp into the graphics module of the VA to define the duration between screen updates. Currently, the new position of the VA can be updated in approximately 30 ms, well under the 40 ms upper boundary considered essential for the purposes of the project.

2.2. Design objective #2

The VA should respond in a manner that is anatomically and physiologically reasonable. That is, the VA should not be stronger or move faster than the subject's actual arm. This objective is achieved through careful selection of muscle parameters and by identifying muscle specific EMG-to-activation coefficients. Muscle parameters and EMG-to-activation coefficients are discussed in detail in Section 4.

3. General data collection

General data collection methods involve sampling force and EMG as the subject performs time varying elbow flexion/extension (F/E) tasks. A fiberglass cast is placed around the distal forearm of the subject. The cast is attached to a six degree-of-freedom load cell that is rigidly fixed to the ground. The distance from the elbow F/E axis to the center of the cast, and the force registered by the load cell are used to calculate the external F/E elbow moment generated by the subject. EMGs are recorded from four elbow-flexor and three elbow-extensor muscles. These muscles include the biceps short head, biceps long head, brachialis, brachioradialis and the three heads of the triceps (i.e., long, medial and lateral). Force from the load cell and EMGs for each muscle are collected synchronously at 1000 Hz. The arm of an instrumented test subject is shown in Fig. 1.

Real-time control of the VA involves a multi-step data normalization and training process. This process involves three distinct phases that may be summarized as follows: (1) determine maximum EMGs for each muscle, (2) determine subject specific EMG-to-activation coefficients for each muscle via off-line optimization and (3) real-time control of the VA. A summary of each data collection phase follows.

3.1. Phase I: determine maximum EMGs for each muscle

EMGs are recorded using bi-polar surface electrodes placed approximately 2 cm apart. Correct placement of the electrodes is verified by functional muscle testing [1]. EMGs are processed according to methods reported by Buchanan et al. [2] and are summarized here. EMGs are pre-conditioned by amplifying (gain of 60 dB) each channel and band-pass filtering (30 Hz–10 KHz) the signal to remove both low and high frequency noise. A second amplification for each channel is undertaken to maximize the magnitude of the EMG activity within the ± 10 V operating range of the analog to digital data acquisition card. The digitized signal is full-wave rectified and linear enveloped using a 4th order low pass Butterworth digital filter set at a cut-off frequency of 4 Hz. This process (i.e., full wave rectification and linear enveloping) is illustrated in Fig. 2. Several isometric elbow flexion/extension maximal efforts are collected and used to determine the magnitude of the peak volitional EMG for each muscle. The peak value of the envelope is considered the peak EMG. All EMGs collected in subsequent phases of the data collection are processed in a similar manner and normalized by the peak values such that the processed EMGs range between 0 and 1 for each muscle.

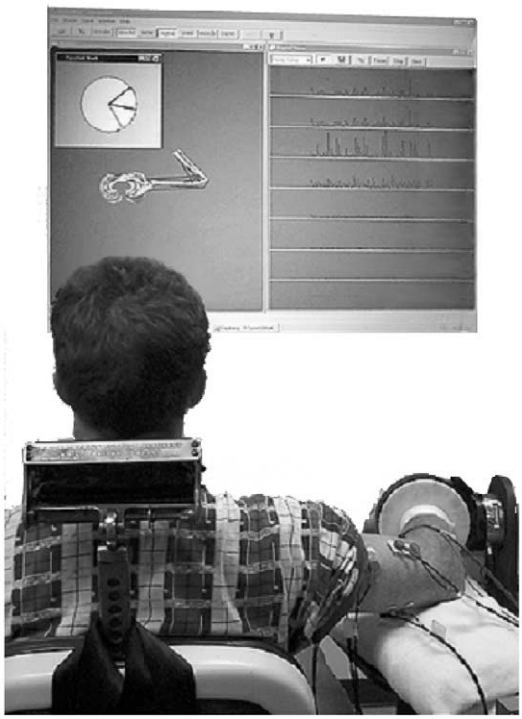

Fig. 1. Arm of instrumented test subject prepared to control the VA in real-time by contracting his muscles. Movement of the VA is controlled by self-modulated changes in EMG. Note: the arm of the test subject never actually moves during the experiment. Projected on the wall is the graphical interface. The current state of the VA is represented by the 3D anatomical model and the pie-chart target angle display. The subject is instructed to move from a starting joint angle of approximately 10° of flexion (approximately 6 o'clock on pie chart) to a target angle of 90° (3 o'clock on pie chart). The green line between the start and target angle represents the current angular position of the VA. Raw EMGs (right panel) are displayed in real-time, primarily for the operator to verify the EMG signals do not exceed ± 10 V. A warning is displayed in yellow when the analog signal is saturated.

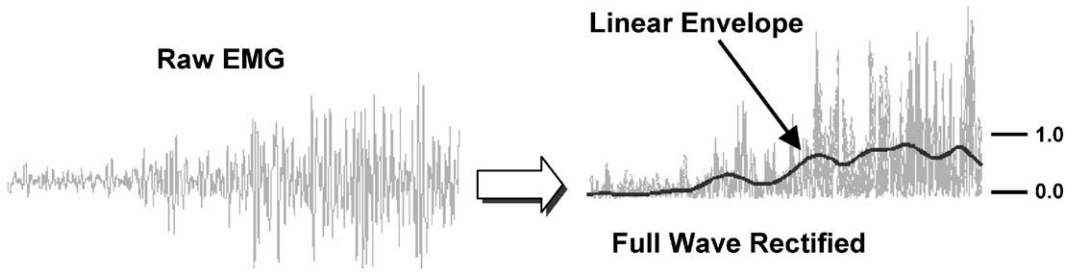

Fig. 2. Raw EMGs are full-wave rectified and linear enveloped. A 4 Hz low pass Butterworth filter is used to envelope the rectified signal. The enveloped signal for each muscle is normalized to the muscle's maximum EMG resulting in a normalized EMG value between 0 and 1.

3.2. Phase II: determine EMG-to-activation coefficients for each muscle

The VA is comprised of 6 distinct and highly integrated components. A Hill-type muscle model is one of these components (see Section 4.3). The role of the muscle model is to calculate the tension developed by each of the muscles in the model when stimulated by muscle activation "*a*". Activation "*a*" is related to the normalized EMG by a non-linear function. The purpose of this phase is to determine coefficients for the EMG-to-activation function. Phase II may be thought of as *training* or *tuning* the VA.

The general VA tuning process proceeds as follows. Force and EMG are sampled during a single trial during which time the subject performs isometric flexion and extension contractions through varying percentages of maximal effort (25–75%). Non-linear optimization is used to determine a set of EMG-to-activation coefficients for each muscle so that the difference between the model predicted joint moment and the recorded external moment from the load cell is minimized. It is necessary to record a range of muscle activation patterns during this trial so that coefficients determined during optimization can be applied to a range of muscular efforts collected during real-time control of the VA (Phase III). The EMG-to-activation coefficients determined during this phase and the peak EMGs collected in Phase I are necessary precursors for real-time control of the VA (Phase III). The EMG-to-activation model, Hill-type muscle model and the optimization procedure (i.e., optimal controller) are described in detail in Section 4.

3.3. Phase III: real-time control of the VA

The subject is given ample time to practice controlling the VA before actual experimental data are collected. During this time the subject practices flexing and extending the VA at varying speeds via self modulated changes in EMG. Typically, the subject feels he can control elbow F/E of the VA within a 15–20 min accommodation period. The objective of Phase III is for the subject to move the VA from an initial elbow angle to a specified target angle. A pie chart is used to represent the starting angle, target angle and the current angular position of the VA. The subject is asked to perform uni-directional flexion, uni-directional extension and cyclical flexion & extension target matching tasks. These virtual movements are performed at various levels of effort (25–75% of maximum effort), consistent with the range of muscle contraction efforts collected during Phase II. Forces and EMGs are recorded as the subject activates muscles of his actual arm and the EMGs are used to drive the VA displayed on the computer screen. EMGs for each muscle are processed as described in Phase I, and the EMG-to-activation coefficients determined during Phase II are used to calculate muscle activations for each of the 7 muscles of the VA. Muscle activation and other parameters (described in detail in Section 4.3) are used as inputs to a Hill-type muscle model from which the force generated by each muscle actuator is estimated. Moment arms for each muscle are estimated from an anatomical model and combined with the model predicted forces to determine the net muscle moment of the VA. The model predicted elbow moment becomes an input to a kinematic model that is used to compute the new position of the VA. The current state of the VA is displayed on the computer screen, providing the subject with the real-time visual feedback necessary to successfully match the target angle. The efficacy of the subject at controlling the VA is evaluated by comparing the elbow angle of the VA and the target angles displayed on the computer screen.

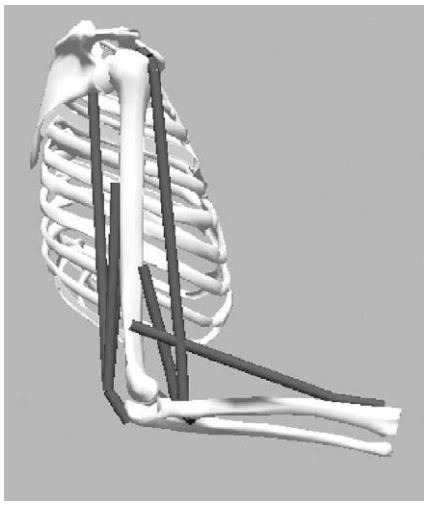

Fig. 3. 3D graphical representation of the muscle actuators and bones of the VA. Muscles are modeled as line segments connected with via points allowing the muscle to wrap around bones and joints. EMGs recorded from the subject are used to actuate muscles of the VA.

4. Components of the VA

The VA is comprised of 6 distinct, but highly integrated components. These components include: (1) anatomical model, (2) EMG-to-activation model, (3) Hill-type muscle model, (4) optimal controller, (5) kinematic model and (6) graphics module. A brief description of each component follows.

4.1. Anatomical model

The anatomical model can be further divided into 2 sub-components corresponding to: (1) muscle architecture and geometry, and (2) bone geometry and joint configuration.

4.1.1. Muscle architecture and geometry

Muscles are modeled as line segments with via points that allow muscles to wrap around bones and joints [3]. The origin, insertion and via points for each muscle of the VA are based on values reported in the literature [4]. In addition, muscle specific parameters such as optimal fiber length, tendon slack length, pennation angle and maximum isometric force for each muscle are based on values reported by Murray and colleagues [5–7].

4.1.2. Bone geometry and joint configuration

The bones of the virtual arm include a 3-D radius and ulna that articulate with a humerus. The humerus is attached to a scapula and clavicle, which are anchored to a 3-D rib cage (Fig. 3). Each bone is constructed from as a series of polygons and contains a local coordinate reference. Relative motion between bones is easily represented by a coordinate transformation of the bones

into a common reference. For the purposes of this project, the only joint about which movement takes place is the elbow. The elbow is modeled as a sliding hinge based on the work of Chao and Morrey [8].

The length of each muscle actuator is a function of the angular position of the VA. Muscle origins and insertions are initially represented in the different bone reference systems and transformed into a common system for the purposes of calculating musculotendon length (MTL). Thus, as the angular position of the VA changes, the relative position of each muscle's origin and insertion changes, and therefore so does the musculotendon length of each actuator. This relationship can be used to calculate the moment arm (MA) for each muscle of the VA as a function of MTL and elbow angle (e.g., An et al. [9]).

$$MA_i = \mathrm{d}\,\mathrm{MTL}_i/\mathrm{d}\theta, \tag{1}$$

where "i" represents the ith muscle and θ is the angular position of the VA.

4.2. EMG-to-activation model

Muscle activation is used to represent the neural excitation of each muscle actuator and is a requisite input to the Hill-type muscle model. The magnitude of the activation is related to the intensity of the muscular contraction and is therefore related to the recorded EMGs. The relationship between EMG and muscle activation is formulated using a two-step process. First, EMGs are transformed into an intermediate variable as per Eq. (2).

$$e_i(t) = \alpha_i \mathrm{EMG}_i(t-d) - \beta_i e_i(t-1) - \gamma_i e_i(t-2), \tag{2}$$

where $e_i(t)$ is the intermediate processed EMG related in a recursive manner to the filtered EMG for muscle "i" at time $(t-d)$, α_i is a scale factor for muscle "i" used to account for inter-subject differences in muscle parameters, d is an electro-mechanical delay and β_i, γ_i are recursive coefficients. The EMG-to-activation model we use is similar to the linear discrete time dynamic model proposed by Thelen et al. [10], but differs in that it accounts for non-linearities in the EMG to force relationship (e.g., see Lloyd et al. [11]). Linear and non-linear relationships have been reported in the literature [12–14]. In this work, the shape of the activation relationship is modeled using the following function:

$$a_i(t) = \frac{(\mathrm{e}^{A_i \cdot e_i(t)} - 1)}{(\mathrm{e}^{A_i} - 1)}, \tag{3}$$

where $a_i(t)$ is muscle activation for muscle "i" at time "t" and the A_i coefficient is a shaping factor specific to muscle "i". The shape of the activation to force relationship is governed by the value of A_i. The process of determining the coefficients for each muscle is described in Section 4.4.

4.3. Hill-based muscle model

Muscle fibers are treated as contractile elements in parallel with a passive elastic component. These elements are in series with a non-linear elastic tendon [15]. The force generated by each muscle actuator is related to the level of muscle activation (a), current length of the musculotendon unit and the following muscle parameters: optimal fiber length (l_o^m), resting tendon length (l_s^t), pennation angle (α) and maximum isometric force ($F^{\max}$). These properties are integrated within the muscle

function shown in Eq. (4). Eq. (4) represents the relationship between the force output (F) of the Hill-type model and muscle input values (a, MTL, l_o^m, l_s^t, α, $F^{\max}$) for one muscle and at one moment in time. A detailed description of Hill-type muscle models is provided elsewhere [15].

$$F = f(a, \mathrm{MTL}, l_o^m, l_s^t, \alpha, F^{\max}) \tag{4}$$

The force generated by each muscle (F_i) is multiplied by the respective moment arm (MA_i) and summed across muscles to yield the net muscle moment of the VA (M_{VA}) as per Eq. (5); where "i" is used to represent each of the 7 muscle actuators.

$$M_{\mathrm{VA}} = \sum_{i=1}^{7} (MA_i \times F_i) \tag{5}$$

4.4. Optimal controller: non-linear optimization

The force developed by each muscle actuator is dependent on the magnitude of the muscle activation. Muscle activation is calculated from the recorded EMGs using the EMG-to-activation model in which the coefficients determine the shape of the activation time series. The optimal controller component of the VA is dedicated to identifying a set of coefficients (α_i, β_i, γ_i, A_i, d) so that the difference between the model predicted muscle moment and the recorded external F/E elbow moment collected during Phase II is minimized (Fig. 4). The external elbow moment is determined by multiplying the force that the subject applies to the load cell with the perpendicular distance from the load cell to the elbow F/E axis. The optimal controller is a generalized reduced gradient nonlinear optimization method [16], which minimizes the objective function reported in Eq. (6).

$$\min \sum_{1}^{n} (M_{\mathrm{VA}} - M_{\mathrm{external}})^2, \tag{6}$$

where M_{VA} is the model predicted elbow moment and M_{external} is the recorded moment from the load cell. The squared difference between the model predicted and the external moment is summed over n samples, where n is the total number of data points in the trial collected during Phase II. For a 5 s trial, the squared differences are summed over 5000 samples.

The optimization process adjusts the activation coefficients for each muscle. As much as possible, coefficients are constrained to operate within physiological limits. For example, the time delay term, d_i, is constrained to be between 10 and 100 ms. Typical values are 40 ms. The non-linear shape factor A_i is constrained to be between 0 and -3, which yields linear (A_i near zero) to non-linear ($A_i = -3$) force-EMG curves that fall within physiological ranges. In addition, activations are constrained to be less than or equal to one.

The solution matrix of EMG-to-activation coefficients is stored and used during the *real-time* computation of the model predicted VA elbow moment. Optimization is performed off-line and generally required approximately 5 min of computing time on a Pentium II, 300 MHz computer. Randomly choosing the coefficients or using values optimized for a different subject generally resulted in poor agreement between the model predicted elbow moment and the measured moment from the load cell. In contrast, excellent agreement was possible when the VA was *tuned* to an individual (see Fig. 5).

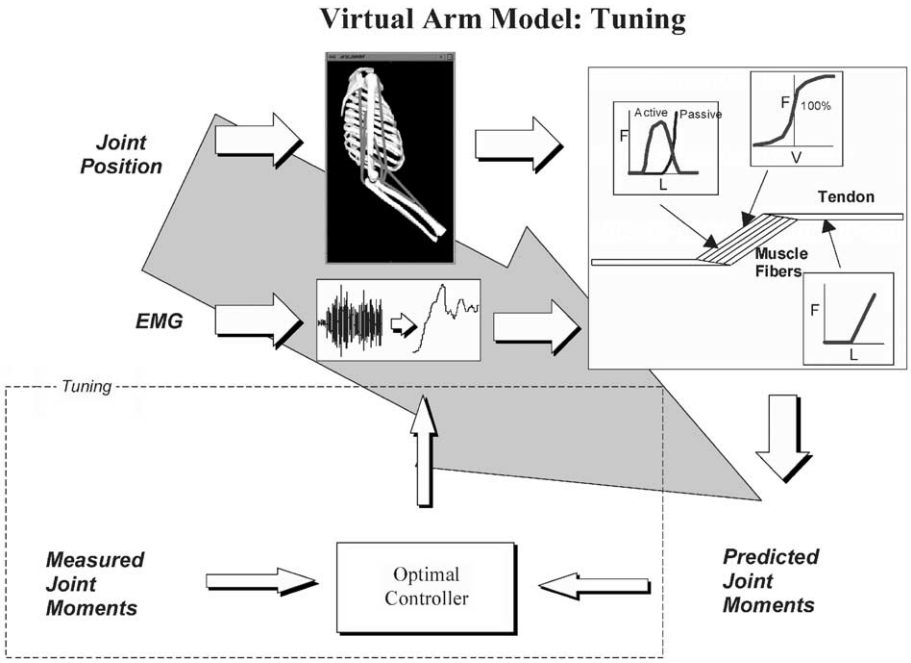

Fig. 4. Flow-chart schematic of Phase II data collection. The purpose of Phase II is to determine subject and muscle specific activation coefficients for the EMG-activation model. The optimal controller selects these coefficients based on minimizing the difference between the model predicted net muscle moment and the measured moment from the load cell. The dashed line encompasses the training part of the model. Once the model is tuned, this portion is removed.

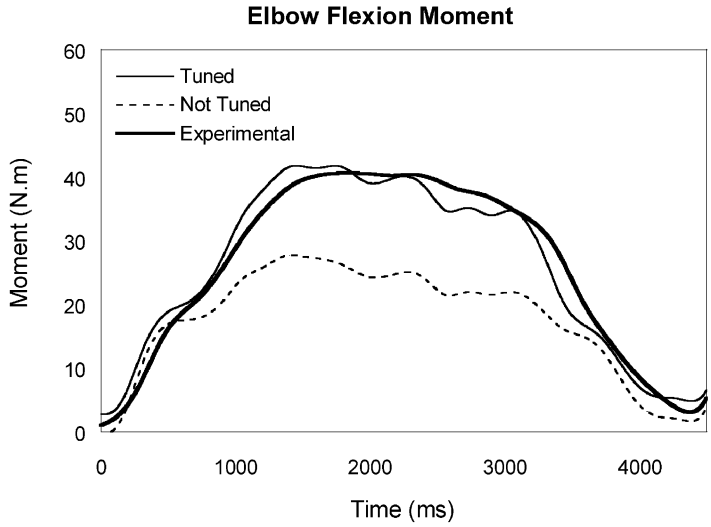

Fig. 5. Experimentally recorded and model predicted estimates of the net muscle moment during 1 cycle of varying isometric flexion moment. Excellent agreement between experimental and model predicted (*tuned*) torque is noted when the EMG-activation coefficients are determined by the optimal controller. In contrast, poor agreement results when another subject's EMG-activation coefficients are used to estimate the elbow moment from EMG (*untuned*).

4.5. Kinematic model

The angular position "P" of the VA is related to the model predicted elbow moment "M_{VA}", the angular velocity "V" of the VA and the moment of inertia "I" of the subject's forearm about the elbow F/E axis. The moment of inertia is estimated from the subject's forearm length, mass and published anthropometric values [17]. The angular position of the VA at time "t" is given by Eq. (7).

$$P(t) = P(t - \mathrm{d}t) + \mathrm{d}t[V(t - \mathrm{d}t) + \mathrm{d}t(M_{VA}/I)] \tag{7}$$

where $P(t - \mathrm{d}t)$ and $V(t - \mathrm{d}t)$ are the angular position and velocity of the VA prior to the time of interest and $\mathrm{d}t$ is the duration between screen updates. Eq. (7) represents a basic formulation of angular position from joint moment. Joint angle "$P(t)$" is passed to the graphics display module and the computer screen is updated with the new angular position of the VA. The kinematic model of the VA contains optional components such as frictional, viscous and spring elements that can be selected by the researcher to simulate a variety of environmental conditions. A description of these optional components has been omitted for the sake of clarity.

4.6. Graphic display module

A 3-D Gourad shaded model of the muscles and bones is displayed on the computer screen and simultaneously projected on the wall providing the subject with *real-time* visual feedback of the VA as he controls F/E via self-modulated changes in EMG. The OpenGL™ graphics library is used to create and manipulate these 3-D objects. A pie chart is used to represent the initial joint angle, the target angle and the current angular position of the VA. Raw EMGs are also displayed, primarily for the researcher to verify that the amplified EMG signals do not exceed the ± 10 V operating range of the data acquisition card (Fig. 1).

A flow chart describing the processing steps of the real-time VA is illustrated in Fig. 6. The optimal controller used in Phase II is removed from the processing flow and replaced with the kinematic model of the VA. The kinematic module interacts with the graphics module to update the new position of the VA on the computer screen.

5. Summary

The purpose of this paper was to present the design objectives, fundamental components and implementation of our EMG-driven virtual arm. The VA was created as a research instrument to assist in our understanding of coordinated arm movements. Several a priori design objectives were essential for the VA to be considered an effective research tool. Two of these objectives include: (1) acquire and process data in less than 40 ms for the subject to perceive real-time control of the VA, and (2) careful selection of muscle parameters and EMG-to-activation coefficients for the VA to behave in a physiological feasible manner. Our experience with the VA suggests that these objectives have been satisfied. For example, subjects can successfully acquire pre-defined targets on the screen and perceive they are controlling the VA even though their real arm remains stationary.

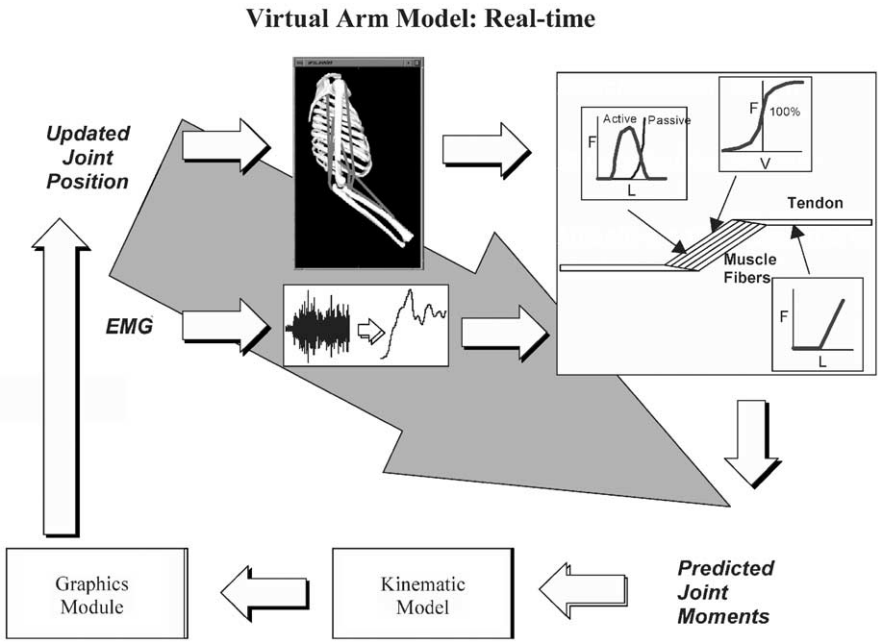

Fig. 6. Flow-chart schematic of the *real-time* data acquisition and processing of Phase III. The optimal controller is removed from the processing framework. Notice there is no feedback in this arrangement. The components of the VA model must be executed within 40 ms for the subject to perceive they are controlling the VA in *real-time*.

To date, the VA has been used to examine muscle synergies involved while performing isometric load directed elbow flexion/extension efforts [18]. In addition, the VA has been used to investigate how these synergies change in response to a simulated neurological injury that might result due to trauma or pathology [19]. Future work on the virtual arm will involve refining individual components of the model and expanding the model to predict dynamic movements at the elbow. This work is currently in progress.

References

[1] Perotto, Anatomical Guide for the Electromyographer, 3rd Edition. Charles C. Thomas, 1994.
[2] T.S. Buchanan, M.J. Moniz, J.P.A. Dewald, W.Z. Rymer, Estimation of muscle forces about the wrist joint during isometric tasks using an EMG coefficient method, J. Biomech. 26 (1993) 547–560.
[3] S.L. Delp, J.P. Loan, A software system to develop and analyze models of musculoskeletal structures, Comput. Bio. Med. 25 (1995) 21–34.
[4] G.T. Yamaguchi, A.G.U. Sawa, D.S. Moran, M.J. Fessler, J.M. Winters, A survey of human musculotendon actuator parameters, in: J.M. Winters, J.L.Y. Woo (Eds.), Multiple Muscle Systems. Biomechanics and Movement Organization, Springer, Berlin, 1990.
[5] W.M. Murray, S.L. Delp, T.S. Buchanan, Variation of muscle moment arms with elbow and forearm position, J. Biomech. 28 (1995) 513–525.
[6] W.M. Murray, A.S. Arnold, S. Salinas, M.M. Durbhakula, T.S. Buchanan, S.L. Delp, Building biomechanical models based on medical image data: an assessment of model accuracy, Med. Image Comput. Comput.-Assist. Interven. 1496 (1998) 539–549.

[7] W.M. Murray, T.S. Buchanan, S.L. Delp, The isometric functional capacity of elbow muscles, J. Biomech. 33 (2000) 943–952.
[8] E.Y.S. Chao, B.F. Morrey, Three-dimensional rotation of the elbow, J. Biomech. 11 (1978) 57–73.
[9] K.N. An, Y. Ueba, E.Y.S. Chao, W.P. Cooney, R.L. Linscheid, Tendon excursion and moment arm of index finger muscles, J. Biomech. 16 (6) (1983) 419–425.
[10] D.G. Thelen, A.B. Schultz, S.D. Fassois, J.A. Ashton-Miller, Identification of dynamic myoelectric signal-to-force models during isometric lumbar muscle contractions, J. Biomech. 27 (7) (1994) 907–919.
[11] D.G. Lloyd, R.V. Gonzalez, T.S. Buchanan, A general EMG-driven musculoskeletal model for prediction of human joint moments, Australian Conference of Science and Medicine in Sport, Canberra, Australia, 1996, pp. 236–237.
[12] J.J. Woods, B. Bigland-Ritchie, Linear and non-linear surface EMG/force relationships in human muscles. An anatomical/functional argument for the existence of both, Am. J. Phys. Med. 62 (6) (1983) 287–299.
[13] C.W. Heckathorne, D.S. Childress, Relationships of the surface electromyogram to the force, length, velocity, and contraction rate of the cineplastic human biceps, Am. J. Phys. Med. 60 (1) (1981) 1–19.
[14] E.N. Zuniga, E.G. Simons, Nonlinear relationship between averaged electromyogram potential and muscle tension in normal subjects, Arch. Phys. Med. Rehabil. 50 (11) (1969) 613–620.
[15] F.E. Zajac, Muscle and tendon: properties, models, scaling, and application to biomechanics and motor control, Crit. Rev. Biomed. Eng. 17 (4) (1989) 359–411.
[16] L.S. Lasdon, A.D. Waren, A. Jain, M. Ratner, Design and testing of a generalized reduced gradient code for nonlinear programming, ACM Trans. Math. Software 4 (1) (1978) 34–50.
[17] D.A. Winter, Biomechanics and Motor Control of Human Movement, Second Edition, Wiley, New York, 1990.
[18] X. Shen, J-Y. Cheng, K. Manal, T.S. Buchanan, Design of a real-time EMG-driven virtual arm, Proc. Am. Soc. Biomech. 23 (1999) 78–79.
[19] T.S. Buchanan, J-Y. Cheng, X. Shen, The control of muscles during virtual movements, Proc. Int. Soc. Biomech. 18 (1999) 266.

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