Eigenposes: Using Principal Components to Describe Body Configuration for Analysis of Postural Control Dynamics

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Abstract— **Many studies of human postural control use data from video-captured discrete marker locations to analyze via complex inverse kinematic reconstruction the postural responses to a perturbation. We propose here that Principal Component Analysis of this marker data provides a simpler way to get an overview of postural perturbation responses. Using short (1, 4, and 16 mm) anterior platform step translations that are on the order of a young adult's normal sway path length, we find that the low order eigenmodes (which we call eigenposes) of the time-series marker data correspond dominantly to a simple anterior-posterior pendular motion about the ankle, and secondarily (and with less energy) to hip flexion and extension. A third much weaker mode is occasionally seen that is represented by knee flexion.**

I. Introduction

Integration of motion capture devices into postural control experiments is essential for analysis of postural control dynamics because body configuration must be known. Using markers at key motion joints, we are able to accurately describe body configurations during testing of postural control response using SLIPFALLS-STEPm, a controlled sliding platform test setup with an associated motion analysis system that tracks the motion of the markers in three dimensional space using a multi-camera system [1,2]. However, even if only a small number (~ 20) of markers are tracked in 3-D Euclidean space, the dynamic marker location data results in a 60-dimension time series. This high-dimensional data representation does not support analysis of postural control dynamics, except where complex inverse kinematics is employed with corresponding assumptions.

These inverse kinematic calculations involved in postural stability and gait analyses require measurement of all appropriate limb segments and joint angles by intensive inverse computation of marker positions. These calculations, coupled with the force reactions of the feet with the platform on which a subject stands and anthropomorphic assumptions about the weight distributions in various body segments, are designed to yield joint torques and moments about each axis of rotation, and hence to discern reactions to perturbations.

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The most used measure of reaction force is *Center of Pressure* or *CoP*, which is the vertical projection of the body's center of mass (CoM) onto the supporting surface [3]. The CoP will change in response to a perturbation of the body in space or of the supporting platform.

Our lab employs a novel way to assess postural stability. Rather than making large, potentially fall- initiating perturbations, we make subtle translational perturbations that are at the edge of detectibility and that are buried within the range of a subject's normal CoP sway path length (i.e., 2 mm rms, 20 mm range). We use iterative psychophysical testing procedures to determine the just detectible level (i.e., threshold) of acceleration at short 1, 4, or 16 mm anterior horizontal platform translations. To analyze differences in perturbations that were correctly detected versus those that were not, we needed an analysis tool take could work within the low signal (i.e. perturbation response) to noise (i.e., normal sway) ratio inherent in our experiment.

Thus, we wondered if it might be possible to take a simpler first-look approach to understanding postural stability — not by intensive back-calculations — but by treating the marker locations themselves as providing rich information about system state. Since the state of any system can be described by its eigenvalues, we felt that the set of marker positions might decompose into a set of physiologically relevant eigen-states. We thus proposed two hypotheses:

H1: The most appropriate state variable for postural control is body configuration, approximated by measuring the position of each rigid element.

The generic ODE model is given by:

$$\dot{x} = F(x,u) \qquad x \text{ - variables of state} \qquad u \text{ - control.} \tag{1}$$

Center of pressure (COP) describes variables of state only under a static condition. Dynamically, one should view COP as a mathematical projection of the body's control signal. Mathematically, we could then assume that:

$$COP = g(u), \quad \text{or, if feedback control,} \quad COP = g(u(x)), \tag{2}$$

to indicate the functional relationship between the control (u) and its observable (COP).

H2: A subject's ability to detect short, near threshold platform motion is affected by the state of the configuration variables at the time of movement. In particular, a subject is less likely to perceive motion if the body is moving toward its natural equilibrium. Part of a subject's "sensation of movement" is based on detecting the neuromuscular control response that is automatically initiated to maintain balance. If the body is moving toward equilibrium when the perturbation is inserted, less muscular action is required to maintain balance.

II. Methods

To perturb the subject's base of support, we used a novel horizontal translating platform and data collection system called SLIP-FALLS-STEPm (for our Sliding Linear Investigative Platform For Assessing Lower Limb Stability with Synced Tracking, EMG and Pressure measures) that has been described elsewhere [1,2]. The dynamics of the perturbation can be completely specified by the investigator. More importantly, using a non-contact linear motor and air bearing slides eliminates any vibration, obviating a potential cue for movement. This highly-instrumented platform and its precisely controlled selection of move distance, acceleration, and jerk are user-specified to tailor a set movement profile for these experiments.

For determining detection threshold, we use a 2-Alternative-Forced-Choice (2AFC) procedure [3]. A subject standing blindfolded on the SLIP is instructed that a move *will* occur in one (and only one) of the two intervals. The controlling computer replays the stored commands *"Ready," "One," "Two," "Decide,"* with the stimulus presented in interval One or Two, each a 3 to 6 s interval of similar length needed to capture the full perturbation move. After the word *"Decide,"* the subject is required to make a forced choice and to press a handheld button once or twice to signal in which interval (s)he felt that the stimulus occurred. At each displacement tested (1, 4 and 16 mm), a series of 30 trials are sequentially presented, and platform test acceleration is iterated towards detection threshold.

The FALLS-STEPm portion of the system collects time-series measures of Anterior-Posterior and Left-Right Centers of Pressure, total subject weight, lower limb electromyography, and the position of small (1 cm) retroreflective markers placed bilaterally over the major joints of the body. The 3-dimensional location of these markers in calibrated local-space coordinates is captured as a function of time via a 6-camera Vicon-Peak system running Nexus software. This paper considers the motion of these markers along the anterior-posterior axis.

Even considering only a small number of markers, the resultant data provides a high-dimension representation of the body movement. It is likely to be highly redundant with respect to kinematic and dynamic information. Principal Component Analysis (PCA) [also known as Proper Orthogonal Decomposition (POD) and the Karhunen-Loeve (KL) transform] uses an eigenvalue decomposition of the covariance matrix to provide an optimal basis for data representation. These techniques have been exploited in the field of partial differential equations (e.g., to study spatiotemporal turbulence). They allow for vast reduction in the dimensionality of the representation of data and are popular within the field of data mining as a technique for factor reduction.

We apply PCA to our marker data time series as follows: For each data trial, we form data matrix ***X***, where each row is associated with a specific marker coordinate and each column to a specific time. Marker positions are sampled at 250Hz.

III. Results

For this paper, we consider only a limited set of markers and only for AP displacement. Additionally, each row of ⍰ has been demeaned, such that the recorded values give deviation from some mean configuration. We use the standard singular value decomposition equation

$$X = U\Sigma V^T \tag{3}$$

where columns of U can be viewed as providing body shape modes that we term eigenposes (see Fig. 1).

This decomposition provides for a simplified approximation of the data by choosing modes associated to the largest singular values. We find that for our data sets, the leading two modes are typically sufficient to represent the data. Inclusion of the third mode ensures that we capture over 99% of the information content.

One typical weakness of PCA is that the eigenmodes are not easily interpreted with any physical relevance. While they may optimally explain the data variance, they often provide little insight into underlying processes. However, for our problem, we find that the marker data provides a natural decomposition into the three key movements associated with a three-segment representation of the human body. The dominant mode (EP1) characterizes gross body motion as a rigid element rotating about the ankle. Mode EP2 captures a hip motion control strategy. And mode EP3 indicates a pronounced knee bend, seemingly balanced by head and arm motion.

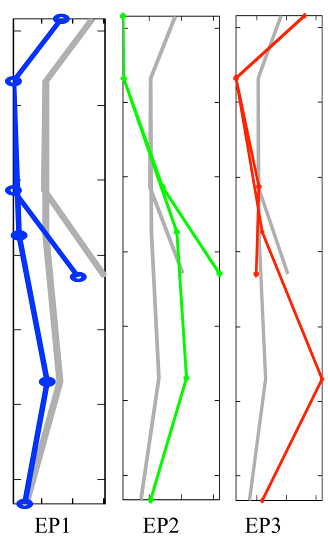

Fig. 1. Eigenposes EP1, EP2, and EP3, compared to the mean body position (in gray). Markers analyzed were located at heel, knee, hip, shoulder, head, elbow and wrist.

We can consider the data in the eigenmodes coordinates by simply apply a change of basis, such that

$$Y = U^T X \tag{4}$$

yields the transformed representation. For a typical trial, a small platform perturbation (relative to the mean sway path length amplitude) may modify the relative mode weights. But we observe that the primary motion modes are active in the pre-, peri-, and post-move environments (see Fig. 2).

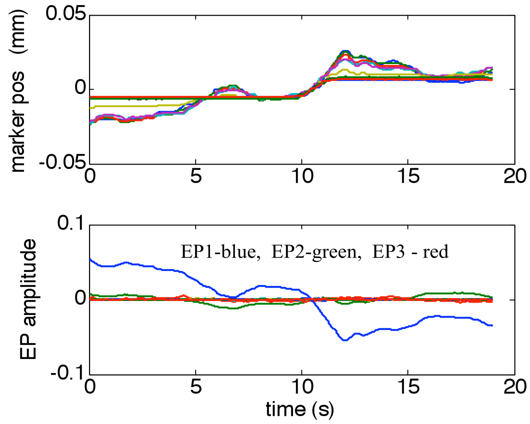

Fig. 2 - Marker positions raw data (top) and decomposed to the EP basis (bottom) for a 16mm platform move at time t=10s. Note that all information from modes four and above is essentially "covered" by the thickness of the line drawn for mode EP3.

IV. Discussion and Conclusion

We find that most of the observed body motion in our experiments can be adequately approximated by using only a small number of eigenposes. The principle mode essentially represents rigid body motion, pivoting at the ankle, while the second mode reflects motion at the hip joint, with arm and upper body motion suitable to maintain center of balance. Although these modes are found by mathematical optimization of the energy representation (such that the fewest number of modes are required), the resulted eigenvalues seem to represent natural positions of the body.

Because PCA is completely data dependent, it need not coincide with any physical model of the system that generated the data. However, to the extent that such models can be developed, they provide credence to the implications of the PCA analysis. Our eigenmodes of postural stance are consistent with the three-segment model of [4,5], where the segments are ideal joints, pinned at ankle, knee, and hip, and with torque actuators at each joint. In that idealization, the eigenmodes are the resultant linearized dynamics. That model was tested against data in [5], where the focus was on purposeful bending of the body while trying to maintain balance.

Continued analysis of posited modal control schemes based on that model were examined in [6], supporting the idea of coexisting modes. These were further emphasized in [7]. Implementation of such control in a real human body (as compared to ideal model) may require some a fuzzy controller. We note that the fuzzy model considered in [8] is consistent with the modal description implied by the data analysis.

We note that our marker also data captures information regarding the movement of the arms and head, which is not reflected in the three segment model. However, the strong correspondence with the models indicates that a reasonable course of investigation should be pointed toward understanding how these balancing gestures may be essential contributors to postural control. Even in the quiet standing condition, dominated by ankle control, we observe “bursting” of small EP3 behaviors. Our intended direction is to modify fuzzy schemes such as [8] to account for these additional activations.

V. References

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