SHARED HUMAN-MACHINE CONTROL FOR SELF-AWARE PROSTHESES

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ABSTRACT

This paper presents a framework for shared, human-machine control of a prosthetic arm. The method employs electromyogram and peripheral neural signals to decode motor intent, and incorporates a higher-level goal in the controller to augment human effort. The controller derivation employs Markov Decision Processes. The system is trained using a gradient ascent approach in which the policy is parameterized using a Kalman Filter and the goal is incorporated by adapting the Kalman filter output online. Results of experimental performance analysis of the shared controller when the goal information is imperfect are presented in the paper. These results, obtained from an amputee subject and a subject with intact arms, demonstrate that a system controlled by the human user and the machine together exhibit better performance than systems employing machine-only or human-only control.

Index Terms— Kalman Filter, Markov decision processes, self-aware systems, movement intent decoder

1. INTRODUCTION

Self-aware systems are capable of extracting high-level goals from data available to them, and automatically adapting their behavior to achieve the extracted goals. Such systems are also able to learn their environment and use this information to achieve the goals. Prosthetic limbs have progressed in the last few decades from cable-driven prostheses controlled by shoulder movements, to systems that use natural control signals to command their movements [1]. Furthermore, highly dexterous robotic arm and hand prostheses have been sensorized to evoke meaningful artificial percepts for closed-loop control of their movements [2–4], and such systems satisfy many characteristics of self-aware systems. In this paper, we consider how shared control of a prosthetic arm between a machine-learning system that has an imperfect understanding of the higher-level goals and the human user of the system improves the overall performance of the prosthetic arm over the machine-only control and human-only control of such devices.

Motor intent decoding with Kalman filters (KF) [5–12], multilayer perceptron [13] networks, recurrent neural networks [14] and extreme machine learning [15] have became popular due to their performance and generalization capabilities. These methods perform incremental predictions of the movements, but do not utilize a higher-level goal (e.g., ultimate location the prosthetic limb aims at moving to). Mulliken *et al.* [16] incorporated goal information in the KF framework by incorporating the goal as KF states. Hotson, *et al.* [17] suggested using cameras to detect objects and their positions and used the position to estimate the higher-level goals with a hidden Markov model.

This paper describes a control system for a high degree-of-freedom (DoF) forearm prosthesis based on electromyogram (EMG) signals and peripheral nerve signals (PNS) acquired from the residual arm. We present a Markov Decision Process (MDP) [18] based method that uses the goal information, EMG and PNS signals, and the states of the prosthetic system to determine the moment-to-moment control inputs to the system. In this paper, we assume that the high-level goal is known or has been estimated, and experimental work is based on this premise. Although, goal estimation is not part of this paper, it is an important component of the system, and we are currently pursuing approaches for estimating the higher-level goals from auxiliary signals acquired by additional sensors placed on or near the prosthetic system. The performance of the shared controller is experimentally validated on a volunteer with intact hands and an amputee volunteer. To model the most likely case where aspects of the goal are not fully understood (e.g., touching versus grasping an object), we assume that the controller only has an imperfect (noisy) estimate of the goal. We present experimental results that demonstrate that a shared human-machine controller that combines the biological information provided by the human and goal information provided by the machine outperforms a controller that uses only the biological information and another that uses only the machine-generated (imprecise) goal information.

2. PROSTHETIC CONTROLLER DESIGN

Broadly, the function of our controller is to interpret the action from biological and other auxiliary signals related to movements and decide the best movement for the prosthetic limb. Similar to the derivation in [13], we use an MDP to model the decision making process. The objective is to estimate a policy $\pi_\theta(u_k|s_k, g_k)$, where s_k is the state for the kth time step, u_k and g_k are the action and the high level goal for the kth time step. The policy, $\pi_\theta(u_k|s_k, g_k)$, can be interpreted as the probability of the system taking the action u_k, given that the system is in the state s_k and has the goal g_k. The policy provides the next estimated action of the controller, by choosing u_k that maximizes $\pi_\theta(u_k|s_k, g_k)$.

The state, s_k, is defined as the union of the most recent H_1 instances of the measured EMG and PNS signals $Z_k = [z_{1,k}, ..., z_{N,k}]^T$ and the most recent H_2 instances of the position of the prosthetic hand $X_k = [x_{1,k}, ..., x_{M,k}]^T$. Here $z_{i,k}$ is the kth measurement from the ith measurement channel, N is the number of EMG and PNS channels, $x_{j,k}$ is the hand position at time k corresponding to the jth degree of freedom, and M is the number of degrees of freedom (DoF) of the hand. That is,

$$s_k = [Z_k, ..., Z_{k-H_1} \bigcup X_k, ..., X_{k-H_2}] \quad (1)$$

The actions are defined by $u_k = [X_{k+1}]$. Finally, g_k is the prosthetic limb's goal (desired limb position) at the k-th time slot.

We assume that the system evolves according to the Markov assumption, where that the next state of the hand, s_{k+1}, only depends on the current state, s_k, $p(s_{k+1}|s_k, ..., s_1) = p(s_{k+1}|s_k)$. For a given set of independent trajectories, $\tau = \bigcup_{a=1}^{A} \tau_a$, where A is the number of trajectories in a training set, the trajectory τ_a is given by $\tau_a = \bigcup_{i=1}^{H_a} (s_i^a, u_i^a)$. Here, H_a is the number of samples in the desired trajectory, and s_i^a and u_i^a represent the i-th state and action, respectively, in the trajectory a. We also define a set of goals for each trajectory given by $\Gamma_a = \bigcup_{i=1}^{H_a} g_i^a$, where g_i^a represents the goal for the ith time bin and the ath trajectory. It is possible to write $p(\tau_a|\Gamma_a)$ parameterized as $p_\theta(\tau_a|\Gamma_a)$ in the following manner:

$$p_\theta(\tau_a|\Gamma_a) = p(s_1^a)p(g_1^a) \times \left[\prod_{i=1}^{H_a-1} p(s_{i+1}^a|s_i^a, u_i^a)\pi_\theta(u_i^a|s_i^a, g_i^a) \right] \times \left[\prod_{i=2}^{H_a} p(g_i^a|g_{i-1}^a, ..., g_1^a) \right] \quad (2)$$

During the training phase, the objective is to learn the set of parameters θ which maximizes the following cost function:

$$J(\theta) = \frac{1}{A} \sum_{a=1}^{A} \frac{1}{H_a - 1} \log(p_\theta(\tau_a|\Gamma_a)) \quad (3)$$

Given that the log function is a monotonically increasing function, maximizing the cost function in (3) is equivalent to maximizing $\prod_{a=1}^{A} p_\theta(\tau_a|\Gamma_a)$. The gradient of $J(\theta)$ is given by

$$\nabla_\theta J(\theta) = \frac{1}{A} \sum_{a=1}^{A} \frac{1}{H_a - 1} \sum_{i=1}^{H_a-1} \nabla_\theta[\log \pi_\theta(u_i^a|s_i^a, g_i)] \quad (4)$$

During the normal operation of the system in real time, we employ a two-step decision process for the controller at each time. In the first step, the system uses the parameter vector θ estimated during the training process to find a preliminary estimate of the control action, $\hat{u}_i = \phi_\theta(s_i)$. In second step, the control signals are modified based on the higher-level goal. We assume a Gaussian policy given by

$$\pi_\theta(u_i|s_i, g_i) = \frac{1}{\sqrt{2\pi}\sigma_1} \times e^{-\frac{||u_i - (1-\beta)\phi_\theta(s_i) - \beta\psi(g_i)||^2}{2\sigma_1^2}} \quad (5)$$

where $\psi(\cdot)$ is a function that approximates the prosthetic system dynamics and is assumed to be known. Similarly $\phi_\theta(\cdot)$ is the motor intent decoder responsible for extracting the intent from the EMG and PNS signals and it is specified by θ. During training phase, we assumed $\psi(g_i) = u_i$, the gradient used in the training phase can be written as

$$\nabla_\theta J(\theta) = \frac{1}{A} \sum_{a=1}^{A} \frac{1}{H_a - 1} \sum_{i=1}^{H_a-1} \{[u_i^a - \phi_\theta(s_i^a)][\nabla_\theta \phi_\theta(s_i^a)]^T\}^T \quad (6)$$

Therefore, the system parameters θ are updated as follows during training

$$\theta = \theta + \alpha \nabla_\theta J(\theta) \quad (7)$$

where α is the learning rate, which should be greater than zero.

Once the system is trained, the parameters θ are kept static while operating the prosthetic system in real time. During the online phase we wish to optimize the actions for the give trajectory in real time. Therefore, we assume that the parameters H_a and A are equal to 2 and 1, respectively. In this situation, the gradient is given by

$$\begin{aligned} \nabla_{u_i^a} J(\theta) =& \nabla_{u_i^a} p(s_{i+1}^a|s_i^a, u_i^a) \\ &- [u_i^a - (1-\beta)\phi_\theta(s_i^a) - \beta\psi(g_i^a)] = 0 \end{aligned} \quad (8)$$

and the control actions are updated as

$$u_i^a = (1-\beta)\phi_\theta(s_i) + \beta\psi(g_i) + \nabla_{u_i^a} p(s_{i+1}^a|s_i^a, u_i^a) \quad (9)$$

where β belongs to the interval $[0, 1]$. The above equation requires an implicit solution, but in many practical cases involving deterministic ϕ, it is possible to show that the $\nabla_{u_i^a} p(s_{i+1}^a|s_i^a, u_i^a) = 0$. The parameter β can be interpreted as responsible for controlling the balance between decoded human intent and machine decision.

The derivation provided above is very general. The decoder, $\phi_\theta(\cdot)$, can be parameterized using multilayer perceptron networks, Kalman Filters, or a number of other methods. The framework of this paper can be interpreted as a hybrid control system, where there is an incremental decoder, $\phi_\theta(\cdot)$, and this decoder output is modified, based on a higher-level goal. The hybrid framework is summarized in Algorithm 1.

Training phase
Collect the training data
Train the policy offline using (6) and (7)
Online Phase
foreach *time instant,* i **do**
  Estimate the goal, g_i^a
  Calculate u_i^a using
   $u_i^a = (1-\beta)\phi_\theta(s_i) + \beta\psi(g_i) + \nabla_{u_i^a} p(s_{i+1}^a|s_i^a, u_i^a)$
  Update the system state, s_{i+1}^a, based on the just updated action, u_i^a
end

Algorithm 1: Prosthetic control Algorithm

3. PERFORMANCE EVALUATION

3.1. Experiment Setup

The results presented herein are for a single individual with an upper limb amputation and a single intact subject. After receiving approvals from the University of Utah Institutional Review Board and informed consent, the amputee subject was implanted with 32 EMG electrodes to acquire intramuscular EMG data from the residual limb and with Utah Slanted Electrode Arrays (USEA) in the median nerve (2 USEAs) and ulnar nerve (1 USEA) proximal to the elbow to acquire peripheral nerve signals [12, 19, 20]. For the intact subject, the EMG signals were collected via up to 32 surface EMG electrodes placed on the subject's arm. Single-ended EMG signals were acquired at 1 kHz and neural spike events (amputee subject only) at 30 kHz by a Grapevine System (Ripple LLC, Salt Lake City, Utah). The EMG signals were bandpass filtered using a 6th-order, 15 Hz Butterworth high pass filter, a 2nd-order, 375 Hz Butterworth low pass filter, and 60, 120, and 180 Hz notch filters. The neural signals were bandpass filtered using a 4th-order, 250 Hz Butterworth high pass filter and 3rd-order, 7500 Hz Butterworth low pass filter. Differential EMG signals were calculated for all pairwise EMG combinations. The mean absolute values (MAV) were calculated for the single-ended and differential EMG channels and the firing rates were calculated for each neural channel, for both over a 33-1/3 ms window, and subsequently smoothed with a 300 ms rectangular window.

The experiments were performed in a virtual environment (Musculoskeletal Modeling Software [21]). This program can model a virtual hand with multiple degrees of freedom (DoF). We only used extension and flexion of the five fingers in these experiments for the intact subject, and used thumb, index and little finger flexion, wrist pronation, wrist flexion and thumb abduction for the amputee subject. For each DoF, the joint position was normalized to fall between -1 (maximum extension/supination/abduction) and +1 (maximum flexion/pronation/adduction). The resting joint position was defined as zero (neither extending nor flexing). In our virtual environment, $\psi(.)$ was a identity matrix. In this case, we can show that the last term on the right-hand side of (9) is zero, yielding $u_i^a = (1-\beta)\phi_\theta(s_i) + \beta g_i$. In our experiments, we assumed that the goal had the only information about the final position of the hand, *i. e.*, $g_i = [X^d]$, where X^d is the desired final position of the hand. Specifically, the goal information did not match the trajectory of the hand.

During training, the subjects were instructed to track the movement of the simulated hand with their phantom or intact limb while the EMG and PNS signals were recorded. Each instructed movement followed a semi-sinusoidal path at a velocity deemed comfortable by the subject. In each training trial, either a single DoF or a combinations of multiple DoFs were instructed to be moved. Five trials of each unique movement type were recorded.

Once the training data was collected, we used a Kalman filter (KF) decoder described in [5, 6]. We used the Kalman decoder for simplicity; other choices involving nonlinear parameterizations could also be used as a decoder [5,13]. During the subsequent online testing phase, the desired hand position was shown on the computer screen and the subject was instructed to move the virtual hand to that position. In each testing trial, one or more DoFs were positioned away from the resting position and all other DoFs were positioned at the resting position. If the subject was able to move the virtual hand to within ± 0.15 normalized units of the desired position and stay within this target region for 300 ms within 30 seconds of trial start in a trial, that trial was considered successful. The position of all DoFs, whether moving or stationary DoFs, had to be within their respective target region over the same 300 ms duration for the trial to be considered successful.

We tested three different controller conditions. In the first condition, we only used the Kalman filter by setting β to zero, and we collected data from 210 and 40 trials with the intact and amputee subject, respectively. In the second condition, we used a hybrid controller with $\beta = 0.25$ and assumed that the goal was perfectly known. We collected data set from 210 and 40 trials for the intact and amputee subject, respectively. We additionally performed a number of pilot tests with the intact subject, and these collected data suggested $\beta = 0.25$ was assistive but not overbearing. In the third condition, we used a hybrid controller with $\beta = 0.25$ and assumed that the goal was not perfectly known. In this condition, we displaced the true goal to create a noisy goal by adding a randomly selected, per-trail offset, where the offset was selected from a Gaussian distribution with zero mean and 0.2 normalized units standard deviation. For a trial to be successful in this condition, all DoFs had to be within the target region of the true goal. We collected data from 108 and 40 trials for the intact and amputee subject, respectively. During the testing with the intact subject, the subject was aware of the particular condition being tested. The amputee was not aware of the particular condition being tested. We also introduced a hypothetical 4th condition based upon the third condition. In this condition, we assumed that we had imperfect knowledge of the goal and the only source of decoding information came from the goal based part of the hybrid decoder. That is, effectively β was unity and the EMG-PNS-based Kalman filter did not influence the decode. In this condition, the system would be successful 55% of the trials based upon the size of the target region and the distribution of the offset between the actual goal and the noisy goal.

3.2. Results

We used four metrics to evaluate the performance, which are the success rate, root-mean-squared error (RMSE) between the target and moving DoFs, and RMSE between the target and stationary DoFs and the trajectory length. Specifically, the moving RMSE is calculated as

$$D_M = \sqrt{\frac{1}{HM_m}\sum_{i=1}^{H}\sum_{j=1}^{M_m}(x_{j,i}^M - x_{j,i}^{DM})^2} \tag{10}$$

where $x_{j,i}^M$ and $x_{j,i}^{DM}$ are the position and goal respectively, of the j-th DoF instructed to move for the i-th time bin, there are M_m moving DoFs and H is the number of time bins in a trial. The stationary RMSE (also called jitter herein) is calculated as

$$D_S = \sqrt{\frac{1}{HM_s}\sum_{i=1}^{H}\sum_{j=1}^{M_s}(x_{j,i}^S - x_{j,i}^{DS})^2} \tag{11}$$

where $x_{j,i}^S$ and $x_{j,i}^{DS}$ are the positions and goals of the j-th stationary DoF for the i-th time bin and M_s represents the number of stationary DoFs. The trajectory length was calculated as

$$D_T = \frac{1}{M_m}\sum_{i=2}^{H}\sum_{j=1}^{M_m}|x_{j,i}^M - x_{j,i-1}^M| \tag{12}$$

To evaluate the relative performance of the three controller conditions, we compared each of the three performance metrics for pairs of conditions with independent two-sample t tests (RMSE and trajectory data) and the success rate using the Wilcoxon rank sum test (per trial success(1) or failure(0) data). To handle the effect of multiple comparisons, we use a Bonferroni correction that reduced the significance level to 0.0167 from 0.05. Finally, we used a binomial test to compare the success rate of the condition of a hybrid decoder with imperfect knowledge of the goal to the hypothetically derived 4th condition.

The relative performance of the three controller conditions and the hypothetical 4th condition are summarized in Tables 1 and 2. The RMSE values and the trajectory lengths are the mean and standard deviation across all trials. As a baseline, the controller based on Kalman filter only had a success rate of 58% for the intact subject and 63% for the amputee subject. As would be expected, adding perfect goal information into the controller increased the performance, with success rates of 92% for both the intact and amputee subjects. When imperfect goal information was provided, the success rate decreased slightly to 88% for both the intact and amputee subjects. Of the improvements found by adding goal information, statistically significant improvements to the success rate were observed for both subjects ($p < 10^{-15}$ for perfect goal information and $p <$

Table 1. Performance Metrics in Different Scenarios For the Intact Subject.

Scenario	Success Rate	D_M	D_S	D_T
KF	58%	0.62±0.18	0.09±0.1	5.71 ± 5.69
KF + Goal	92%	0.36±0.09	0.01±0.02	1.88 ± 2.86
KF + Noisy Goal	88%	0.36±0.09	0.01±0.02	1.91 ± 2.94
Machine Alone	55%	N/A	N/A	N/A

Table 2. Performance Metrics in Different Scenarios For the Amputee Subject.

Scenario	Success Rate	D_M	D_S	D_T
KF	61%	0.38±0.04	0.040±0.05	4.94 ± 5.48
KF + Goal	92%	0.21±0.03	0.003±0.01	1.52 ± 2.79
KF + Noisy Goal	88%	0.25±0.07	0.002±0.01	1.44 ± 2.03
Machine Alone	55%	N/A	N/A	N/A

1.6×10^{-8} for imperfect goal information for the intact subject and $p < 10^{-3}$ for perfect goal information and $p < 9 \times 10^{-3}$ for the imperfect goal information for the amputee subject). Further, the addition of the subject-provided decoding information when the goal was imperfectly known improved the success rate significantly when compared to machine control alone (binomial test, probability of observed success rate given hypothetical performance with only goal driven controller, $p < 0.0008$ and 1.38×10^{-13} for the amputee and intact subject, respectively). We interpret these results as the a demonstration of human intent, guided by sensory (visual here) feedback, being able to overcome the error in the estimated goal to successfully complete the task.

The addition of goal information, even when imperfect, improved the performance of the task as measured by two RMSE metrics and the trajectory length as well. In the intact subject, we observed a 42% reduction in the movement RMSE for both hybrid systems, and this change was statistically significant ($p < 10^{-24}$ for both hybrid systems). The amputee subject had a 44% reduction in for the case of perfect goal knowledge but only 34% reduction when the goal information was imperfect. Both changes were statistically significant ($p < 10^{-5}$ for both hybrid systems). The reduction in instructed to move DoF RMSE's implies the subject moved to the goal more effectively. Furthermore, the jitter RMSE decreased 89% for the intact subject and 95% for the amputee subject for both hybrid systems. Again, these changes were statistically significant ($p < 3 \times 10^{-6}$ for all cases). These effects can be easily observed in Figure 1. Kalman-filter-alone controller manifested more movement cross talk than either hybrid controller, and such cross movements likely made it more difficult for the subjects to complete the tasks. Finally, trajectory path decreased 67% for the intact subject and 70% for the amputee subject for both hybrid controlled systems. These changes are significant ($p < 3 \times 10^{-4}$ for all cases). These improvements can be interpreted as the subject being able to perform the desired tasks more precisely.

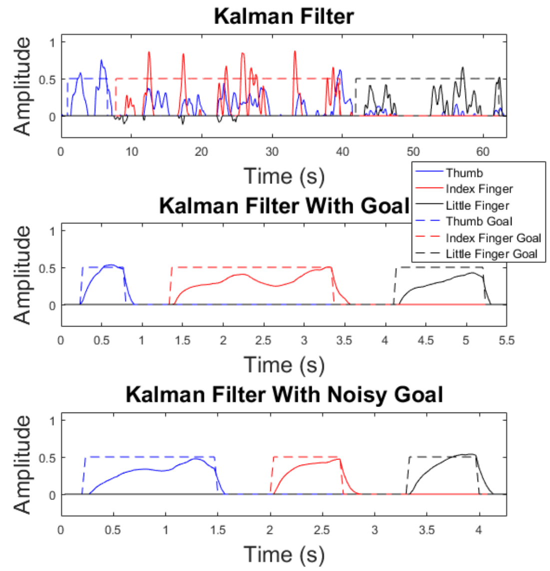

Fig. 1. Representative examples of the performance for the three controller conditions with the amputee subject. All cases represent the testing phase, where the amputee's EMG and PNS signals were used to derive the movement action via a previously trained Kalman filter and the subject could see both the goal and his performance in achieving the goal. For each condition, the dashed line represents the true goal and the solid line represents the controller's real-time prediction of the desired position. The color of each line represents a particular joint.

4. CONCLUSION

The preliminary results presented in this paper suggest that incorporating goal information into the decision making process improves the ability of the subject to control the prosthetics. Prosthetics with shared control between humans and machines systems demonstrated higher success rates, more precise control, and less cross movements between DoFs. Additional experiments using an amputee subject as well as in depth explorations of the effect of noise in the goal estimates on the shared controller are also underway. Further studies on how to update the parameters online based on the goal and the decisions made by the decoder can be beneficial to the overall controller performance.

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