Preprints of the 19th World Congress
The International Federation of Automatic Control
Cape Town, South Africa. August 24-29, 2014

Human elbow joint torque estimation during dynamic movements with moment arm compensation method

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Abstract: In this paper we propose a method for human joint torque estimation with surface-electromyogram (sEMG) during dynamic joint movements. sEMG measurement is non-invasive and costs less than external force measurement. Typical torque estimation methods from EMG are available for isometric movements. Our method works also during dynamic movement and outputs the torque time-history data. Their proposed torque estimation method is tested with one subject. We measured sEMG related to the flexion-extension of the elbow joint torque computed. The root mean square error is lower than 5 % of the maximum torque. This result is comparable to recent research on isometric movement.

1. INTRODUCTION

Robot operations in uncertain environment nearby human beings are currently under study with the development of humanoid robots and active prosthesis. In this situation, human-machine force interaction must be controlled to achieve safety and stability (D. Vanthienen et al., 2011), as well as to be practically used.

For the operation of such systems, force control methods are studied such as impedance control and compliance control. A. Ajoudani et al. identified the human joint impedance and implemented it in a manipulator robot to achieve robust interactive task (A. Ajoudani et al., 2012). Human-robot force interaction was also studied in welfare or surgical areas (T. Haidegger et al., 2009).

The human structure/movement strategy is studied for robot or prosthesis in uncertain environment (G. van Oort et al., 2011), so human joint torque estimation is an important problem. However, human joint torque cannot easily be measured directly due to the complexity of the human body kinematics and the nature of actuation.

Dynamics calculation approaches based on individual human model and motion capture exist (G. Venture et al., 2008). However, the use of motion capture systems limit's the area of applications and the potential usage. Moreover, without sufficient equipment, it is not possible to reconstruct torque, for example when the external forces are unknown. External forces measurement needs additional equipment and a-priori assumption about the force apply point, so it cannot be used in uncertain situations.

Then, the study of the inner mechanism of the human body offers one possible solution to address this issue. Muscle works as actuators of the human body, so muscle-based torque estimation can allow computing the joint torque. Surface-electromyogram (sEMG) allows to measure muscle excitation signals on the surface of the skin. A few joint active prosthesis sEMG operated are now on the market. One major control strategy is mode change that uses sEMG as on-off switches (C. Wallace, 2002).

More complex operations require more complex control strategies, and this is a major challenge, such as multi-DoF joint or hand posture control (H. Sakakihara, 2007). Wrist rotation motion operation with sEMG-based classification was also studied (G. Lisi et al., 2011).

Numerical approaches are one of the major sEMG processing methods. Human intention classification from sEMG had been tried (G. Lisi et al., 2011).

Kinematical data estimation such as joint angle estimation method was recently improved (A.A. Nikooyan et al., 2012, Zhang, Q. et al. 2013), and implemented to control a robot arm (P. K. Artemiadis, 2010).

In (E. A. Clancy, 2012), the authors proposed a force estimation method polynomial model. L. Qi proposed spectrum analysis (L. Qi, 2011). Their methods work during dynamic joint movements. On the other hand, most of the joint torque estimation methods are only for isometric conditions. Humans or robots force interaction includes dynamic motions. Muscle moment-arm changes in accordance to joint angle change (G.J.C. Ettema et al., 1998). Then, muscle tension and joint torque relationship changes. Practically or experimentally, time-history force data is useful for robot operation, prosthesis operation and human motion analysis. Force estimation method should be robust to joint angular velocities. And that method should output time history data, if possible online (in real-time or pseudo real-time) if the goal is control and interaction. So muscle isometric or isotonic contractions are a too restrictive assumption.

In this study, we propose sEMG-based torque estimation method and estimate torque during dynamic joint movements.

This paper is organized as follows. Section II describes the elbow joint structure that is the estimation object. Section III proposes torque estimation method. Section IV describes the experimental setup. Section V shows our experiment result. And Section VI concludes this work.

2. HUMAN JOINT STRUCTURE

2.1. Muscle

Human skeletal muscles are a structure of contractile proteins that change chemical energy into kinetic energy. In the dynamic model of the human body, muscles have a role of actuator. They act actively and generate a relative motion between 1 or 2 joints: mono-articular muscles or bi-articular muscles. Muscle cells are excitable and the excitation is highly correlated with muscle contraction. One muscle cell's excitation is an exchange of ions and is observed as a movement of one electric dipole (P. Konrad, 2005). When a muscle contracts, many muscle cells are excited in different cycle and different voltage. Therefore surface-Electromyogram's waveform is like a noise as can be seen from Fig. 1 raw waveform of sEMG of the Biceps. sEMG is the total excitation voltage measured at the surface of one muscle through the skin and the soft tissues. sEMG is a non-invasive and painless method and prove to be relatively reliable, so it is often used in sports research rehabilitation research, and also in prosthesis' control research.

Some muscle's sEMG are not easy to measure because of other muscles or fat. Thus, it may be difficult to compare quantitatively directly sEMG because of large individual differences. However, because sEMG are a convenient way to measure muscle activity during movement, it is interesting to investigate the relation between sEMG signals and macro-dynamic signals such as the joint torque generated. It can contribute directly to applications in athletes' performances evaluation, rehabilitation and prosthetics device control.

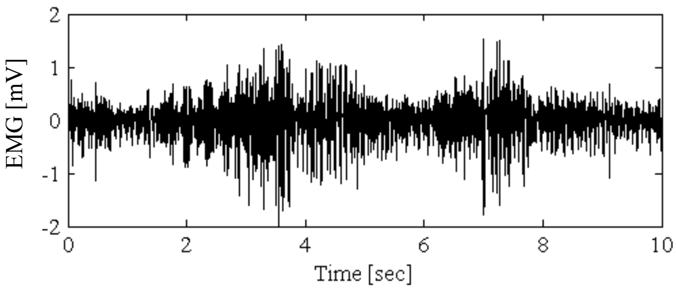

Fig. 1 Example of surface EMG wave for the Biceps

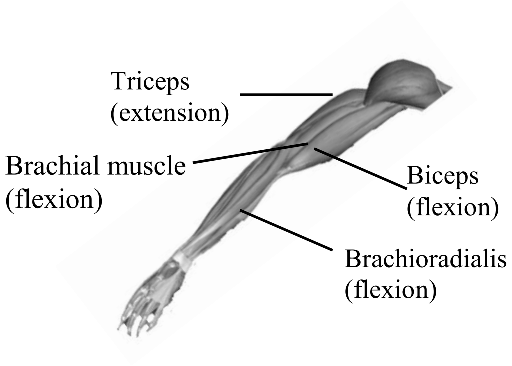

Fig. 2 Skeletal muscles involved in the flexion-extension of the elbow joint

2.2 Elbow joint

Compared to any other joint in the human body, the elbow joint has 3 benefits that motivated our choice to consider this joint in our experiments (D. A. Neumann, 2009):

- During flexion/extension it can be regarded as a 1 degree of freedom (DOF) hinge joint,
- Muscles involved in flexion extension are large, as can be seen from Fig. 2. Consequently, sEMG levels are high and relatively easy to measure,
- Related muscle number is 4, which is less than any other joints.

Brachial muscle, Biceps Brachii, Brachioradialis are the elbow joint's flexors. Triceps Brachii is its extensor.

The Brachial muscle is related to only elbow joint movement. Biceps Brachii and Brachioradialis contribute to two motions: the elbow joint flexion and the external rotation of the shoulder. The Triceps Brachii contributes mainly to the elbow joint extension.

3. TORQUE ESTIMATION METHOD

3.1. Polynomial model

In this study, we used some signal processing techniques. First, we calculated the sEMG amplitude within a window function and integrated the sEMG as shown in (1).

$$\sigma[m] = \sum_{n=1}^{100} \left| v[100m + n] \right| \tag{1}$$

where v : sEMG signal
σ : sEMG amplitude
m: frame number after downsampling

We modelled the sEMG-joint torque relationship with polynomial model as shown in (2). This model was confirmed at constant joint angle (E. A. Clancy, 2012).

$$\tau[m] = a_0 + \sum_{k=1}^{K} \sum_{d=1}^{D} \sum_{q=0}^{Q} a_{k,q,d} \sigma_k{}^d [m-q] \tag{2}$$

where a: constant coefficients
K: signal source number
D: model degree
Q: reference frame number

Second and higher order models can model non-linear relationship between the sEMG and joint torque. In this study, K is three because of the electrodes number. D, Q are defined as D = 2, Q = 15 experimentally.

There is many other models and processes such as neural network or machine learning. But our method has the following benefits:

- Easy to implement and transplant to other joints and systems
- Use less computation power than complex models

3.2 Moment arm change compensation

The muscle moment arm can be defined as being the distance from the muscle's line of action to the joint's center of rotation. It changes as joint moves and it is a function of the joint angle. Then, the sEMG-joint torque relationship changes also with moment arm. We model the

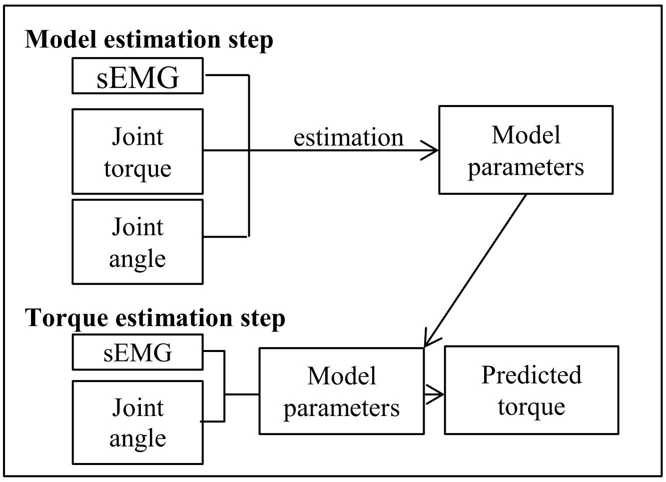

Fig. 3 Data flow of torque estimation using sEMG

moment arm as a second degree polynomial function of the joint angle (G.J.C. Ettema et al., 1998). The relation is given in (3).

As it is well-known, the moment arm is subject-specific, since it depends of muscle insertions. So the model parameter should be identified experimentally. In this work we made models with some parameters ($\pi/10 \le \theta_0 \le 9\pi/10$, $0.1 \le b \le 1.0$) and finally used one model that output's RMSE was the least.

$$l[m] = -b(\theta[m] - \theta_0)^2 + 1 \tag{3}$$

$$\hat{\sigma} = \sigma l \tag{4}$$

b: constant
$\hat{\sigma}$: compensated sEMG amplitude
l: normalized moment arm
θ_0: constant
θ: the joint angle

3.2. Estimation data flow

The joint torque estimation data flow is given in Fig. 3. It consists of two steps: the model estimation step and the torque estimation step. In the model estimation step, the model parameters are calculated from the sEMG, known joint torque and joint angle data. In the torque estimation step, the unknown joint torque is calculated from the sEMG and the joint angle data. In addition, step 2 performs under unknown external force condition.

4. EXPERIMENTS

4.1. Experimental equipment

In order to obtain different levels of contraction and different joint torques a load is applied at the forearm with a winder and pulley device as can be seen on Fig. 4.

Most of the load is due to the gravity force of load, the inertia of the arm and the mass of the forearm can be neglected compare to the load mass. The load is tied to the winder through pulley with steel wires. A board is fixed on the winder. The subject extends his/her forearm under the chosen constraint applied by the load.

Two types of weights enable to obtain two different levels of contractions. The load is applied to the forearm, therefore the palmar flexion and the dorsal flexion affects slightly the sEMG measurement, in particular for the Brachioradialis. The subject's upper arm is fixed on the board to avoid the gravity of self-maintaining the arm to work around the elbow joint. Consequently the muscles only actively contribute to the elbow flexion or extension.

With the joint angle θ [rad], the load torque τ [Nm] can be calculated as follows:

$$\tau = mr(g - r\ddot{\theta})\cos\theta + I_f\ddot{\theta} \tag{5}$$

r [m]:winder radius
I_f:winder moment of inertia
m [kg]: Weight mass

The measuring device used for our experiment is detailed in Fig. 4. The sEMG are measured for the three surface muscles that actuate the elbow joint flexion/extension: Biceps, Triceps and Brachioradialis as shown in Fig. 5. sEMG from Brachialis is supposed to be identical as the one measured at the Biceps brachii. Since the relation between the parameters is linear is not taken into account explicitly, but through the Biceps brachii sEMG signal. A potentiometer is attached to the winder and outputs the joint angle. The surface electromyogram measurement system used is a "Myon 320". The specifications are given in Table 1. "Blue Sensor N-00-S" by Ambu Corp are used. They are wet type electrodes, since it is known that wet electrodes have a better signal to noise ration than dry ones.

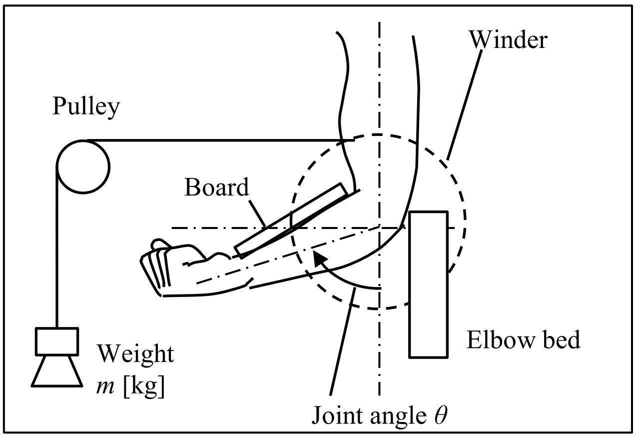

Fig. 4 Torque estimation equipment and experimental set-up

Table 1 Electromyography specifications

Parameters	Value
Range	± 2.5 mV
Resolution	3.05×10^{-4} mV
Sampling rate	4000 Hz
Bandwidth	5..500 Hz

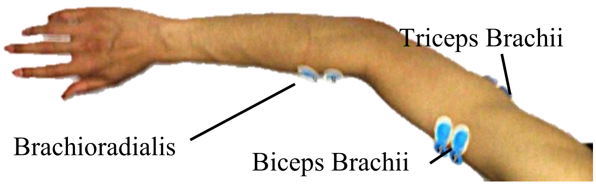

Fig. 5 Electrode position during our experiments

Table 2 Electrode specification

Parameters	Value
Size of electrode	44.8×22 mm
Size of adhesive part	30×20 mm
AC impedance	600 Ω
DC offset Voltage	0.2 mV
Materials	Silver/ Silver chloride
Conduction	Wet gel

4.2. Experiments

The joint angle θ ranges from 30 deg to 120 deg. The weight m set as a load is respectively 5 kg and 10 kg. The movement cycles vary with 3 levels of frequency: 0.125 Hz, 0.25 Hz and 0.375 Hz. To adjust with these frequencies, the subject is asked to flex and extend the elbow following a metronome.
The duration of one trial is about 20 sec, to avoid fatigue longer trials are avoided. Three trials are recorded for each of the six situations with a rest period between each. A total of 18 motions are thus recorded. Additionally we measured sEMG while the subject arm was relaxed. The subject is a healthy young adult male.
All data analysis is implemented in MATLAB 2010b.

5. RESULTS

We connected second and third trial data in the situation and made one time-history data. The model parameters are calculated from the second trials. The torque is cross-validated with the third trials. The first trials are not used for analysis but just used as a test-data for familiarisation with the system. The results are given in Fig. 7, Fig. 8 and Table 4.

Table 3 Moment arm model parameters

	b [-]	θ_0 [deg]
Biceps	1.0	126
Triceps	1.0	90
Brachioradialis	0.1	54

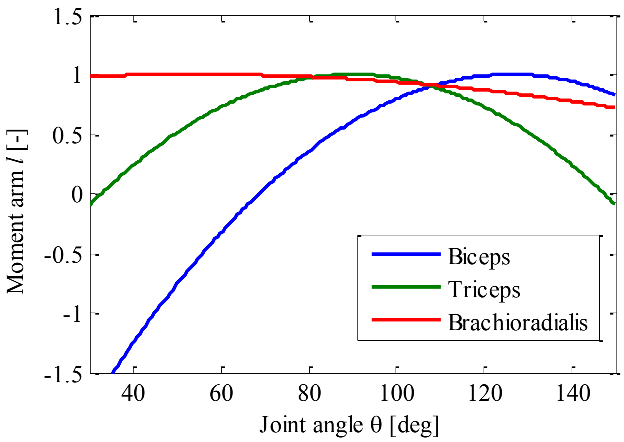

Fig. 6 Results of moment arm variation estimation, function of the joint angle, for the Biceps, The triceps and the Brachioradialis

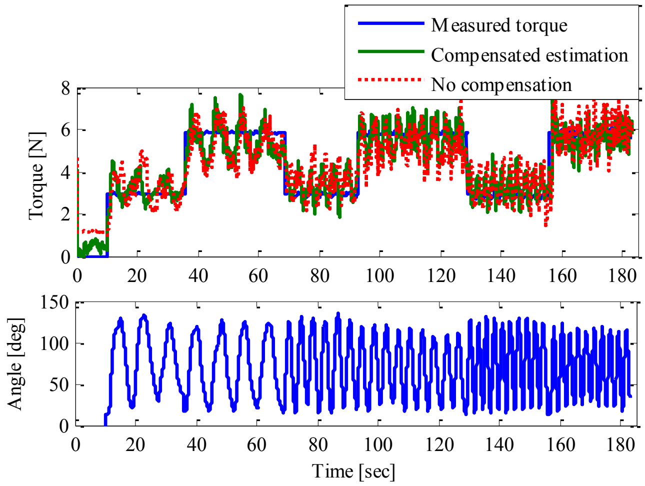

Fig. 7 Top: Torque estimation result (Direct validation); Bottom: Joint angle

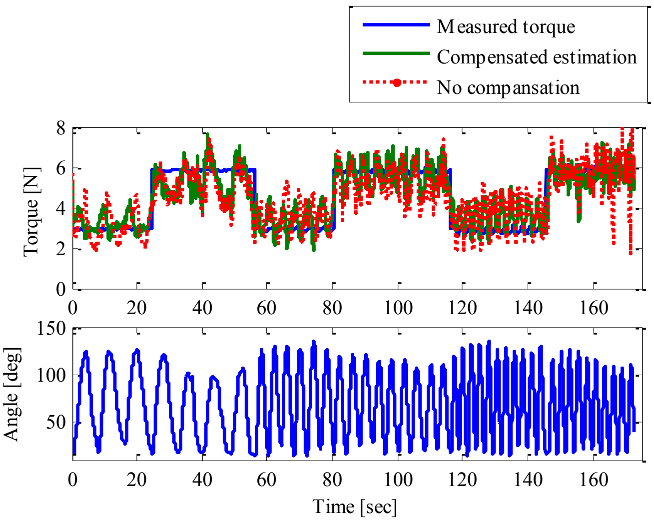

Fig. 8 Top: Torque estimation result (Cross validation); Bottom: Joint angle

Table 4 RMSE at each setting for cross validations

Setting name	Weight [kg]	Moving frequency	Root mean square error

		[Hz]	[%MVC]
Light slow	5	0.125	2.9
Light middle		0.250	4.2
Light fast		0.375	7.2
Heavy slow	10	0.125	12.4
Heavy middle		0.250	13.1
Heavy fast		0.375	14.4
All setting average	All	All	4.9

5.1 Compensation

The muscle moment arm function parameters are determined using an exploratory method. With this method, parameter b ranges from 0.1 to 1 in 0.3 increments and θ_0 ranges from 90 ± 36 deg in 36 deg increments. We chose the parameters which minimizes the root mean square error as given in Table 3. In addition, Fig. 6 shows the normalized moment arm variations with the joint angle for the three muscles considered.
Biceps' moment arm shows maximum value at 126 deg. Brachioradialis' moment arm value at *54* deg. This differs to mechanical experiment result (Neumann D. A. et al. 2009) about 30 deg. In this work, weight could make impact load and it could affect sEMG amplitude-joint torque relationship. Here, Brachioradialis contributes less than Biceps to joint torque; it may affect the difference between the calculated moment arm and past one.

5.2 Torque estimation

Fig. 7 and Fig. 8 show the torque estimation results during direct validation and cross validation. In the upper box, the blue line is the ground truth obtained from (5), the green one is the estimation result that is compensated with moment-arm, red one is not compensated. Bottom graph gives the joint angle. Table 4 shows root mean square error (RMSE) for each situations. RMSE is normalized with subject's maximum voluntary contraction (MVC) torque value (18 Nm).
The variation of joint angle affects slightly the estimation of the joint torque; however the mean value is correctly estimated. This is true both in direct and cross validations.
The RMSE increases as weight increases or as joint rotation speed increases. Generally, a muscle's sEMG amplitude increases when its contraction velocity or active contraction force increases. Model degree might be not enough to approximate sEMG-torque relationship. And in this case, heavy weight and fast movements might make the muscle's fatigue and affect the sEMG signals.

6. CONCLUSION

In this paper, we proposed a joint torque estimation method that should have the following features:
- It output time history data of joint torque;
- It can calculate in real time the joint torque, thus can be used for several applications;
- It works at variable joint angle;
- It works at variable joint angular velocities.

We compensate the moment arm changes based on a second degree model. The experiment was performed with one subject for 6 different conditions. The average RMSE was 4.9 %. This result is comparable to previous researches about constant joint angle joint torque estimation (E. A. Clancy, 2012).
These result may have some limitations. So future works should focus in:
- Increasing the number of subjects to study the variations due to subject-specific parameters;
- In order to use fully this method, it is necessary to add more movement directions and record more muscles;
- The position of the electrode might be a source of noise and error, the influence of the position's change must be investigated.

These experiments were run with one healthy male subject. Human muscles vary personally due to age, sex, sports, handicaps etc. The torque estimation accuracy should be verified on a broader population of subjects. And model parameters can be compared to other subjects. Eventually using, a normalization method for sEMG might prove efficient.
We studied about the elbow joint flexion-extension. However, more experimental data during elbow joint extension should be added in order to confirm our results. A generalization to more degrees of freedom is also necessary in order to practical and extended use the method.
Finally, our experiments were performed during one day. The surface electrodes were put on subject and all the data was collected at once. In a real situation, the electrode-skin conduction and the position of the electrodes would unavoidably change by settings. Future works should focus on collecting data with different electrodes placement and analyze the electrode setting effects. If the effect is not negligible, it should be calibrated or compensated by the model.

REFERENCES

Artemiadis P. K., K. J. Kyriakopoulos (2010). EMG-Based Control of a Robot Arm Using Low-Dimensional Embeddings, *IEEE Transactions on Robotics*, **VOL. 26, NO. 2**, 393-398.

Ajoudani A., N. G. Tsagarakis and A. Bicchi (2012). Tele-impedance: Teleoperation with impedance regulation using a body-machine interface, *The International Journal of Robotics Research published online*, **Vol. 31 No. 13**, 1642-1656.

Clancy E. A., S. Member, L. Liu, P. Liu, and D. V. Zandt Moyer (2012). Identification of Constant-Posture EMG–Torque Relationship About the Elbow Using Nonlinear Dynamic Models, *IEEE Transactions on Biomedical Engineering,* **Vol. 59 No. 1**, 205-212.

Ettema G.J.C., G. Styles, V. Kippers (1998). The moment arms of 23 muscle segments of the upper limb with varying elbow and forearm positions: Implications for motor control, *Human Movement Science*, **Vol. 17**, 201-220.

Haidegger T., B. Benyó, L. Kovács, Z. Benyó (2009). Force Sensing and Force Control for Surgical Robots, *Proceedings of the 7th IFAC Symposium on Modelling and Control in Biomedical Systems*, 413-418

Konrad P., (2005). The ABC of EMG, Noraxon INC., 5

Lisi G., P. Belluco, D. Cattaneo, G. Gini (2011). From the Classification of EMG Signals to the Development of a New Lower Arm Prosthesis, *18th IFAC World Congress*, 6493-6498

Liu L., P. Liu, A. Clancy, E. Scheme, K. Englehart (2012). Electromyogram Whitening for Improved Classification Accuracy in Upper Limb Prosthesis Control, *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, **Vol. 21, No. 5**, 767-774

Neumann D. A. (2009). *Kinesiology of the Musculoskeletal System: Foundations for Physical Rehabilitation*, Mosby Inc., 199

Nikooyan A.A., H.E.J. Veeger, P. Westerhoff, B. Bolsterlee, F. Graichen, G. Bergmann, F.C.T. van der Helm (2012). An EMG-driven musculoskeletal model of the shoulder, *Human Movement Science*, **Vol. 31**, 429-447

Nikooyan A.A., H.E.J. Veeger, P. Westerhoff, B. Bolsterlee, F. Graichen, G. Bergmann, F.C.T. van der Helm (2013). Relation between object properties and EMG during reaching to grasp, *Journal of Electromyography and Kinesiology*, **Vol. 23**, 402-410

Oort G., R. Reinink, S. Stramigioli, (2011). New Ankle Actuation Mechanism for a Humanoid Robot, *18th IFAC World Congress*, 8082-8088

Qi L., James M. Wakeling, M. Ferguson-Pell (2011). Spectral properties of electromyographic and mechanomyographic signals during dynamic concentric and eccentric contractions of the human biceps brachii muscle, *Journal of Electromyography and Kinesiology*, **Vol. 21**, 1056-1063.

Sakakihara H. (2007). Development of Myoelectrically-controlled Below-elbow Prosthesis with Wrist Rotation Function, *IEICE Technical Report MBE*, **Vol. 107 No. 154**, 67-70

Subasi A. (2012). Classification of EMG signals using combined features and soft computing techniques, *Applied Soft Computing*, **Vol. 12**, 2188-2198

Vanthienen D., T. D. Laet, W. Decre, H. Bruyninckx, J. D. Schutter (2012). Force-Sensorless and Bimanual Human-Robot Comanipulation, *10th IFAC Symposium on Robot Control*, **Vol. 10 Part 1**, 1-8

Venture G., K. Ayusawa and Y. Nakamura (2008). Motion Capture Based Identification of The Human Body Inertial parameters, *IEEE EMBS Conference*, 4575-4578.

Wallace C. (2002). Unique device-selection strategies for powered elbows, *MyoElectric Controls/Powered Prosthetics Symposium Fredericton*

Yuan K., J. Zhu, Q. Wang, L. Wang (2011). Finite-State Control of Powered Below-Knee Prosthesis with Ankle and Toe, *18th IFAC World Congress*, 2865-2870

Zhang, Q., R. Hosoda, G. Venture. (2013). Human joint motion estimation for electromyography (EMG)-based dynamic motion control, *Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE*, 21-24