# Time-series-bitmap Based Approach to Analyze Human Postural Control and Movement Detection Strategies during Small Anterior Perturbations

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## Abstract

Studying human postural control mechanisms not only includes the analysis of diverse time-series datasets including position and acceleration of perturbation and changes in a subject's anterior-posterior center of pressure (APCOP), but also whether the subject correctly detected whether a perturbation occurred. For small perturbations imbedded in the normal pattern of sway, this translates to being able to detect an anomaly in a time-series profile of the variable under study. Thus, we use a time-series-bitmap (TSB) approach to indicate the anomalies present in the APCOP profile. These anomalies point to how the subject reacted physically as well as psychologically to the platform movement, thus helping to correlate a subject's physiological and psychophysical responses. This method not only facilitates in understanding APCOP profiles in a much different way, but also helps determine the validity of the data collected. The anomaly detection technique uses two concatenated, lag and lead windows that slide across the time-series. Each window converts a subsequence into symbolic form using the Symbolic Aggregate approXimation (SAX) algorithm, followed by a level-two calculation and normalization of alphabet frequency. The distance between two windows at each time instance gives anomaly score. A high anomaly score is reported for any large variation in the time-series data. The score provides an indicator of a subject's physiological detection response where one felt movement, and aids in correlating it with the psychophysical response of the subject.

## Introduction

As an individual sways, there are subtle changes in the activation of lower limb muscles (as measured by EMGs), and in the position of the Center of Pressure (related to the vertical projection of the Center of Mass onto the platform upon which this person stands). The EMG and COP profiles are continuous time-series variables. A question of interest in studying postural stability is to what extent the EMGs and COPs are changed by subtle anterior perturbations of the platform, when these perturbations are shorter than the mean sway path or the sway path range. In this regard, studying the postural control mechanism not only includes the analysis of diverse time-series datasets such as position and acceleration of the platform and for instance the subject's anterior-posterior center of pressure (APCOP), but also if the subject correctly detected whether a move occurred. Our protocol uses a psychophysical test procedure called the Two Alternative Forced Choice (2AFC) method, where a subject is required to decide in which of two intervals was a stimulus presented. We typically use a run of 30 trials, each of 15 s duration. Each trial has four sequential intervals: Ready (4s), One (4s), Two (4s), and Decide (3s). These commands are sent to the subject's headphones from an audio output card in the controlling computer. The subject signals via one or two presses of a telemetered pushbutton in which of the two intervals they thought that the move occurred.

We want to find changes in one or more physiological or biomechanical variables that correlated with detection correctness. If the testing is done with movement parameters that are at the subject's psychophysical detection threshold (i.e., the subject consistently detects 75% of the trials), then on average one in four of the trials should be a guess. The difficulty exists when trying to determine whether detection correctness can be predicted by one or more signature changes in peri-threshold data caused by the perturbation. Moreover, at threshold, even a "correct" detection could be the result of a Guess. Hence, we seek profiles in our data that can be used to distinguish physiological changes seen during correct detections (Hits) from those detections caused by Guesses or False Positives. The corollary in the non-stimulated interval is that True Negative responses should be distinguishable from Misses.

The mechanisms of human postural control play an important role in the maintenance of upright stance. Failures of these mechanisms to correct unexpected displacements of the body are a major contributor to falling[1]. Many studies have looked at postural control during quiet stance as well as during highly perturbed stance. In contrast, our protocol employs quasi-static, short perturbations whose lengths are within the normal distance of sway range. To avoid extraneous clues due to movement vibration, we developed test hardware and software that we collectively call SLIP-FALLS-STEPm (for Sliding Linear Investigative Platform For Assessing Lower Lim Stability with Synced Tracking, EMG and Pressure measurements[2]). This equipment allows precise vibration-free horizontal translations.

A test like SLIP-FALLS-STEPm that characterizes responses to very small anterior perturbations that lie within the normal sway range, and that provides no external cues, should be a better predictor of a postural control response[2]. Processed SLIP-FALLS-STEPm data from past experiments provides a Legacy Data Set containing various time-series signals that include position, acceleration, APCOP, and EMG data. For each subject, a maximum of 30 trials are performed per run, and each trial collects these and other time-series data. The 15 s epoch data that we collect represents about three sway cycles (at a nominal sway frequency of 0.5 Hz). This is not enough data to use typical time-domain cross-correlation techniques. However, other means exist to tease out trends in time-series data. To study postural stability and movement detection strategies, reduction of data dimensionality is needed. Symbolic representation of abstracted data makes analysis more easy and accurate.

We apply here a time-series-bitmap (TSB) approach to pull out potential anomalies present in the APCOP response, and then to see if the presence of anomalies corresponds to correct detection. These anomalies illustrate how the subject reacted physically as well as psychologically to the platform movement thus helping to differentiate between the subject's physiological and psychophysical responses. This method not only helps in understanding

APCOP profiles in much different way but also helps in determining validity of the data collected for the particular trial.

The TSB based approach used in this paper allows testing over diverse data streams. Data are categorized into Hit, Miss, False Positive, True Negative and Guess categories, based on a subject's detection of a perturbations and the actual interval of movement. This helps in studying movement detection strategies. Detection of anomalies during pre, peri or post move states helps resolve the question of what underlies the subject's movement detection decision. The effect of the peri-move state on the response of a subject can be easily analyzed by looking at pre-move anomalies. This lead us to design an analysis routine based on time-series-bitmap techniques to for predict postural control responses during perturbed stance.

## Methods

### a) Subjects

Various groups of subjects underwent testing on the SLIP-FALLS-STEPm. Here we consider the Healthy Elderly Adult (HEA) group of individuals set over 50 yrs old, without diabetes and without lower limb peripheral neuropathy (as verified by clinical nerve conduction testing) from our Legacy Data Set.

### b) Experimental Procedures

Our Sliding Linear Investigative Platform For Analyzing Lower Limb Stability and Synced Tracking, EMG and Pressure mapping (SLIP-FALLS-STEPm) is a novel device and a data collection system designed to study human postural control mechanism. The 2-Alternative-Forced-Choice (2AFC) protocol forced subjects to choose one of the two sequential intervals in which a perturbation was presented. The subject receives the commands "Ready", "One", "Two" and "Decide", in intervals of 3 to 4s each, with a stimulus either in interval One or Two. After the word "Decide", the subject presses a doorbell button once or twice to signal in which interval one felt the stimulus occurred. A data collection system collects data such as platform displacement and acceleration, and detection interval signal. All data is recorded at a sampling rate of 1000 Hz.

### c) Time-Series-Bitmap Based Analysis

### c1) Background

Analyzing time-series data has always been challenging. The diversity in our data streams makes the task more difficult. The Symbolic Aggregate ApproXimation (SAX) is one solution to reducing the complexity of our data. SAX is a good method for symbolic representation techniques used in detection of anomalies. Our hypothesis is that the unexpected or anomalous pattern in subject's APCOP time-series data explains detection strategies behind subject's response. Brief definitions of some terms will help to understand the application of SAX and other time-series-bitmap techniques to our data. Dividing a lengthy time-series into subsections makes it easier to discern data behavior. These subsections are called subsequences.

*Time-Series:* A time-series $T = t_1, ..., tm$ is an ordered set of m real-valued variables[3].

*Subsequence:* Given a time-series $T$ of length m, a subsequence $C$ of $T$ is a sampling of length $n<m$ of contiguous position from $T$, that is, $C = t_p, \ldots, t_{p+n-1}$ for 1<= p <= m-n+1[3].

*Anomaly Detection:* Given a time-series Q, and some model of “normal” behavior, find all sections of Q that contain anomalies, or “surprising/interesting/unexpected/novel” behavior[4].

**c2) Data Abstraction**

*Piecewise Aggregate Approximation (PAA)* is used as an abstraction method. A time-series C of length n can be represented in a *w*-dimensional space by a vector $\overline{C} = \overline{c}_1, \ldots, \overline{c}_w$. The i[th] element of $\overline{C}$ is calculated by the following equation:

$$\overline{c}_1 = \frac{w}{n} \sum_{j=\frac{n}{w}(i-1)+1}^{\frac{n}{w}i} c_j$$

To reduce the time-series from *n* dimensions to *w* dimensions, the data is divided into *w* equal sized “frames”. The mean value of the data falling within the frame is calculated and a vector of these values becomes the data-reduced representation[4].

**c3) Symbolic Representation**

We used SAX in our symbolic representation approach. PAA, a data abstraction method, provided data for conversion of time-series into symbols for SAX. PAA replaces equally sized frames by their mean values. PAA symbols undergo discretization to produce SAX words that are strings of SAX alphabets. The alphabet size is an arbitrary integer a, where a > 2. For alphabet size of three, a = 3, {a, b, c}. Figure 1 shows a short time-series being converted into SAX word **baabccbc**.

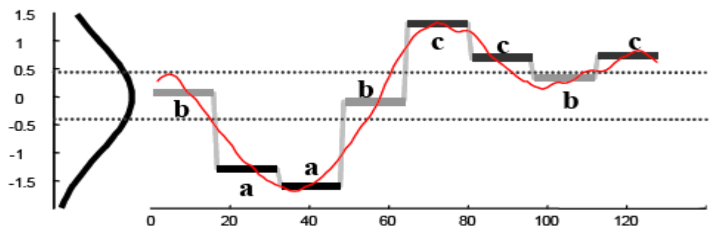


*Figure 1: A real valued time-series can be converted to the SAX word baabccbc*[5]

Because our data contains long time-series, the ability to convert subsequences of time-series data and converting them into SAX word that makes analysis more efficient.

**d) Time-Series Anomaly Detection**

Our approach to time-series anomaly detection is inspired by work done by Li Wei et al[5]. Time-series-bitmaps are based on idea behind Chaos game theory. Chaos game bitmaps are defined for sequences with an alphabet size of four[5]. As reported by many authors, cardinality of four is considered as excellent choice for diverse datasets[5]. After undergoing discretization the time-series using SAX, the frequency of SAX subwords of length L is calculated, where L represents the desired level of recursion, in our case, L = 2. These frequencies are then normalized by dividing it by the largest value.

Based on the anomaly detection technique, two concatenated windows are created and are slid across the time-series[5]. Each window looks at a subsequence of specific length. The latter one is called the lead window and the former one as the lag window. For each window, the subsequence under analysis is converted into its SAX representation, and frequencies of SAX subwords are then calculated and normalized (see Figure 2). The distances between the two windows are measured at each time instance and stored as an anomaly score. For two windows of the same size (Same level of recursion), the distance between them is calculated as the summation of the square of the distance between each pair of pixels. At each step of the sliding window, a new data point is incrementally ingressed and an old data point is egressed in constant time to make the time complexity linear in the length of the time-series[5].

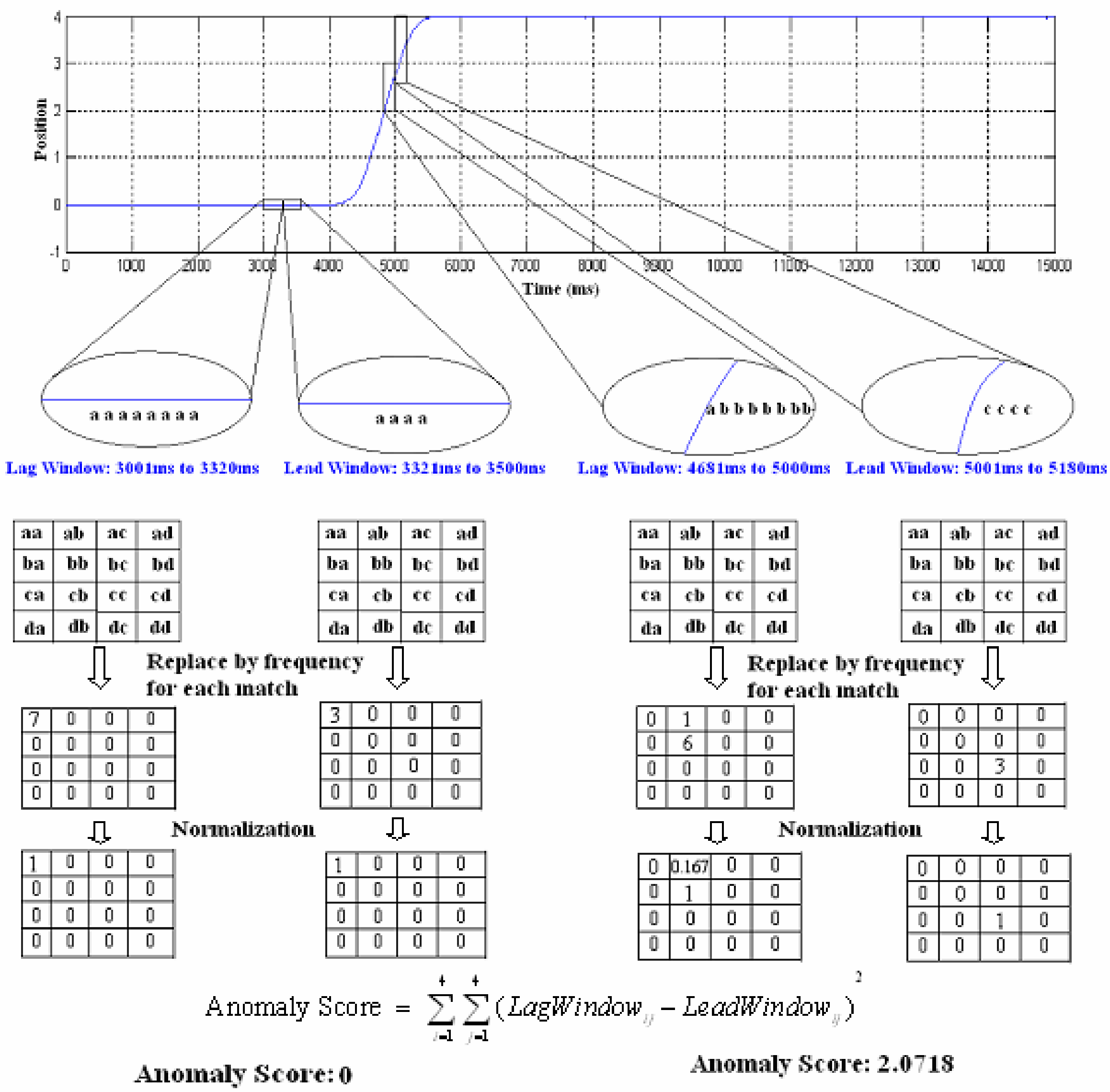


*Figure 2: Method illustrating Time-Series-Bitmap Algorithm and how it converts subsequences into SAX symbols to calculate anomaly scores for each instance of the lag and the lead windows using the known time-series data of platform position taken from a move in Interval 1*

**Results**

**a) Implementation of time-series-bitmap algorithm**

Anomaly detection algorithm indicates presence of anomaly at a specific time. Figure 2 shows our successful detection of anomalies in the time-series data of platform position. This section describes the time-series-bitmap and shows how the algorithm is applied to our data. We first test the algorithm on the position signal, since it has a specific known transition from one value to another. A bin size of 40 was used for the SAX algorithm since that size (i.e., 25 Hz) most suits our data. All the data used for the descriptive analysis here is from a 67 yr old, healthy female responding to a 4 mm perturbation. Figure 3 demonstrates how the lead and lag windows are translated across the time-series with the example of position time-series data of Figure 2, if:

Word Length: 8 Lead Window Size: 180

Lag Window Size: bin size * word length = 320

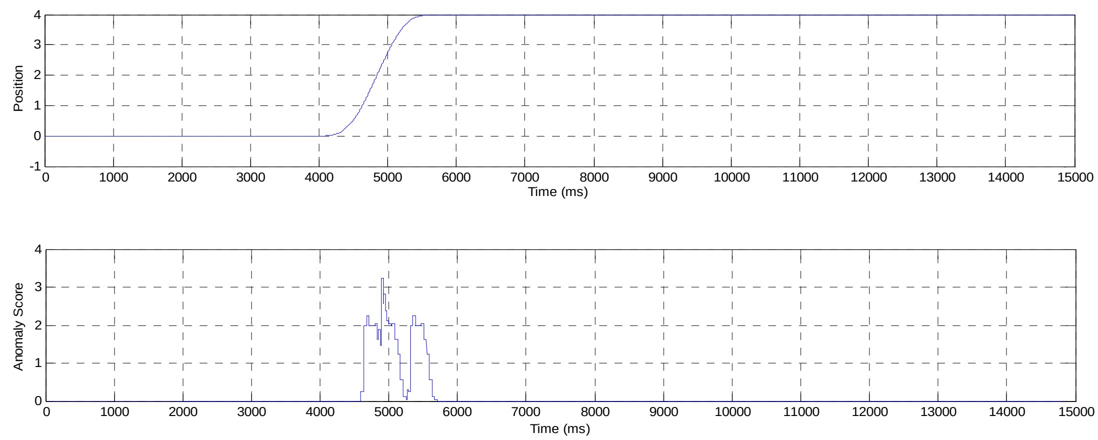


*Figure 3: Time-series records of platform position and anomaly score indicating where actual movement has occurred (Interval 1)*

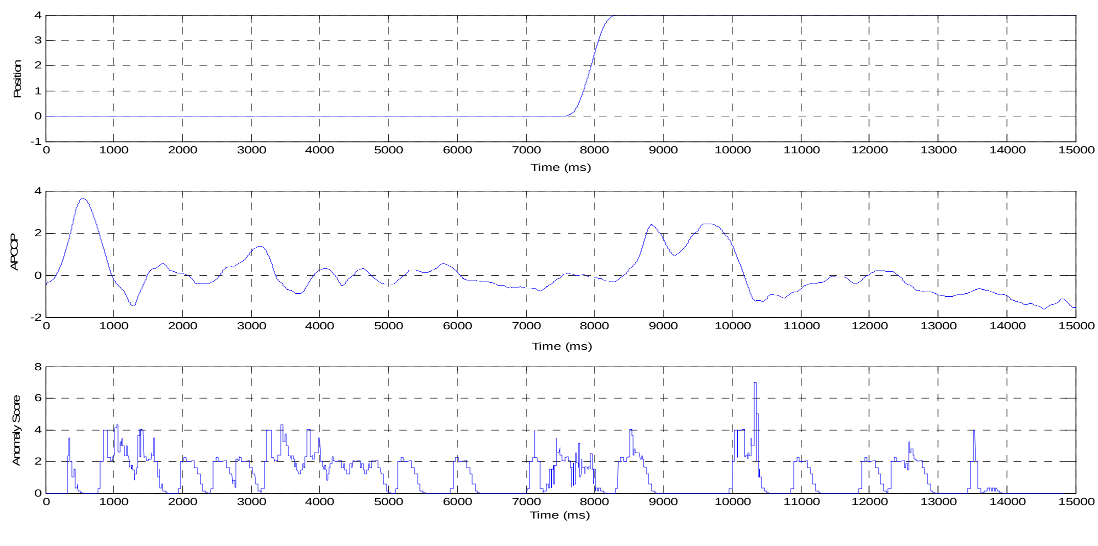


*Figure 4: Time-series records of platform position and subject's APCOP with the anomaly score for the APCOP (with the move in Interval 2)*

Center of pressure (COP) is used as measure of postural control[3]. AP represents the anterior-posterior direction, and APCOP would be expected to be influenced by an anterior perturbation. Thus, we chose the APCOP as the time-series of most interest upon which to test the anomaly detection algorithm. The APCOP data is irregular and linking it with detection correctness is complex task. Figure 5 shows where anomalies are seen. Here it correlates well with where the subject felt movement occur. We get high anomaly score during 8000 ms to 9000 ms (the time of the move in Interval 2). Note that there is a clear deterministic response apparent here in the APCOP, which is not seen often.

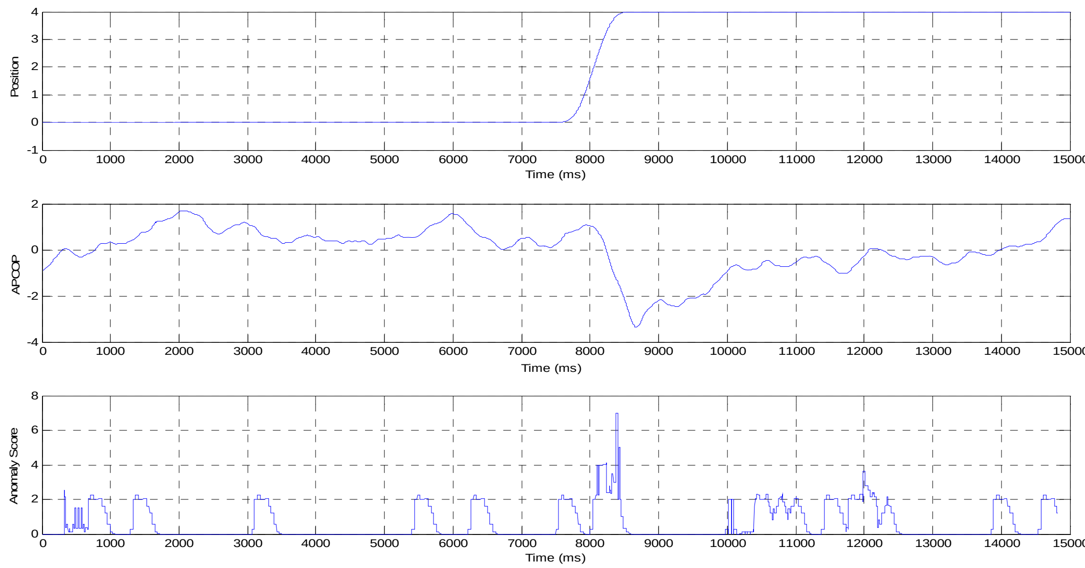


*Figure 5: HIT, with a high anomaly score in the interval (2) where subject actually felt and detected movement.*

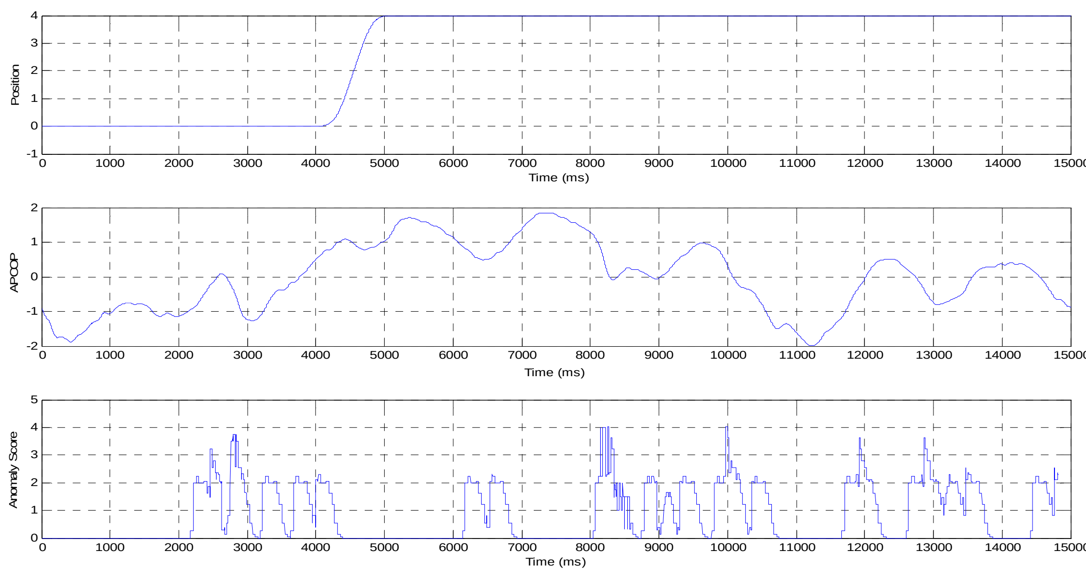


*Figure 6: a FALSE POSITIVE, with a low anomaly score in interval 1 where the movement was given and with high anomaly activity in Interval 2 (i.e., at and after 8000 ms)*

The presence of anomalies in either of the stimulus or non-stimulus intervals helps to distinguish between a Hit or a Miss, and False Positive or True Negative. This is our major task in understanding the psychophysics of postural control.

A physiological response is one's neurophysiological (i.e., EMGs) or biomechanical (e.g., ΔAPCOP) response to a perturbation and the subject's psychophysical response indicates where the subejct felt the movement. In Figure 5, the subject's physiological and psychophysical responses both exist in the same interval, which can be viewed as a HIT. The perturbation was given in interval two and subject responded in the same interval.

In contrast, in Figure 6 there is no significant anomaly score present in the stimulus interval 1. Excessive anomaly activity is seen in interval 2 (the non-stimulated one), which leads to the classification of FALSE POSITIVE. The interesting point that could be argued here is that this subject made the incorrect choice of interval 2 based on the increase in anomalous activity there. It is though the sensory input "fooled" the subject into choosing the wrong interval, or that the subject perceived the wrong stimulus interval and the reacted to an imaginary stimulus. We have a seen a number of examples of these FALSE POSITIVES.

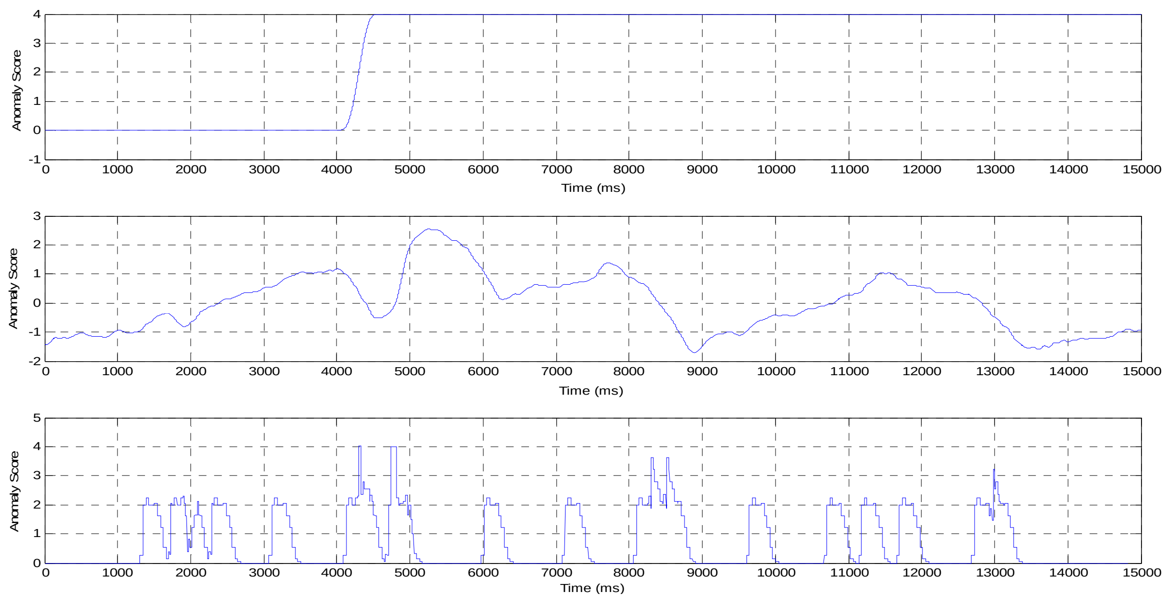


*Figure 7: GUESS, with the presence of high APCOP anomalies in both the intervals, yet with correct detection in the stimulus interval.*

Figure 7 presents a particular case where the subject psychophysically correctly detects the movement interval. Yet one biomechanical response (the APCOP) has high anomaly scores in both intervals. If APCOP was the sole basis upon which this subject made a decision, then this response needs to be characterized as a GUESS. In addition, the background anomaly scores are consistent throughout the entire test sequence. This background "noise" could be construed as making detection difficult, again if APCOP was the variable upon which detection is based.

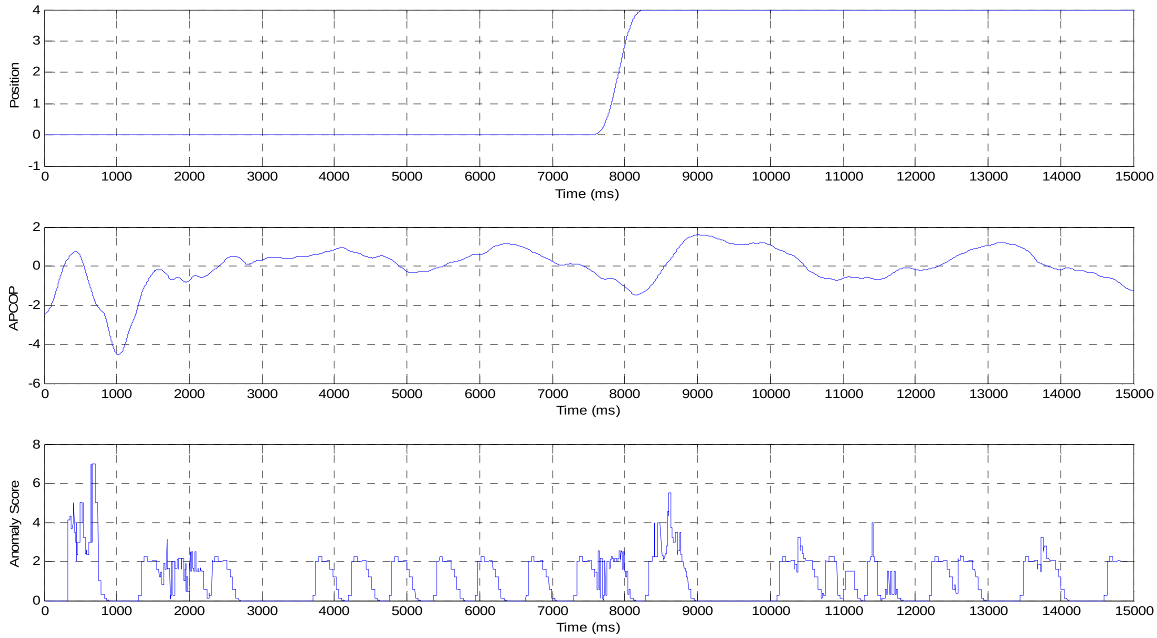


*Figure 8: MISS, with higher activity in the stimulus interval, but with incorrect psychophysical detection.*

In Figure 8, the higher anomaly score in Interval 2 indeed correlates with the presence of the stimulus there. Yet the subject chose the other interval. This is then classified as a MISS, since the response should have triggered a correct detection.

## Ensemble Averaging

As shown in the previous section, the SAX technique can be applied to single trials. We next use it for ensemble averages that are constructed via point-by-point time averages of the APCOP time-series acquired from 30 trials in a 4 mm run for this subject, with all Interval 1 simulation/ Interval 1 choice (S1C1) profiles averaged together (i.e. correct detection). Similar ensemble time averages are produced for interval 1 stimulation/ Interval 2 choice (S1C2) profiles (i.e., incorrect detection), and for S2C2 and S2C1.

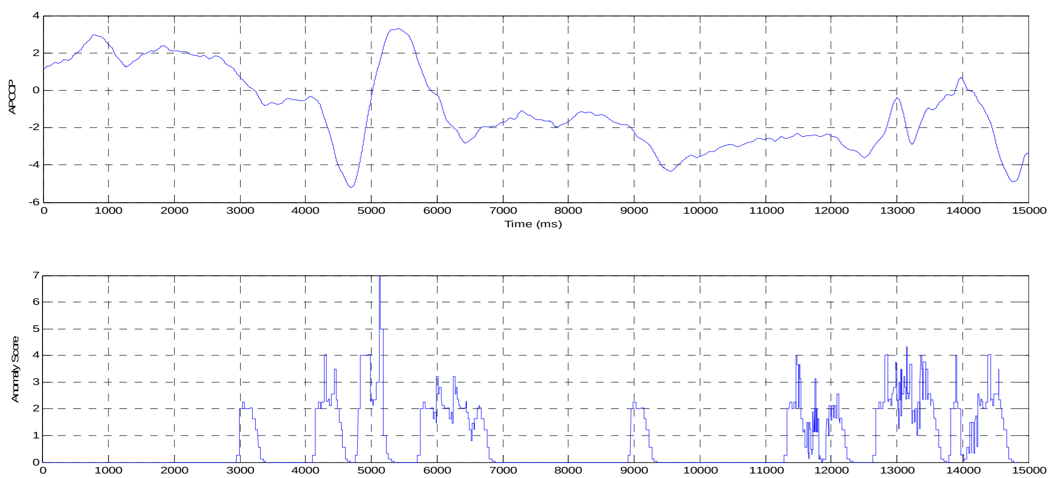


*Figure 9: HIT from Interval 1 Correct Detect (point by point averaged APCOP), and TRUE NEGATIVE from lack of responses in the non-stimulated interval*

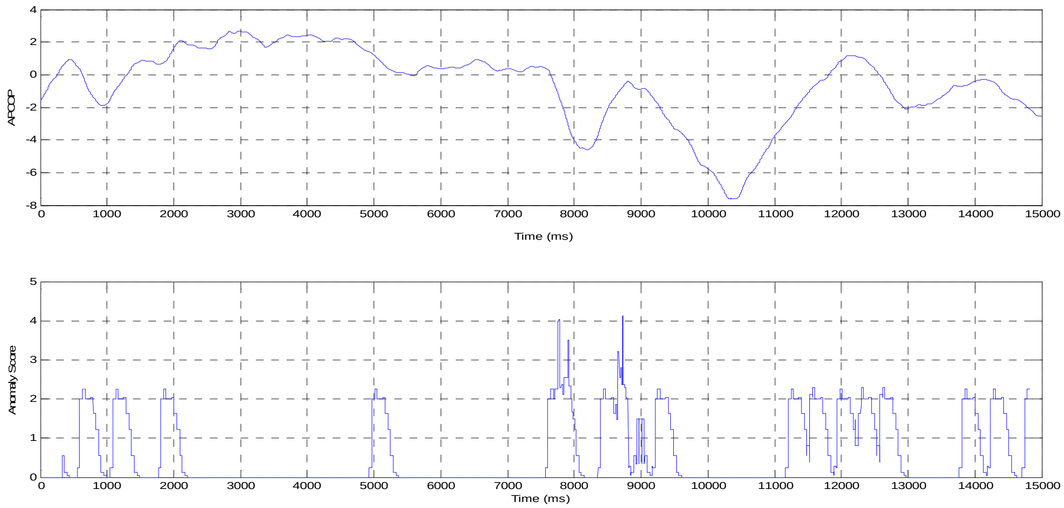

*Figure 10: Similar to Fig. 9, with a HIT in Interval 2 for Correct Detect (point-by-point averaged APCOP), and TRUE NEGATIVE from lack of responses in the non-stimulated interval*

Figures 9 and 10 more vividly show highly contrasting anomaly scores between the stimulus interval and the non-stimulated one in ensemble APCOP averages of corrected detected trials for Interval 1 stimulation (Fig. 9) and Interval 2 stimulation (Fig. 10). Based on the stark differences in anomaly scores between the stimulated and non-stimulated intervals, we could tentatively conclude that APCOP anomalies could serve as a basis for detection decision making. However, the corollary must then be proven — that incorrect decisions arise from a lack of contrast in the APCOP anomaly scores between stimulated and non-stimulated intervals, requiring a GUESS. Indeed, as shown in Figure 11, the lack of contrast is exactly what is observed!

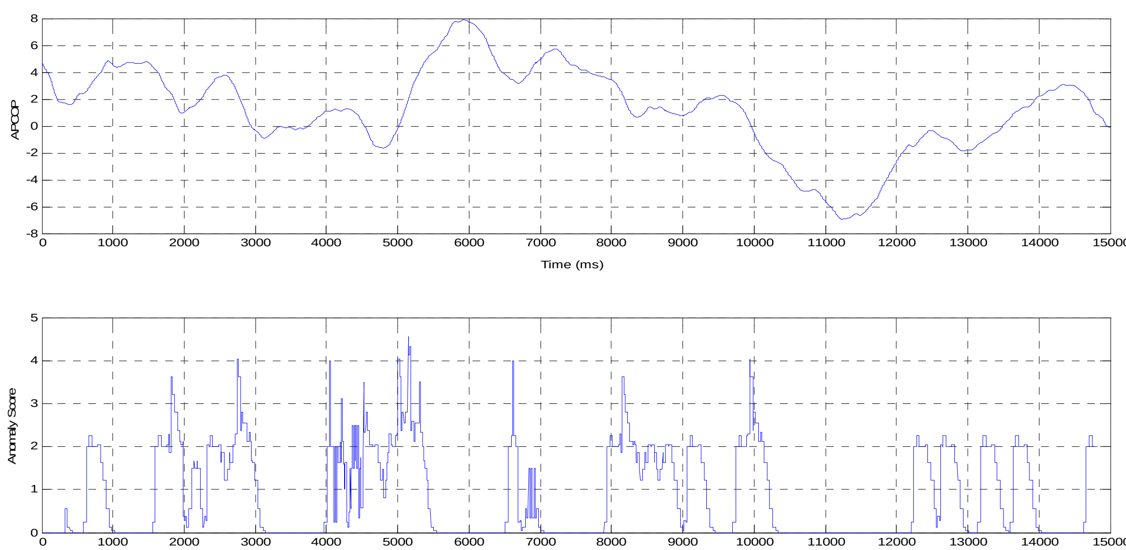

*Figure 11: Interval 1 non-detected APCOP profiles are ensemble averaged. No differences in anomaly scores exist between Intervals 1 and 2. A similar lack of differences is seen for Interval 2 stimulations not correctly detected.*

## Discussion

Applying the time-series-bitmap based approach to analyze human postural control is innovative. As a novel technique, it can differentiate physiological responses (APCOP changes) based on psychophysical responses (i.e., correct or incorrect decisions). This algorithm gives high anomaly scores when there are transitory variations in a subject's APCOP response. This approach helps in categorizing responses to the perturbations into Hit, Miss, False Positive, True Negative and Guess classes. Ensemble averaging of the APCOP itself can visually reveal differences between detected and non-detected trials[2]. Nevertheless, the time-series-bitmap algorithm gives us a tool to categorize these differences formally.

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