

An Adaptive Hybrid Data Fusion Based Identification of Skeletal Muscle Force with ANFIS and Smoothing Spline Curve Fitting

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Abstract—Precise and effective prosthetic control is important for its applicability. Two desired objectives of the prosthetic control are finger position and force control. Variation in skeletal muscle force results in corresponding change of surface electromyographic (sEMG) signals. sEMG signals generated by skeletal muscles are temporal and spatially distributed that result in cross talk between adjacent sEMG signal sensors. To address this issue, an array of nine sEMG sensors is used with a force sensing resistor to capture muscle dynamics in terms of sEMG and skeletal muscle force. sEMG and skeletal muscle force are filtered with a nonlinear Teager–Kaiser Energy (TKE) operator based nonlinear spatial filter and Chebyshev type-II filter respectively. Multiple Takagi-Sugeno-Kang Adaptive Neuro Fuzzy Inference Systems (ANFIS) are obtained using sEMG as input and skeletal muscle force as output. Outputs of these ANFIS systems are fitted with smoothing spline curve fitting. To achieve better estimate of the skeletal muscle force, an adaptive probabilistic Kullback Information Criterion (KIC) for model selection based data fusion algorithm is applied to the smoothing spline curve fitting outputs. Final fusion based output of this approach results in improved skeletal muscle force estimates.

Keywords – sEMG; TKE; ANFIS; KIC

I. INTRODUCTION

In the United States, 1.6 million people lived with amputations during 2005 [1]. This increase reflects on the war effects in Afghanistan and Iraq since 2003 [2]. During the same period of time, the fields of prosthetic design and development research for prosthesis has received increased attention. Precise and timely control of prosthesis is critical for

its applicability, which necessitates the replacement of conventional algorithms by intelligent systems and decision methods. Therefore, a natural means of interface between the user and prosthesis is required. sEMG signals from skeletal muscles are a convenient means for users who do not want to deal with additional surgeries and regular hygiene problems. sEMG signals are simply electric voltages ranging between -5 and +5 [mV] which can be recorded on the skin surface of a hand amputee's forearm. Skeletal muscles generate a base sEMG even without a limb movement which changes with different movements and applied forces. This makes sEMG signals useful for position and force control of prosthesis. Presently available prosthetic hands have no tactile or proprioceptive feedback for grasping and only user's direct vision as a sensory feedback is available for its position control. Afore mentioned reasons cause 30–50% of the upper extremity amputees to choose not to use their prosthetic hand on a regular bases [3-4].

Effective grasping of any object requires the knowledge of force and its feedback. Since the hand amputee uses only sEMG signals collected from skeletal muscles, there is no hand force information directly available. sEMG is a measure of the nervous excitation that ultimately is responsible for activating the skeletal muscles, which in turn generate the finger forces with the help of the link kinematics of human hand. Therefore, a model or estimation scheme is needed for the dynamic estimation of skeletal muscle force from sEMG

signals. There have been numerous efforts in this direction and some of the recent are evident in the research work of [5-10].

The present work proposes a novel scheme of skeletal muscle force identification using sEMG signals. An array of nine sEMG sensors is used to record sEMG signals and skeletal muscle force signals recorded with a force sensing resistor from the arm of a healthy subject, which respectively is explained in detail in Section II and III. Eight Takagi-Sugeno-Kang ANFIS with different membership functions each with a rule base of ten are designed. The training of each ANFIS is done using a hybrid optimization method with zero error tolerance and 40 epochs. Each of the force signals simulated using these ANFIS and measured force signals are applied to a smoothing spline curve fitting method. Figure 1 shows the flow chart of the proposed approach. Final estimated force signal shows good match with the measured signal. This approach is tested on two different data sets of 45 and 60 seconds duration and the results seem promising. The paper is organized in eight sections. Present section follows the experimental set-up and then signal processing, ANFIS modeling, smoothing spline curve fitting, data fusion, results and discussion and conclusion and future work is presented respectively.

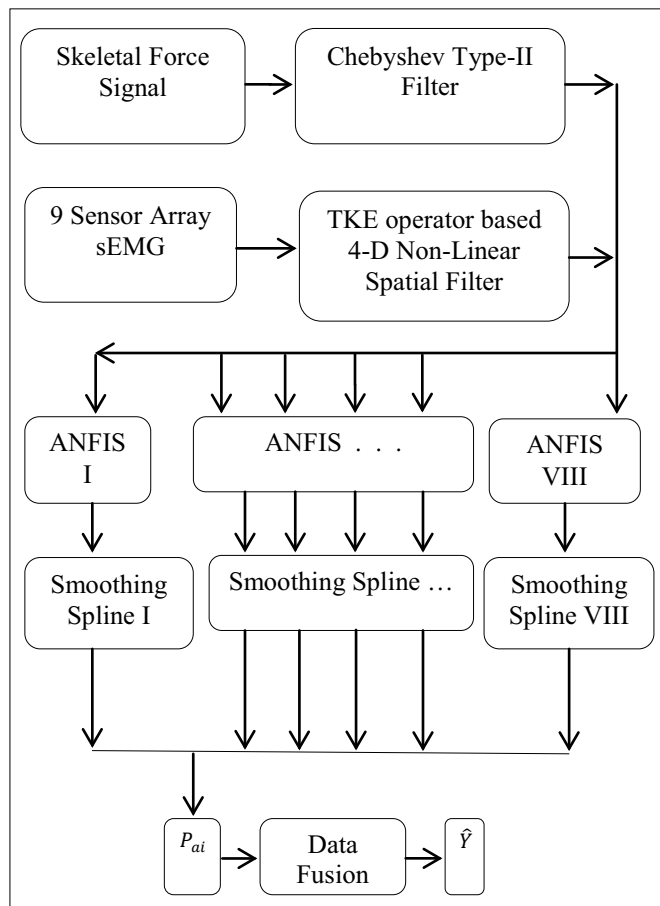


Figure 1. Flow chart of the approach used in this research work.

II. EXPERIMENTAL SET-UP

Based on the set-up of a sEMG sensor array in [11], an experiment set-up was developed using DELSYS® Bagnoli-16 EMG system with nine DE-3.1 sEMG sensors to capture sEMG signals from skeletal muscles. Here, the array involves nine sensors covering four directional spatial distributions of the sEMG signal. The middle three sEMG sensors were attached directly on the skin surface above the motor point of the flexor digitorum superficialis muscle (FDS) which controls the flexion of the ring finger. Appropriate sEMG electrode attachment point for the flexion of the ring finger was identified using a wet probe muscle stimulator at the FDS (RICH-MAR, HV 1000).

Prior to placing the sEMG sensors, the skin surface of the subject was prepared according to International Society of Electrophysiology and Kinesiology (ISEK) protocols. The thumb movement was restricted in this experiment using a thumb splint. However, the corresponding force data was captured using NI ELVIS™ with Interlink™ Electronics FSR 0.5" circular force sensor. Experimental set-up is shown in Figure 2, where 9 sensors are shown on a healthy subject forearm, holding a stress ball for force measurements. The sEMG and finger force data was collected at a sampling rate of 2000 Hz using LabVIEW™ in conjunction with DELSYS® Bagnoli-16 EMG and NI ELVIS™. With this experimental set-up we conducted several experiments of 30 seconds, 45 seconds and 60 seconds durations.

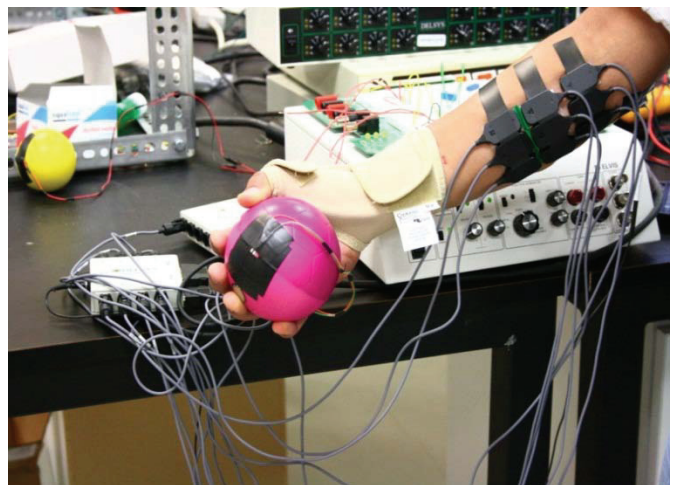


Figure 2. Experiment set-up.

III. SIGNAL PROCESSING

The recorded sEMG signal is filtered using nonlinear spatial filtering for multichannel surface EMG. As given in [12], this nonlinear spatial filter is derived from “Nonlinear Teager-Kaiser Energy (TKE) Operator.” As given in [11], the

TKE operator in the time domain on sEMG signal is defined by Equation (1).

$$\Psi[x(n)] = x^2(n) - x(n+1) * x(n-1). \quad (1)$$

Here, Ψ is the TKE operator and $x(n)$ is the time domain sEMG signal. Based on the TKE operator, the four-dimensional nonlinear spatial filter is given by Equation (2).

$$\Psi_{d,4}[x(m,n)] = 4 * x^2(m,n) - x(m-1,n) * x(m+1,n) - x(m,n-1) * x(m,n+1) - x(m-1,n+1) * x(m+1,n-1) - x(m-1,n-1) * x(m+1,n+1). \quad (2)$$

Figure 3 shows a comparison between the measured and nonlinear spatial filtered sEMG signals.

A Chebyshev type II infinite impulse response (IIR) low pass filter with a 550 Hz pass band frequency is used to filter the skeletal muscle force signal. Figure 4 shows the comparison between the measured and Chebyshev type II filtered skeletal muscle force signal.

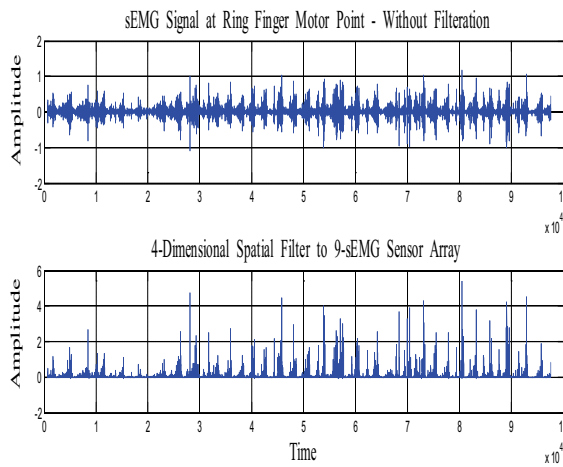


Figure 3. sEMG signal from ring finger.

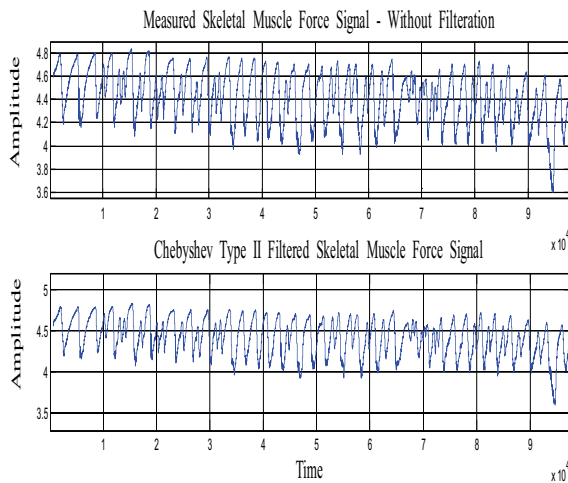


Figure 4. Skeletal muscle force signal from ring finger.

IV. ANFIS MODELING

In 1965 professor Lofti A. Zadeh introduced the concept of “Fuzzy Sets”, which are sets with imprecise amplitudes [12]. Dr. Zadeh stated that the “membership” in a fuzzy set is a matter of degree and not a matter of affirmation or denial. For last four decades, this proposal has gained recognition as an important point in the evolution of modern concept of imprecision and uncertainty [12]. This innovation represents a paradigm shift from the classical sets or the crisp sets to “Fuzzy Sets” [12].

Fuzzy set and fuzzy logic theory can be used to capture the natural phenomenon of the imprecision and uncertainty [12]. The membership function is the characteristic of fuzzy set, which is a function whose range is an ordered membership set within the closed unit interval [12].

A crisp set which is a collection of distinct objects is defined in a way to partition objects in a given domain of discourse into two groups: members and non-members [12]. On the other hand, a fuzzy set can be formed by assigning a membership value (which represents the degree to which an object belongs to a fuzzy set) to each object in the interval of 0 to 1 [12]. Fuzzy membership functions can be of different forms such as triangular, trapezoidal, pi, bell and Gaussian form.

Fuzzy Inference System (FIS) in fuzzy logic can be used to model a system which is an inference system based on empirical knowledge based linguistic rules [13]. The fuzzy inference system is composed of five steps: fuzzification of the input variables, application of the fuzzy operator (AND or OR) in the precedent, implication from the precedent to the subsequent, aggregation of the subsequents across the rules, and defuzzification. In the fuzzification process, the membership values coming from quantitative measurements are converted to linguistic values based on the membership functions [13].

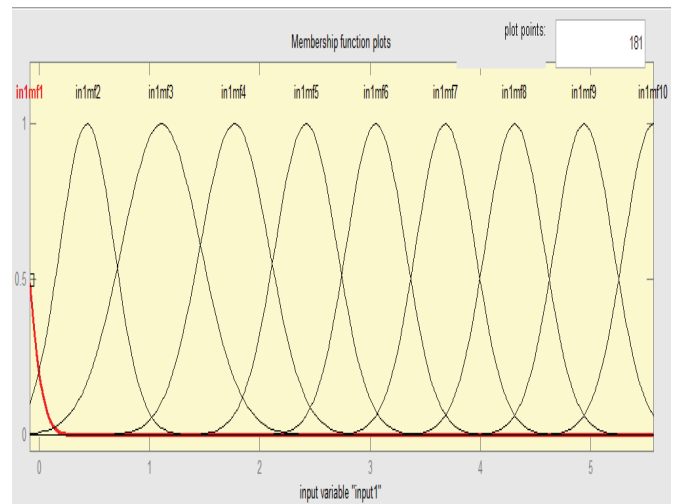


Figure 5. Gaussian membership functions for sEMG.

Figure 5 shows the plot of Gaussian membership functions for fuzzification of sEMG. The process of fuzzification followed by IF .. AND.. THEN ..OR ELSE type control or relation/estimation rules [13]. The output of the rules is computed as a max-min composition [13]. In the defuzzification process, the output of the rules has to be converted to a crisp value [13].

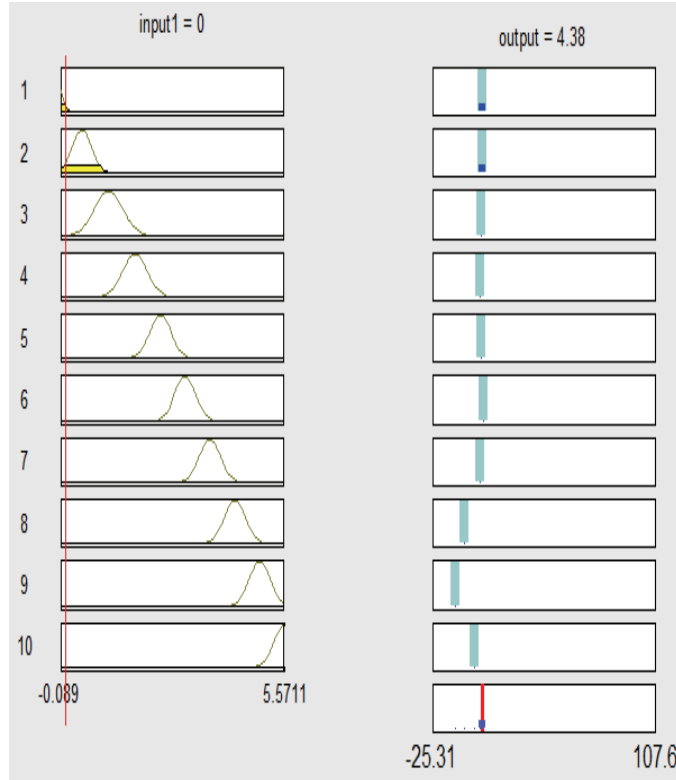


Figure 6. Illustration of ANFIS inference mechanism.

TABLE I. MEMBERSHIP FUNCTIONS

S. No.	Membership Function
1.	Gaussian (GAUSSMF)
2.	Gaussian combination (GAUSS2MF)
3.	Difference between two sigmoidal membership functions (DSIMF)
4.	Generalized bell-shaped (GBELLMF)
5.	Π-shaped (PIMF)
6.	Product of two sigmoidally shaped membership functions (PSIMF)
7.	Trapezoidal-shaped (TRAPMF)
8.	Triangular-shaped (TRIMF)

Using eight different membership functions types we designed eight single-output Sugeno-type adaptive neuro-fuzzy inference systems (ANFIS) using a grid partition on the data. The output membership function in each of these is linear. Each ANFIS has ten rules and connection type is ‘And’ with a weight of 1. For the ‘And’ method ‘product’ and for ‘Or’ method ‘probabilistic’ types are used for each ANFIS. Deffuzification is achieved using weighted average (wtaver) from each rule. Figure 6 shows the rules for ANFIS with Gaussian membership functions and illustrate the ANFIS inference mechanism. The membership functions used are tabulated in Table 1.

A Gaussian function is given by $f(x; \sigma, c) = e^{\frac{-(x-c)^2}{2\sigma^2}}$ for some real constants c and $\sigma > 0$, and $e = 2.718$. Gaussian combination membership function (GAUSS2MF) depends on the c and σ parameters [14]. The sigmoidal membership function is given as $f(x; a, c) = \frac{1}{1+e^{-a(x-c)}}$ and depends on the two parameters a and c . The difference between two sigmoidal membership function (DSIMF) which is the difference between two sigmoidal functions depends on the four parameters a_1, c_1, a_2 , and c_2 [14]. Generalized bell-shaped membership function (GBELLMF) is given as $f(x; a, b, c) = \frac{1}{1+|\frac{x-c}{a}|^{2b}}$ and depends on three parameters a, b , and c where parameter a and b decide the width of the curve and parameter c locates the center, usually $b > 0$ [14]. Pi-shaped membership function (PIMF) is given by

$$f(x; a, b, c, d) = \begin{cases} 0, & x \leq a \\ 2 \left(\frac{x-a}{b-a} \right)^2, & a \leq x \leq \frac{a+b}{2} \\ 1 - 2 \left(\frac{x-b}{b-a} \right)^2, & \frac{a+b}{2} \leq x \leq b \\ 1, & b \leq x \leq c \\ 1 - 2 \left(\frac{x-c}{d-c} \right)^2, & c \leq x \leq \frac{c+d}{2} \\ 2 \left(\frac{x-d}{d-c} \right)^2, & \frac{c+d}{2} \leq x \leq d \\ 0, & x \geq d \end{cases}, \quad \text{and}$$

evaluated at the points given by vector x . The “feet” of the curve is determined by parameters a and d whereas parameters b and c decides its “shoulders” [14]. The Product of two sigmoidally shaped membership functions (PSIMF) is simply the products of two sigmoidal functions as given before. The trapezoidal shaped membership function (TRAPMF) is given by

$$f(x; a, b, c, d) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ 1, & b \leq x \leq c \\ \frac{d-x}{d-c}, & c \leq x \leq d \\ 0, & d \leq x \end{cases} \quad \text{which depends on}$$

four scalar parameters a, b, c , and d . The triangular shaped membership function (TRIMF) is given by

$$f(x; a, b, c) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ \frac{c-x}{c-b}, & b \leq x \leq c \\ 0, & c \leq x \end{cases} \text{ which depends on the}$$

scalar parameters a, b and c [14].

V. SMOOTHING SPLINE CURVE FITTING

MATLAB® Curve Fitting Toolbox™ is a useful tool for fitting curves and surfaces to acquired data [15]. It can be used to do exploratory data analysis, preprocessing and post-processing of the data, comparing candidate models, and for removing outliers [15]. Weights for each smoothing spline curve fit are calculated by subtracting the ANFIS output from the measured skeletal muscle force output. A graphical user interface is used to fit the smoothing spline curve to each output from eight ANFIS with respective weights. Smoothing spline which is a piecewise polynomial computed from a smoothing parameter (p) of 0.92 is fitted to each of eight outputs of ANFIS. Smoothing parameter (p) is a number between 0 and 1. Change in the value of p from 0 to 1 results in the change in smoothing spline. For $p = 0$ the smoothing spline is a least-square straight-line approximation to the data whereas for $p = 1$ it gives the "natural" cubic spline interpolant to the data [15].

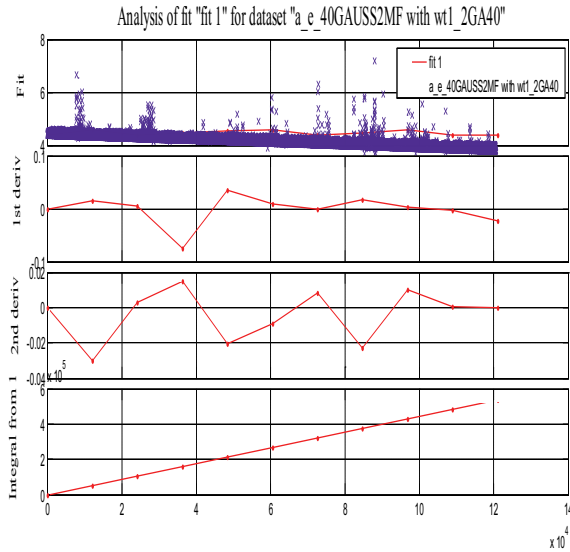


Figure 7. Analysis results for smoothing spline curve fitting to the output of ANFIS with Gaussian membership function.

For the specified weight (w_i) and smoothing parameter (p) a smoothing spline s is formed which minimizes the parameter J given by Equation (3).

$$J = p \sum_i w_i (y_i - s(x_i))^2 + (1 - p) \int \left(\frac{d^2 s}{dx^2} \right)^2 dx, \quad (3)$$

where x_i and y_i are predictor and response data respectively. The smoothing parameter p should be chosen to make the error $E(s) = \sum_i w_i (y_i - s(x_i))^2$ and roughness $\int \left(\frac{d^2 s}{dx^2} \right)^2 dx$

small. In this work the smoothing parameter p is chosen as 0.92 [15]. Figure 7 shows the analysis results for smoothing spline curve fitting to the output of ANFIS with Gaussian membership function.

VI. DATA FUSION

Data fusion of multiple outputs of smoothing spline curve fittings is done by assigning a particular probability to each individual output [16]. This method gives good estimation of the skeletal muscle force. The goodness of the fit of each smoothing spline output can be measured using System Identification (SI) model fit value which is given by Equation (4).

$$FIT = [1 - |Y - \hat{Y}| / |Y - \bar{Y}|] * 100 \quad (4)$$

In Equation (4) Y is measured, $\hat{Y}$ is estimated and $\bar{Y}$ is mean output signal. The model selection criterion used in this paper is Kullback Information Criterion (KIC) which has shown to perform well for sEMG sensor data fusion [7-10]. The sum of two directed divergences, which is the measure of the models dissimilarity, is known as Kullback's symmetric or J-divergence [17], as given by Equation (5).

$$KIC(p_i) = \frac{n}{2} \log R_i + \frac{(p_i+1)n}{n-p_i-2} - n\psi\left(\frac{n-p_i}{2}\right) + g(n), \quad (5)$$

where $g(n) = n * \log(n/2)$.

The fusion algorithm as given by [16] is applied for data fusion of the outputs of eight smoothing spline curve fit outputs which are obtained from eight different ANFIS models:

- (I) Find smoothing spline curve fit outputs $M_1, M_2, \dots, M_k$ for k number of outputs.
- (II) Compute the residual square norm

$$R_i = \|Y - \Phi_i \hat{\Theta}_i\|^2 = \|Y - \hat{Y}\|^2, \text{ where } \hat{\Theta}_i = \{\Phi_i^T \Phi_i\}^{-1} \Phi_i^T Y, \text{ and}$$

$$\Phi = \begin{bmatrix} Y_p^T & u_p^T & Y_{p-1}^T & \dots & u_1^T \\ Y_{p+1}^T & u_{p+1}^T & Y_p^T & \dots & u_2^T \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ Y_{n-1}^T & u_{n-1}^T & Y_{n-2}^T & \dots & u_{n-p}^T \end{bmatrix}$$

- (III) Calculate the model criteria coefficient using Equation (5).

- (IV) Compute the model probability $p(M_i|Z) = \frac{e^{-l_i}}{\sum_{j=1}^{k_1} e^{-l_j}}$, where

l is model selection criterion, i.e. $KIC(p_i)$.

- (V) Compute the fused model output $\hat{Y}_f = \sum_{i=1}^{k_1} p(M_i|Z) \hat{Y}_i$.

- (VI) Compute the overall model from $\hat{Y}_f$ and skeletal muscle force data.

Here all the computation from step (II) to (VI) is adaptive i.e. the residual square norm, $KIC(p_i)$, model probability

$p(M_i|Z)$, and fused model output $\hat{Y}_f$ are being updated with time or for each data point. Figure 8 shows the flow chart for fusion of outputs and adaptive probability of KIC.

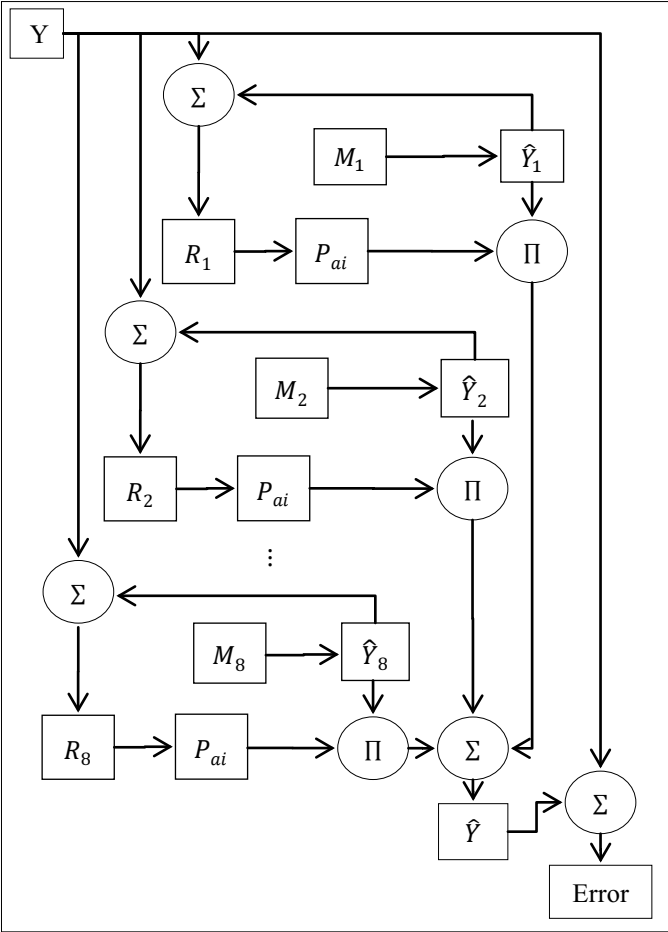


Figure 8. Flow chart for fusion of outputs and adaptive probability.

VII. RESULTS AND DISCUSSION

The proposed method gives good estimation of the skeletal muscle force. A data set of 45 seconds is used to estimate the output. Figure 9 shows the measured and estimated skeletal muscle force using this method.

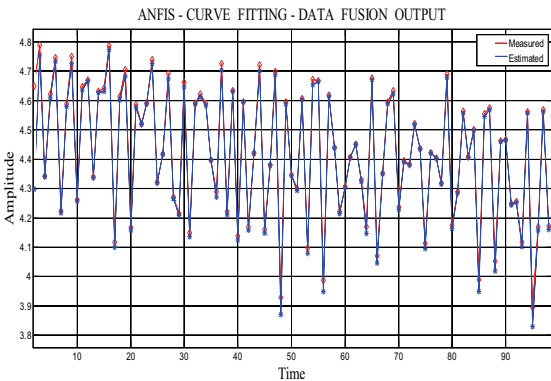


Figure 9. Plot of measured and proposed method estimated skeletal muscle force.

Figures 10 and 11 are the validation plots for 45 seconds and 60 seconds of data sets respectively. All of these three plots show a very close follow up of the measured signal by the estimated signal using this approach. Figure 12 shows the percentage error between the measured force signal and estimated finger force signal for 45 seconds of data set. The percentage error reduced to the lower values and the maximum percentage error value is 1.7 percent. The mean fit value between the measured and estimated output is 91.3 percent.

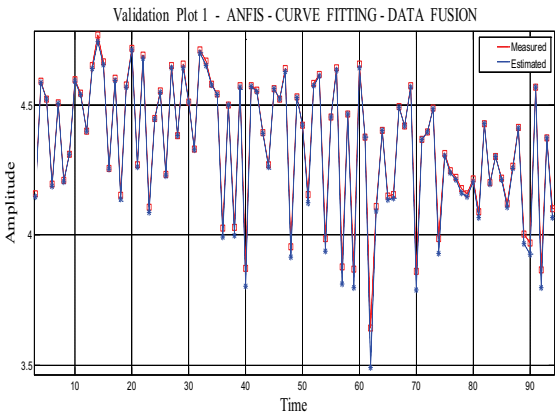


Figure 10. Validation plot 1 using different data set.

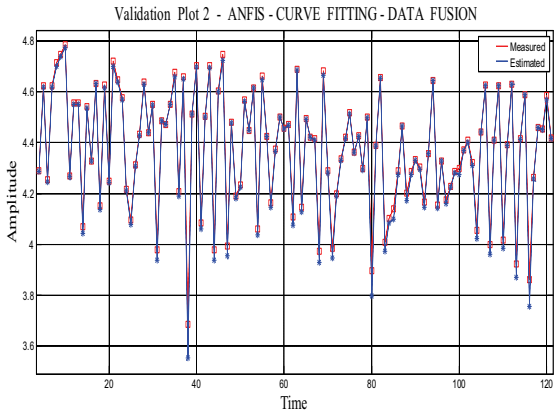


Figure 11. Validation plot 2 using different data set.

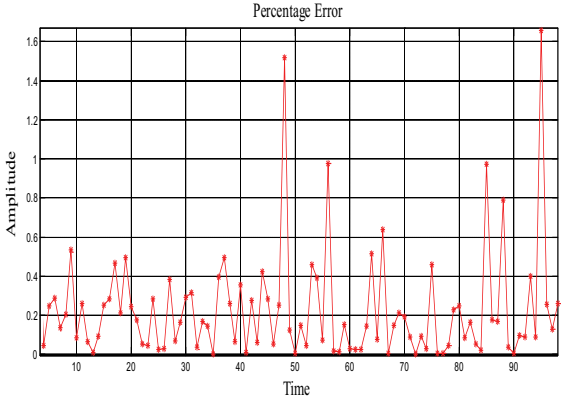


Figure 12. Percentage error plot.

Figure 13 shows the percentage error plot for different data set of 60 seconds duration. Percentage error reduced to lower values and the maximum percentage error value is 3.7 percent. The mean fit value between the measured and estimated output is 40 percent. The mean fit value for another 45 seconds of data set is 73 percent.

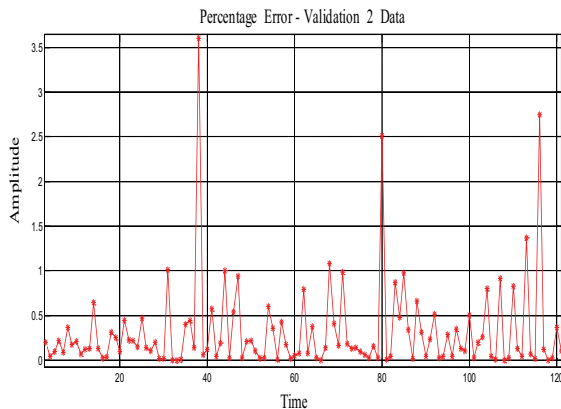


Figure 13. Percentage error plot for 60 seconds data set.

VIII. CONCLUSION AND FUTURE WORK

Using sEMG and skeletal muscle force as input and output data, eight ANFIS were designed and tested. Output of these ANFIS were fitted with smoothing spline curve fit and resultant outputs were fused using a KIC based data fusion algorithm. This approach has been validated using two separate data sets. Results are promising and show good estimation of skeletal muscle force which can be applied to design, application and improvement of prosthetic hands for amputees.

Future work will address the improvement of data collection techniques, sEMG sensor design, use of this approach for finger angles and stiffness estimation from sEMG signals. Different modeling techniques with this approach and combined probability of different model selection criteria such as Akaike Information Criterion (AIC), Kullback Information Criterion (KIC) and the Bayesian Information Criterion (BIC) together will give improved results.

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