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Continuous Movement Decoding Using a Target-dependent Model with EMG Inputs

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Abstract—**Trajectory-based models that incorporate target position information have been shown to accurately decode reaching movements from bio-control signals, such as muscle (EMG) and cortical activity (neural spikes). One major hurdle in implementing such models for neuroprosthetic control is that they are inherently designed to decode single reaches from a position of origin to a specific target. Gaze direction can be used to identify appropriate targets, however information regarding movement intent is needed to determine when a reach is meant to begin and when it has been completed. We used linear discriminant analysis to classify limb states into movement classes based on recorded EMG from a sparse set of shoulder muscles. We then used the detected state transitions to update target information in a mixture of Kalman filters that incorporated target position explicitly in the state, and used EMG activity to decode arm movements. Updating the target position initiated movement along new trajectories, allowing a sequence of appropriately timed single reaches to be decoded in series and enabling highly accurate continuous control.**

I. Introduction

PATIENTS who have spinal cord injuries at the C5-C6 level typically maintain residual function in their shoulder and elbow flexors, but lose the ability to extend the arm [1]. This provides limited control of shoulder and arm movement, but results in an inability to reach. Residual muscle activity can be measured using electromyography (EMG) and used as a control signal to drive restorative devices or models of predicted movement intent [2].

The Kalman filter (KF) is a method of probabilistically predicting the evolution of a system's state over time [3]. It recursively combines information from an *observation* model, which describes the relationship between measured variables and the system state, with that of a *trajectory* model describing how the state changes probabilistically over time. In the example of predicted reach dynamics, the arm would represent the system, and its state would typically include kinematic measures (e.g. position, velocity, and/or acceleration) of limb segments and/or joint angles. KFs have been used to control computer cursors, prosthetic devices, and functional electrical stimulation using biological signals such as neural spikes and EMG [4-6].

EMG activity can be interpreted as a noisy observation of the limb state and used to predict the evolution of arm movement over time. The accuracy of predictions, however, depends on both the variety of muscles recorded from and the range of trajectories used to train the model. When a single reach trajectory is of interest, movement along this trajectory can be accurately reconstructed from a very sparse number of control sources. As the number of possible trajectories increases, however, limited degrees of freedom in the control signal can cause the KF to degrade to essentially a random drift model. If the number of potential targets is limited, a mixture of trajectories model (MTM) can be implemented based on known target information [7]. Alternatively, information about the position of the intended target can be included as a component of the Kalman filter's state (KFT) [8, 9]. This dramatically improves the accuracy of predicted movements toward even novel targets across a broad workspace, without the need for increased degrees of freedom in the control signal.

Information about the intended target during an active reach can be derived using gaze tracking, based on the fact that individuals tend to look at intended targets prior to reaching for them [10]. The timing between gaze and movement toward an intended target may vary, however. To compensate for this, multiple gaze points representing multiple potential targets can be combined probabilistically in a mixture of Kalman filters (mKFT) that allows for uncertainty in the target information [9].

mKFTs have been shown to predict limb movements from EMG activity during discrete reaches with high accuracy, however functional clinical implementation would likely require movements to be decoded in continuously. Using the same framework, new arm movements can be initiated in an efficient way by merely updating the target information. Doing so for a series of discrete reaches would result in continuous control. The challenge therefore lies in selecting a command signal to trigger target updates that is intuitive to

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the user and can differentiate active reaches to targets the subject is likely to look at from withdrawal movements that are likely to be unrelated to gaze direction. Machine learning techniques have previously been shown to detect state transitions accurately from movement related neural data, allowing discrete changes in decoder architecture to be made on the fly during continuous decoding [11]. Similar methods could be applied to the movement related EMG activity that is already being used as a control signal for the mKFT in order to detect state transitions and update target information in the decoder.

Here, we have investigated the ability of an mKFT to decode movement continuously from a limited set of EMG signals during a series of reaches. To gauge the ideal performance of this method, we initially updated target information based on changes in measured velocity of the actual movement signal and the known target locations. In order to gauge more realistic performance without the need for an explicitly generated transition signal, we also investigated a method of detecting movement onset from a limited set of EMG signals recorded during the different phases of a normal reach combined with gaze information to determine possible target locations.

II. Methods

A. Data Collection

To date, one healthy male subject has completed this study. Informed consent was provided prior to participation and the experimental protocol was approved by the Northwestern University Institutional Review Board.

The subject performed unconstrained three-dimensional reaches to a bank of 16 LEDs that were just within reach and covered a large workspace on two intersecting vertical planes [9]. The positive x, y, and z directions corresponded roughly with forward, right, and down from the subject's perspective. Eighteen blocks of reach trials were analyzed, each lasting 160s. Six of the blocks comprised reaches made at normal speed, six were fast reaches and six were slow reaches.

Each trial began with the subject's right arm in a neutral position with the hand resting in his lap, followed by the appearance of a target LED. The subject was instructed to fixate the LED, which was lit for 1s prior to an auditory "go" cue. Following the "go" cue, the subject was instructed to reach toward the LED in a natural manner consistent with the intended speed of the trial. Once the LED was reached, the subject was instructed to hold his finger in place until a second auditory cue was given, after which the hand was withdrawn and returned to the neutral resting position.

Throughout the experiment, the subject's wrist was fixed in mid-position with the index finger extended. Movements were tracked in three dimensions with a sampling rate of 60 Hz by a commercial motion analysis system (Optotrak 3020, Northern Digital Inc., Waterloo, Canada). EMG activity was recorded from the ispilateral trapezius, anterior deltoid, and middle deltoid muscles. EMG activity was bandpass filtered between 10 and 1000 Hz and sampled at a rate of 2400 Hz. Prior to further analysis, EMG signals were averaged over windows of 16.7 ms to provide overall sampling equivalent to that of the motion tracking system. The direction of the subject's gaze was recorded at a rate of 60 Hz using a head mounted eye tracking system (EYETRAC-6, ASL, Bedford, MA).

B. Detection of Movement State Transitions

We used linear discriminant analysis (LDA) to detect movement transitions based on recorded EMG data. Each trial was divided into two periods: (1) *reach* and (2) *withdrawal*. The *reach* period began when the subject first moved his hand away from the neutral position toward a target and ended when the subject began to withdraw his hand from the target. The *withdrawal* period included the time the subject began to move from the target toward the neutral position to the time he began to move toward a new target (the start of the next trial). Ground truth movement transitions were defined as the times when the finger speed increased above a threshold equal to 2% of the maximum speed for each block of trials.

EMG data were rectified and then low-pass filtered at a frequency of 3 Hz to obtain the EMG envelope prior to use in the classifier. Classifier inputs included the envelope and time derivative of the envelope for EMG recorded from the anterior and middle deltoids. A refractory period of 0.5s was enforced following each movement state transition, during which the new state was fixed and transition back to the previous state was not allowed.

C. Predicting Movement from EMG and Gaze

Three models of continuously predicted limb movements were compared: (*GKF*) – a generic Kalman filter with no target information; (*KFT*) – a Kalman filter that incorporated known target information as a component of the state and updated target position based on ground truth movement transitions; and (*mKFT*) – a mixture of Kalman filters that incorporated target information derived from gaze tracking and updated target position based on movement transitions determined by the LDA classifier. (For more detail on Kalman filter implementation see [9, 12].) The observation model in each of these cases was built on the windowed EMG signals from the ipsilateral trapezius and anterior and middle deltoids. The KFT was intended to provide a best-case scenario for continuous decoding using the proposed algorithm, while the mKFT represented a more realizable implementation.

To define target positions for the mKFT, gaze points were first determined by projecting from the eye along the direction of gaze to the planes on which the surrounding LEDs resided. When the start of a new reach was detected, the gaze point at that moment and the individual gaze points preceding the transition by 0.5 and 1s were selected as three possible intended reach targets (note that these did not necessarily correspond with the locations of the LEDs). The remaining gaze points within the second preceding the transition were each clustered with the potential target of closest proximity. The relative numbers of total gaze points within each of the three clusters defined priors over the potential targets. When the subject began to withdraw his hand from the target, the eye-tracking data were ignored and the new target was simply set to the starting neutral location.

Each algorithm was trained with data from five blocks of trials of a given speed and cross-validated by testing on the remaining block of that same speed. This was repeated such that each block of trials was used once as the testing block. Trials with incorrect eye-tracking calibration were discarded for the purposes of mKFT testing. Prediction performance was measured using the multiple correlation coefficient, R^2 [13].

III. Results

Both the KFT and mKFT predicted finger position during fast reaches with high accuracy (Fig. 1). Two types of errors are visible in the mKFT data presented here: during the withdrawal that occurred at 74s the classifier detected the movement transition slightly early, and during the reach that occurred at 78s an incorrect target was included in the mixture with a fairly large prior that caused the mKFT trajectory to deviate from that of the KFT. The mKFT was able to overcome both of these errors to converge ultimately to the correct targets. The GKF had some difficulty tracking position, and tended to drift over time. Its performance was best in the *z* direction, which corresponded roughly with arm elevation and was therefore the most directly related to trapezius and deltoid activity. For fast reaches the KFT produced R^2 of 0.98 ± 0.003 (mean ± SD), the mKFT produced R^2 of 0.98 ± 0.003, and the GKF produced R^2 of 0.52 ± 0.08.

The KFT predicted finger position nearly as well during normal reaches as in the fast condition, however the mKFT predictions were less accurate (Fig. 2). This is largely because the classifier had difficulty determining movement transition points with the shallower rise and fall of EMGs during normal reaches. This resulted in frequent delays between actual and detected movement onset, which translated into delayed target updates. Over time, the mKFT generally converged to the appropriate target, however, not as accurately as did the KFT. The GKF again had difficulty tracking position, and tended to drift over time. For normal reaches the KFT produced R^2 of 0.96 ± 0.01, the mKFT produced R^2 of 0.87 ± 0.02, and the GKF produced R^2 of 0.55 ± 0.08.

The performance of the KFT during the slow reaching condition was equivalent to its performance at normal speed. However, mKFT accuracy declined even further due to transition detection delays and occasional oscillation of detected states near the transition points. For slow reaches the KFT produced R^2 of 0.96 ± 0.01, the mKFT produced R^2 of 0.84 ± 0.06, and the GKF produced R^2 of 0.62 ± 0.06.

To further address the question of how delayed transition detection could affect prediction accuracy, we systematically

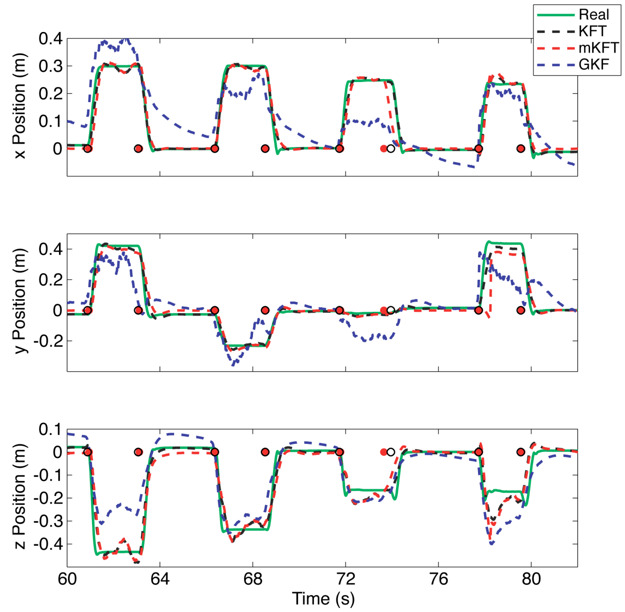

Fig. 1. A series of fast reaches with predictions made by the KFT, mKFT, and GKF. Ground truth transitions are indicated by open circles and LDA-based transitions are indicated by closed red circles.

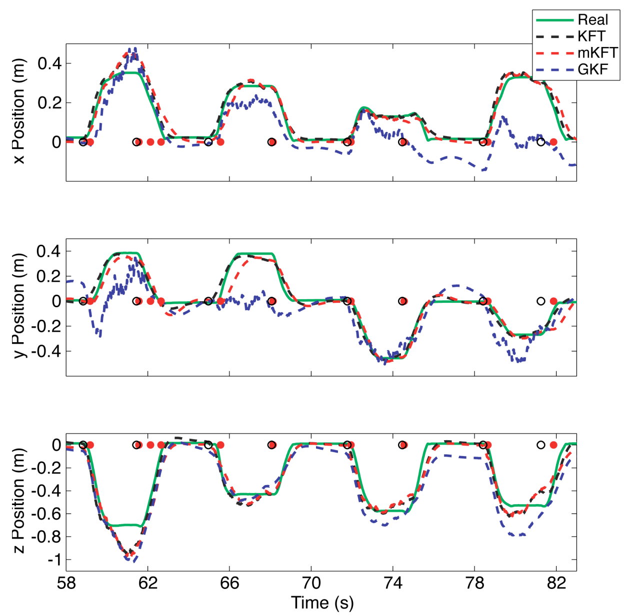

Fig. 2. A series of normal reaches with predictions made by the KFT, mKFT, and GKF. Ground truth transitions are indicated by open circles and LDA-based transitions are indicated by closed red circles.

delayed the movement transitions in the KFT model (Fig. 3). Relative endpoint error was defined as the difference between the predicted and actual finger position at the conclusion of the reaching movement, scaled by the length of the reach. While prediction accuracy (R^2) decreased as a function of transition delay, endpoint error did not. This demonstrated that even when predictions of new reaches were initiated late, they tended to converge to the correct location. Fast reaches resulted in the lowest endpoint error but their overall prediction accuracy was more sensitive to transition delays than that of normal and slow reaches.

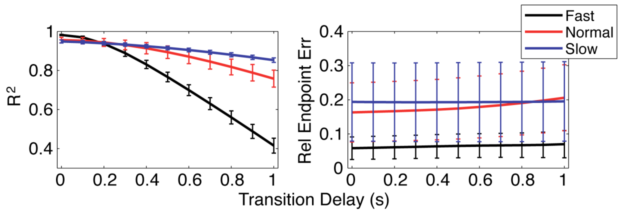

Fig. 3. Overall prediction accuracy (R^2) and relative endpoint error plotted as a function of the imposed transition delay and reach speed for the KFT. Lines are mean values across all blocks at the given speed and error bars indicate standard deviation.

Removing the refractory period between movement state transitions resulted in occasional oscillations between classified movement states at the transition points, however this did not significantly affect the mKFT predictions.

IV. Discussion

Both the KFT and mKFT predicted finger endpoint position continuously during a series of reaches by updating target information at the start of each new movement. High prediction accuracy was achieved using a noisy control signal that contained limited degrees of freedom. Limitations in performance were due primarily to difficulties in detecting movement state transitions and/or incorrect target information. The effect of the first of these was reported here (Fig. 3), while the effect of the second is reported elsewhere for the single reach case [12].

The method of detecting state transitions presented here worked well for fast reaching movements characterized by strong and abrupt changes in EMG activity. As the intended reach speed decreased, however, detection accuracy also decreased and adversely affected performance of the mKFT. Fortunately, continuous predictions of slower reaches were less sensitive to transition delays than predictions of fast reaches were, such that the cost of decreased state detector performance was less in conditions where the state detector struggled.

Note that the prediction accuracy of the KFT, which used ground truth movement state transitions, was not affected by movement speed. Therefore the actual movement decoding is robust to speed changes. In order to more reliably signal movement onset, the user could emphasize movement at the beginning of the reach and then continue along the trajectory at his or her own self-selected speed by using an extended version of the mKFT [9].

Our analysis demonstrates that target-dependent trajectory models can be paired with simple state detection methods to continuously predict a series of reaches. The state detector presented here performed well for the experimental task and would be appropriate for reaches to and from a home position. Other methods might be better suited for more general applications, including movements between remote targets. Such methods could require information from other sources, such as additional muscles, since EMG modulation in the deltoids would likely not be a good indicator for the onset of all types of reaching movements. The principles elicited here, however, should inform the design of such state detectors.

The accuracy of single reach decoding with mKFTs generally increases with the quality of target information and with the degrees of freedom in the control signal [12]. Techniques similar to those presented here could be applied to neural recordings, which represent a very rich control signal containing detectible movement state transition information [11, 14]. This could potentially provide a highly accurate and intuitive method for continuously decoding reaching movements for severely impaired patients.

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