

# Estimation of Angle Based on EMG Using ANFIS

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**Abstract**—There are wide varieties of human movement possible that involves a range from the gait of the physically handicapped, 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. Modeling each case with a muscle model is difficult. Intended action data can also be extracted from surface Electromyography (EMG) signal which may include intended torque, angle and impedance parameters of the knee joint dynamics. In this paper, Adaptive Neuro-Fuzzy Inference System (ANFIS) has been used in trying to estimate angle. As EMG signal is a function of angle, velocity and muscle activation level (load lifted), an adaptive machine learning technique is most desirable. Many different EMG signal intensity is possible at the same extension angle for different velocity of lower limb movement about knee joint. The EMG signal has been extracted from two different muscles and their patterns are very unique from velocity to velocity for entire range of extension angle. So a learning method of a Neural structure whose connections are based on rules is required to be able to estimate the angle at various speed about the knee joint as the slope of EMG signal intensity for each case of velocity varies significantly. The EMG signal has been collected from volunteer who has completed the knee joint extension in 15 Sec, 10 Sec, 8 Sec, 5 Sec, 3 Sec, 1 Sec, 0.5 Sec and 0.35 Sec respectively. RMS feature has been used to smooth the raw EMG signal. ANFIS is able to estimate angle adaptively although EMG pattern is changing with respect to speed. The simulation has shown experiment of comparative performance of angle estimation by different membership function and features.

**Keywords**- EMG, Knee Joint Torque, Extension and Flexion

## I. 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. A design of an effective wearable exoskeleton controller to achieve bidirectional interaction is possible where minimum interaction force is expected, since patient becomes an active element of a closed loop control system due to EMG signal. Human body has a closed loop control system, where brain and somatic nervous system (SNS) are the controllers that generates necessary signal for muscle which is the DC motor

actuator. The human proprioception is a distinct sensory modality that provides internal feedback solely on the status of the body internally. On the other hand in the exoskeleton device, Robot is the controller and generate necessary signal for the actuator [1]. Signal from EMG, knee joint angle, torque, patient-exoskeleton interaction force are proprioceptive feedback to the robot controller about the status of exoskeleton performance while interacting with human limb. When patient's brain is affected due to stroke or any other injury, then brain cannot generate necessary signal for limb movement or perceive the motion status of their legs. Then Robotic Rehabilitation Device shares most of the joint activities and help patient perform required movements. Being inspired by the closed loop control system of human, a bidirectional human machine interface has been proposed in this paper. Knee and hip joint of lower limb robotic rehabilitation device requires a certain data 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. 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 [2]. Neural drives, muscle length, cross sectional area are inputs to mathematical model of a muscle. But only EMG is the input to our proposed Model.

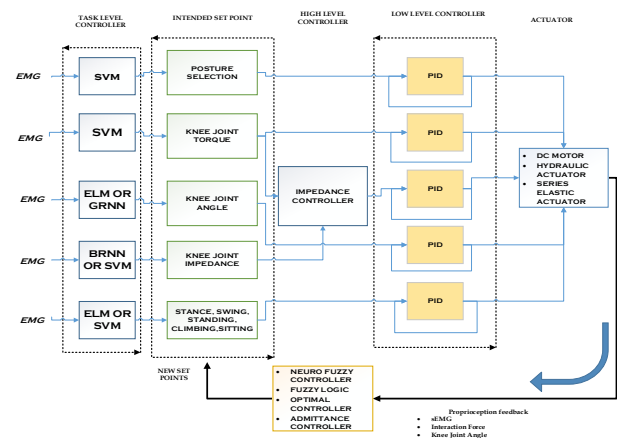


Figure 1. Control Schematics

Before anything about the estimation of torque or angle is proposed, it is required that the two types of muscle contractions are well understood. 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. Each muscle has finite number of motor unit and they are controlled by separate nerve ending and exhibit different activation characteristics. 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 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. When the tension is reduced, the reverse process takes place. Muscle force is modified by joint position (P) because different muscle has MVC (Maximum Voluntary Contraction) at different angle, mode of contractions (C) and speed of action (V). So muscle force or EMG signal is effectively a function of  $F = f(P, C, V)$ . From various research works it is prominent that EMG signal fluctuate with the strength of the muscle contraction. After a proper signal processing of EMG signal where EMG is filtered and full wave rectified, the envelop of the EMG signal closely resembles to muscle tension curve. The muscle turns on time is 200ms and turn off time is 300ms. Turn on time is short but turn off time is long. 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). 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 [3].

So there is variation of EMG from load to load and velocity to velocity of lower limb movement.

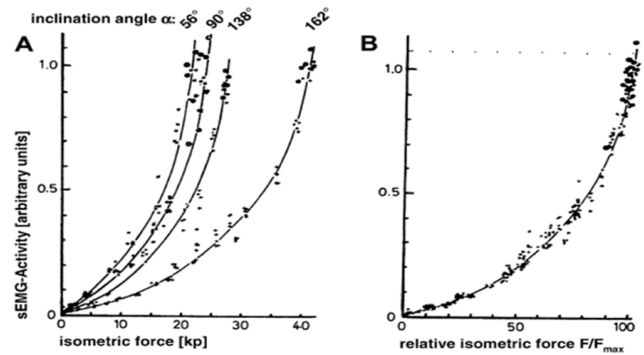


Figure 2 EMG signal activity at angle against load.

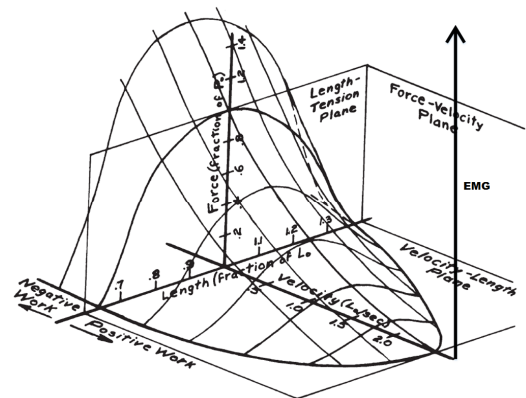


Figure 3 Three dimensional EMG activity against velocity, angle and muscle length

Figure 2 shows as to how isometric 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 signal at any particular angle 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 angle.

So we are 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 angle. For the simplicity of the work in the current work we are only considering EMG variation against speed of the lower limb. In figure 9 it is prominent that the EMG signal of Rectus femories is active in the lower limb movement of any speed. But EMG activity of Vastus medialis is visible only when lower limb is involved into a vigorous movement activity like running, climbing stairs or jumping. So the semitendinosus EMG pattern is only seen when the lower limb moves about the knee joint at very fast speed or high load lifting [4].

## II. DATA ACQUISITION

Thought Technology EMG recording device has been used to collect muscle EMG signal and Bio-dex device has been used to collect data of torque, angle and velocity.

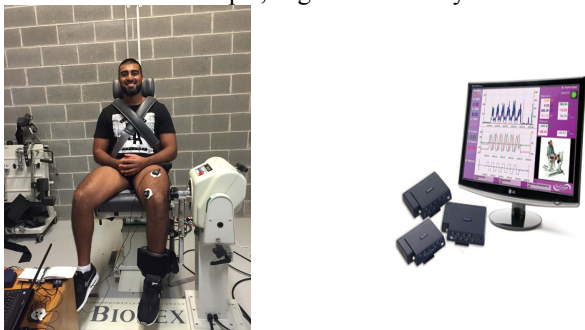


Figure 4 Biodex and EMG Recording Thought Technology device

Quadriceps consists of Rectus Femoris, Vastusmedialis and vastuslateralis is responsible for extension. Hamstring which consists of bicep femoris, semitendinosus and semimembranosus, is responsible for flexor movement. Rectus femoris and Vastusmedialis are selected to observe the effect of load on torque and angle of knee joint extension muscle. sEMG measuring device called flexiComp from Thought Technology is used to record sEMG data at a sampling rate of 2048Hz of these muscles simultaneously. Bio-dex has been used to record torque and extension angle. Each of 5 subjects was requested to perform a complete cycle of flexion and extension for five consecutive trials and complete the range of extension angle (0°-90°) in 0.5, 1, 1.5, 3, 5, 8, 10 and 15 Sec. Figure 5 shows the location of the muscles respectively for flexion and extension.



Figure 5 Flexion and Extension Muscle

## III. METHODOLOGY APPLIED TO CHOOSE PATTERN

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 [5]. 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. What has been observed in figure 2 during experiment is that EMG signal intensity is higher at higher angle of knee joint extension. At 10°- 30° there is hardly any motor unit that is recruited to excite tension across the length of the muscle, but between 70°-95° tensions starts building up significantly across the length of the muscle.

To be able to understand EMG activity better, Mean Frequency (MNF), Median Frequency (MDF), Mean Power (MNP), Total Power (TTP), Power Spectral Density (PSD), Spectral Moment (SM), and Power Spectral Ratio (PSR) are few frequency domain features extracted from the Fourier Transform of the EMG signal. The figure 2 shows the variation of EMG from angle to angle about knee joint during extension in terms of various frequency domain features mentioned above [6][7].

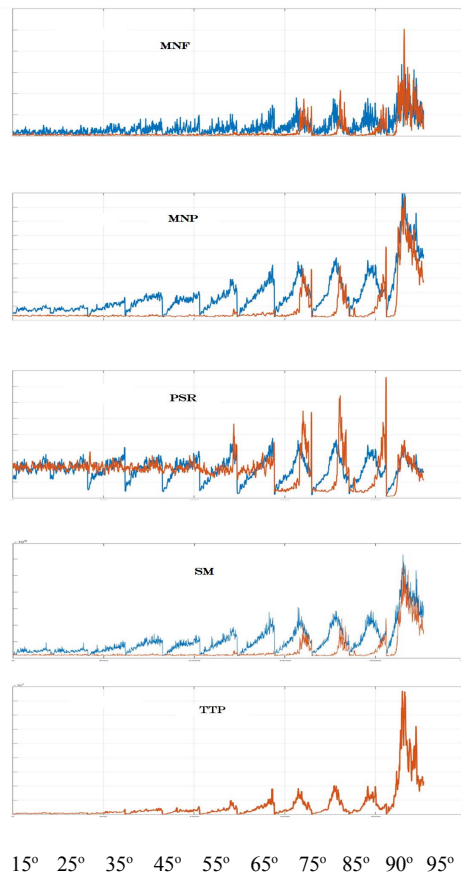


Figure 6. EMG signal intensity at different angle.

High degree of tension also built up across the length if the lower limb lifts 5kg, 12kg and 19kg. It is clear from the figure 6 which shows the power spectrum of the muscle while lifting these three weights. Maximum power varies significantly from weight to weight [8].

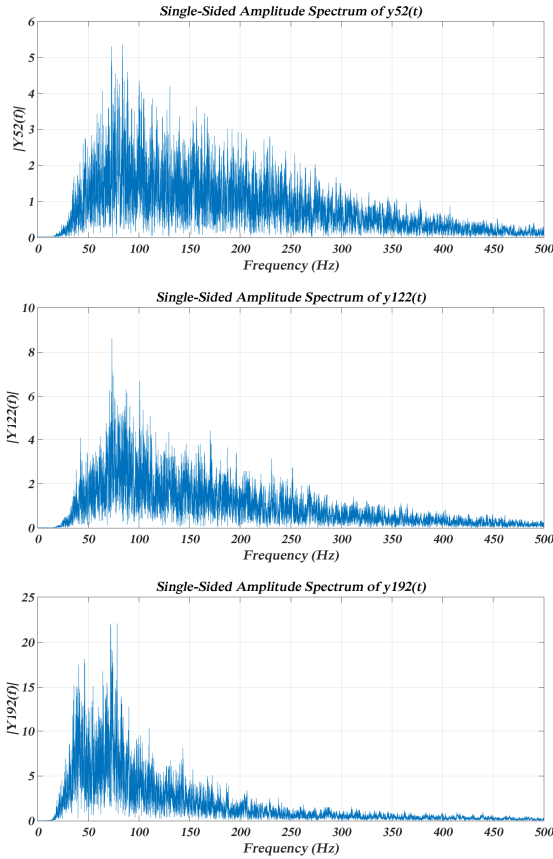


Figure 7 Power Spectrum of 5Kg, 12Kg and 19 Kg

Usually the knee joint torque for flexion and extension at normal condition without any lifting of weight is about 20N-m. A torque measuring device called Biodex is able to measure torque while lower limb is lifting weights or exerting force against higher impedance of the exoskeleton knee joint. To be able to see as to how power spectrum of muscle EMG signal varies across 15°, 25°, 35°, 45°, 55°, 65°, 75°, 85°, 90°, 95° in normal condition, the frequency domain features have been used.

$$MNF = \frac{\sum_{j=1}^M f_j p_j}{\sum_{j=1}^M p_j} \quad (1)$$

$$MNP = \frac{\sum_{j=1}^M p_j}{M} \quad (2)$$

$$SM = [SM1 = \sum_{j=1}^M p_j f_j \quad SM2 = \sum_{j=1}^M p_j f_j^2 \quad SM3 = \sum_{j=1}^M p_j f_j^3] \quad (3)$$

$$PSR = \frac{\sum_{j=f_0-n}^{f_0+n} p_j}{\sum_{j=-\infty}^{\infty} p_j} \quad (4)$$

$$TTP = \frac{1}{2} \sum_{j=1}^M p_j \quad (5)$$

Here,  $P_j$  is the EMG power spectrum at the frequency bin  $j$ , and  $M$  is the length of frequency bin [9].

So before there is any estimation of angle from EMG signal, the EMG patterns can be categorized into different speed. The volunteer participated into the data collection of EMG has been advised to move his leg at different speed. Thought Technology EMG recording device has been used to collect the EMG data. Biodex device has been used to collect velocity, angle and torque data of the lower limb movement about knee joint. Figure 4 shows the EMG signal of two muscles collected from Rectus femoris and Vestus Medialis.

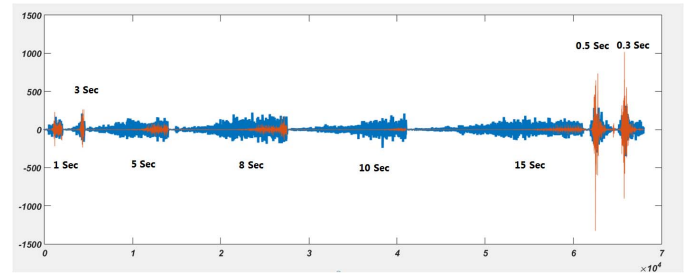


Figure 8 EMG signal pattern of Bicep and Semitendinosus.

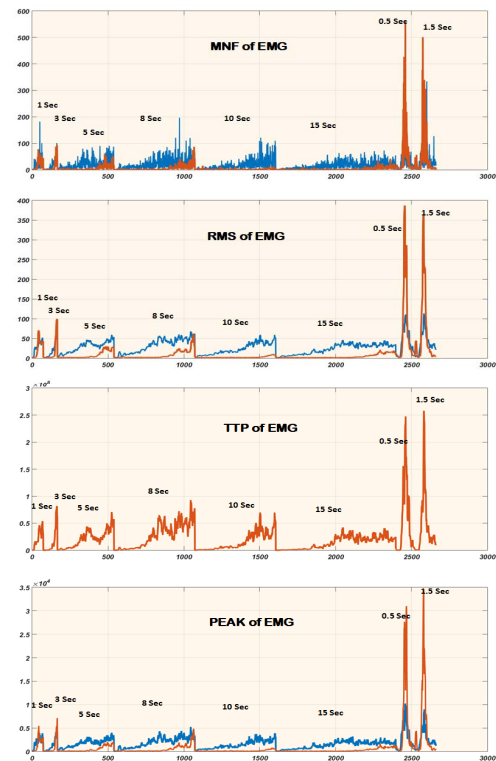


Figure 9 Various Feature of EMG signal

In the figure above the raw EMG signal of two muscles 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 2<sup>nd</sup> order digital filter has been used to further smooth the EMG signal. This is the EMG pattern which is now ready for training our Adaptive Neuro Fuzzy Inference System. Although ANFIS has the ability to learn as well as ability to make decision, yet it has few limitations. The ANFIS is never trained with the set of EMG patterns and one pattern as input may bring deficiency in the learning. More than one pattern instead of one will tune the internal parameter of structure and overcome the deficiency of learning [10].

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,

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

Where  $e_j(t)$  is the feature data, full wave is rectified and low-pass filtered EMG of muscle  $j$  at time  $t$ ,  $u_j(t)$  the post-processed EMG of muscle  $j$  at time  $t$ ,  $\alpha$  the gain coefficient for muscle  $j$ ,  $\beta_1, \beta_2$  the recursive coefficients for muscle  $j$ ,  $d$  is the electromechanical delay. To achieve a positive stable solution of Eq. (1), a set of constraints are employed, i.e.

$$\beta_1 = C_1 + C_2$$

$$\beta_2 = C_1.C_2$$

Where,

$$|C_1| < 1 \quad \text{and} \quad |C_2| < 1$$

The value of  $C_1 = C_2 = 0.9847$ . In addition to the above constraints, the unit gain of this filter has been maintained by ensuring [11],

$$\alpha - \beta_1 - \beta_2 = 1.0$$

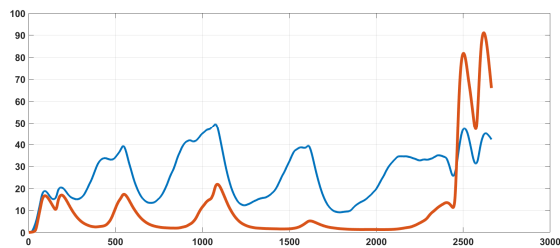


Figure 9 RMS feature of EMG digitally filtered by 2nd order digital filter.

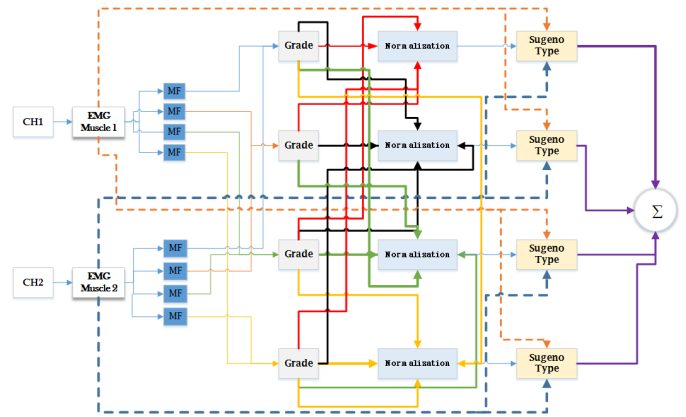


Figure 10 ANFIS architecture



Figure 11 Estimation of angle by ANFIS based on features

TABLE I. ANFIS PERFORMANCE

No. of MF	Performance of ANFIS with different Membership Function (MF)		
	Pattern or Feature	Membership function	Accuracy
8	RMS	Gaussmf	2.5679e03
		Gauss2mf	2.5586e03
		gbellmf	2.5658e03

No. of MF	Performance of ANFIS with different Membership Function (MF)		
	Pattern or Feature	Membership function	Accuracy
			trapmf
RMS		trimf	2.5489e03
		pimf	2.5410e03
		dsigmf	2.5584e03
		psigmf	2.5584e03
		trimf	2.5489e03

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 respectively of 0.5 sec, 1 sec, 1.5 sec, 3 sec, 5 sec, 8 sec, 10 and 15 sec. The vector dimension of these collected EMG data are 2000x2, 2500x2, 3001x2, 4001x2, 9500x2, 13500x2 and 19968x2 respectively. Root Mean Square features of these vectors with window size of 200 and window increment of 25 produce pattern vector of 73x2, 93x2, 113x2, 153x2, 373x2, 533x2 and 791x2 respectively. So a target vector of angle with similar dimension has been produced to generate a training dataset. The value of target vector varies between 1° – 90°. 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 membership function variables (such as too low, low, moderately low, medium, moderately high, high, too high) and take different routes to the estimation of angle 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 membership function parameters and back propagation to tune membership function parameters. Numbers of membership functions are limited to eight.

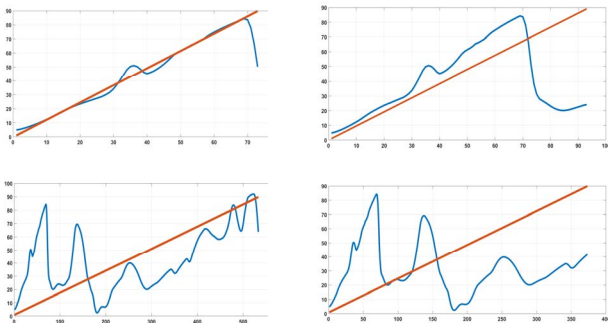


Figure 12 estimation of angle for EMG recorded in 1sec, 3 sec, 15 sec and 10 sec.

For cross validation, angle estimation is tested for EMG recorded in 1 sec, 3 sec, 15 sec and 10 sec. Figure 12 shows how accurately the estimated angle follow the desired knee joint angle.

#### IV. CONCLUSION

The ANFIS is able to exhibit the desired performance with 8 “pimf” membership functions for each EMG channel. RMS of EMG is filtered with second order digital filter to remove the high frequency component from raw EMG for smoothing. From figure 11 it is clearly visible that the estimated angle (green) is closely following the desired angle (red). The rule based ANFIS connectivity has been proved to very effective in estimating the angle from EMG patterns which depends on the speed of the lower limb about knee joint. The same network has been tested with other patterns from frequency domain like Median frequency, Peak frequency, Total power, Spectral Moment. RMS feature with ‘trimf’ ensures least error with 2.5489e03 which is relatively best of other feature and membership function.

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