Hand Movement Discrimination Using Particle Filters

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***Abstract*—Powered prosthetic devices can be driven using task-specific information from surface electromyogram (sEMG) signals recorded over the relevant muscles. The task-specific information can be extracted from sEMG signals using the state-space framework, which models movement planning and execution by the central nervous system (CNS). The proposed state-space model consists of a nonlinear system dynamics model and a linear measurement model based on the hypothesis of muscle synergies. The unknown system state, which is to be estimated, consists of synergy activation coefficients and is constrained to be non-negative on average due to physiological reasons. To solve this constrained nonlinear estimation problem, we propose a modification to the particle filter, which first draws particles from the unconstrained posterior distribution and then enforces the constraints by sampling from a high probability region. This method is termed MEan DEnsity Truncation (MEDET) in contrast to an approach that constrains the entire posterior density. The constrained state estimates, i.e., synergy activation coefficients are later used to discriminate between six different tasks including hand open, hand close, wrist flexion, wrist extension, forearm pronation and supination of three participants. The newly proposed PF-MEDET algorithm was able to discriminate hand tasks with more than 97% accuracy.**

I. Introduction

The ease and accuracy in the performance of activities of daily living (ADL) hide the actual complexity of the underlying neuromuscular processes involved in planning and execution of voluntary tasks. This complexity is revealed when a part of the body (e.g., a hand) is missing owing to trauma or congenital disability. In such situations, limited functionality for performing ADL can be restored using externally powered prosthetic devices which are driven by the surface EMG (sEMG) signals recorded from leftover muscles [1], [2]. A popular approach is to use pattern classification or machine learning algorithms [3]. These algorithms are first trained using the processed sEMG signals and are later used to discriminate between various intended tasks given the similar sEMG signals [1]–[3]. The pattern classification algorithms, as well as EMG signal acquisition and processing techniques have continuously improved over the last decades and now classification accuracies exceeding 90% are generally reported in the literature [2], [4], [5]. However, the user acceptability of these devices is still limited [6], [7]. One possible reason for this disparity between reported classification accuracies and low usability of these devices is related to how the sEMG information is processed by machine learning algorithms [8]. These algorithms may not directly incorporate all available information about the system physiology, e.g., the dynamics of movement planning at the central nervous system (CNS) level and the presence of muscle synergies at the central/peripheral nervous system level [9].

Recently, a linear state-space model was proposed for planning and execution of voluntary tasks at the CNS and skeletal muscles level [8], [10]. The system dynamics were modeled using a linear random walk process and the measurement model was constructed using the hypothesis of muscle synergies. The state-space representation modeled the linear evolution of the synergy activation coefficients (i.e., the unknown latent system state) in the CNS over time and the resulting output in the form of sEMG signals [8]. The muscle synergies, as used in the proposed measurement model, represent fixed relative activation levels of different muscles that enable their recruitment by a small number of independent control signals from the CNS [9]. The synergy activation coefficients were constrained to be non-negative on average as they represent the contribution of each muscle synergy towards the final muscle activation [3]. A state constrained Kalman filter was used to estimate the unknown state which, in turn, was used to discriminate between various hand and wrist tasks [8]. However, due to the nonlinear transformations performed by neurons including transportation delays, firing saturation, and thresholding actions, the system state may evolve nonlinearly over time [11]. We, therefore, propose a nonlinear system dynamics model that can capture firing saturations and thresholding actions.

Particle Filters (PFs) are extensively used for state estimation in nonlinear/non-Gaussian dynamic systems [12]. PFs are based on a powerful sampling technique and find an optimal estimate of the state using a set of random weighted samples (also called particles) [12]. PFs are known to converge asymptotically to the true posterior density of the state as the number of particles increases [12]; however, it is not straightforward to incorporate constraints imposed on the unknown state [13]. Generally, the given constraints are imposed by constraining all particles of the PF; we refer to such schemes as Point Wise Density Truncation (PoDeT) [14]–[17]. PoDeT constrains the support of the posterior density function of the state by removing all particles that violate the constraint. This may lead to more stringent conditions than desired as the original constraint was imposed on the conditional mean of the state rather than the state posterior distribution [18].

In this paper, we propose a novel algorithm for constrained PF estimation referred to as *MEan DEnsity Truncation* (MEDET), which imposes the constraint on the unknown state by perturbing the unconstrained posterior density using only one particle. We compared PFs with both state constraining schemes, i.e., MEDET and PoDeT as well as Kalman Filter (KF) for discrimination of six different hand and wrist tasks.

II. Mathematical Preliminaries

A. Constrained State-Space Model

Consider a discrete-time state-space model described by the state transition and measurement models:

$$x_{n+1} = f_n(x_n) + u_n, \tag{1}$$

$$y_n = h_n(x_n) + v_n, \tag{2}$$

where x_n and y_n represent the unknown system state and observation vector at time n, respectively. f_n and h_n represent possibly nonlinear mapping functions. u_n and v_n represent zero-mean state and observation noise sequences, respectively, with known probability density functions (pdf).

For the problem of task discrimination, we consider the following nonlinear state transition function [11]:

$$x_{n+1} = \frac{x_n}{\sqrt{1+x_n^2}} + u_n. \tag{3}$$

The system state x_n represents the synergy activation coefficients that originate at the CNS i.e., $x_n = [x_n^1, \cdots, x_n^k]^t$, where k is the total number of muscle synergies and t represents the matrix transpose [11]. The hypothesis of muscle synergies is used to derive the for system measurement model:

$$y_n = W x_n + v_n, \tag{4}$$

where y_n represents the sEMG signals recorded from the forearm muscles and W represents the muscle synergy matrix. The activation signals from the CNS x_n are translated into individual muscle activation by the muscle synergy matrix W. The synergy activation coefficients are always nonnegative, i.e., zero when the muscle is not active and positive once the muscle is active and contributing to force production, i.e.,

$$E[x_n] \geq, 0 \quad \forall\ n. \tag{5}$$

B. Unconstrained State Estimation

In the Bayesian estimation framework, optimal inference of the state sequence x_n using all the available measurements $y_{1:n} = [y_1, \cdots, y_n]$, relies upon the posterior density $p(x_n|y_{1:n})$. The particle filter approximates the posterior density using a set of N particles and their associated weights $\{x_n^{(i)}, w_n^{(i)}\}_{i=1}^N$:

$$p^N(x_n|y_{1:n}) = \sum_{i=1}^{N} w_n^{(i)} \delta(x_n - x_n^{(i)}), \tag{6}$$

where δ is the Dirac delta function.

Ideally, the particles should be sampled from the true posterior distribution $p(x_n|y_{1:n})$, which is unavailable. Thus, another distribution, referred to as the *proposal distribution* $q(x_n|x_{n-1}, y_n)$, is used [12]. The importance weight of every particle $x_n^{(i)}$ is calculated using:

$$\tilde{w}_n^{(i)} = w_{n-1}^{(i)} \frac{p(y_n|x_n^{(i)}) p(x_n^{(i)}|x_{n-1}^{(i)})}{q(x_n^{(i)}|x_{n-1}^{(i)}, y_n)}, \tag{7}$$

where the normalized weights are given by $w_n^{(i)} = \tilde{w}_n^{(i)} / \sum_{j=1}^{N} w_n^{(j)}$.

Finally, the conditional mean of the state is given by:

$$E[x_n|y_{1:n}] = \int x_n\ p^N(x_n|y_{1:n})\ dx_n = \sum_{i=1}^{N} w_n^{(i)} x_n^{(i)}. \tag{8}$$

The weights of the particles may perish and thus require resampling [12]. The particles are resampled according to their weights, i.e., removing particles with very small weights and duplicating particles with large weights. Thus, equal weights ($\frac{1}{N}$) are assigned to all selected N particles.

C. Constrained State Estimation

We consider a general constraint of the form:

$$a_n \leq \phi_n(\hat{x}_n) \leq b_n, \tag{9}$$

where ϕ_n represents the constraint function at time n. It is important to affirm that the constraint must only be satisfied by the state estimate presented by the conditional mean as specified:

$$a_n \leq \phi_n(\widehat{x}_n) = \phi_n(E[x_n|Y_n]) \leq b_n. \tag{10}$$

In the sequel and without loss of generality, we consider ϕ_n to be the identity function for all n.

a) Point Wise Density Truncation (PoDeT): Constrained state estimation in PFs is generally performed by constraining each sampled particle. For an interval constraint $\hat{x}_n \in [a_n, b_n]$, each sampled particle is tested against the constraint and violating particles are rejected [14], [15]. Constraining every particle to be in the interval $[a_n, b_n]$ is equivalent to constraining the support of the posterior distribution $p(x_n|y_{1:n})$. However, the original constraint was for the conditional mean of the posterior density only. Consequently, the PoDeT approach may result in significant estimation errors unless the unconstrained density already has a bounded support with the constraining interval [13].

b) Mean Density Truncation (MEDET): We propose a new approach by perturbing the unconstrained density using only one particle sampled from a high probability region to satisfy the constraint on the conditional mean. Consider drawing N unconstrained particles from the importance distribution. If the N-order approximation satisfies the constraints, the estimate is kept. Otherwise, one particle after the resampling is removed and a new particle from a high probability region is sampled to enforce the constraints. MEDET can be viewed as a "minimal perturbation" of the unconstrained posterior distribution using only a single particle. Consider a time step n after resampling. All particles have the same weight $w_n^{(i)} = \frac{1}{N}$, for all $1 \le i \le N$. We remove the particle that is furthest from the constrained region and add another particle $(x_n^{(N)}, \frac{1}{N})$ that enforces the constraint on the mean estimate as follows:

$$a_n \le \frac{1}{N}\sum_{i=1}^{N-1} x_n^{(i)} + \frac{1}{N}x_n^{(N)} \le b_n, \tag{11}$$

$$a_n' \le x_n^{(N)} \le b_n', \tag{12}$$

where $a_n' = Na_n - \sum_{i=1}^{N-1} x_n^{(i)}$ and $b_n' = Nb_n - \sum_{i=1}^{N-1} x_n^{(i)}$.

III. Methods

The study received approval from the Institutional Review Board of the University of Arkansas at Little Rock and three volunteers participated in the study. The participants performed six single-DOF tasks $(s_1, \cdots, s_6 \in S)$ including hand open (HO), hand close (HC), wrist flexion (WF), wrist extension (WE), forearm pronation (FP), and forearm supination (FS). During processing of the sEMG data, a rest (RT) class (s_7) was also added.

We placed eight sEMG electrodes around the circumference of the forearm of each participant symmetrically with the first electrode placed beneath in line with the medial epicondyle of the humerus. We used Noraxon TeleMyo Direct Transmission System (DTS) (Noraxon USA Inc) with wireless sensors to record the EMG data. We used disposable, self-adhesive silver/silver chloride (Ag/AgCl) snap electrodes with two circular conductive areas of 1 cm each and an inter-electrode distance of 2 cm. We used a NI-USB 6009 (National Instruments Corporation, Austin, Texas) data acquisition card to acquire and digitize the EMG data at the rate of 2000 samples per second. We modified the BioPatRec software to acquire and process the EMG data [5]. Before start of the data collection, each participant sat comfortably in a chair with right arm resting over a table in front. Visual cues were provided to participants to guide them throughout the data collection process. Participants performed each task for 5 secs with a 5 sec rest between two consecutive tasks. A single trial consisted of performing all tasks once. Participants were instructed to maintain a comfortable and repeatable force level for all tasks.

The sEMG data from all trials was randomly divided into two bins with 75% of the data in the first bin and the remaining 25% in the second bin. The first bin

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Algorithm 1 Task Discrimination using PF with MEDET

Get sEMG data for all tasks Y^s, where $s = 1, \cdots, S$
Partition Y^s into synergy extraction and testing sets
Extract muscle synergy matrices W^s using first data set
Run S constrained PFs on test data set as following:
PF - Initialization
Define $C_n = \{x_n : a_n \le \phi(\widehat{x}_n) \le b_n\}$.
for j = 1, 2, $\cdots$, N **do**
  Generate $x_0^{(j)} \sim \mathcal{N}(x_0^{(j)}, R_n)$.
  Compute the initial weights using (7) and normalize.
end for
for n = 1, 2, $\cdots$, T **do**
  Unconstrained estimation
  for j = 1, 2, $\cdots$, N **do**
    Generate sample $x_n^{(j)}$ from state transition model (3).
    Compute weight using: $\tilde{w}_n^{(j)} = \tilde{w}_{n-1}^{(j)} p(y_n|x_n^{(j)})$.
  end for
  Normalize particle weights $w_n^{(i)} = \tilde{w}_n^{(i)} / \sum_{j=1}^{N} \tilde{w}_n^{(j)}$.
  Resample $\{x_n^{(i)}, \frac{1}{N}\}_{i=1}^{N}$.
  Compute the weighted mean $\widehat{x}_n = \sum_{i=1}^{N} \frac{1}{N} x_n^{(i)}$.
  Constrained estimation
  if $\widehat{x}_n \notin C_n$ **then**
    Remove the furthest particle $x_n^{(i)}$.
    Add a new particle x_n^N using Eqs. (11)-(12).
    Compute the constrained weighted mean $\widehat{x}_n = \sum_{i=1}^{N} \frac{1}{N} x_n^{(i)}$.
  end if
end for
Reconstruct muscle activation $\hat{y}_n^s = W^s\, \widehat{x}_n^s$.
Find cosine distance between estimated and actual muscle activation $d_n^s = \mathrm{Cosine}[\hat{y}_n^s, y_n]$.
Identified task is: $I_n = \mathrm{Min}[d_n^1, \cdots, d_n^S]$.

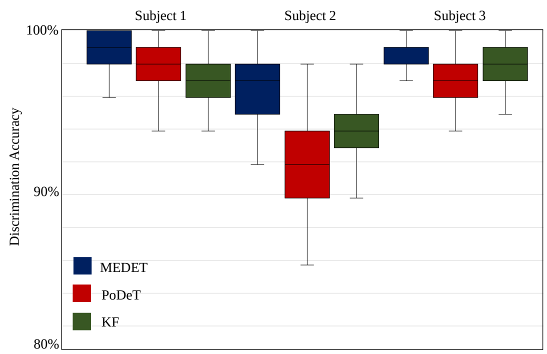

Figure 1. Average task discrimination accuracy results for three subjects using PFs with MEDET (blue), PoDeT (red) and KF (green) are presented using box plot. The subjects performed six single-DOF hand tasks including hand open/close, wrist flexion/extension and forearm pronation/supination. In all three cases, the MEDET constraining scheme performed better than the PoDeT and KF.

was used for synergy extraction while the second bin was used for task discrimination. A total of ten epochs were run and the results presented are average values across all ten runs. Given the processed sEMG data Y^s where $s \in S$, we estimated task-specific muscle synergy matrices W^s using:

$$Y^s = W^s \times X^s. \tag{13}$$

We used probabilistic independent component analysis (pICA) to estimate the muscle synergy matrix W and synergy activation coefficients X [8], [19]. We used 5000 particles for the PF and employed both PoDeT and MEDET state constraining schemes. Steps of constrained state estimation and task discrimination using PF with MEDET are presented in algorithm 1.

IV. Results

Figure 1 shows task discrimination accuracy results for MEDET (blue), PoDeT (red) and KF (green) using box plot for all three participants. It is evident that all three algorithms (MEDET, PoDeT and KF) were able to attain high discrimination accuracy for the given tasks. However, the MEDET outperformed PoDeT and KF in all three cases with higher mean accuracy and lower variance.

We presented confusion matrices for a representative subject in Fig. 2 for MEDET (top), PoDeT (middle) and KF (bottom). We observed that for the MEDET (average discrimination accuracy of 98%), the ‘hand open’ was confused with the ‘rest’, and the ‘hand close’ with the ‘forearm pronation’. On the other hand, the PoDeT (average discrimination accuracy of 95%) confused ‘wrist extension’ and ‘forearm pronation’ with the ‘hand open’, ‘hand close’ and ‘forearm pronation’ with the ‘wrist extension’, ‘hand open’ with ‘forearm pronation’, as well as ‘forearm pronation’ and ‘wrist flexion’ with the ‘rest’. In addition, the KF (average discrimination accuracy of 96%) confused ‘hand close’ with ‘hand open’, ‘wrist extension’ with ‘hand close’, ‘hand close’ with ‘forearm pronation’ as well as ‘hand open’ and ‘hand close’ with ‘rest’.

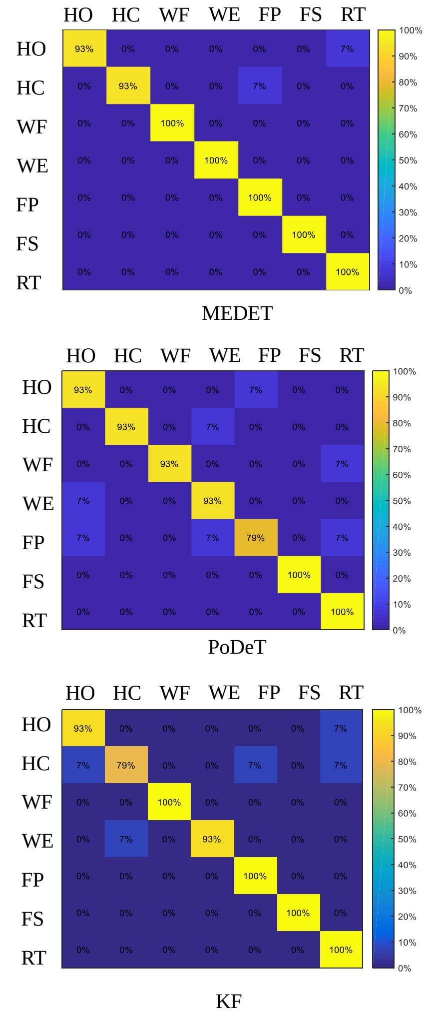

Figure 2. Confusion matrices for six tasks and ‘rest’ are presented for MEDET, PoDeT and KF. HO - Hand Open, HC - Hand close, WF - Wrist Flexion, WE - Wrist Extension, FS - Forearm Supination, FP - Forearm Pronation, and RT - Rest.

V. Conclusion

We developed a nonlinear state-space model for task discrimination using the hypothesis of muscle synergies and with the physiological constraint of non-negativity on the unknown system state. We presented a new algorithm, referred to as MEDET, for mean constrained state estimation in particle filtering. The proposed scheme minimally perturbs the unconstrained posterior distribution of the state to adjust for its mean as opposed to the PoDeT scheme that constrains the support of the posterior density. We showed that MEDET was able to discriminate hand tasks with high accuracy ($\approx 98\%$).

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