Video based analysis of standing balance in a community center

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Abstract—**Postural sway is a well known measure of postural stability in the elderly. Sway measurements, however, are typically made using expensive equipment in a laboratory. We report on efforts to make clinically significant and quantitative measurements of postural sway in a community center with a single un-calibrated video camera. Results indicate that simple tracking technologies can capture some aspects of sway in a community center in a way that is perceptually accurate and capable of distinguishing expert-assigned levels of balance performance in an elderly, balance impaired cohort.**

I. Introduction

Increased postural sway as recorded during quiet standing has been found to correlate both with ageing [1,2] and an increased likelihood of falling [3,4,5]. Traditionally, postural sway has been measured by recording an individual's center of pressure (COP) with a posturographic platform [1,6,7] or by inferring center of mass trajectories using kinematic estimates provided by commercial motion tracking devices [8]. Both measurement systems are extremely accurate, but they are also expensive, not readily portable, and require the subject to wear potentially cumbersome markers.

As new technologies develop, however, it is becoming increasingly possible to measure movements like postural sway more cheaply, in a wider range of situations and environments, and without the need for on-person markers. Accelerometers, for example, have proven to accurately detect abnormal postural sway in the elderly [8]. Unfortunately, accelerometers still require individuals to wear external sensors.

Movement data recorded by video cameras provide a potential alternative for affordable capture of human motion in a wide range of settings, possibly without markers. Markerless motion capture, in fact, has received a great deal of recent attention from the computer vision and biomechanics community [10,11], and, in some circumstances, has proven to yield kinematic reconstructions comparable to those from high cost tools, even when based on single camera views [12]. The clinical applications of such tracking technologies, however, have not been extensively explored until recently. Markerless video tools have be used for posture identification for ergonomic workplace analysis [13], biomechanical analysis of sit to stand movements [14], and as input to assistive functional electric stimulation (FES) devices [15].

The purpose of this paper is to determine if a single un-calibrated camera in a community center can measure clinically meaningful statistics of postural sway among an elderly, balance impaired cohort. We are not using dense or multi-camera stereo methods as in [11]; our focus, rather, is on the clinical utility of coarse camera-based measurements that can be made robustly and quickly. Our work is most closely related to [16], wherein a single camera was used to distinguish between standing conditions (eyes open, eyes closed, etc.) among a population of young subjects. Our work builds upon this research in several important ways. First, we explore the use of a camera positioned in front of subjects as opposed to laterally with respect to the subject. This provides access to medio-lateral sway measurements, which have been shown to increase with age [4]. Second, we explore the use of un-calibrated cameras in a real world scenario that involves balance impaired elders. Finally, we validate accuracy of measurements by determining if they capture expert determined levels of functional balance performance in the elders we record. The opinions of human experts are the common "gold standards" for clinical measurement of functional balance in community centers, so we use these opinions as our "gold standards" as well.

II. Methods

A. Experimental Paradigm

TABLE I

Subject Demographics

ID	Age	Total BBS	Postural Sway BBS	Medical History
1	81	37 (49)	3 (4)	Arthritis, stroke, knee replacement
2	86	3 (7)	0 (0)	Arthritis, macular degeneration
3	77	41 (44)	4 (4)	Arthritis, Parkinson's, hip replacement
4	85	23 (26)	0 (0)	Stroke
5	87	19 (22)	1 (3)	Arthritis, diabetes

Table 1. The total BBS is the summed score achieved across all "items" on the Berg Balance Scale (range is 0 to 56). The Postural Sway BBS score is the score received on the Berg item which demands that subjects stand, feet together, for 1 minute (range is 0 to 4). Scores outside of parentheses were recorded BEFORE the balance classes. Scores in parentheses were recorded AFTER classes were completed.

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Five community living elderly individuals participated in the study. Each had a history of falls and had been referred by a healthcare professional to participate in an eight week exercise course at a local community center. Their course consisted of two weekly 60 minute exercise sessions containing strength, endurance and functional balance exercises that were led by a licensed physical therapist. Exercises were selected based on clinical measures, including the BBS. The mean age of the cohort was 83 years (4.1 years standard deviation) and all provided informed consent. Basic demographics of the group are in Table 1.

Before and after the balance training classes, each participant was recorded with a video camera as they were assessed by a physical therapist for balance performance. The assessment used was the Berg Balance Scale (BBS), which consists of 14 movement items such as standing in place and reaching forward. Scores are assigned based on the time to complete each action, the degree of assistance required and the perceived quality of the underlying motion. The assessment was chosen because it is common, has high inter-rater and intra-rater reliability, and has been found to be specific and sensitive when it comes to the detecting likely fallers [17].

The camera used to make recordings was a Sony Handycam DCR-DVD 108 camcorder. This camera was placed by the physical therapist approximately 10 meters directly in front of each participant before assessments. Recordings were made on mini-DVD at a rate of 30 frames per second and a resolution of 740 by 480 pixels. Cameras were un-calibrated and the distance between the camera and subject varied from recording to recording. This simplified the recording task for therapists at the cost of creating variability in the character of each video.

To analyze postural sway, video corresponding to performances of the "Standing Feet Together" item on the BBS was manually extracted. The beginning and ends of the extracted videos were synchronized with points in time when the attending therapist was seen to hit a button on his or her stopwatch. The duration of each extracted video was one minute in length, except for videos corresponding to subject 2. This individual was not able to complete the task.

B. Data Processing

To track postural sway in the extracted videos a template tracker was engineered to track the position of individuals' heads and feet. This template tracker required the definition of "targets", or regions of image intensities in an example image. In every image subsequent to this example, the motion of targets was assumed to be explainable by translations. To track "targets", the translation required to maximize the normalized correlation between intensities in the original target template and corresponding regions in any subsequent image was identified. More complex template trackers might allow for various target region deformations or for the template to adapt and change over time. Template tracking is well represented in computer vision applications; examples include [18,19].

In our application, templates for the head were 60 by 60 pixels in size, while templates for the feet were 40 by 40 pixels in size. Templates were initialized by a human operator in the first image of every video sequence. Search windows for estimates of template positions were confined to regions 100 by 100 pixels wide and surrounding prior location estimates.

Once the movement tracks for each body part were computed, they were substantially smoothed to remove noise caused by occlusions, shadows or momentary changes in lighting. Smoothing involved first identifying and discarding "spurious" translations between image frames; these spurious translations were defined as those greater than 20 pixels in length. Next, tracks were filtered with a median filter that was 500ms in width. Finally, tracks were smoothed with a fourth order low pass Butterworth filter and their spatial accuracy was validated by human inspection.

Figure 1. Images of three subjects recorded by therapists in a community center setting. An outline surrounds the area spanned by head movement during recordings. Lines also indicate the recorded paths of feet, which are very small.

Example head movements recorded from three subjects are illustrated in Figure 1. In the figure, lines surround the area in which head movements were recorded. Lines also indicate the recorded trajectories of either foot. In all cases, trajectories were confined to relatively small image areas.

Before computing any statistics, all head and foot displacements were 'standardized' across subjects by dividing them by the average width between subjects' feet. All statistics that are reported, then, are in units determined by the base of support of each individual.

From 'standardized' tracks of heads and feet, a variety of mobility statistics were computed to characterize the velocity and overall medio-lateral displacement of the head as well as the smoothness and regularity of body sway. To parameterize head displacement, displacement tracks were mean centered and both the standard deviation and absolute medio-lateral range of displacement was computed. In addition, the overall image area spanned by head movement was calculated by means of the convex hull surrounding all head positions. Means and standard deviations were also computed for head velocities.

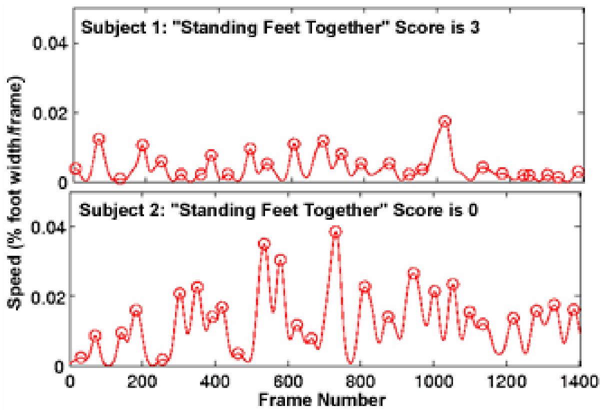

Figure 2. Recorded head velocities for subjects with high and low Standing Feet Together scores. Time is reported as the frame number in the recording. Red dots denote detected "peaks" in velocity profiles. Low scoring individuals were found to exhibit peaks with more average magnitude and variability in timing.

To parameterize smoothness and periodicity, the number and spacing of "peaks" in recorded profiles was explored. These "peaks" were detected by scanning profiles, and locating spots where the values of profiles were elevated relative to neighbors in time. Statistics computed from detected peaks included the mean number of peaks per second, the average temporal spacing between peaks and the deviation in spacing between peaks. Examples of smoothed head velocities for two subjects and the "peaks" associated with these profiles are shown in Figure 2.

To determine the ability of each statistic to accurately quantify functional balance performance, statistics were related to clinical performance measures. In specific, we report Pearson correlations between computed statistics and therapists' BBS scores for the "Standing Feet Together" item. The best possible score for this item is 4, which indicates the ability to stand stably without supervision for a minute. The lowest score is 0, which indicates the need for assistance or an inability to hold the position. We also report 95% confidence intervals surrounding correlations as well as the p-value for each correlation. Significance was defined by a p-value below .05. Finally, for statistics with significant correlations, we report on regressions relating statistics to Standing Feet Together scores. Specifically, we report r-squared and F-test results.

III. Results

Results for the correlation analysis are shown in Table II. The average head velocity was found to have a significant and inverse relationship to Standing Feet Together scores. The same negative relationship was found to exist between scores and both the standard deviations in head displacement and the absolute range of head displacement. In addition, the number of extremely large velocity peaks (i.e. those over 100% of the foot width per second) as well as the average amplitude of velocity peaks was found to correlate with Standing Feet Together scores.

In Table III are the results for regression analyses relating statistics with significant correlations to Standing Feet Together scores. The R-squared values for each regression are reported in the table in addition to F statistics and P-values. The number of high amplitude peaks per second was found to be statistic that best explained variance in scores; this R-squared is 0.48.

TABLE II
RELATIONSHIP BETWEEN MEASURED STATISTICS AND FUNCTIONAL SCORES

Statistic	Corr.	P
mean head **velocity**	-0.67 (-0.91, -0.07)	0.03*
standard deviation in head **velocity**	-0.62 (-0.9, 0.021)	0.06
number of head **velocity** peaks/second	-0.03 (-0.65, 0.61)	0.93
num. head **velocity** peaks > foot width per second	-0.69 (-0.92, -0.12)	0.03*
mean amplitude of head **velocity** peaks	-0.67 (-0.91, -0.07)	0.03*
variance in time b/t head **velocity** peaks	0.6 (-0.049, 0.89)	0.07
standard deviation in head **position**	-0.67 (-0.91, -0.07)	0.03*
range of head **position** (max – min)	-0.65 (-0.91, -0.03)	0.04*
num. of head **position** peaks (i.e. points of max deviation from mean)/second	0.4 (-0.31, 0.82)	0.26
mean amplitude of head **position** peaks	-0.64 (-0.9, -0.015)	0.05
variance in time b/t head **position** peaks	0.23 (-0.47, 0.75)	0.53
volume spanned by head **position**	-0.54 (-0.87, 0.13)	0.10
mean foot **velocity**	-0.54 (-0.87, 0.14)	0.11
standard deviation in foot **velocity**	-0.56 (-0.88, 0.1)	0.09

Table 2. The correlations between item specific BBS scores and each measured motor statistic are reported in addition to the 95% CIs surrounding these correlations. P-values for each correlation are also reported and those below .05 are indicated with an asterisk.

TABLE III
REGRESSION STATISTICS FOR VARIABLES WITH SIGNIFICANT CORRELATIONS

Statistic	R-squared	F-statistic (1,5)	P
mean head **velocity**	0.45	6.54	0.05
number **velocity** peaks > foot width per second	0.48	7.45	0.04*
mean amplitude of **velocity** peaks	0.45	6.54	0.05
standard in head **position**	0.45	6.52	0.05
range of head **position** (max – min)	0.45	5.71	0.06

In Figure 3 we illustrate the regression relating the number of high amplitude velocity peaks to the BBS score for the "Standing Feet Together" item. Statistics for each subject have been color coded. Statistics measured before classes are indicated with the suffix "(a)" while statistics measured after classes are indicated with the suffix "(b)". Although there is an obvious overall inverse relationship between the number of peaks in individuals' velocity profiles and their expert assigned scores, a change in score is not consistently reflected by a decrease in sway. For individuals with scores other than zero, the amount of sway measured before balance classes is larger than that measured after classes. For those with a score of zero, however, there is an *increase* in sway after classes relative to before. This increase, however, is not reflected in decrease in score. Likewise, for subject 3, who had a higher overall BBS score than other subjects (41/56 before classes, 44/56 after), a decrease in sway does not improve an already maximal item score of 4. Thus, sway measurements may highlight known ceiling and floor effects in the BBS [20].

IV. Discussion

Prior work has shown that postural sway increases with

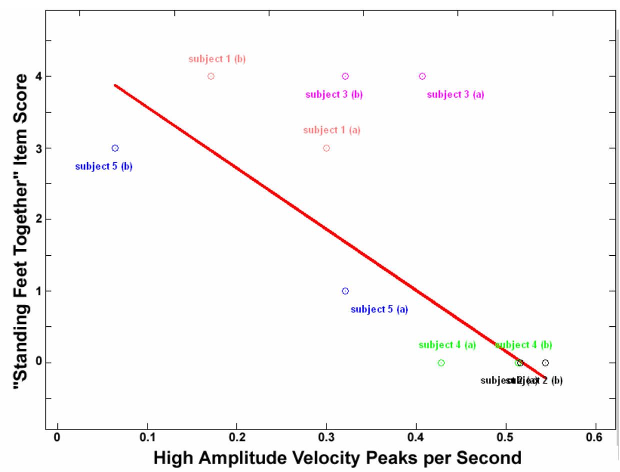

Figure 3. The number of high amplitude head velocity peaks per second. High velocity is defined as a peak over 150% of an individual's foot width per second. An (a) indicates data recorded before classes began, and a (b) indicates data recorded after classes.

age [1,2] and, moreover, that it may be an indicator of falls risk [3,4,5]. In [4], for example, the average speed of sway in institutionalized elderly, measured both laterally and front to back, was found be greater for those who fell one or more times in the past year than for those who did not fall. The amount of sway that has been fount to distinguish young from old individuals, however, tends to be small (on the order of 3 mm/sec when looking at COP trajectories [21]). It may therefore be possible to distinguish extremely impaired from less impaired individuals using a camera based sway measurement, as we have done; distinguishing young from old, for example, may require more detail in measurement that a single camera can provide.

The effect of age on the smoothness and timing of postural corrections has also been documented in prior literature [21,22]. In [22], for example, Fourier analysis was used to show that elderly individuals have a less consistent period of sway relative to younger individuals, and that this inconsistent periodicity is manifest in the dispersion of frequencies found in COP trajectories. The authors of [22] found this inconsistency, moreover, to be particularly manifest in the medio-lateral direction. Instead of utilizing spectral analysis, we have chosen to look at the variation in timing between velocity peaks as a measure of aperiodicity.

Although our results validate analyses that have previously been done in highly instrumented labs, the pertinent result indicates that low cost tools in community center settings can be used to perform some postural sway analyses that are consistent with the assessments of human clinicians. Vision based tools may therefore be able to perform some quantitative balance assessment in real world settings both economically and effectively. In future work, we will relate similarly coarse measurements made with low cost cameras to analyses of stability from standard clinical instruments, like commercial motion capture devices and force plates.

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