34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

Predicting the initiation of minimum-jerk submovements in three-dimensional target-oriented human arm trajectories

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***Abstract*— Target-oriented human arm trajectories can be represented as a series of summed minimum-jerk submovements. Under this framework, corrections for errors in reaching trajectories could be implemented by adding another submovement to the ongoing trajectory. It has been proposed that a feedback-feedforward error-detection process continuously evaluates trajectory error, but this process initiates corrections at discrete points in time. The present study demonstrates the ability of a feed-forward Artificial Neural Network (ANN) to learn the function of this error-detection process. Experimentally recorded human target-oriented arm trajectories were decomposed into submovements. It was assumed that the parameters of each submovement are known at their onset. Trained on these parameters, for each of three participants, an ANN can predict presence of corrections with sensitivity and specificity > 80%, and can predict their timing with R^2 > 40%.**

I. INTRODUCTION

As able-bodied humans perform target-oriented arm reaches, feedback or feedforward processes evaluate the current state of the system relative to the target and modify the remaining portion of the trajectory to correct for errors [1], [2].

If these corrections are made at discrete points in time, then the overall movement can be described as the summation of a set of discrete submovements. Studies of individuals recovering from stroke [3], [4] provide support for this hypothesis. Prior to stroke recovery, reach trajectories are composed of separate isolated submovements. As individuals recover, these submovements progressively overlap and coalesce.

Submovements have been observed in movements requiring accuracy [5], and are the basis of several models of human motor control [6], [7], [8], [9], [2].

One popular mathematical representation of a submovement is the minimum-jerk trajectory [10]. It has been shown that arm reaching movements can be represented as the sum of minimum-jerk submovements [11], [12]. In addition, minimum-jerk trajectories can be described using only a few parameters. This feature is useful when decomposing a recorded trajectory into its component submovements, a computationally expensive optimization problem [13].

*This work was supported by NICHD under N01-HD-5-3403

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The objective of the current study is to investigate whether the initiation times of the submovements can be predicted using an Artificial Neural Network (ANN). This study assumes that target-oriented reaches are composed of minimum-jerk submovements whose parameters are known when they are initiated, and that feedback-feedforward processes continuously evaluate error but trigger separate trajectory-correcting submovements at discrete points in time [14]. Under these assumptions, it will be demonstrated that the ANN can mimic the ability of the continuous error evaluation process to determine whether corrections are required. To accomplish this, three-dimensional arm reach trajectories are decomposed into minimum-jerk submovements. Then, an ANN is trained to predict whether a corrective submovement is necessary.

II. METHODS

Three able-bodied right-handed human participants provided written informed consent in accordance with the MetroHealth Medical Center Institutional Review Board. Each participant made a series of right-hand reaching movements from a fixed resting arm position to a series of distal targets positioned in the reachable workspace. The distal target was presented on the end of a robotic arm (HapticMaster, Moog in The Netherlands, Nieuw-Vennep, The Netherlands). The target was presented as a hollow sphere octant of radius 25mm, and participants were required to imagine the rest of the sphere.

The robotic arm was used to position the target sphere at various locations in the reachable workspace. When the target was correctly positioned, an audible cue instructed the participant to reach from the resting position to the target. Participants were required to reach and hold their fingertip inside the target sphere for one second. Following the hold period, the robotic arm moved to its home position and the participant returned their arm to the resting arm position. After a brief pause, the target was repositioned and an audible cue signaled the next reach. Each participant made 250 reaching movements.

Fingertip position was recorded using an optical tracking system (Optotrak 3020, Northern Digital Inc., Waterloo, Ontario, Canada). The participants wore a rigid assembly containing an index-finger brace and an LED marker cluster. The markers were held over the dorsal aspect of the right hand. After calibration, the position of the fingertip was continuously calculated relative to the position and orientation of the marker cluster. Additional LED markers were attached to the robotic arm. Data was recorded at 100 Hz and collected on a single desktop computer running custom

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Simulink (Mathworks Inc., Natick, MA, USA) software. The software also controlled the positioning of the robotic arm.

Post-processing was done offline in Matlab (Mathworks Inc., Natick, MA, USA). First, the recorded trajectories were low-pass filtered at 10 Hz using a zero-phase digital filter. Then, each reaching movement was decomposed into a series of summed minimum-jerk submovements. Once the individual submovements were determined, the initiation times were modeled.

A. Submovement Decomposition

The decomposition was based on an optimization approach [15], [16], [13] applied in three-dimensions. The measured reach trajectory is reconstructed using one or more minimum-jerk submovements of the form:

$$\begin{aligned}\dot{x}(t) &= 30D_x\left(\frac{(t-t_0)^4}{t_d^5} - 2\frac{(t-t_0)^3}{t_d^4} + \frac{(t-t_0)^2}{t_d^3}\right)\\ &\quad t_0 \le t \le t_0 + t_d\\ \dot{x}(t) &= 0\\ &\quad otherwise\end{aligned} \tag{1}$$

where $\dot{x}(t)$ is the x velocity, D_x is the displacement of the submovement, t_0 is the start time, and t_d is the submovement duration. If more than one submovement is used, the summation of the submovements represents the reconstructed trajectory:

$$F_x(t) = \sum_i^N \dot{x}_i(t) \tag{2}$$

where N is the total number of submovements and $\dot{x}_i(t)$ represents the x velocity of submovement i.

Submovements are three-dimensional, so similar expressions exist for $\dot{y}(t)$ and $\dot{z}(t)$. Therefore, each submovement has five parameters: D_x, D_y, D_z, t_0, and t_d. An optimization was performed to find the parameters that minimize the following cost function:

$$\begin{aligned}Cost = &\sum_t (F_x(t) - G_x(t))^2\\ &+\sum_t (F_y(t) - G_y(t))^2\\ &+\sum_t (F_z(t) - G_z(t))^2\\ &+\sum_t (F_{speed}(t) - G_{speed}(t))^2\end{aligned} \tag{3}$$

where F_x, F_y, and F_z represent the x, y, and z velocity components of the reconstructed trajectory, and G_x, G_y, and G_z represent the x, y, and z velocity components of the measured trajectory. F_{speed} and G_{speed} were introduced to prevent simultaneous submovements of opposite displacements from occurring [16]. They are defined as follows:

TABLE I
INPUTS FOR ARTIFICIAL NEURAL NETWORK

Input Name	Description
Scaled Amplitude	Amplitude of current submovement relative to distance-to-target at submovement initiation
Distance	Remaining distance-to-go in current submovement
Error	Distance from current position to target
Scaled Error	Error relative to distance-to-target at submovement initiation
% Remaining Time	Remaining time relative to submovement duration
Elapsed Time	Time since current submovement began
Velocity	Sum of velocities of current and previous submovements
Speed	Tangential velocity

$$\begin{aligned}F_{speed}(t) &= \sqrt{F_x(t)^2 + F_y(t)^2 + F_z(t)^2}\\ G_{speed}(t) &= \sqrt{G_x(t)^2 + G_y(t)^2 + G_z(t)^2}\end{aligned} \tag{4}$$

The number of submovements N is unknown a priori, so for each reach, decomposition was repeated for $N = \{1, \ldots, 10\}$. As the number of submovements increases, the cost decreases. The optimal number of submovements was determined using an algorithm that detects the point of maximum curvature in the cost-per-submovements curve [17], selecting the minimum number of submovements required for near-asymptotic performance.

B. Initiation-Time Prediction

From the optimal set of submovements, a number of parameters were calculated. These parameters, described in Table I, were used as inputs for a feed-forward ANN with one hidden layer containing 10 neurons.

The data was divided into separate training and testing sets. For each submovement, at each point in time, the ANN was trained to produce 1 if the subsequent submovement had begun, and 0 otherwise. The network was trained using Bayesian regulation backpropagation.

The testing sets were used to evaluate network performance. For each submovement in the testing sets, the ANN was evaluated on the inputs at each point in time. The first timestep with ANN output exceeding 0.5 was determined to be the initiation time t_0 for the subsequent submovement.

Cross-validation was performed by repeated random subsampling. In total, the data was resampled 300 times and the ANN was trained 300 times.

III. RESULTS

For each testing set, the true positives, false positives, true negatives, false negatives, sensitivity, specificity, positive predictive value, and negative predictive value were calculated. The means of these values over all testing set samples for participant C are shown in Table II. The corresponding values for participants A and B are similar but not shown.

TABLE II

ACTUAL CORRECTIONS VS PREDICTED CORRECTIONS

Actual Correction		No Actual Correction	
Predicted Correction (True Positive)	83.0	Predicted Correction (False Positive)	4.8
No Predicted Correction (False Negative)	13.8	No Predicted Correction (True Negative)	45.2
Related Values			
Sensitivity	85.8%	Specificity	90.4%
Positive Predictive Value	94.6%	Negative Predictive Value	86.4%

Note: values shown are means taken over all testing sets for participant C

True positives represent submovements for which there was a correction and the correction was predicted successfully. False positives represent submovements for which there were no actual corrections but a correction was predicted. True negatives represent submovements for which there were no actual corrections and no correction was predicted. False negatives represent submovements for which there was an actual correction but a correction was not predicted.

For the true positive cases, the actual time of correction was plotted against the predicted time of correction (Fig 1). Initiation times are shown relative to the time the previous submovement began. This was repeated over the 300 testing sets and a histogram of the R^2 values is also shown (Fig 2).

In total, data from three participants were analyzed. The mean R^2 for participants A, B, and C were 40.2%, 58.8%, and 61.5% respectively.

IV. DISCUSSION

The current study shows that an ANN can trigger submovements in a way that mimics the initiation timing of submovements derived from actual 3D target-oriented human arm trajectories. It has been proposed that a feedforward-feedback process continuously evaluates errors over the course of a trajectory, but that corrective submovements are initiated at discrete points in time [14]. Results suggest that a simple feed-forward ANN can function as the continuous error-evaluation process, predicting whether (Table II) and when (Figures 1 and 2) corrections should happen.

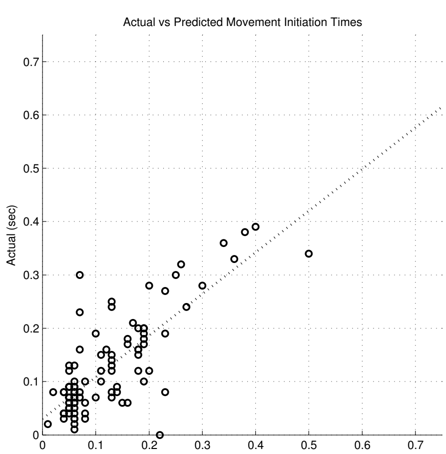

Fig. 1. Actual versus predicted movement initiation times for one testing set from participant C. Initiation times are shown relative to the time the previous submovement began. The dotted line represents the linear regression on this testing set, with $R^2 = 62.6\%$. Only true positives are included in the calculation of R^2.

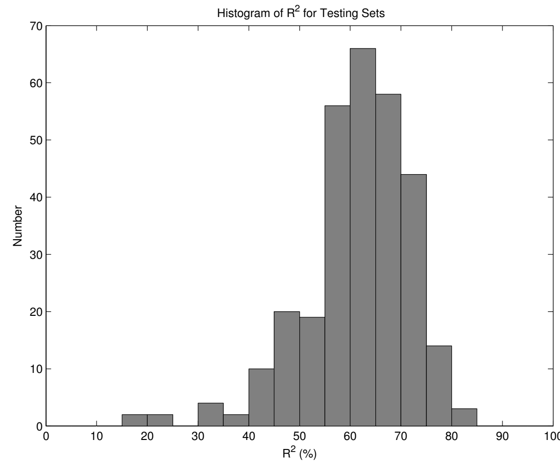

Fig. 2. Histogram of true positive cross-validation results for participant C. Cross-validation was performed by repeated random subsampling of the data into training and testing sets. For testing set, a single R^2 is calculated from the actual versus predicted movement initiation times for all true positive cases (Fig.1). This histogram contains all of the R^2 values from each testing set. The mean R^2 value is 61.5%.

Feed-forward ANNs can learn any input-output relationship given enough hidden layer neurons [18]. The current study suggests that there is a relationship between the submovement parameter inputs (Table I) and whether a correction is necessary. However, no assumptions are made regarding the components of the underlying motor processes that generate submovements.

A previous study demonstrated the ability to predict the timing of the second submovement in a one-dimensional monkey arm-pronation-supination task [14], achieving R^2 values of 50% and 56% for two monkeys using a simple model to predict whether corrections are necessary. In the present study, human participants perform 3D arm reaching movements and an ANN performs the prediction. If only the second submovement of each reach are included in the R^2 calculation, the values for participants A, B, and C change to 35.3%, 54.1%, and 65.8% respectively.

Use of R^2 as a performance metric has limitations because cases where there are no actual correction times or no predicted correction times cannot be represented in Figures 1 or 2. For instance, the false-positive case happens when there is no actual correction, as in the terminal submovement of each reach, yet there is a predicted correction. There is no way to include this case without biasing R^2. False-positives and false-negatives should somehow penalize the performance metric. True-negatives should somehow reward the performance metric. However, there is no unbiased way to represent these cases using R^2.

An attempt was made to represent these cases using the sensitivity and specificity in Table II. These show that the model can predict to some degree whether a corrective submovement is or is not necessary. However, the current analysis is limited, and more work is necessary to understand the influence of a certain model specificity or R^2 value on the quality of arm reaches generated in part by that model.

There are sources of variability in arm trajectories that are not accounted for in the current study. These limit the ability of the ANN to predict when submovements occur. Neural sources of variability include uncertainty associated with planning and noise during motor execution [19], [20], [21]. The dynamics of the arm may play a factor [22]. Also, there may be measurement noise associated with calculating the position of the fingertip. Reducing the mass of the rigid finger-hand assembly and moving the optical tracking markers closer to the fingertip may mitigate this source of variability.

The ANN represents the average behavior for each participant over all of the reach trajectories. In the future, this model could act as a component of a closed-loop simulation of reaching movements. The ANN would function as an error-evaluator, and other components would generate subsequent submovements when triggered by the ANN.

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