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A State-Space Model for Finger Tapping with Applications to Cognitive Inference

Daniel Austin, *Student Member, IEEE,* Johanna Petersen, *Student Member, IEEE,* Holly Jimison, *Member IEEE*, and Misha Pavel, *Senior Member, IEEE*

***Abstract*—Sensory-motor functions have been repeatedly linked to both cognitive and physical functions. One common test of sensory-motor performance frequently used for neuropsychological evaluation is the Halstead-Reitan finger tapping test (FTT). While this test has been normed and used extensively, the underlying sensory, motor and cognitive processes mediating tapping behavior during the test are not well understood. As a first step towards investigating the behavioral aspects manifested by these processes, we describe a state-space model for finger tapping during the FTT. This state-space model exploits quasiperiodicity to decompose tapping into a set of time-varying states corresponding to the instantaneous amplitude of the finger oscillation, the instantaneous frequency (or speed) of tapping, and a phase that keeps track of the current finger position during the cycle. We evaluate the model by showing a good fit between estimated and actual measurements, and outline an experiment that will relate features from the model to cognitive function.**

I. Introduction

Motor function is an important predictor of both cognitive and physical function. Motor slowing in elderly patients has been shown to precede cognitive impairment[1-3] and has also been linked to cognitive function[4, 5] and risk of future disability[6, 7]. Measured levels of motor dysfunction have been used to differentiate between normal aging and different levels of dementia[8, 9], and excessive motor speed asymmetry has been seen in patients diagnosed with probable Alzheimer's disease[10].

One specific task that is often used to assess motor function is finger tapping. While many tapping tasks exist, one of the most commonly used for neuropsychological evaluations and diagnoses[11] is the Halstead-Reitan Finger Tapping Test (FTT)[12]. This test is scored as the average number of times a patient depresses a key with his or her index finger (each hand is tested separately) in a series of trials on a manual finger-tapping device, where each trial lasts 10 seconds. The test nominally consists of 5 tapping trials, but will continue until either the counts on all trials are within five of each other or 10 trials are administered [13].

Despite the popularity and wide-spread use of the FTT, the underlying phenomena of tapping during this test are not well understood. As a comprehensive understanding of tapping behavior during the test will allow more precise inferences about the cognitive processes that regulate and mediate tapping, it is increasingly important to study and understand this behavior. Recent research supports this assertion by demonstrating that motor phenomena other than absolute speed – such as variability and accuracy - are also predictive of future cognitive decline[14], are impaired in early stage dementia[15], and are related to cognition[16]. In terms of tapping, empirical observations demonstrate motor change on multiple time scales during the course of the FTT. For example, tapping speed and range of finger movement can change both on a tap-to-tap basis and more persistently over time, perhaps due to fatigue or distraction. None of these features of tapping are captured when average number of taps across trials is the only recorded measure of performance, but – consistent with the research cited above - these behavioral aspects may contain important information about the cognitive processes mediating tapping behavior.

In an effort to better understand tapping behavior and the cognitive processes underlying this behavior, we instrumented a manual finger-tapper with a potentiometer and an ADC that samples a voltage proportional to the angle of the tapping lever, which is in turn proportional to the position of the lever. We then developed a state-space model of tapping during the FTT that relates measurements of the lever angle into an easily interpretable set of behavioral characteristics (states) of the finger, such as tapping frequency and the amplitude of finger oscillation. As will be shown, this set of behavioral characteristics allows study of both short term fluctuations in tapping behavior – such as sample-to-sample or tap-to-tap variability – and persistent changes that may be related to phenomena such as fatigue or learning. In this paper, we describe the state-space model in detail and present a preliminary validation of the model on data collected from two subjects who each participated in four trials of the FTT.

II. Methods

A. Manual Finger Tapper

The manual finger-tapper was built using a Veeder-Root brand counter (model 0727235-002) as an exact replica of

D. Austin is a graduate student with the Biomedical Engineering Department, Oregon Health & Science University, 3303 SW Bond Ave, Portland, OR 973239 USA (corresponding author, phone: 503-418-9332; email: austidan@ohsu.edu).

J. Petersen is with the Biomedical Engineering Department, Oregon Health & Science University, 3303 SW Bond Avenue, Portland, OR 97239 USA (e-mail: feuerste@ohsu.edu).

H. Jimison is with the Department of Medical Informatics, Oregon Health & Science University, 3181 SW Sam Jackson Park Rd, Portland, OR 97239 USA (email: jimisonh@ohsu.edu).

M. Pavel is with the Biomedical Engineering Department, Oregon Health & Science University, 3303 SW Bond Ave, Portland, OR 973239 USA (email: pavelm@ohsu.edu).

the Reitan Neuropsychology Laboratory manual tapper (www.reitanlabs.com). A potentiometer was installed on the shaft of the tapping lever with one wiper arm connected to a USB-1208FS DAQ (Measurement Computing, Norton, MA) to sample the voltage at a frequency of 512 Hz. The resulting measurements were voltages proportional to the angle of the tapping lever. Fig. 1 shows the manual finger tapper used in this experiment during an FTT trial.

B. Subjects, Data Collection, and Analysis

Two healthy subjects, a 32 year old male and a 24 year old female, were recruited for the preliminary evaluation of the model. Both subjects were right handed. Each subject was instructed to tap the manual lever of the finger tapper as quickly as possible with their dominant hand for 15 seconds. We used a longer duration than with the normal FTT administration as the estimation approach used takes time to "lock-on" and track the model states, and to have a longer data record to test the model. A short break was given between each trial lasting between 15 seconds and 1 minute. Before estimation, the measured voltage was normalized to a unitless 0/1 scale to aid in interpretation, where 0/1 correspond to the bottom/top lever positions, respectively.

To estimate the model for each FTT trial for both subjects, we used a variant of the Unscented Kalman Filter (UKF). To validate performance, we calculated the mean-square error (MSE), maximum absolute error, and average absolute error between the measurements and the model predictions of the measurements. The first two seconds of data were excluded from these calculations to allow the filter to "lock-on" and track the states.

III. State Space Model

We developed the model based on the assumption that finger tapping is quasi-periodic. This is driven primarily by the fact that tapping during the FTT is a repetitive action constrained by the position of the tapping lever. Specifically, the physical behavior of tapping on the manual tapper is a series of flexions and extensions of the finger that cause corresponding depressions and releases of the tapping lever. As the lever will only move along a certain trajectory, the flexions and extensions must be done in approximately the same way to perform the test. Based on this assumption, we adapt a commonly used measurement model of quasi-periodic behavior referred to as the rectangular model[17]. The rectangular model is a Fourier expansion that relates the current measurement of an assumed quasi-periodic signal, y_n, to a set of parameters (the current system states) as:

$$y_n = a^1 \sin\theta_n + \sum_{k=2}^{\infty}\left[a^k \sin k\theta_n + b^k \cos k\theta_n\right] \qquad (1)$$

with

$$\theta_n = \sum_{i=0}^{n} T\omega_i + \theta_{-1} \qquad (2)$$

In (1) and (2), y_n is the measurement at time n, the a^k and b^k are the Fourier coefficients of the kth harmonic, θ_n is the phase at time n, with n=-1 indicating the initial phase, ω_i is the angular frequency at time i, and T is the sampling time.

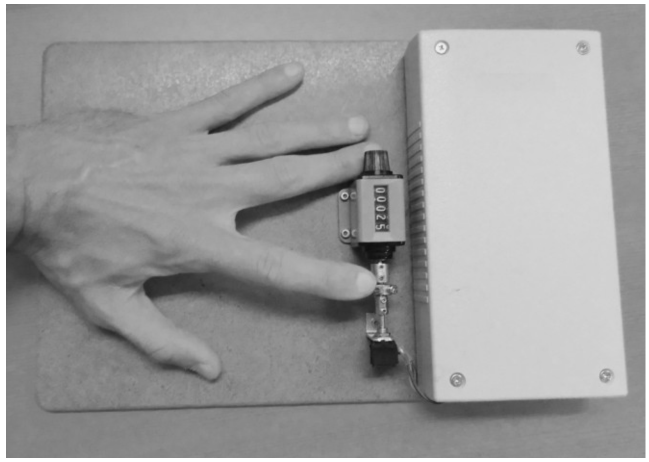

Figure 1. Manual finger tapper board instrumented to sample voltage proportional to lever angle.

Before defining the tapping model, we describe one other important phenomenon that must be modeled. Specifically, we measure a voltage proportional to the position of the finger tapping lever. The distinction of measuring the position of the lever (as opposed to the finger) is important because the tapping lever has a finite range of motion and thus measurement of the position of the finger is truncated on both sides of its range. During a complete tapping cycle, the finger leaves the lever at the end of the release phase and remains out of contact momentarily as it finishes the release phase and starts the depression phase. At the end of the depression phase the finger is obstructed from moving lower than the bottom position of the lever. We model this device limitation directly as a truncation of the measurement.

Adapting (1) and (2), and including the truncation mentioned above, we propose the following state-space model for finger tapping:

$$y_n = \begin{cases} u + w & \text{if } \bar{y} + A_n \cos\theta_n > u \\ \bar{y} + A_n \cos\theta_n + w & \text{if } l \le \bar{y} + A_n \cos\theta_n \le u \\ l + w & \text{if } \bar{y} + A_n \cos\theta_n < l \end{cases} \qquad (3)$$

and

$$\begin{bmatrix} A_{n+1} \\ \omega_{n+1} \\ \theta_{n+1} \end{bmatrix} = \begin{bmatrix} A_n \\ \omega_n \\ \theta_n + T\omega_n \end{bmatrix} + \begin{bmatrix} v_1 \\ v_2 \\ v_3 \end{bmatrix} \qquad (4)$$

In (3), the measurement equation, u and l are the upper and lower thresholds of the device based on the finite range of the finger tapper lever, $\bar{y}$ is the mean voltage measured over the test, A_n is a time-varying amplitude, θ_n is the phase at time n as defined in (2), and w is a Gaussian distributed additive noise source with variance R. Here we have specialized (1) to the case of a single, time varying cosine, where cosine was chosen over sine because the starting position of the lever is at the top when the FTT begins. A single time varying cosine is used for the sake of simplicity as it seems to be sufficient for modeling tapping behavior during the FTT, as we demonstrate below. The states in (4) come directly from the necessary parameters to describe the measurement model (3), in light of (1) and (2). Specifically, we have A_n, the time varying amplitude, ω_n, the time varying frequency, θ_n, the phase at time n, and the v_i as three additive Gaussian noise sources with diagonal covariance matrix Q. In (4), A_n and ω_n have been modeled as random walks.

Two of the three state variables in (4) have nice physical interpretations that we will exploit when making behavioral inferences from the model. The time varying frequency, ω_n, models the instantaneous rate (speed) of tapping, and can be used to derive measures of regularity related to tapping rate. The time varying amplitude, A_n describes the instantaneous size of the finger movement with larger values of A_n corresponding to larger sized oscillations of the finger. The time varying phase, θ_n is not used directly to make inferences from the model, but keeps track of the current phase of the finger during tapping.

Before presenting the results of the model validation, we briefly discuss estimation of the model parameters. In general, state space models are estimated with a recursive approximation to the minimum mean square error (MMSE) estimator. For the well known case of a linear model with additive Gaussian noise, the exact solution is the celebrated Kalman Filter [18]. For nonlinearity in the measurement or state equations, approximations to the MMSE solution are employed. Since our measurement equation is nonlinear and is not everywhere differentiable, we used a variant of the unscented Kalman Filter (UKF) to generate the results discussed below. The UKF is a derivative free approximation to the MMSE solution based on propagating a deterministic approximation of the prior distribution through the nonlinear dynamics to estimate the posterior distribution, and hence to form an MMSE estimate at each time step[19]. However, the UKF is just one of the available options for estimating a nonlinear state-space model; a particle filter or one of the other variants of the sigma point Kalman filters could also be used. As the UKF is well understood and described in the literature ([19], for example), and because a particular estimator is not central to the research described here, we omit a description of the complete UKF algorithm.

IV. Results and Discussion

The results of applying the UKF to the FTT model are shown in Table I. The small MSE of less than 0.001 on all trials suggests that the model provides a reasonable representation for the observed data. The maximum absolute error is not greater than 0.19 across trials. This is on the large size compared to the tapping signal range of 1, but the average absolute error of less than 0.025 indicates that errors this large are uncommon, and that most are less than 3% of the signal range.

Fig. 2 shows what an estimated measurement signal looks like compared to the true measured values. This plot visually demonstrates the closeness of fit between measurements and estimates evaluated quantitatively in table I. The top half of the plot shows the results for an entire 15 second FTT trial from one of the subjects, while the bottom plot shows a close-up of a half-second period in the middle of the test. As can be seen in both halves of the plot, the model accurately predicts the measurements.

Table I
Performance results of fitting the model to each of the four FTT trials administered to each subject.

Subject	Trial	MSE	Maximum Absolute Error	Average Absolute Error
1	1	0.00087	0.158	0.020
1	2	0.00094	0.186	0.021
1	3	0.00096	0.173	0.021
1	4	0.00096	0.184	0.022
2	1	0.00063	0.122	0.018
2	2	0.00059	0.121	0.018
2	3	0.00071	0.129	0.019
2	4	0.00082	0.154	0.020

Now that we have demonstrated the ability of the model to accurately generate the phenomena observed during tapping, we discuss the interpretation of the state estimates. Fig. 3 shows the state estimates over time for the middle 5 seconds of the same data shown in fig. 2, where only 5 seconds is shown for ease of visualization. The instantaneous amplitude estimates are shown in the top plot of fig. 3. It can be seen that during this trial, the subject did not tap with constant amplitude. Instead small fluctuations over time are clearly visible in this plot, including a dip in the size of finger movement slightly before the 7.5 second mark and slower trends of increasing and decreasing amplitudes over the course of the test. The middle plot of fig. 3 shows the instantaneous frequency of tapping plotted against time. What is striking here is the persistent decline in frequency over time. This shows that not only did the subject not tap at a constant rate, but this subject slowed consistently over the course of the test. While not shown completely in the plot, this subject began tapping at an initial speed of 5.5 taps/second, and ended the trial tapping at only 5 taps/second. This is a loss of over 9% in tapping speed during the full 15 seconds of the test, perhaps due to short-term fatigue. None of these short or long term fluctuations is captured by the current method of scoring the FTT as an average number of taps across trials.

One shortcoming of this work is the lack of patient data used. While our intent was only to describe the model and show that it captures characteristics of tapping not measured by the current scoring method of the FTT, the usefulness of the model lies in its ability to help us study and make inferences about cognition. We are currently designing an experiment to explore the relationship between cognitive function in the elderly and features of tapping derived from the data using the proposed state-space model. Based on the research cited in the Introduction, we expect that we will be able to make much more precise inferences about cognitive function than are currently available with the FTT.

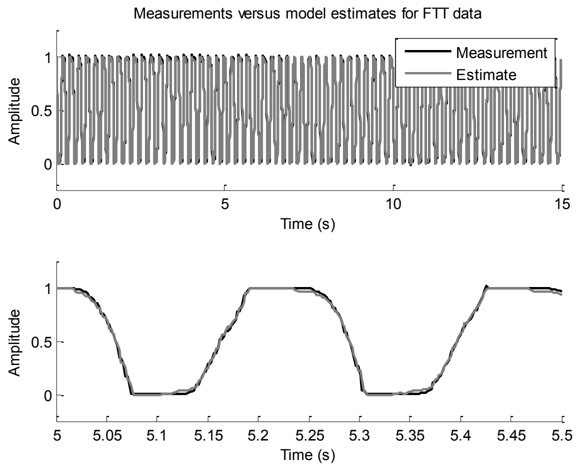

Figure 2. Estimated measurements (gray) and actual measured values (black) for one trial from one subject of the whole FTT (top) and a half-second of the test (bottom).

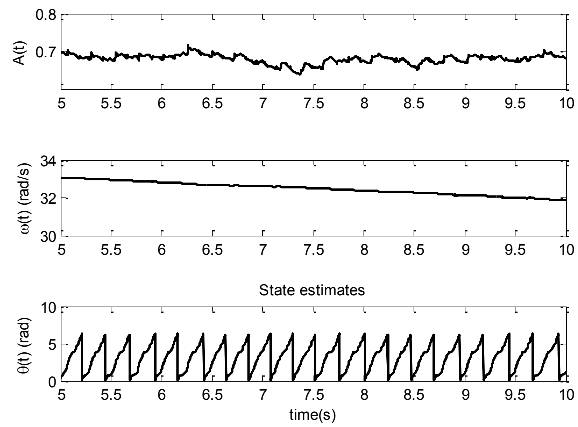

Figure 3. Estimates of the amplitude (top), frequency (middle), and phase (bottom) versus time for the middle five seconds of the data shown in fig. 2.

V. CONCLUSION

In this paper, we described a novel state-space model for finger tapping during the FTT. We showed how this model can track changes in behavioral characteristics of tapping – size of the finger oscillation and frequency, or speed, of tapping – not measured during the traditional FTT. Based on recent research, we expect that these behavioral characteristics will allow more precise inferences about cognition, and we outlined a planned experiment that will test this hypothesis as future work.

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