A STUDY OF KALMAN FILTERING APPLIED TO MYOELETRIC SIGNAL STATE TRACKING

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ABSTRACT

The goal of this work is to reduce the response time of pattern recognition based myoelectric prostheses without compromising stability. A Kalman filter (KF) was applied in feature-space to track class transitions and to determine when features have converged towards steady-state class. The system was tested against data collected during continuous movement where subjects transitioned between seven forearm and hand motions. For various data acquisition times, the signal-to-noise-ratio obtained from filtered and non-filtered features were compared, and the system classification accuracy and processing time were compared against state-of-the-art systems. Results show that while applying the proposed system, data acquisition time can be reduced from 100ms to 20ms without compromise to the system's classification accuracy.

INTRODUCTION

Pattern recognition (PR) based myoelectric prostheses have come a long way from conventional myoelectric prostheses, but there exists a trade-off between system stability and system response time. A stable system should be able to accurately determine the selected class while in steady-state class (C_{SS}) and to precisely determine when users are in a class transition (C_T). This requires a precise estimate of the signal, and a quick and precise response to selected classes.

Conventional proportional control methods relate the velocity of prosthesis to the amplitude estimate which is obtained by low/high pass filtering, intensity estimating, and smoothing [1] of the raw EMG. But all smoothing process requires a significant time history of data [2], or data acquisition time (T_{aq}). A larger T_{aq} improves the signal estimates, but slows down the system's response as the smoothed signal will lag the original signal [2]. To improve the signal estimate, pre-processing methods [3,4,5], intensity estimators, and smoothers have been studied [6,7,8,9,10], either requiring significant T_{aq} or processing times (T_p).

Accurate estimation of the EMG amplitude is less important for on-off systems as decisions are made using a threshold, but it is important to design a system that is sensitive enough to respond to the activity of the muscle while being selective enough not to respond to the activity of undesired noise [1] caused by the inherent randomness of the EMG signal. PR systems are sophisticated on-off systems [11], but state-of-the-art systems (Figure 1) lack response. Although they require little T_p and are stable in steady-state class given sufficient T_{aq}[12], this is problematic in transient conditions; larger T_{aq} generate time delays in transient conditions. To improve the system's performance under transient conditions, various classifiers [13,14], features estimation method [13,14,15], and post-processing methods [16], have been proposed where optimal stability has been obtained using a linear discriminant classifier (LDA) to classify time domain (TD) features [17]. But all exhibit poor responsiveness or uncertainty in C_T.

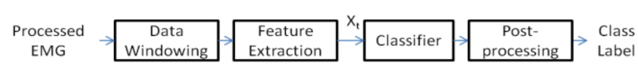

Figure 1: State-of-the-art systems.

The trade-off between system stability and system response time needs to be addressed. A KF tracking state-transitions in feature-space is proposed. For short T_{aq}, the KF minimizes variability in the feature estimate improving C_{SS} stability. Although it is unclear how the system should respond to C_T, or how to measure the system's performance in C_T, short T_{aq} improves the system's responsiveness while in C_T.

METHODOLOGY

Tracking in feature-Space

Tracking in feature-space involves determining when a user is beginning to transition, estimating the path of the EMG-features, and determining when a new targeted class is reached. This is illustrated in Figure 2.

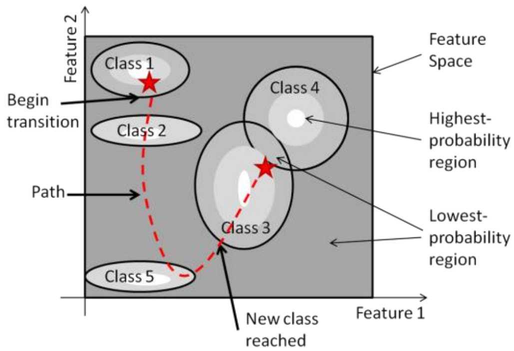

Figure 2: Contour plots of class distribution in 2-D features space.

In LDA-based systems, the class selected by the LDA may be false if an inadvertent class is on the path of the EMG-features being tracked, or if they fall in low-probability feature space regions. Features may fall within low-probability regions if: the user is transitioning to a new class, the user is conducting force varying contractions, or the T_{aq} is too short resulting in feature estimates with high variance. In either case, a change in the system's output may occur which may cause misclassifications. Two problems need to be addressed when considering conventional LDA-based systems while users are transitioning:

1) The features can only be tracked if they do not move beyond high-probability regions;
2) The stability of the system is compromised for short data acquisition time.

These can be solved by tracking in feature-space, and detecting C_{SS} using a KF with LDA-observations (KF-LDA) and a convergence detector (CD) as shown in Figure 3.

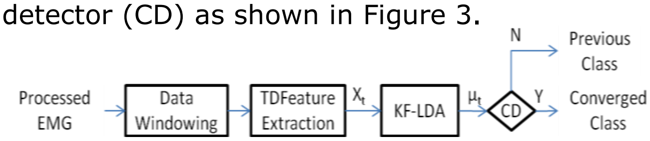

Figure 3: Proposed systems.

Kalman filter and steady-state detector

The KF [18] can be summarized into two steps: 1) the time update from *t-1* to *t*, modeled by the designer, and 2) the belief update computed using the KF algorithm. These steps are summarized in Table 1. The state belief (μ_t, Σ_t) is the output of the KF.

Table 1: Kalman filter summary.

1- Motion Model:	$X_t = A_t X_{t-1} + \epsilon_t \qquad \epsilon \sim N(0,R)$
Measurement Model:	$Y_t = C_t X_{t-1} + \delta_t \qquad \delta \sim N(0,Q)$
2- Estimate update: $\overline{P(X_t)} \sim N(\bar{\mu}, \bar{\Sigma})$	$\bar{\mu}_t = A_t \mu_{t-1}$ $\bar{\Sigma}_t = A_t \Sigma_{t-1} A_t^T + R_t$
Innovation:	$\Delta = Y_t - C_t \bar{\mu}_t$
Kalman gain:	$K_t = \bar{\Sigma}_t C_t^T (C_t \bar{\Sigma}_t C_t^T + Q_t)^{-1}$
True state estimate: $P(X_t) \sim N(\mu, \Sigma)$	$\mu_t = \bar{\mu}_t + K_t(\Delta)$ $\Sigma_t = (\mathrm{I} - \mathrm{K_t C_t})\bar{\Sigma}_t$
$X \equiv State$	$Y \equiv State\ measurement$
$A \equiv Transition\ matrix$	$C \equiv Measurement\ matrix$
$R \equiv Motion\ noise\ variance$	$Q \equiv Measurement\ noise\ variance$

The proposed time update is modeled as in Table 2. As a result, the predicted EMG-features μ_t would fall somewhere in between the extracted features at time t and the class mean selected by the LDA at time *t-1*, depending on their confidence, R_t and Q_t. Also, as transitions occur, features converge towards the most frequent LDA-output. A threshold base CD can be designed to detect C_{SS} as the tracked EMG-features converge towards the locus of a class, given a pre-determined threshold Th_{CD}.

Table 2: Modeled KF with LDA-observations.

Motion Model:	$X_t = X_{t-1} + \epsilon_t \ = Extracted\ EMG features$ $R_t \sim \lvert X_t - X_{t-t} \rvert^2$
Measurement Model:	$Y_t = X_{t-1} + \delta_t = Locus\ of LDA\ selected\ class$ $Q_t \sim \lvert Y_t - X_{t-t} \rvert^2$

An important condition to the proposed system is that the EMG-features must be continuous and the features at time t must depend on those at time *t-1*. TD-features obey the second condition, but zero-crossing and turns are discontinuous in nature as they lose resolution for short T_{aq}. Features used for the application are mean absolute value (MAV) and wavelength (WL).

Data Collection and Processing

Data were collected for seven healthy subjects while performing wrist flexion, wrist extension, wrist supination, wrist pronation, chuck grip, hand open, and no motion. Data acquisition was done using a custom Matlab-based software [19]. For training, subjects conducted a steady-state contraction for 4-seconds with a 3-second break between prompts. Classes were prompted twice in random order. For testing, each contraction was prompted four times, in random order, and subjects were given 8-seconds to both transition and reach steady-state. They were given a 3-second rest (no motion) between contractions. No feedback was provided. Data were continuously collected even when subjects were at rest. Testing was repeated 6-times with 2-minutes break between each set. Each subject performed the data collection twice on two different days. Data were collected for 8-channels at 1000Hz.

For comparison purposes, features were extracted from various acquisition window lengths (T_{aq}) ranging between 5ms and 100ms. Features for training and testing had the same T_{aq}. The LDA-classifier for the KF-LDA was trained prior to applying testing features to the system.

RESULTS

KF-LDA feature estimation precision

Since the true signal is unknown, it is difficult to measure the accuracy of the filtered features. But high signal-to-noise ratio (SNR), measured as the ratio of the mean to the standard deviation of the estimated features, indicates a smoother, or more precise, feature estimate. There exists a direct correlation between stability and the SNR of the amplitude estimate[3]. The SNR while in steady-state of the features' estimate obtained using the KF-LDA, μ_t, and without KF, X_t, were compared. This comparison was done in steady-state class. Figure 4 shows the SNR of the features while in steady-state for different T_{aq}. The last 4-seconds of each contraction was used to measure the SNR, results were averaged across all channels and contractions.

Performance of steady-state CD

Since it is unclear how to measure the performance of the system while in $C_{T,}$ only its performance in C_{SS} was evaluated and compared against systems using LDA-classification with and without MV post-processing. Figure 5 shows the average steady-state classification accuracy (C_{ac}) across all contractions for different T_{aq}. The last 4-seconds of each contraction was used to measure the C_{ac}. For simplicity, the convergence threshold Th_{CD} of the CD and the decision time (128ms [16]) of the MV were kept constant.

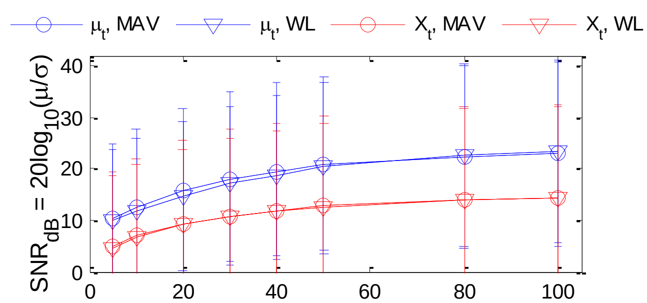

Figure 4: Steady-state SNR of feature estimates.

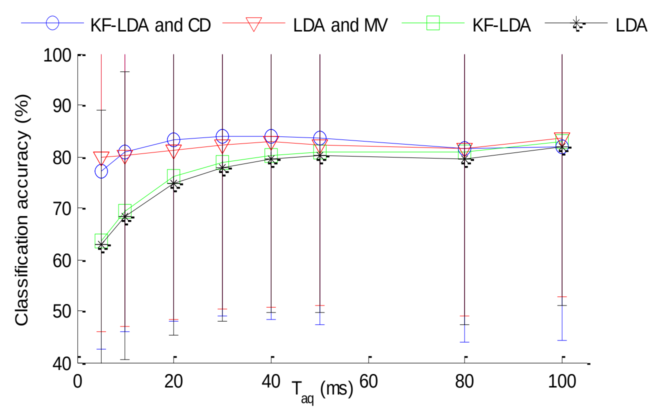

Figure 5: Steady-state classification accuracy.

Response Time

Response time is affected by the T_p and the T_{aq}. The T_p consist of the time delay required to compute a class label given a window of processed EMG has been input to the system. The KF-LDA with CD requires ~0.21ms and the LDA-MV system requires 0.13ms of T_p. Although there is a slight increase in the T_p, this is a small fraction of T_{aq}.

DISCUSSION

From these results, it is evident that the KF-LDA improves the feature estimate precision, and that CD and MV improve the C_{aq} while in steady-state for short T_{aq} (<80ms). It is unclear how C_T stability should be measured or how the system should respond to C_T, but since the KF-LDA provides a more stable feature estimate, the proposed system may improve the system's stability while in C_T.

Although the T_p is increased while using the KF-LDA (~0.1ms), this increase is insignificant compared to the T_{aq} improvement. The KF-LDA with CD is stable while in C_{SS} for 20ms T_{aq}, and since the CD does not require a post-processing decision time, as the MV, the proposed system may improve the system's responsiveness to C_T. It must be realized that system response time is also affected by the CD; it may take some time before features converge towards C_{SS}. For robust evaluation, the system response time needs to be evaluated in real-time [20].

CONCLUSION

There exists a trade-off between system stability and system response time for state-of-the-art PR systems. To progress this tradeoff, this paper proposes a KF design that combines stable LDA-classification during steady-state conditions with the KF's ability to track non-linear progressions. Preliminary investigations show promising results, future work should investigate a method to measure C_T performance, how the system should respond to C_T, optimal Th_{CD}, and the system's real-time performance.

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