Robust Control of a Prosthetic Hand Based on a Hybrid Adaptive Finger Angle Estimation

AMIR FASSIH, D.SUBBARAM NAIDU, STEVE CHIU, PARMOD KUMAR
School of Engineering
Idaho State University
921 S. 8th Ave, Pocatello, Idaho
U.S.A
fassamir@isu.edu

Abstract: - This paper presents a robust control approach to control the movement of a prosthetic hand based on an estimation of the finger angles using surface electromyographic (sEMG) signals. All the available prosthesis uses the motion control strategy which is pre-programmed get initiated when some threshold value of the measured sEMG signal is reached for a particular motion set. Here we use a novel approach to model the finger angle which utilizes System Identification (SI) techniques. The dynamic model obtained allows the instantaneous control for the finger motions. sEMG data is acquired using an array of nine sensors and the corresponding finger angle is acquired using a finger angle measuring device and a data glove. A nonlinear Teager–Kaiser Energy (TKE) operator based nonlinear spatial filter is used to filter sEMG data whereas the angle data is filtered using a Chebyshev type-II filters. An EMG-angle estimation model is proposed then the estimated angles are used to control to control movement of a prosthetic hand using a robust approach which can deal with modeling uncertainty. The overall performance of the prosthetic hand are measured based on numerical simulation. The resulting fusion based output of this approach plus the robust controller gives improved the prosthetic hand motion control.

Key-Words: Robotics, Control, Prosthetics, Robust Control, sEMG, Finger Angle Model, System Identification.

1 Introduction

over 1.6 million people were reported to have amputations during 2005 in the United States, [1]. The ongoing wars in the Afghanistan and Iraq results in the continuously increase of this number, [2]. This makes it important to have an efficient and dexterous prosthesis that can improve the daily lives of the amputees. Currently available prosthesis lacks the tactile or proprioceptive feedback for grasping which makes the 30-50% of the upper extremity amputees not to use their prosthesis [3, 4]. One of the most important aspects of the prosthesis is to have a good control for the daily life tasks which is a prime factor to make the amputee to accept the device for regular use. There is lots of work need to be done before we reach to have a fully dexterous hand and the precise and effective control is of high demand. The prosthetic hand need to be able to have good control for the intended finger angle sand forces to perform a certain task. The input signal for the control of the prosthesis is the surface electromyographic (sEMG) which is originates from the mind of the amputee. The sEMG signals can be acquired from skeletal muscles on the residual part of the upper extremity. In this work, we assume that the amputation is transradial, and hence sufficient muscle mass is accessible for sEMG data acquisition. There are two types of EMG electrodes available for use, one that needs to be imbedded in the muscle mass i.e. needle electrodes and the others are the surface electrodes. This makes the sEMG an obvious choice as a control input signal because it eliminates the problems associated with surgeries and regular hygiene for the user of implanted electrodes. sEMG signal is an electric voltage signal with amplitude ranging between -5 and +5 [mV]. The sEMG signals are highly dynamic in nature which changes with different limb movements and required/applied forces for these movements and other tasks. The issue of muscle fatigue makes the sEMG signal further intricate. Therefore to have prosthesis with good control of hand/finger positions, required forces and at the same time that can compensate for the issue of muscle fatigue, the sEMG seems to be the best choice. Almost all of the currently available prosthetics using EMG or sEMG

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sensors and compute some threshold value of this signal – for example the RMS value – to activate a pre-programmed motion and/or force set of the artificial prosthetic hand. The user only initiates the resulting motion/force, but the further control is not available which is quite different than what a healthy subject uses to control his/her hand. The natural hand of a non-amputee executes the complex motion sets by controlling the motion of the fingers at every instance in time. To mimic this characteristic of the natural hand, we propose to use dynamic models relating sEMG data with finger movement. The potential of such models is obvious from the operational point of view, but also allows the incorporation of muscle fatigue dynamics to be included in the control algorithm [9-13].

The control algorithm of a prosthetic hand can be divided into two parts. The first part is extracting information from sEMG signal to find the intended motion, and the second part is using this command signal to control a robotic hand.

Previously there have been numerous efforts to extract the useful information the sEMG signals [5]. Some of these methods are based on the wavelet analysis, artificial neural networks, and other feature extraction methods to make use of sEMG for prosthetic control [5]. sEMG is presented as an autoregressive (AR) model with the delayed intramuscular EMG signal as the input in the research work of [6]. In our work, we rely only on sEMG since no injected electrodes will be used to obtain EMG signals. Hence the task is to develop a model and an estimation scheme for describing the dynamics of the skeletal muscle force and finger angles from the sEMG signals. Some of the recent efforts in this direction are evident in the research work of [7-13].

Present research focus on the dynamic modeling and estimation of the angles of the proximal interphalangeal (PIP) joint of the index and the middle finger with the corresponding sEMG signal and Robust Control design for prosthetic hand to follow this signal. Two different systems and experimental set-ups are used to acquire the data for the index and middle finger angles and the corresponding sEMG signals. For the index finger data an array of nine sEMG sensors is used to record sEMG signals and joint angles are recorded using a wheel potentiometer from the arm of a healthy subject. For the middle finger data an array of three sensors is used to record sEMG signals and joint angles are recorded using a NODNA X-IST

2 EMG Angle Estimation Model

The filtered sEMG and angle data is smoothed with a smoothing-spline curve fitting. Smoothing spline is a piecewise polynomial computed from a smoothing parameter (p) of 0.993 is fitted to the filtered sEMG and angle data. Smoothing parameter (p) is a number between 0 and 1. By varying the value of p from 0 to 1 we can change the 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 [1]. Smoothing spline s is designed for a specific weight (w_i) and smoothing parameter and minimizes the function J, which is given as:

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

where x_i and y_i are predictor and response data respectively. By choosing a suitable value of the smoothing parameter p we make the error $E(s) = \sum_i w_i (y_i - s(x_i))^2$ and roughness $\int (\frac{d^2 s}{dx^2})^2 dx$ small. In our case we took the smoothing parameter p as 0.993 [1].

Both the filtered and smoothed sEMG and angle data (input and output) are used to make model by applying System Identification (SI) techniques. The sEMG is the input to the system and the intended PIP joint angle is the output. Multiple linear and nonlinear models are obtained for modeling of sEMG and PIP joint angle signals for the index finger of the dominant hand of a healthy subject. Five linear and three nonlinear models are obtained for the input and output data set.

The model order of the various models used in this work are as follows: linear models for the input and output data set, OE model of order 16, ARX model of order 18, ARMAX model of model order 16, State-Space model with subspace method (N4SID) of order 18 and a State-Space model with prediction error/maximum likelihood method (PEM) of order 12 are obtained using SI, [2].

The nonlinear models for the input and output data set are obtained as, the nonlinear Wiener-Hammerstein models with nonlinearity estimators of 'piecewise linear – pwlinear,' 'sigmoidnet,' and 'wavelet network,' [2].

All these linear and nonlinear models are simulated and the simulated output i.e. estimated angle data and the measured angle data is used in an adaptive data fusion based algorithm to obtain the final fusion based output. The final fusion based output is used as a control signal to design a controller which controls the angles of the joint of the two link robot. Results are presented in the following parts. Fig. 1 shows the measured and data fusion based angle signal. This signal is used as a control input for the controller.

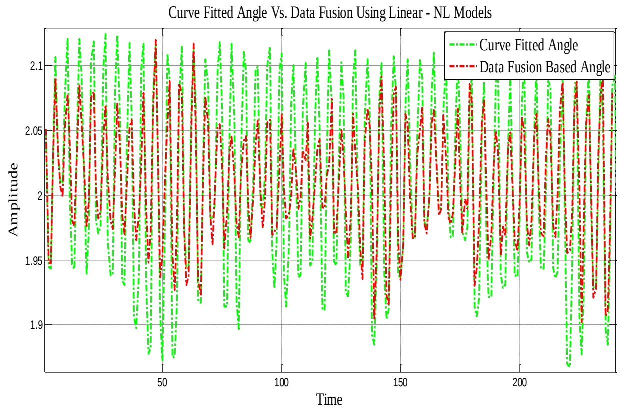

Fig. 7: Curve Fitted Vs. Data Fusion Based Angle Using Linear-Nonlinear Models.

3 Prosthetic Hand Control

The controller performance of a prosthetic hand is relying on two factors. Accurate intention estimation model and powerful control algorithm to which use the command signal from the estimation model and provide accurate movement for robotic part of the hand. The later part good performance requires the consideration of efficient dynamic models and sophisticated control approaches. Traditionally, control law is designed based on a good understanding of system model and parameters. Thus, a detailed and correct model of a robotic hand is needed for this approach [21, 22].

A finger can be considered as a 3 link robot, while in extracting the model for angle estimation, the PIP joint (the second) angle is considered, the third link angle normally has about 70% of the second joint angle and the first link angle is not considered in this research. As a result a two-link planar robot is considered as a plant to investigate the control approach performance.

A dynamic model can be derived from the general Lagrange equation method. The modeling of a two-link planar nonlinear robotic system with assumption of only masses in the two joints can be found in the literature, e.g., [3, 4]. However, in practice, the robot arms have their mass distributed along their arms, not only masses in the joints as assumed. Thus, it is desired to develop a detailed model for two-link planar robotic systems with the mass distributed along the arms. We present a new detailed consideration of any mass distributions along robot arms in addition to the joint mass. Moreover, it is also necessary to consider numerous uncertainties in parameters and modeling. Thus, robust control, robust adaptive control and learning control become important when knowledge of the system is limited. We need robust stabilization of uncertain robotic systems and furthermore robust performance of these uncertain robotic systems. Robust stabilization problem of uncertain robotic control systems has been discussed in [21-24] and many others. Also, adaptive control methods have been discussed in [21,23] and many others. Because the closed-loop control system pole locations determine internal stability and dominate system performance, such as time responses for initial conditions, papers [26,28] consider a robust pole clustering in vertical strip on the left half splane to consider robust stability degree and degree of coupling effects of a slow subsystem (dominant model) and the other fast subsystem (non-dominant model) in a two-time-scale system. A control design method to place the system poles robustly within a vertical strip has been discussed in [22, 23], especially [24] for robotic systems. However, as mentioned above, for accurate prosthetic hand control there is a need of a detailed and practical two-link planar robotic system modeling with the practically distributed robotic arm mass for control.

Therefore a practical and detailed two-link planar robotic systems modeling and a robust control design for this kind of nonlinear robotic systems with uncertainties considered for robust control approach with both $H\infty$ disturbance rejection and robust pole clustering in a vertical strip. The design approach is based on the new developing two-link planar robotic system models, nonlinear control compensation, a linear quadratic regulator theory and Lyapunov stability theory.

4 Modeling of Prosthetic Hand Systems

The dynamics of a rigid revolute robot manipulator can be described as the following nonlinear differential equation [21, 22, 24]:

$$F_c = M(q)\ddot{q} + V(q,\dot{q})\dot{q} + N(q,\dot{q}) \quad (2)$$

$$N(q,\dot{q}) = G(q) + F_d\dot{q} + F_s(\dot{q}) \quad (3)$$

where $M(q)$ is an n x n inertial matrix, $V(q,\dot{q})$ an n x n matrix containing centrifugal and coriolis terms, $G(q)$ an n x 1 vector containing gravity terms, q(t) an n x1 joint variable vector, F_c an n x1 vector of control input functions (torques, generalized forces), $F_d$an n x n diagonal matrix of dynamic friction coefficients, and $F_s(\dot{q})$ an n x 1 Nixon static friction vector.

However, the dynamics of the robotic system (2,3) in detail is needed for designing the angle control, i.e., especially, what matrices $M(q)$, $V(q,\dot{q})$ and $G(q)$ are.

Consider a two-link planar robotic system representing the prosthetic hand finger in Fig. 8, where the system has its joint mass m_1 and m_2 of joints 1 and 2, respectively, robot arms mass m_{1r} and m_{2r} distributed along arms 1 and 2 with their lengths l_1 and l_2 , generalized coordinates q_1 and q_2 , i.e., their rotation angles, $q = [q_1, q_2]$, control torques (generalized forces) f_1 and f_2 , $F_c = [f_1, f_2]$.

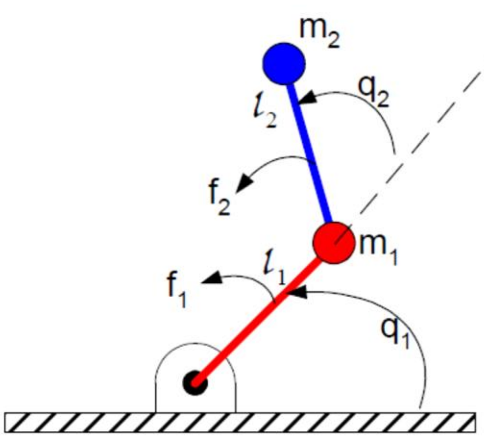

Fig 8- A two link robot system representing prosthetic hand

5 Robust Control

In view of possible uncertainties, the terms in (2,3) can be decomposed without loss of any generality into two parts, i.e., one is known parts and another is unknown perturbed parts as follows [22, 23]:

$$M = M_0 + \Delta M,\ N = N_0 + \Delta N,\ V = V_0 + \Delta V \quad (4)$$

where M_0, N_0, V_0 are known parts, $\Delta M, \Delta N, \Delta V$ are unknown parts. Then, the models in previous section can be used not only for the total uncertain robotic systems with uncertain parameters, but also for a known part with their nominal parameters of the systems.

Following [24], we develop the torque control law as two parts as follows:

$$F_c = M_0(q)\ddot{q}_d + V_0(q,\dot{q})\dot{q} + N_0(q,\dot{q}) - M_0(q)u \quad (5)$$

where the first part consists of the first three terms in the right side of (5), the second part is the term of u that is to be designed for the desired disturbance rejection and pole clustering, q_d is the desired trajectory of q, however, the coefficient matrices are with all nominal parameters of the system. Define an error between the desired q_d and the actual q as:

$$e = q_d - q \quad (6)$$

From (2) and (4)–(6), it yields:

$$\ddot{e} = M^{-1}(q)[\Delta M(q)\ddot{q}_d + \Delta V(q,\dot{q})\dot{q} + \Delta N(q,\dot{q}) + M_0(q)u] = w + E\dot{e} + Fu + u \quad (7)$$

$$E = -M^{-1}(q)\Delta V(q,\dot{q}),$$

$$F = -M^{-1}(q)\Delta M(q),$$

$$w = -F\ddot{q}_d - E\dot{q}_d + M^{-1}\Delta N \quad (8)$$

From [24], we can have the fact that their norms are bounded:

$$\|w\| < \delta_w,\ \|E\| < \delta_e,\ \|F\| < \delta_f \quad (9)$$

Then, it leads to the state space equation as:

$$\dot{x} = Ax + Bu + B[0\ E]x + BFu + Bw \quad (10)$$

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$$x = \begin{bmatrix} e \\ \dot{e} \end{bmatrix} = [e_1\ e_2\ \dot{e}_1\ \dot{e}_2]', \quad (11)$$

$$A = \begin{bmatrix} 0 & I \\ 0 & 0 \end{bmatrix},\ B = \begin{bmatrix} 0 \\ I \end{bmatrix} \quad (12)$$

The last three terms denote the total uncertainties in the system. The desired trajectory q_d for manipulators to follow is to be bounded functions of time. Its corresponding velocity $\dot{q}_d$ and acceleration $\ddot{q}_d$, as well as itself q_d , are assumed to be within the physical and kinematic limits of manipulators. They may be conveniently generated by a model of the type:

$$\ddot{q_d}(t) + K_v\dot{q}_d(t) + K_p q_d(t) = r(t) \quad (13)$$

where $r(t)$ is a 2-dimensional driving signal and the matrices K_v and K_p are stable.

The design objective is to develop a state feedback control law for control u in (7) as

$$u(t) = Kx(t) \quad (14)$$

such that the closed-loop system:

$$\dot{x} = (A - BK + B[0\ E] - BFK)x + Bw \quad (15)$$

has its poles robustly lie within a vertical strip Ω:

$$\lambda(A_c) \in \Omega = \{s = x + jy| - \alpha_2 < x < -\alpha_1 \leq 0\} \quad (16)$$

and a δ-degree disturbance rejection from the disturbance ω to the state x, i.e.,

$$||T_{xw}(s)||_\infty = ||(sI - A_c)^{-1}B||_\infty \leq \delta \quad (17)$$

$$A_c + A - BK + B[0\ E] - BFK \quad (18)$$

we derive the following robust control law to achieve this objective is discussed in [20,24].

Consider prosthetic hand uncertain system (15) with (2)–(18) where the unstructured perturbations in (8) with the norm bounds in (9), the disturbance rejection index $\delta \geq 0$ in (17), the vertical strip Ω in (16) and a matrix $Q > 0$.

With the selection of the adjustable scalars ε_1 and ε_2, i.e.,

$$(1 - \delta_f)/\delta_e > \varepsilon_1 > 0\ ,(1 - \delta_f - \varepsilon_1\delta_e)\delta > \varepsilon_2 > 0 \quad (19)$$

there always exists a matrix $P > 0$ satisfying the following Riccati equation:

$$A'_{\alpha 1}P + PA_{\alpha 1} - \left(1 - \delta_f - \varepsilon_1\delta_e - \frac{\varepsilon_2}{\delta}\right)PBB'P + \left(\frac{\delta_e}{\varepsilon_1}\right)I + \left(\frac{1}{\varepsilon_2\delta}\right)I + Q = 0 \quad (20)$$

where

$$A_{\alpha 1} = A + \alpha_1 I = \begin{bmatrix} \alpha_1 I_2 & I_2 \\ 0 & \alpha_1 I_2 \end{bmatrix} \quad (21)$$

Then, a robust pole-clustering and disturbance rejection control law in (7) and (14) to satisfy (17) and (18) for all admissible perturbations E and F in (11) is as:

$$u = -Kx = -rB'Px \quad (22)$$

if the gain parameter r satisfies the following two conditions:

(i) $r \geq 0.5$ and (23)

(ii) $2\alpha_2 P + A'P + PA - \left(\frac{\delta_e}{\varepsilon_1}\right)I - [2r(1 + \delta_f) + \varepsilon_1\delta_e]PBB'P > 0$ (24)

Proof for the approach is provided in [24].

It is also noticed that:

$$BB' = \begin{bmatrix} 0 & 0 \\ 0 & I_2 \end{bmatrix} \quad (25)$$

It is evident that condition (i) is for the α_1 degree stability and δ degree disturbance rejection, and condition (ii) is for the α_2 degree decay, i.e., the left vertical bound of the robust pole-clustering.

There is always a solution for relative stability and disturbance rejection in this form. It is because the Riccati equation (20) guarantees a positive definite solution matrix P, and thus there exists a Lyapunov function to guarantee the robust stability of the closed loop uncertain robotic systems. The nonlinear compensation part in (7) has a similar function to a feedback linearization.

6 Numerical Simulation

Based on the proposed control approach, a two link robot is modeled considering uncertainties. Then the input signal from sEMG-Angle estimation model is used as reference signal to the plant and the performance is evaluated.

The system parameters are: link mass: $m_2 = m_2 = 0.05\text{Kg}$, lengths $l_1 = l_2 = 0.03\text{m}$, angular positions $q_1, q_2(\text{rad})$, applied, torques $f_1, f_2(\text{Nm})$.

The initial states are set as $q_1(0) = q_2(0) = 0$, and $\dot{q}_1(0) = \dot{q}_2(0) = 0$. The parametric uncertainties are assumed to satisfy (11) with $\delta_f = 0.05$, $\delta_e = 0.4$, $\delta_n = 0.1$. Select the adjustable parameters $\varepsilon_1 = 0.01, \varepsilon_2 = 0.01$ from (19), disturbance rejection index $\delta = 0.1$, the relative stability index $\alpha_1 = 0.1$, and the left bound of vertical strip $\alpha_2 = 2000$ since we want a fast response. We solved the Riccati equation (20)

to get the solution matrix P and the gain matrix as:

$$P = \begin{bmatrix} 12693I_2 & 1584I_2 \\ 1584I_2 & 1643I_2 \end{bmatrix}$$

$$K = rB'P = [950I_2\ 985I_2]$$

Numerical simulation is done in Matlab software. For the plant the above mentioned parameters is used. Two sets of simulation are done. In the first simulation nominal plant is used and for the second simulation the perturbed model considering uncertainty is tested. The input signal for both simulations is measured angles from the above mentioned experiments from PIP joint. For the third joint the 70% of the measured angle of PIP joint used which is a good estimate of that signal.

The system response with nominal plant and perturbed plant to the input signal respectively are shown in Fig. 9 and Fig. 10. As it is shown the input and output signals are close and system is capable of following the command signal with sufficient accuracy. Obviously the system has a better performance in case of nominal plant compare to the perturbed model in which the uncertainties are applied.

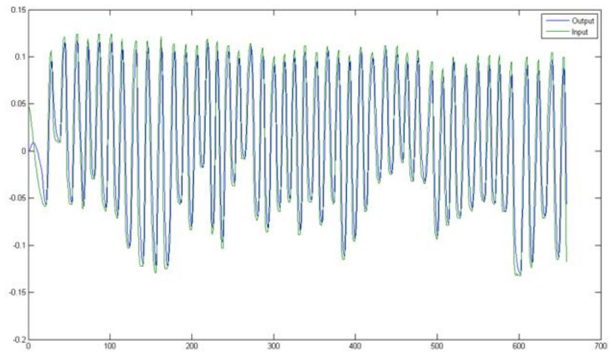

Fig. 9- System response to the nominal plant

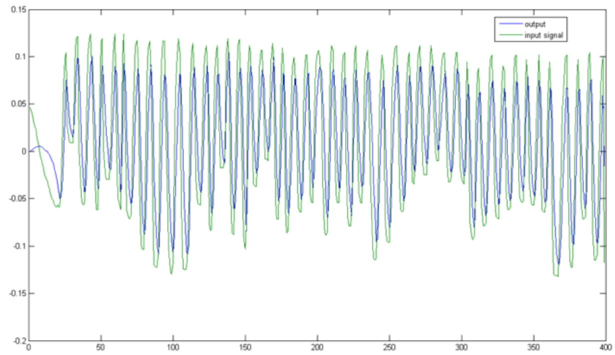

Fig. 9- System response to the perturbed plant

7 Conclusion

The dynamic modeling of the filtered and smoothed sEMG and PIP joint angle of the index and middle finger is achieved using SI with sEMG as the input and the joint angle as the output. Multiple linear and nonlinear models are obtained for the input and output data. To achieve a better estimate of the finger angles, an adaptive probabilistic Kullback Information Criterion (KIC) for model selection based data fusion algorithm is applied to the linear and nonlinear models outputs. The estimation method is mixed with a robust control algorithm for a two link robot to show the performance and functionality of the prosthetic hand.
As this initial study shows potential in the pursuit of controlling an artificial hand on an instantaneous basis, we will further this work in the future by improving the data collection techniques and optimizing the experimental procedure as well as using other advanced control techniques as adaptive control.

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