Review of EMG-based neuromuscular interfaces for rehabilitation: elbow joint as an example

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Abstract: Assistive robots have made great contributions to disabled people in physiotherapy and rehabilitation areas. The interface between patients and medical devices plays a significant role for patients to operate these kinds of robots. This review introduces the current research and development of neuromuscular interfaces, especially the new research directions with special focus on modelling of musculoskeletal systems for interfacing purposes. The paper also summarises the function and prominent advantage of using surface electromyography (sEMG) signals for the interface. The elbow joint was used as an example to go through the working steps of both human biological systems and neuromuscular interfaces. Further developments were also discussed to improve the interface to meet medical demands.

Keywords: electromyography; EMG; rehabilitation; neuromuscular model; elbow; human-robot interface.

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1 Introduction

Throughout the world, the increased number of diseases such as arthritis, stroke and paralysis, have introduced new challenges to the healthcare sector. Traditional artificial rehabilitation training can no longer meet the current medical needs. Robotic technologies provide new solutions for rehabilitation and support for disabled people. For all kinds of rehabilitation therapies, the human-robot interface stands out because it can accurately and quickly simulate the structure and movement of the human body (Figure 1) (Lo and Xie, 2012). Traditionally, biomechanists have developed complex human limb models which combine neural signals with kinematic and kinetic data to study human control strategies (Buchanan et al., 2004a; Piazza and Delp, 1996; Schutte et al., 1993; Murai et al., 2010; Lloyd and Buchanan, 1996). However, due to their complexity, the computational blocks inside the models can only execute individually and tuning methods are also required to accommodate changes and variations. This slows down the processing time and makes them hard to be used in real-time applications.

In this decade, many researchers are trying to use new methods to suit real-time applications, and this has promoted a big leap in the development of human-robot interfaces. This review focuses on some new improved models which contain new types of signals [such as electromyography (EMG) or electroencephalography (EEG)], new kinds of models (such as neuromuscular model or artificial neural network model), new calculation algorithms, and new control strategies (Cavallaro et al., 2006; Fleischer and Hommel, 2008; Ferris et al., 2006; Dollar and Herr, 2008).

This review mainly covers the development of EMG-based neuromuscular interfaces (Pau et al., 2010, 2012a, 2012b) and related fields. Section 2 briefly gives an overview of the biological system as a biological underpinning for our research. In Section 3, we discuss the advantage of using EMG compared to other kind signals input. Section 4 gives some detailed information about three main kinds of interface and especially introduces the musculoskeletal model. Section 5 summarised more related researches in EMG-based neuromuscular interface. The last section concludes the paper and presents future developments in this area.

2 Biological system

If researchers want to successfully establish a human-robot interface to help the disabled patients, it should be clear and imitate how the real human joints, muscles and skeleton work. By analysing the physiological characteristics of neuromuscular systems, researchers can gain the user's movement intention and control the robot directly.

Figure 1 The flowchart from patients moving intention to devices (see online version for colours)

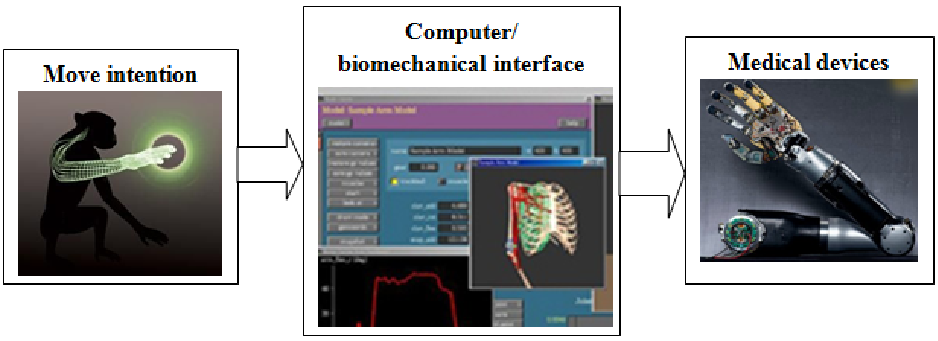
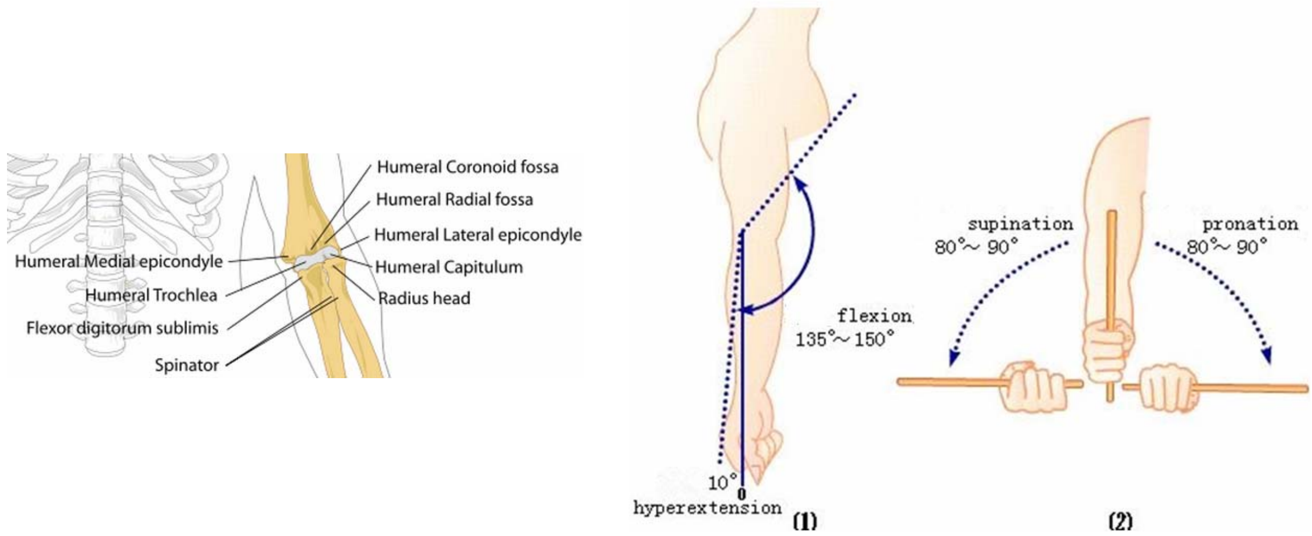


Figure 2 Biological system of human elbow joint (see online version for colours)



The elbow joint is a hinge joint connected by humerus, radius and ulna. It includes humeroulnar joint (combined with trochieahumeri and incisuratrochlearis of ulna), humeroradial joint (combined with capitulumhumeri and fovea articularis of caput radii) and ticulatioradio-ulnarisproximalis (combined with circumferential articularis of caput radii and incisuraradialis). The first two are used for flexion and extension, and the last one is used for turning. The axis of elbow's flexion and extension movement runs through the centre of trochieahumeri and capitulumhumeri. The outside angle between this and the long axis of humeral is 83°–85°. During flexion, it may be up to 145°. And it is about 10° during hyperextension. Theradioulnarsyndesmosis is combined by ticulatioradio-ulnarisproximalis, articulatio radio-ulnarisproximalis and interosseous membrane of forearm. It can achieve the pronation and supination motion of forearm. The axis of rotation is from the centre of caput radii to the processusstyloideus of ulna. The axis of revolution is from the centre of distal radius to the second metacarpal bone. The angle of pronation is up to 90°, and the one of supination is to 110° [Figure 2 (Fornalski et al., 2003; Alcid et al., 2004)].

The contribution for elbow torque from each muscle is different. The biceps, brachialis and brachioradialis are the most helpful muscles for the elbow flexion, especially the biceps. Also, triceps and anconeus contribute to the elbow extension, butanconeus is quite weak. In order to measure the degree of muscle force, MVC (Maximum voluntary contraction) of all these muscles are calculated, as a result, the brachioradialis, biceps and triceps brachialis will affect the elbow movement most (Ferris et al., 2006; Dollar and Herr, 2008). Through computer simulation and cadaver specimens, it was found that the biceps flexion moment arm peaks in a more extended elbow position and has a larger peak when the forearm is supinated (Cavallaro et al., 2006; Murray et al., 1998). Also, Koo found that: for the flexion and extension without load, the activation of biceps brachii and brachioradialis are quite small, and branchialis contributes most to these two movements; for the flexion and extension with load, other muscle start working besides branchialis. KOO also found that, the smooth stretch elbow joint relays on the cooperation of different muscles (Murray et al., 1998). Koo's research did neither fully model the influence range between different muscles, nor accurately simulate in real-time. These may because of the unreliable nature of branchialis.

3 EMG

After deciding which muscles to take into account, choosing a high quality signal form is the second important part. The human-device interface requires a qualitative and quantitative analysis, an accurate and rapid sensible input, and a quick response according to operator's movement and intention. Therefore, a new type of information access method is needed as a parallel and complementary input. To achieve this, the information bandwidth of input should be expanded, the efficiency of input should be improved and the naturalness of human-robot interaction should be enhanced. Currently, the information sources for the control of prosthetic upper limb are pictures from computer vision, signals from generic sensor, Electroencephalogram (EEG), and EMG (Cavallaro et al., 2006; Pau et al., 2010; Cososchi et al., 2006; Reyes et al., 2012; Manal et al., 2002; Prentice et al., 2001; Lloyd and Besier, 2003; Moeslund and Granum, 2001)

- Input from computer vision

  The original characters of human movement are motion's time and position. Thus, the easiest and most accurate way to record movement is capturing moving images (Moeslund and Granum, 2001). Human movement is mainly reflected by joint movement. Computer vision-based human motion analysis collects moving image in sequences by means of three-dimensional video or high-speed camera, then, processes the image sequence or video to analyse joint motion parameters and trajectory (Nixon and Aguado, 2012; Zhang et al., 2011). This method has a large measurement space and easy to use. Since it uses non-contact way to record, it does not need to impose any constraints to the human body. Thus it can reflect actual human movement. However, during human joint movement, the computer vision is easily affected by changes of ambient light, interference of background chaos, shadow and occlusion of the moving target and so on. These may increase the difficulty of motion recognition. Meanwhile, the sequence of images requires a large storage space, and the analysis algorithms of image are complexity which makes it difficult to real-time processing.

- Input from generic sensor

  This method installs some generic information sensor between user and interface to obtain the real-time dynamic data of human body (or parts), and then use appropriate mathematical models to obtain the motion information of the human body. The common sensors are position sensor, angle sensor, acceleration sensor, force sensor, inertial sensors, and so on (Loeb et al., 2003; Hosticka, 2007). Keith MW in Metro Health centre implanted MEMS force sensors and optical sensors in the disabled patients, to measure the force and torque information of limb joints and muscles. At the same time, Keith used the Hall effect sensor to provide angle information for rehabilitation research. Through more than two years study, he gained many useful results (Kilgore et al., 1997). However, due to the human body's biological reject testability and individual differences, the signal interference is quite large. He cannot rely on implanting too many kinds of sensors to complete the task of acquiring human motion information.

- Input from EEG

  The subjective will of human motion usually comes from cerebral cortex, and the EEG signal from cerebral cortex does not need to relay on residual limb muscles to convey the excitement characteristics (Cososchi et al., 2006; Reyes et al., 2012). Thus, the information acquisition based on EEG is theoretically the best method to help disabled people communicate with others (Xing et al., 2012; Song et al., 2012; McDaid et al., 2013). Roberts put the detected EEG signals through an 8-order AR model and Bayesian logic classifier to classify the data in order to control the up and down movement of the mouse. The overall performance researched 82%. Brain as the centre of human nervous system contains complex electrical signals. And the working mechanism of brain still has many unsolved part. Therefore EEG-based action identifying and control is limited to simple body movements. For diverse and complex action, there still needs in-depth research.

- Input from EMG

  EMG signal is a kind of bioelectricity released by neuromuscular excitability of human's voluntary movement. The EMG information reflects the functional state of muscle, so it can be used for sensing the body's state of motion and predicting future actions. In well-controlled conditions, the change of the EMG may quantitatively reflect the muscle activity and variation of the central control features, such as the level of muscle strength, muscle activation patterns, the excitability conduction velocity of the motor units, the local fatigue degree of the muscle activity, multi-muscle coordination and so on. At the same time, surface electromyography (sEMG), because of the advantages like non-invasive, real-time and simple operation, has been regarded highly by its important academic value and been widely used in various disciplines.

EMG can be used to recognise human movement patterns, especially in the joint motion identification of the upper and lower limb (Pau et al., 2012a; Manal et al., 2002; Lloyd and Besier, 2003; Feng et al., 1999). The recognition results have already been widely used in the control strategy of humanoid mechanical and artificial prosthesis. Meanwhile, as a nerve stimulation signal, it can also contribute to further applications in human rehabilitation therapy. In general, the EMG signals are commonly used in detailed action analysis. The application method is general training through a complex black box system or using a human model to gather action data in order to analysis and predict human movement.

4 Interface

The next important step to transfer human intention to the devices is to develop a robust biomechanical model. At present, the most widely used model is a physiological model of the musculoskeletal system, which is also called a virtual human (Ackerman, 1998; Crampin et al., 2004a, 2004b). The worldwide virtual human research projects are in Table 1.

The physiological musculoskeletal models aim to establish an interface between the EMG signal of disable patients and medical devices. In order to achieve this process, three modelling approaches have been developed, including assumed function model, muscle physiology model and neural network model (Figure 3).

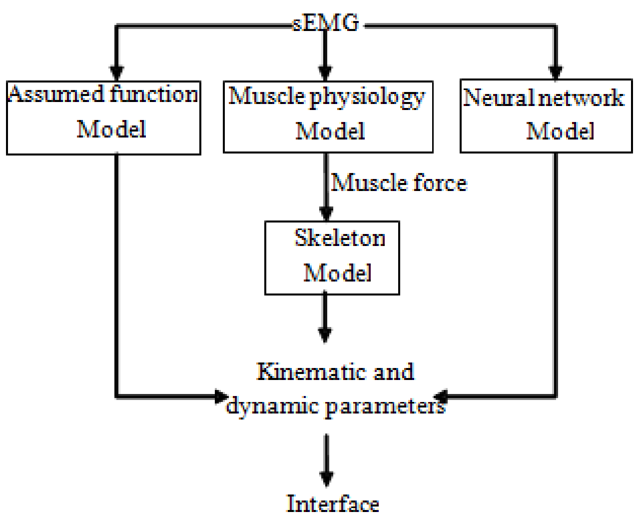
4.1 Assumed function model

The assumed function model was established by using statistical theory to reflect neuromuscular activity and obtain human motion parameters. For example, Song and Ge (2008) used the Cosine tuning function based on periodic regression theory to describe the neuromuscular activation. In order to estimate the elbow angle, an upper limb model was developed to clarify the relationship between the sEMG readings and the direction of movement of the elbow in the horizontal plane. A genetic algorithm was used not only to tune the model parameters, but also to verify whether the triple cosine tuning function was sufficiently accurate to describe the muscle activity. Song and Ge also proposed the usage of fractal theory in analysing sEMG signals. They analysed system characteristics from the different levels of signal fractals, extracted the speed signal of limb movement and provided information for real-time control.

Table 1 Virtual human research projects

Project	*Sources of funding*	*Aim*
Visible human	NLM	Obtain anatomical data
IUPS physiome	Various	Multiscale modelling
US physiome	Various	Integration of the model
Virtual soldier	DARPA	Battle damage simulation
Virtual astronaut	NASA	Medical training
EU biosim	European FW6	medicines simulation
Living human	European FW6	Biomechanics
AIMS	TATRC	Medical training
SIMS	Various	Medical training
SIMDOT	Various	Medical training

Figure 3 The flowchart of physiological musculoskeletal model



Since EMG comes from a group of muscles, it is random and easily gets chaotic, so the accuracy of the elbow angle estimated by this model remains to be further improved. Also, the placement of electrodes and human skin conditions limit this model's adaptability for different patients.

4.2 Neural network model

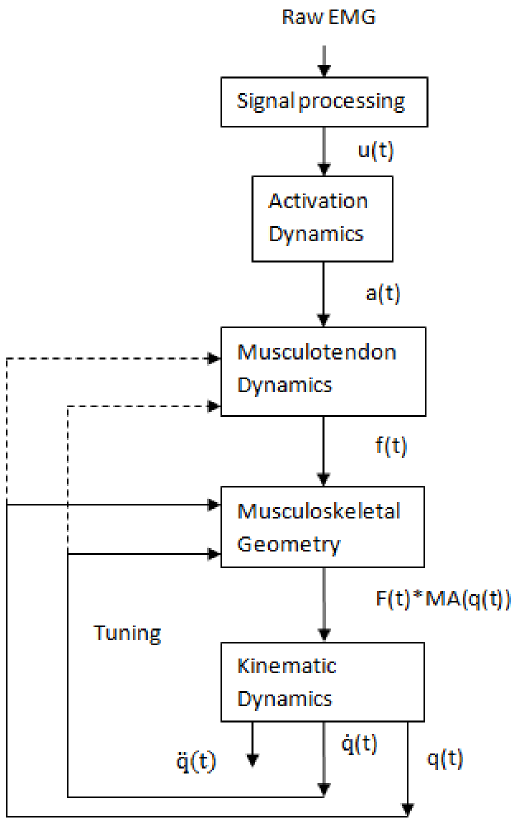
In recent years, researchers attempted to use neural network methods to analyse human musculoskeletal function. Neural network-based models were used to build up a relationship between EMG signals and the correspondent kinematic data of human movement (Prentice et al., 2001; Micera et al., 2001; Sepulveda et al., 1997; Jamwal and Xie, 2012). Compared with the original method of solving the inverse model, neural network-based models are much simpler, because they do not have complicated mathematical formula or time delays which are generated and associated by EMG. One neural network model can address multiple muscle activation models. For example, Heller established a single hidden layer neural network and reconstructed the EMG signal of semitendinosus and vastusmedialis from the kinematic data (Jamwal and Xie, 2012). Sepulveda developed an EMG model with joint features of two single hidden layer neural networks. The input for the model is the data for 16 muscles through normalised EMG values, and the output is the angle and torque of the hip, knee and ankle (Sepulveda et al., 1997). The system was later improved for neuro-fuzzy control (Micera et al., 2001) and emotion-based interaction (Leon et al., 2004). Another representative neural network model is Prentice's model. It used a two-step rate frequency sinusoidal signal as input and the EMG of eight lower limb muscles as output. Later, the author upgraded the model's input with 21 kinematic parameters to describe the muscle activation (Prentice et al., 2001).

The common issue for neural network-based models is that they need to collect a large amount of experimental data. Also, the effectiveness normally depends on the training process and is only applicable within the range of motion of the training samples. In addition, this kind of model is not built on the basis of biomechanics, so it cannot explain the biological laws of motion systems.

4.3 Muscle physiology and skeleton model

With the recent development of modelling human biological systems, it is now possible to establish a basic understanding of the biomechanics of the human skeletal system. Based on this human biological system and muscle physiology, a skeleton model can be established to predict joint movement. It combines with the muscle physiology model (which uses elastoplastic elements to simulate human muscle, tendon and joints) and skeleton model (which uses rigid body to represent human skeleton structure), so it also been called *neuromuscular interface* (*NI*) (Pau et al., 2012a, 2012b). Since this kind of model is simpler and faster in calculating, researchers choose it to realise real-time possessing. Normally the approach of NI consists of four models including muscle activation dynamics model, musculotendon dynamics model, musculoskeletal geometry model and kinematic dynamics model (Figure 4).

Figure 4 The flowchart of neuromuscular interface



4.3.1 Muscle activation dynamics model

Aiming to change the EMG signal to the activation, this model contains EMG acquisition, feature extractions and filtering. When using EMG signals to predict muscle force, the amplitude expresses the level of muscle activation. Therefore, the effective elimination of noise and extraction of muscle strength characteristics are essential to predict muscle force.

For signal acquisition, since sEMG is a non-invasive measurement technique, the interference and cross talk among muscle are particularly severe. How many muscles to choose and where to put electrodesis quite important. For feature extraction, using time-domain characteristics is simpler than the frequency-domain's, but as muscle contraction force changes, its feature changes which reduce the stability of identification. It has been used mostly in myoelectric prosthetic hands and occasionally used for predicting muscle force (Manal et al., 2002; Buchanan et al., 2005). Frequency-domain method is relatively stable and conducive to the follow-up EMG pattern recognition. However the traditional Fourier transform can only model the overall frequency characteristics, it cannot represent time features. Therefore it applies only to steady-state signal analysis. Time-frequency methods may provide time-domain and frequency domain information at the same time and pay more attention to non-stationary signal analysis.

For signal filtering, low-pass filters (such as a Butterworth filter) was mainly used to form a linear envelope (Manal et al., 2002; Buchanan et al., 2005), because it was able to see the value of EMG signal change over time. However, Buchanan believed that the raw EMG change was an artefact, not the signal emanating from muscle. He recommended to use a high-pass filter instead of the low-pass one (Buchanan et al., 2004a). To combine these two ideas, recent researchers use high-pass filter to remove movement artefacts. A full wave rectifying device and a low-pass filter with a 6 Hz low-pass cut-off frequency (Lloyd and Besier, 2003) are used in later stages.

4.3.2 Musculotendon model

Since muscle, tendon and joint combine into a mechanical redundancy system, muscle force cannot be uniquely determined. In order to forecast or measure the muscle force during exercise, a physiological-musculoskeletal-model needs to be developed. The physiological-musculoskeletal-model is a muscle physiology model to gain the muscle force, then using skeleton model to get the joint angle. In recent years, the most representative models of musculoskeletal are based on the traditional Hill model, Huxley model and rheological model.

In 1938, Hill first proposed the three-element muscle model: non-linear contractile elements arranged in series with linear elastic elements, then parallel the elastic element. It assumes that the contractile elements are truly linear elastic when muscle is stationary and use the length changes to describe the change of muscle force and distribution between elastic and contractile elements (Hill, 1938). Even though many improvements have been made to adapt to newly discovered muscle structures, the Hill model still contains the limitation that its accuracy is based on a series of assumptions. Without these assumptions, it cannot correctly distribute the muscle force. Also, these models do not consider the factors of neural regulation which means the models cannot be directly used in dynamic situations.

The Hill model contains muscle physical and mechanical properties. However, it still has some limitations. First the transformation from muscle activation to muscle force is not completely understood. Secondly, it is hard to determine muscle-tendon moment arms and the lines of action. There are lots of difficulties with measuring in cadavers, and even harder in a living person accurately. Finally, it is difficult to estimate joint moments because to accurately obtaining estimates of force from each muscle is prone to error, and there are seldom standards to verify whether the forces predicted are correct (Buchanan et al., 2005).

Huxley (1957) proposed a cross-bridge kinetics model, also named as the Huxley model, which was combined by cross-bridge and actin-binding. Based on the anatomical structure and physiological contraction of muscles, this model expressed the constitutive model of muscle contraction and gave the relationship between tension and speed in microcosmic point. However, the Huxley model is a one-dimensional model and does not take the impact of neural networks into consideration.

The muscle rheological model is a further development of the Huxley model. Different from the Huxley model, it considers the inherent flexibility of each muscle microfilament and uses non-linear contraction (CE) instead of the cross-bridge. Also, the one-dimensional rheological model is similar to the Hill model, but it only describes the muscle movement in continuum mechanics within the scope of continuum mechanics and regards a whole muscle as the combination of a series of such rheological models.

Through the way of contraction dynamics, the musculotendon model associates the muscle activation to the musculotendon force as a result. This block simulates muscle as an active tissue, models the interaction between the muscle fibres and the tendon, and considers the mechanical properties of the tendon tissue (Pipeleers et al., 2007).

When talking about the mechanical properties of muscle, its parameters and equations traditionally result from the experiments of in vitro muscles. When applying this to muscles in the body, they bring some deviation or non-applicability. In addition, to test the muscle force in the human body is impossible because of the test-rejection of biological barriers. Taking these into account, EMG is used to indirectly assess muscle strength nowadays. However, we cannot ensure that only one single muscle is involved in the measurement which means the EMG interference between different muscles cannot be excluded (Kistemaker et al., 2007). Indirect measurement gets more complex collaboration and confrontation from human muscle function group than the implantable measurement. The tendon around muscle also plays an important role to limit and affect the range of human motion, so it must be reflected in the musculotendon model. As a result, establishing a rational and scientific muscle model and determining the appropriate model parameters are the most important parts of the musculotendon modelling.

4.3.3 Musculoskeletal model

To calculate both the length and the moment arm for a musculotendon unit, a musculoskeletal geometry model is required. It must account for the muscle-tendon lengths and moment arms when joint angles change, and include the bone geometry information and the complex relationships related by joint kinematics (Piazza and Delp, 1996; Buchanan et al., 2005). The input is muscle force and output can be the joint movement.

In this model, several main physiological parameters are required:

- Muscle moment arms and lengths
- Optimal fibre length, tendon slack length, and pennation angle which can be measured from cadaver studies (Buchanan et al., 2005). Among these three, the tendon slack length is the most difficult one to measure, but it can be unlimited approximated using a numerical method (Schutte et al., 1993).
- Maximal muscle force can be estimated from measurements of physiological cross-sectional areas of muscles (Murai et al., 2010).

These parameters in the model need to be tuned to accommodate individual variations so that the interface can be used by different patients. The tuning process requires a defined objective function and a search algorithm to minimise the error. By using non-linear optimisation, Buchanan et al. (2005) reduced the chances of converging to a local minimum. Also, some researches, such as Fleischer and Hommel (2008), provided experimental values and scope of muscle length and joint angles. Though, the more parameters that have been used, the more the possible of estimated joint moments and the measured joint moment fit better, but too many parameters may not be good (Buchanan et al., 2004a). Such as, in some of the parameters chosen have limited predictive ability, when the model determines and revaluates too many of these kinds of parameters at each instant, the model is 'overfit' and has very limited predictive power (Zheng et al., 1998).

Before passing to the kinematic model, another parameter, the length of each muscle, is quite important. It is a function of the arm's angular position. As the position changes, the relative position of each muscle's origin and insertion changes, and so does the muscle-tendon length (Doheny et al., 2009). This relationship can be shown as:

$$r_i(\theta) = \frac{dMTL_i}{d\theta} \tag{1}$$

where $r_i(\theta)$ is the moment arm, MTL_i is the calculating musculotendon length, θ is the elbow angle (Manal et al., 2002).

4.3.4 Kinematic model

After all the muscle forces (F_i) have been gathered from the musculotendon models, their contributions to the joint moment can be formed by multiplication. If this has been done for all the muscles at a particular joint, the corresponding joint moment (M_j) can be seen in equation (2) (Buchanan et al., 2004a)

$$M_j(\theta) = \sum_{i=1}^{n} \left(r_i(\theta) \times F_i(\theta, t) \right) \tag{2}$$

where 'i' is used to represent each of the muscles and 'n' stands for the overall number of muscles taken into experiment (Manal et al., 2002).

The contributions from the parameters of each individual muscle to the lumped muscles are all dependent on the relative contribution of total joint moment. Moment arms were related to the length of the muscle-tendon complex and joint angle (see in musculoskeletal model) (Kistemaker et al., 2007).

If there are some external loads or intersegment dynamics or gravitational forces due to moments. All of these must be summed to calculate the total joint moment (Buchanan et al., 2004a). The movement caused by joint moments can be computed by basic dynamics (i.e., Lagrangean or Eulerian dynamics). Also, the equations depend on the number of joints and the number of degrees of freedom at each joint (Buchanan et al., 2004a).

This method is widely accredited nowadays; however it still has some limitations. Once the joint movement is beyond a simple single-joint one, the equations can become very complex. Also, in order to solve these equations, inertial parameters must be estimated for each of the moving body segments (Buchanan et al., 2004a).

5 Other researches on EMG-based neuromuscular interface

From Sections 3 and 4, we could found more and more interface researchers using EMG signal as their information source and neuromuscular system as their processing method for human movement prediction. This EMG-based neuromuscular interface not been limited to elbow joint only, but also other different anatomical locations, such as elbow (Buchanan et al., 1998), shoulder (Laursen et al., 1998), knee (Lloyd and Buchanan, 1996; Lloyd and Besier, 2003; Lloyd and Buchanan, 2001), ankle (Ferris et al., 2006; Hussain et al., 2012), jaw, lower back (Nussbaum and Chaffin, 1998) and wrist (Buchanan et al., 1993). The theoretical basis is that: if the EMG signals can be measured precisely and processed adequately to reflect the activation of each muscle crossing the joint and if the activation can be modulated properly by models, it is possible to accurately estimate individual muscle forces over a wide range of tasks and contraction modes.

Buchanan et al use a mixed method of forward dynamics and inverse dynamics to prove that EMG-driven model generates a very good prediction, through more than 200 knees flexion test. Also, if the muscle-tendon parameters of model keeps unchanged, his model can be used for more than two weeks prediction without a loss of prediction capacity (Buchanan et al., 2004b). However, this model is offline and uses a lot of time for calculation. Koo proposed that supplemental test with different tasks and test configurations should be completed before the EMG-driven model treated as a reliable tool to estimate muscle force. He proposed the matching parameter of joint trajectory and RMS as two indicators to test the performance of his model. Cavallaro (2010) proposed four available performance indicators (maximum error, root mean square error, correlation coefficient, percentage of the absolute error less than a certain threshold) to assess model's predictive ability. Shao and Su (2010) improved Buchanan's model to more adapt human anatomical structures, and used parallel simulate anneal arithmetic (SAA) as tuning block. Sartori put forward two methods to achieve the models' real-time: treat the tendon as a high stiffness tendon, or, design a new data processing method. Lloyd in year 2012 found that EMG signal has a low repeatability and the same motion can be generated by different EMG signal pattern. This means a same tuning model may not work to suit all EMG input mode. The most representative EMG-based NI system is concluded in Table 2.

To summary most researches in EMG-based neuromuscular interface, the main problems in this area are: the issue of improving model's accuracy, the task-dependence character, and to achieve models real-time. Available solutions for these gaps are improving the accuracy of each block inside the model, improving the feedback mechanism of the human-machine interface and improving the online tuning algorithm for the interface.

6 Conclusions and further development

The neuromuscular interface based on non-invasive EMG has gained research interest in recent years. The main advantage is that it makes it possible to estimate joint movements by measuring muscle forces. The interface can lead to many medical applications including the control of prosthetic devices and assessment of rehabilitation performances.

This paper reviewed the recent development of neuromuscular interface for controlling the upper limb. It was found that the main research focus is placed on how to develop accurate models for online or real time applications. The traditional statistical or neural network-based modelling methods are found hard to achieve online operation and real-time.

The accuracy (especially the musculoskeletal geometry model) is still greatly influenced by the accuracy of the anatomical data. Also, the differences in individual's neuromuscular control system should be taken into consideration. A calibrated model and tuning model may be used to improve it.

Table 2 The summary of EMG-based NI systems research

Author	*Mechanical structure*	*Number of muscles*	*Signal processing (filter)*	*Activation dynamics*	*Musculotendon dynamics*	*Musculoskeletal geometry*	*Tuning*	*Number of tuning parameters*
Buchanan et al. (2004a)	1 DOF	7	4th Butterworth	Non-linear processing	Hill-based muscle model	Muscle force line: polyline	Genetic algorithms (GA)	11
University of Washington						Parameter: other articles		
Pau et al. (2010, 2012a, 2012b)	1 DOF	2	Butterworth	Linear envelope	Hill-based muscle model	Muscle force line: line	Many calibration trials	
The University of Auckland						Parameter: other articles		
Koo and Mak (2005)	1 DOF	7	Butterworth	Linear envelope	A unit of three parallel components (CE, PE, VE)	Muscle force line: SIMM	Nelder-Mead	8
The Hong Kong Polytechnic University						Parameter: some subjective criteria, and SIMM		
Buchanan et al. (2004a)	1 DOF	7	Butterworth	Non-linear processing	Hill-based muscle model	Muscle force line: line	Non-liner least square optimisation	
University of Delaware						Parameter: cadaver measurement		
Shao et al. (2009) related to Ferris et al. (2006)	1 DOF (knees)	4	Butterworth	Non-linear processing	Hill-type muscle model		Parallel simulate anneal arithmetic (SAA)	10
University of Delaware								
Sartori et al. (2010)	7 DOF (lower limb)	13	Butterworth	Non-linear processing	Hill-type muscle model	Parameter: SIMM	Simulate anneal arithmetic (SAA)	
University of Padova								

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