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Sensor-fault tolerant control of a powered lower limb prosthesis by mixing mode-specific adaptive Kalman filters

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Abstract— **Machine learning methods for interfacing humans with machines is an emerging area. Here we propose a novel algorithm for interfacing humans with powered lower limb prostheses for restoring control of naturalistic gait following amputation. Unlike most previous neural machine interfaces, our approach fuses control information from the user with sensor information from the prosthesis to approximate the closed loop behavior of the unimpaired sensorimotor system. We present a Bayesian framework to control an artificial knee by probabilistically mixing of process state estimates from different Kalman filters, each addressing separate regimes of locomotion such as level ground walking, walking up a ramp, and walking down a ramp. We show its utility as a mode classifier that is tolerant to temporary sensor faults which are frequently experienced in practical applications.**

I. Introduction

THE quality of life after leg amputation is highly dependent on how well users can ambulate with artificial limbs. Artificial legs have traditionally been passive, but recent advances in battery technologies and low-weight actuators have made it practical to actuate the joints. State-based control using information measured from onboard electro-mechanical sensors is currently used to control these powered prostheses [1, 2]. Electromyographic (EMG) signals measured from the user's residual limb may also add important information to improve the control of the devices [2, 3]. Locomotion is a cyclical task that depends on the coordinated movement of the legs and the upper body. During such a dynamical task, the challenge is in synergistically actuating the powered prosthetic device with user's unimpaired body by inferring the user intention. The gait cycle is commonly divided into discrete gait phases and a finite state controller switches the phases based on sensor feedback. The finite state controller needs to incorporate not only various gait phases but also various regimes of locomotion such as level-ground walking (level-walk), walking up a ramp (up-ramp), walking down a ramp (down-ramp), stair-ascent, stair-descent, etc. Huang et. al. showed that EMG generated by residual limb muscles has significant information related to user's neural intent [3]; however, the intent estimation was not continuous and was only estimated at four discrete points in the gait cycle Information extracted from EMG signals combined with information from onboard electro-mechanical sensors may improve the user's ability to continuously control the powered prosthesis.

In this preliminary study, we represent the prosthetic knee as a dynamical system in a state space that operates in three regimes of locomotion: up-ramp, down-ramp, and level-walk. We present a sensor-fault tolerant Bayesian inference system that probabilistically combines mode-specific adaptive Kalman filters based on EMG from the muscles in the residual limb and signals from physical sensors embedded in the prosthesis. We demonstrate that the inference system can accurately perform mode classification at the sample rate of the sensors.

II. Methods

Locomotion was divided into three regimes which are frequently encountered: level-walk, up-ramp, and down-ramp; the gait cycle in each regime was further divided into two phases: stance phase when the prosthetic foot is on ground and swing phase when the prosthetic foot is in air. The three regimes and two gait phases constituted six modes of operation for the prosthetic knee. The prosthetic knee was described by a mode-specific discrete-time linear model,

$$x_{k+1} = Ax_k + w_k \tag{1}$$

$$y_k = C^{\text{mode}} x_k + v_k \tag{2}$$

Where A, C^{mode} are transition matrices of compatible dimensions, $x_k \in \Re^n$ is the state vector, $y_k \in \Re^m$ is the measurement vector, $w_k \in \Re^n$ and $v_k \in \Re^m$ are the process and measurement noise vectors, respectively.

A probabilistic Mixture of Trajectory Model (MTM) [4] was created as shown below:

$$x_{k|k} = \sum_{\text{mode}=1}^{6} x_{k|k}^{\text{mode}} \frac{\prod_{j=1}^{k} p(y_j \mid y_{1\ldots j-1})^{\text{mode}} p(\text{mode})}{\sum_{\text{mode}=1}^{M} \left(\prod_{j=1}^{k} p(y_j \mid y_{1\ldots j-1})^{\text{mode}} \right)} \tag{3}$$

where $x_{k|k}^{\text{mode}}$ is a mode specific adaptive Kalman filter

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(see Appendix A), $\prod_{j=1}^{k} p(y_j \mid y_{1\ldots j-1})^{\text{mode}}$ is the corresponding likelihood, and p(mode) is the subjective prior information. An 'argument of maximum' test was then performed for selecting the intended mode d_k at each sample time k

$$d_k = \operatorname{argmax}_{\text{mode}} \left(\frac{\prod_{j=1}^{k} p(y_j \mid y_{1\ldots j-1})^{\text{mode}} \, p(\text{mode})}{\sum_{\text{mode}=1}^{M} \left(\prod_{j=1}^{k} p(y_j \mid y_{1\ldots j-1})^{\text{mode}} \right)} \right)$$

The state vector (x_k) for the prosthetic knee system consisted of knee angle (θ_k), knee angular velocity ($\dot{\theta}_k$), knee angular acceleration ($\ddot{\theta}_k$), thigh vertical orientation in sagittal plane (φ_k), and thigh rate of change in vertical orientation ($\dot{\varphi}_k$): $x_k = [\theta_k \quad \dot{\theta}_k \quad \ddot{\theta}_k \quad \varphi_k \quad \dot{\varphi}_k]^T$ i.e. $n = 5$. The measurement vector y_k consisted of digitally filtered and standardized signals consisting of whitened EMG from thigh muscles: Gluteus Maximus, Semitendinosus, Sartorius, Tensor Fasciae Latae, Adductor Magnus, Gracilis, Vastus Medialis, Rectus Femoris, Vastus Lateralis, Biceps Femoris; 6-DOF load-cell signals at the ankle, 6-DOF inertial measurement unit on the thigh, and goniometer at the knee i.e., $m = 23$.

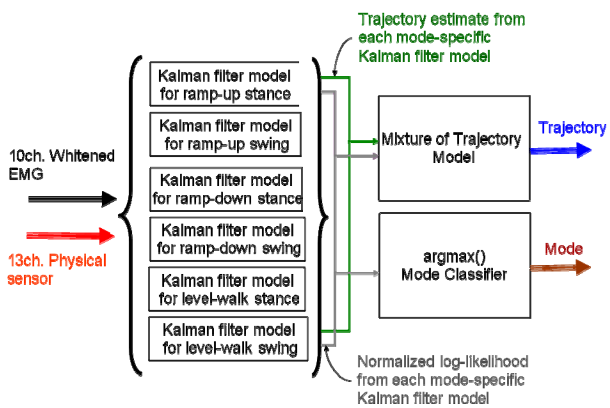

Fig. 1. Schematic of the Bayesian inference system showing six modes

We assumed that the initial state vector and noise vector are independently and identically distributed (i.i.d.) Gaussian random variables with initial state, $x_0 \sim N(\bar{x}_0, P_0)$, process noise $w_k \sim N(0, Q)$, measurement noise $v_k \sim N(0, R_k)$ where covariance matrices P_0, Q^{mode}, R_k^{mode} are symmetric positive definite matrices. Furthermore, we assumed that x_0, w_k and v_k are mutually uncorrelated

The model was discretized at time steps (T) of 0.001sec. The state transition matrix A was found from the equations of motion assuming a constant acceleration,

$$A = \begin{bmatrix} 1 & T & \frac{T^2}{2} & 0 & 0 \\ 0 & 1 & T & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & T \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (4)$$

The maximum likelihood estimates of $C^{\text{mode}}, Q^{\text{mode}}$, and R_0^{mode} were found with Expectation Maximization (EM). The initial conditions were assumed to be $\bar{x}_0 = [\pi \quad 0 \quad 0 \quad 0 \quad 0]^T$ and $P_0 = 0.1 \times \mathrm{I}_{5x5}$ where $\mathrm{I}_{5\times5}$ is 5×5 identity matrix. Figure 1 displays a block diagram of the Bayesian inference system used in this work.

The reliability of steady-state classification (or mode execution) was found from the percent of correct mode selections (d_k) made after foot-off prior to foot-strike in the new mode to the last foot-off while performing level-walk, up-ramp, and down-ramp walking. The foot off prior to the first foot strike in a new regime was defined as the instant of regime transition and was identified manually from video frames.

A. *Experimental protocol and data collection*

The experimental data was collected from a unilateral (right leg) above-knee female amputee who provided written informed consent to participate in this study. The experimental protocol consisted of three locomotion regimes including walking on level ground, down-ramp walking (slope=5 degrees) and up-ramp walking (slope=5 degrees) in a laboratory setting. The subject started each trial standing still for approximately 3 seconds to initialize the inertial measurement unit and then walked 2-3 strides on level ground, transitioned to the specified locomotion regime (e.g. down-ramp or up-ramp walking), transitioned back to level ground walking for 2-3 strides and ended the trial by standing still. We collected 15 trials of each regime for training data and 10-fold cross-validation.

B. *EMG sensor fault rejection*

The surface EMG electrodes in the prosthetic socket picked electromagnetic noise during temporary liftoff from the skin which was simulated by embedding a 60Hz, 2-volt peak-to-peak sinusoid over one time-period in all the EMG channels.

To reject such temporary faults, an adaptive Kalman filter was developed (see Appendix A). The innovation sequence i.e. $z_k^{\text{mode}} = y_k - C^{\text{mode}} x_{k|k-1}^{\text{mode}}$ for an optimal Kalman filter should be Gaussian white noise [5]. The autocorrelation function ($\Psi_{k-N+1}^{k\ \text{mode}}$) would go out of its confidence interval if the Kalman filter is sub-optimal [6] so we buffered the innovation sequence in a sliding window of length $N = 200$ data points to estimate $\Psi_{k-N+1}^{k\ \text{mode}}$ at each time step k. We found from the training data that the deviation in $\Psi_{k-N+1}^{k\ \text{mode}}$ from its confidence interval was much greater during simulated sensor fault than due to mode changes. Therefore a threshold for detecting these occasional EMG sensors fault was selected empirically in order to adapt the covariance of the measurement noise R_k^{mode} during temporary faults with that estimated from the buffered data [6].

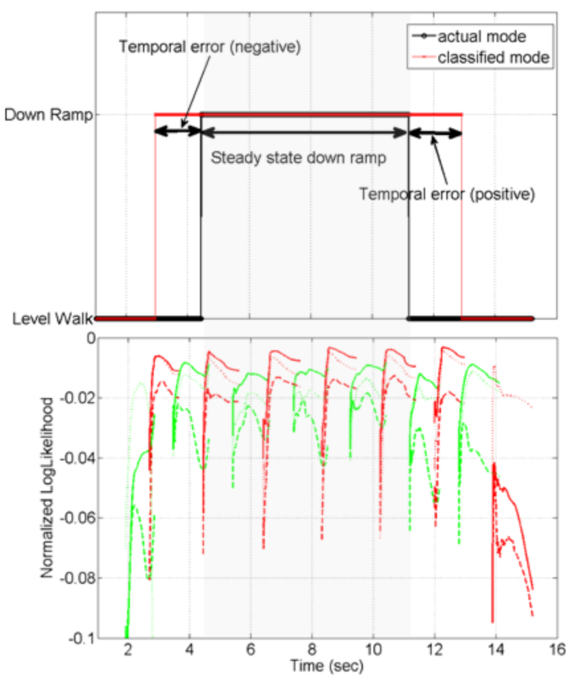

Fig. 2. Normalized loglikelihood from mode-specific Kalman filters during down-ramp walking and corresponding temporal classification error (green: stance phase of prosthetic side, red: swing phase of prosthetic side, solid line: down-ramp Kalman filter, dotted line: level-walk Kalman filter, dashed-line: up-ramp Kalman filter).

III. Results

A. Argmax() classifier performance

The mode classifier was evaluated during steady-state modes as well as during mode transition. Figure 2 shows a representative plot of the variation in normalized log-likelihood of the down-ramp Kalman filter (solid line), the level-walk Kalman filter (dotted line), and the up-ramp Kalman filter (dashed line). The gait cycle was divided into stance (green line) and swing (red line) phases of the prosthetic side as shown in Figure 2. The patient transitioned from level walking to down-ramp at approximately 4.5 seconds, and transitioned back to level ground walking at approximately 13 seconds. The temporal error during regime transition (mode transition) is presented as the time difference between the actual regime transition identified by the experimenter using the recorded video (actual mode) and that inferred by the classifier (classified mode). The percent misclassification errors during steady state regimes as well as temporal error during regime transitions are tabulated in Table 1.

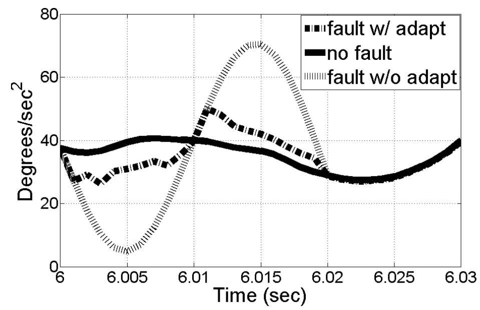

Fig. 3. Estimation of knee angular acceleration in sagittal plane by level-walk Kalman filter with and without adaptation. The absolute error from no fault condition (solid line) was 8.89±6.26 deg/sec^2 with adaptation (dashed line) and 20.48±11.88 deg/sec^2 without adaptation (dotted line).

B. Simulated sensor fault rejection

The knee angular acceleration estimated with a level-walk Kalman filter with adaptation (dashed line) and without adaptation (dotted line) during simulated sensor fault is shown in Figure 3. The absolute error with respect to the no fault condition (solid line) was 8.89±6.26 deg/sec^2 with adaptation and 20.48±11.88 deg/sec^2 without adaptation.

TABLE I. Mode Classification. Diagonal terms are for Steady State Errors while off diagonal terms are for mode transition temporal error

Modes From	to level walk	to up ramp	to down ramp
level walk	2.78 %	-0.65±0.58 sec	-1.18±0.26 sec
up ramp	0.83±0.41 sec	1.84%	
down ramp	1.23±0.27 sec		1.25%

IV. Discussion

The Bayesian inference system estimated the state trajectory as well as classified the mode at each time step which transitioned from one regime to another. The regime transitions had temporal errors of approximately 1sec (Table I). We assigned the transition event to be the time of toe-off of the prosthesis before entering the next regime. It is possible that the actual transition occurs either before or after this time or that the transition time is regime dependent. Varol et al [7] presented a multi-class classifier based on physical sensor data which had temporal errors of approximately 500ms for transitions between sitting, standing, and walking. The temporal error may be reduced by improving the mode-specific Kalman filter model [8] thus improving the discrimination ability of the loglikelihood during transitions using argmax() test. For example, we assumed constant acceleration to derive the state transition matrix which may not be appropriate during the transitions. However the time of the actual regime transition still remains unclear.

Our steady-state mode classification rate was over 97% (misclassification error < 3%) across the modes (Table I). Huang et al. [3] presented an overall classification error of approximately 8.5% in two unilateral transfemoral amputees for pre-toe-off phase of gait during different regimes of locomotion: standing, contra-turn, ipsi-turn, stair ascent, stair descent, obstacle, level walking. Pre-defined transition rules implemented via p(mode) in equation 3 will remove unlikely modes during argmax() classification and may further improve the classification accuracy. Our presented framework provides classification at each time step unlike Huang et al [3] and can be easily extended to more modes addressing other regimes of locomotion like stair-ascent, stair-descent, etc. Moreover, the Kalman filter temporarily adapted the measurement covariance in order to reduce the effect of simulated EMG sensor fault on state estimates. However, a permanent failure of a sensor will need a long-term adaptation strategy such as online identification of measurement covariance [6].

V. Conclusion

We showed a principled way for combining signals from multiple sources into state estimates of a dynamical system. We have presented a framework for temporary sensor-fault tolerant Bayesian inference system which estimated the mode of operation at each time step. It can be used for contextual switching of mode-specific static parameters of a controller.

Appendix

Mode-specific adaptive Kalman filter algorithm:

1. Initialization

$$k := 0,\ x_{0|-1}{}^{\text{mode}} := \bar{x}_0{}^{\text{mode}},\ P_{0|-1}{}^{\text{mode}} := P_0{}^{\text{mode}}$$

The initialization values $\bar{x}_0{}^{\text{mode}}$ and $P_0{}^{\text{mode}}$ found from training data for each mode.

2. Correction step

$$x_{k|k}{}^{\text{mode}} = x_{k|k-1}{}^{\text{mode}} + K_k{}^{\text{mode}} z_k{}^{\text{mode}}$$

where $z_k{}^{\text{mode}} = y_k - C^{\text{mode}} x_{k|k-1}{}^{\text{mode}}$ is innovation sequence

$$\mathrm{K}_{\mathrm{k}}{}^{\text{mod}\,e} = P_{k|k-1}{}^{\text{mode}} C^{\text{mode}^T} \left(C^{\text{mode}} P_{k|k-1}{}^{\text{mode}} C^{\text{mode}^T} + R_k{}^{\text{mode}} \right)^{-1}$$

is the Kalman gain

$$P_{k|k}{}^{\text{mode}} = P_{k|k-1}{}^{\text{mode}} - K_k{}^{\text{mode}} C^{\text{mode}} P_{k|k-1}{}^{\text{mode}}$$

3. Fault detection and adaptation

$$N = 200,\ \Psi_{k-N+1}^{k}{}^{\text{mode}} = \frac{\sum_{i=k-N+1}^{k} z_i{}^{\text{mode}} z_i{}^{\text{mode}^T}}{N},$$

$$\Phi_{k-M+1}^{k}{}^{\text{mode}} = \frac{\sum_{i=k-N+1}^{k} C^{\text{mode}} P_{i|i-1}{}^{\text{mode}} C^{\text{mode}^T}}{N}$$

$$\text{If} \begin{pmatrix} k > N \,\&\, \text{diag}\left(\Psi_{k-N+1}^{k}{}^{\text{mode}} - \Phi_{k-N+1}^{k}{}^{\text{mode}} - R_0{}^{\text{mode}} \right) \\ > \text{threshold} \end{pmatrix}$$

$$\text{then } R_k{}^{\text{mode}} = \Psi_{k-N+1}^{k}{}^{\text{mode}} - \Phi_{k-N+1}^{k}{}^{\text{mode}}$$

$$\text{else } R_k{}^{\text{mode}} = R_0{}^{\text{mode}}$$

The threshold for detecting sensor fault was found empirically.

4. One-step prediction

$$x_{k+1|k}{}^{\text{mode}} = A x_{k|k}{}^{\text{mode}},\ P_{k+1|k}{}^{\text{mode}} = A P_{k|k}{}^{\text{mode}} A^T + Q^{\text{mode}}$$

5. Update $k := k+1$ and go to 2.

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