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Procedia Computer Science 105 (2017) 197 – 202

Procedia Computer Science

2016 IEEE International Symposium on Robotics and Intelligent Sensors, IRIS 2016, 17-20 December 2016, Tokyo, Japan

Estimation of Torque Based on EMG Using ANFIS

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Abstract

There are wide verities of possible human movements that involve a range from the gait for the lifting of a load by a factory worker to the performance of a superior athlete. Output of the movement can be described by a large number of kinematic variables like knee joint angle, torque. This paper proposes a system that contains a non-parametric model with EMG signal of two muscles is used as input to estimate torque. The mapping of EMG to any joint dynamics is very subject dependent. It also depends on walking, running, jumping or climbing. Each type of posture consists of combination of isometric, eccentric and concentric type of muscle contraction with different intensity level depending on velocity, angle and lifted weight (muscle activation level). To capture the EMG signal pattern which is complex and so dynamic in time and space, an adaptive feature in computational intelligence is desired which will not only learn but also make decision based on EMG channel signal pattern to estimate torque. The EMG signal has been collected from volunteer who has completed the knee joint extension with maximum voluntary contraction (MVC) at different degree/sec ranging from 5deg/Sec to 360deg/Sec. The volunteer was also asked to perform extension with moderate and low effort against different impedance like 5deg/Sec, 20deg/Sec, and 45deg/Sec. RMS feature along with 2nd order digital filter has been used to smooth the raw EMG signal. The proposed study is intended to explore an ANFIS like Neuro-Fuzzy type knowledge based adaptive network with embedded RBF kernel neuron to estimate torque.

Peer-review under responsibility of organizing committee of the 2016 IEEE International Symposium on Robotics and Intelligent Sensors(IRIS 2016).

Keywords:

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1877-0509
Peer-review under responsibility of organizing committee of the 2016 IEEE International Symposium on Robotics and Intelligent Sensors(IRIS 2016).
doi:10.1016/j.procs.2017.01.209

1. Introduction

The conventional Robotic Rehabilitation Device (RRD) is still in the pattern of industrial robot which behaves like master-slave manner. One of the main objectives of a RRD is to obtain a smooth human machine interaction in different phases of gait cycle at the interaction point by considering patient-exoskeleton interaction is bidirectional rather than unidirectional. Knee and hip joint of lower limb robotic rehabilitation device requires a certain set of joint kinematics and dynamics extracted from EMG muscle signal to be able to perform flexion and extension with different velocities about knee joint. Most of the time, it is difficult to derive exact muscle model to the related the joint dynamics and kinematics with EMG. Different Non Linear computational method like Neural Network, Support Vector Machine and Extreme Learning Machine are very useful to model the muscles dynamics or kinematics based on EMG signal. Neural drives, muscle length, cross sectional area are inputs to mathematical model of a muscle. While in our work, only EMG is the input to our proposed Model. But Angle, Angular velocity can also be incorporated into the list of input to ANFIS. Before the estimation of torque is processed, it is required that the two types of muscle contractions are well understood. Excitation of neural EMG lead to excitation of motor unit of muscle fiber and excitation of motor unit lead to excitation of knee joint variables. They are all time varying signals. Each muscle has a finite number of motor units, each of which is controlled by a separate nerve ending. Excitation of each unit is an all or nothing event. The electrical indication is a motor unit action potential; the mechanical result is a twitch of tension. An increase in tension can, therefore, be accomplished in two ways: by an increase in the stimulation rate for that motor unit or by the excitation (recruitment) of an additional motor unit (large muscle). More motor units there are excited, more the EMG signal intensity is. In the Isometric muscle contraction, muscular contraction is taking place against a resistance in which the length of the muscle remains same. For example, someone is holding an empty glass of water at a particular angle. As the glass is getting filled with water, there is a work done by the muscle and there is EMG activity, but there is no motion. In Isotonic or Isokinetic muscle contraction; there are once again two types of muscle contraction. They are eccentric and concentric muscle contractions respectively. In eccentric muscle contraction, muscle lengthens during contraction (muscle tension increases) process. In concentric type muscle contraction, muscle length shortens during contraction process. The appearance of EMG signals not necessarily an indication of a motion of lower limb about the knee joint. Muscle force or EMG is modified by joint position (P) because different muscle has Maximum Voluntary Contraction (MVC) at different angle, mode of contractions (C) and speed of action (V). So muscle force or EMG signal is effectively a function of F = f (P, C, V).A filtered and full wave rectified EMG envelop signal closely resembles to muscle tension curve [3]. Different mathematical model has been used to establish the EMG-Torque relationship. A 3rd order polynomial model to estimate torque in elbow joint was used under isometric and quasi-isometric cases. An exponential force-velocity function was also used. Most recently Hill Muscle Model is used extensively to the estimation of torque from EMG signal. There are potentially three “inputs” to a Hill Muscle model. They are Muscle load, Muscle length, muscle stimulation. Neural stimulation to the muscle can be of impulse, step, ramp, sinusoidal or white noise type. The force and velocity are two measured output trajectory parameters (Doorenbosch and Harlaar 2004).

$$\boldsymbol{F_m = a_f . F_{max} . F_i(L_f) . F_v(V_f)} \tag{1}$$

Each muscle has finite number of motor unit and they are controlled by separate nerve ending and exhibit different activation characteristics $\boldsymbol{a_f}$. There are muscles which have as few as only three fibers of motor unit (for example, fingers, face and eye) or there are muscles which has as many as 2000 fibers of motor units. Each motor unit produces an electrical action potential and outcome of this motor unit action potential is the mechanical tension $\boldsymbol{F_i(L_f)}$ across the length of the muscle. So the increase in tension can be achieved in two ways, Firstly by increasing in the stimulation rate for that motor unit and Secondly, recruitment or excitation of an additional motor units. The activation of increasing number of muscle fibers results in greater force $\boldsymbol{F_v(V_f)}$. When the tension is reduced, the reverse process takes place. In a RRD the exoskeleton knee joint is desired to be spring mass damper type of joint rather than rigid knee joint. Without the damping element of the joint dynamics, the exoskeleton will oscillate indefinitely and induce instability from one type of inertia to another. So to damp the oscillation, we need to adjust the damping coefficient of controller law from time to time. The damping force is a linear function of velocity. The coefficient that represents the proportionality between damping force and velocity are referred to as damping co-efficient. Damping coefficient of ankle, elbow, wrist and finger are under damped. It is somewhat surprising that human are able to stop a rapid voluntary limb movement without noticeable oscillation. Stretch reflex (When the nerve activity is increased) is responsible for rapid damping. Joint impedance of knee joint (the damping coefficient is part of impedance) changes with its length and electrical activation that it receives. A single joint has two muscles act together. They produce opposite torque at one joint. Extension muscle generates forward torque and flexion muscle generates backward torque. A feed forward signal is activated by the extension posture that is sent down to the agonist (the muscle that produces the positive torque in the joint) and flexion gesture sends signal to antagonist muscle (Muscle that produces the negative torque) (Hayashibe and Guiraud 2013).

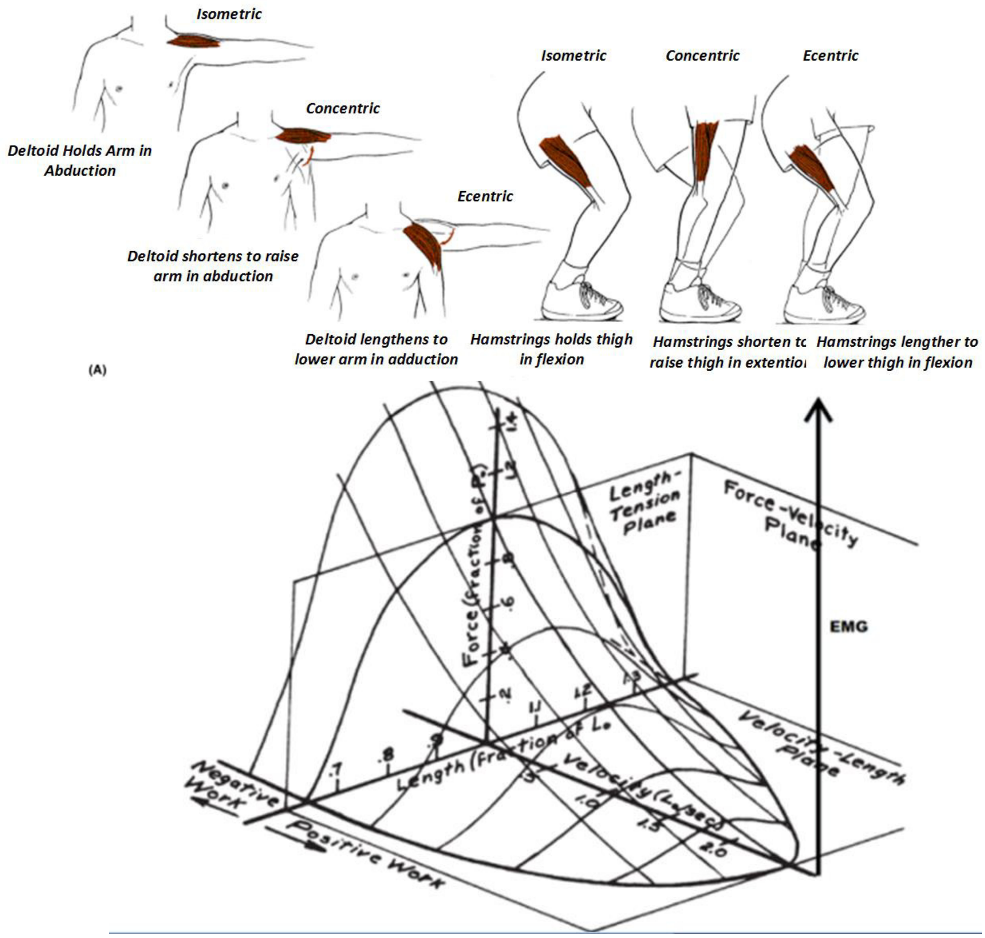

Fig. 1 Three dimensional EMG activity against Velocity, angle and Muscle length

To perform a single joint task, firstly the agonist muscle is fired to accelerate the limb towards the target. The size of the burst of EMG activity will increase if the subject wants to increase the speed. Second burst of EMG activity decelerates the limb by the antagonist activation. Finally when the limb reaches the target, the third phase starts which maintains the limbs posture at a target position by the continual activation of the agonist muscle. The three phases can be adjusted so that task is done with the required amplitude, duration and velocity. When patient is affected with stroke or injuries, the patient learns or adopts new impedances to optimize the motion that lead to stability. The joint impedance also removes the effect of the noise. The damping is coordinated depending on how fast or slow the limb wants to reach an object. As a result stability is achieved by impedance. From this synergic feature of muscle (Muscle EMGs are in different phase in time domain), damping coefficient can also be mapped from the difference of flexion and extension muscle EMG activities. So there is variation of EMG from load to load and velocity to velocity of lower limb movement. Figure 1show as to how Muscle Contraction force varies along with EMG activity with the change of load lifted by the muscle at any particular angle. So to assume any particular pattern of EMG signals at any particular angle or instance would be impractical. The lower limb may choose to move at different speed to reach any particular extension angle or the lower limb may choose to move while lifting different loads while approaching any particular lower limb extension angular position. So this work is looking for an adaptive type of Machine learning tools that consider the issue of EMG pattern variation against load and velocity and at the same time estimate the torque (Clancy, Bida et al. 2006).

2. Methodology applied to estimate torque

For the simplicity in the current work we are only considering EMG variation against speed of the lower limb. EMG activity of Vastusmedialis is visible only when lower limb is involved into a vigorous movement activity like running, climbing stairs or jumping. So the Vastusmedialis EMG pattern is only seen when the lower limb moves about the knee joint at very fast speed or high load lifting. In the figure 2 the RMS (root mean square) of raw EMG signal of two muscles (Rectus Femories, vastusmedialis) have been filtered with a band pass Butterworth filter to limit signal to 20Hz – 450Hz. Then root mean squares have been extracted of the filtered EMG signal. Yet there is too much fluctuation of the signal in EMG signal intensity variation. So a second 2nd order digital filter has been used to further smooth the EMG signal. A recursive filter has been used which is a second order discrete linear mode to model muscle excitation from the rectified and the low-pass filtered EMG data. The filter used is as follows (Fleischer and Hommel 2006),

$$u_j(i) = \alpha e_j(t-d) - \beta_1 u_j(t-1) - \beta_2 u_j(t-2) \tag{2}$$

Where $e_j(t)$ is the feature data, full wave is rectified and low-pas filtered EMG of muscle j at time t, $u_j(t)$ the post-processed EMG of muscle j at time t, α the gain coefficient for muscle j, β_1, β_2 the recursive coefficients for muscle j, d is the electromechanical delay. To achieve a positive stable solution of Eq. (2), a set of constraints are employed, i.e.

$$\beta_1 = C_1 + C_2 \,,\ \beta_2 = C_1 . C_2 \,,\ |C_1| < 1 \,,\ |C_2| < 1$$

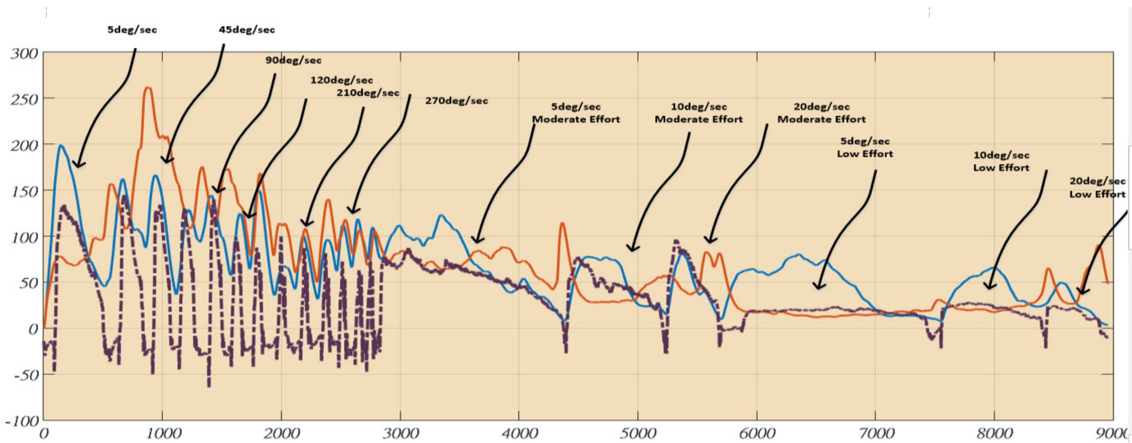

Fig 2 EMG channels (Red and Blue, Thought Technology Device) at input and Torque output (Purple, Bio-Dex Device).

As we can see in figure 3 that EMG-torque relationship will vary from type of contraction to contraction. It is polynomial type for concentric, exponential type for eccentric and exponential with steep slope in case of isometric type contraction. This established fact in research is a proof of the existence of different EMG pattern from isometric to isotonic type of muscle contraction. This phenomena justifies proposed method to have rule based connectivity from hidden to output layer. In each type of contraction the EMG signal pattern can also be further divided into High, Moderate and Low intensity EMG signal. EMG signal has been collected for different speed of the lower limb knee joint movement. There are vector of two columns of two EMG channels of Maximum Voluntary Contraction at different impedance level with vector size of 571x2(5deg/Sec),301x2(45deg/Sec),261x2(60deg/Sec), 200x2(75deg/Sec), 250x2(90deg/Sec), 131x2(120deg/Sec), 201x2(150deg/Sec), 01x2(180deg/Sec), 180x2(210deg/Sec), 170x2(240deg/Sec), 140x2(270deg/Sec), 130x2(300deg/Sec), 100x2(330deg/Sec) and muscle activation with low effort with vector size of 1851x2(5deg/Sec), 891x2(10deg/Sec), 526x2(20deg/Sec) as well as muscle activation with moderate activation with vector size of 1571x2(5deg/Sec), 851x2(10deg/Sec), 461x2(20deg/Sec. So a target vector of Torque with similar dimension has been produced by Biodex device recording of Torque during EMG muscle activation. So a training vector with all EMG patterns based on speed has been prepared to train the ANFIS. EMG intensity patterns of two channels are separated due to Fuzzy linguistic Gaussian type membership function variables (such as too low, low, moderately low, medium, moderately high, high, too high) and take different routes to the estimation of Torque output. ANFIS applies hybrid optimization method for auto tuning of the input membership function parameter and consequent parameters. Least Square Method is used to tune consequent parameters and back propagation to tune membership function parameters.

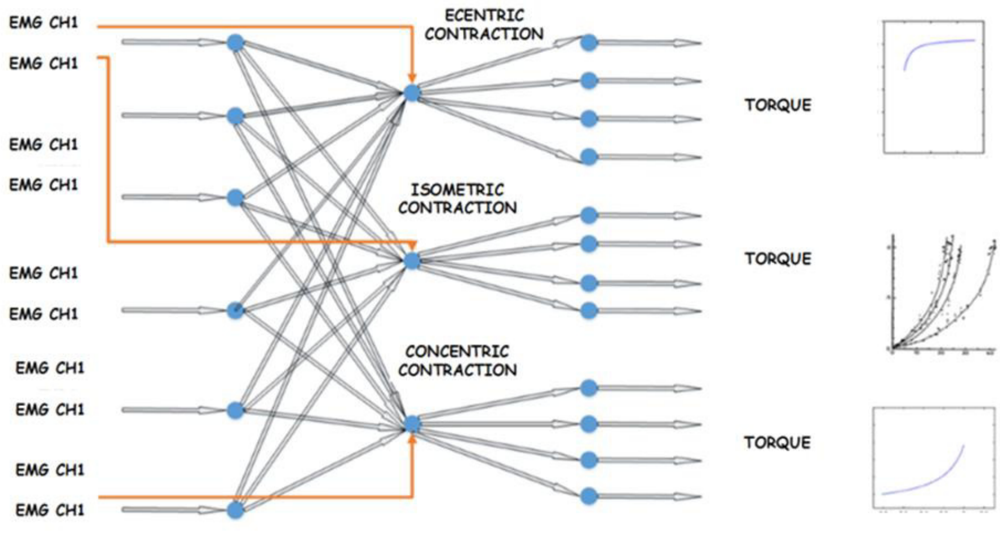

Fig 3 Rule (Knowledge) Based Neuro-Fuzzy Network to estimate Torque at different Type Contraction

Figure 4 shows Sugino type ANFIS with constant as output membership function ensures error of 27.4403. ANFIS with linear output membership function ensures error of 23.090. So there is a significant improvement in accuracy. The same training data set has been tried on Generalize Regression Neural Network (GRNN) to look at the performance of Radial Basis Function as activation function to estimate the torque. The figure 4 shows the estimated torque closely follow the desired torque output with accuracy as high as 95%.

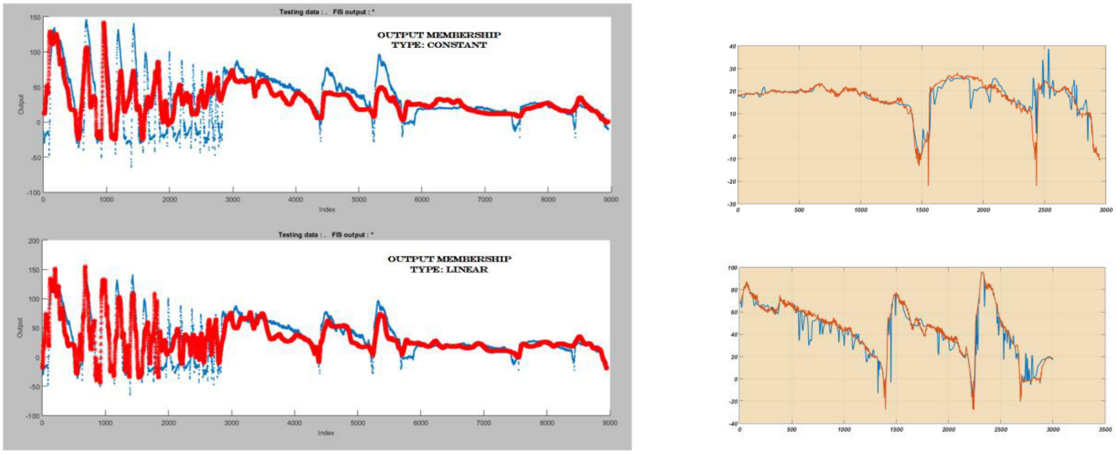

Fig 4 (a) Estimation of Torque by ANFIS, (b) Estimation of Torque with GRNN with RBF

3. Conclusion

All endeavours in this paper is to find the suitability of Neural-Fuzzy type rule based connectivity between layers to adapt the decision making ability to comply with the established EMG-torque relationship as knowledge which we like to be embedded into the network. Also the suitability of Radial Basis Function (RBF) kernel as activation function at the output membership function has been justified with GRNN. RBF being nonlinear is able to estimate torque with 95% accuracy in high dimension space.

Acknowledgements

Acknowledgements and Reference heading should be left justified, bold, with the first letter capitalized but have no numbers. Text below continues as normal.

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