

Recurrence Quantitative Analysis of Postural Sway using Force Plate and Smartphone

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Although modern medicine and new medical technologies offer enormous potential to improve diagnosis and treatment of many diseases, mortalities from fall accidents are steadily on the rise for the elderly. Since postural stability characteristics are considered to be important in maintaining functional independence free of falls and healthy life style especially for the growing elderly population, there is an imminent need in inexpensive and portable device that can assess balance. While inertial sensors embedded in smartphone are seen as an alternative to force plate (ground truth) to unobtrusively assess postural stability in home environments, no study has yet reported the non-linear physiological information captured by smartphone affixed at pelvic region. By using recurrence quantitative analysis (RQA), this study investigates non-linear dynamical features of postural sway measured from force plate and smartphone. The resultant position vector of postural sway from the two systems was highly coherent and was used for non-linear analysis. Even though most of RQA measures collected from the projected postural sway using the smartphone were significantly different than measures collected using the force plate, deterministic characteristics of postural sway were not found significantly different. This study opens new prospects of easy clinical testing using postural variables that may be relevant for assessing fall risks at home and patient environment in future.

INTRODUCTION

Many studies have examined postural sway, complex movement of the body during upright stance, to better understand the complex mechanism. Traditional postural sway analyses are usually conducted by measuring the center of pressure (COP) from force plate and numerous studies often report the means and variances of different measures (e.g. path length, velocity, area, etc.). Some studies have used body-worn sensors such as inertial measurement unit (IMU) to measure center of mass (COM) to investigate postural control. In recent years, smartphones have also become very popular due to their smaller and less power consuming accelerometers, gyroscopes, and magnetometer, which enable collecting body motion noninvasively. Lee, Kim, Chen, and Sienko (2012) have used an iPhone on the waist via an elastic belt to measure an anterior-posterior (A/P) and a media-lateral (M/L) body tilt and warn user with vibrotactile feedback when the either tilt exceed the threshold.

However, these measures do not contain information of how sway changes over time. Thus, people have used newer methods based on nonlinear dynamic systems models to investigate patterns and structure of postural fluctuations (Hasson et al., 2008). One such method, recurrence

quantification analysis (RQA), is a nonlinear data analysis method that can be used to quantify the recurrences of a dynamical process of a time series (Marwan, Carmen Romano, Thiel, & Kurths, 2007; Riley, Balasubramaniam, & Turvey, 1999; C. L. Webber & Zbilut, 1994). It evaluates structure present in recurrence plots (RP), a visual representation of the recurrent patterns in time series data, and quantifies the repeatability, complexity, and local dynamic stability of dynamical systems (Hasson et al., 2008).

While dynamical properties of postural sway have been characterized by force plate, no study has yet used RQA to observe non-linear dynamical features of postural sway using smartphone. Therefore, the aim of this study was to investigate the non-linear dynamical structure of postural sway using the smartphone and determine if it is capable of measuring same information as the force plate.

METHODS

Participants

Twelve young adults (6 males and 6 females) with age (mean = 26 years, standard deviation [SD] = 4 years), height (mean = 162 cm, SD = 9 cm), and weight (mean = 68 kg, SD = 17 kg) with no previous history of neurological

disorders participated in this study. Prior to participation, all subjects provided their written informed consent document approved by the Virginia Tech Institutional Review Board.

Procedure

Participants were instructed to stand upright on a force plate with their feet approximately hip-width apart and arms relaxed at their sides for 60 seconds. Subjects were asked to look forward towards a target that is 4 meters away. Within the first 10 seconds of data collection, the participants were asked to tap their right foot for synchronization purpose. Trial was repeated three times for each subject.

Apparatus

All postural stability experiments were conducted on a force plate (BERTEC #K80102, Type 45550-08, Bertec Corporation, OH 43212, USA) with a smartphone (iPhone) attached at pelvic region by a clip. The postural sway data projected at floor level using smartphone was calculated using method that Mayagoitia, Lötters, Veltink, and Hermens (2002) used for their accelerometer. It is also called COP in this study for comparison and collected using application developed by the Locomotion Research Laboratory at Virginia Tech. The output signals from both systems were matched at the tapping peak and truncated for 50 seconds of data. The force plate data was sampled at a rate of 100 Hz and then resampled to 30 Hz whereas the smartphone was sampled at a rate of 30 Hz. From the truncated data (50 seconds), the two COP coordinates were computed in A/P and M/L directions for forceplates (COPx and COPy). For smartphone, Acc COPx and Acc COPy do not represent A/P and M/L directions of human movement, since it was not positioned in frontal (coronal) nor sagittal (median) plane.

Data analysis

All calculations were performed in MATLAB (Mathworks, Inc., Natick, MA) and the MANOVA test was used to compare RQA variables

observed from the two systems using JMP (SAS Institute Inc., Cary, NC) with α set at 0.05.

Postural stability variables. Since directions for x and y do not match between force plate and smartphone, comparing them was not appropriate. Thus, resultant COP values were used which was calculated as following:

$$COP_{res} = \sqrt{(COP_x)^2 + (COP_y)^2} \quad (1)$$

Recurrence quantification analysis (RQA). RQA requires careful selection of several input parameters related to phase space reconstruction and thresholds for identifying recurrence data. The parameters include the embedding dimension m , the time delay τ , the radius ϵ , and the minimum number of points to define a line segment l_{min} . Based on the literatures and preliminary data analyses, appropriate set of input parameters was selected (Brain, 1998; Pellechia & Shockley, 2005; Ramdani, Tallon, Bernard, & Blain, 2013; Riley et al., 1999; Seigle, Ramdani, & Bernard, 2009; C. L. Webber, Jr. & Zbilut, 2013; C. L. Webber & Zbilut, 1994). The embedding dimensions m was set to 8 first, and the average displacement (AVD) analysis was performed to choose the time delay. It was recommended to use different delays ranging from 3 to 9 for the smartphone. According to Hasson et al. (2008), this may be caused by the fact that RQA variables are highly sensitive to noise that is possibly due to distortion from the reconstruction process. Smartphone data contains more noise than force plate data where even a small amount of noise can decrease the reliability of RQA calculations (Thiel et al., 2002). Thus, Butterworth 3rd order low-pass filter with zero phase lag was applied to the smartphone data and then constant delay of 6 was observed (Figure 1). The radius was selected as 7% and 12% of the mean distance between the points for force plate and smartphone, respectively. It was adjusted so that the percent recurrence (%REC) values are acceptable (1-10%) (Ramdani et al., 2013; Seigle et al., 2009). Finally, the minimum number of successive points defining a line segment was set to 3.

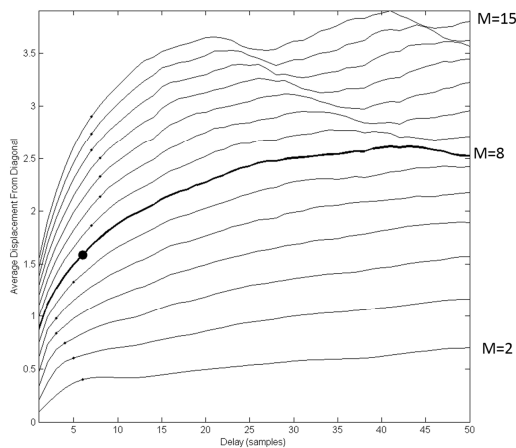


Figure 1. Result of the average displacement (AVD) analysis using different time delays and embedding dimensions

One of the main quantitative measures of RQA is the %REC, which implies how often a trajectory visits similar state space locations (time-independent) and it is quantified as the percentage of recurrent points in the recurrence matrix (Hasson et al., 2008). Another important measure is the percent determinism (%DET), which quantifies how often the trajectory repeatedly re-visits similar state space locations (time-dependent), computed as the ratio of recurrence data points which form diagonal lines to all recurrence points (Hasson et al., 2008). A random data will produce no diagonals or short diagonals, which leads to very small value of %DET, whereas a deterministic system data will produce long diagonals with high value of %DET (Marwan et al., 2007). Entropy, which is based on the concept of Shannon entropy, quantifies the complexity (irregularity) of a frequency histogram by measuring the probability distribution of the lengths of a diagonal line parallel to the main diagonal (Marwan et al., 2007). Max Line, a measure of dynamic stability, is quantified as the length of the longest diagonal line segment in the RP. Trend quantifies the amount of drift and non-stationarity whereas percent laminarity and trapping time are measures related to vertical lines in the RP (Clark & Riley, 2007; Hasson et al., 2008).

RESULTS

Figure 2 shows sample resultant COP time series and recurrence plot of the same time series data for both smartphone and force plate systems.

Similar COP_{res} data was observed in smartphone and force plate time series (Figure 2 (a) and (b)) but different corresponding recurrences of a dynamical process (Figure 2 (c) and (d)).

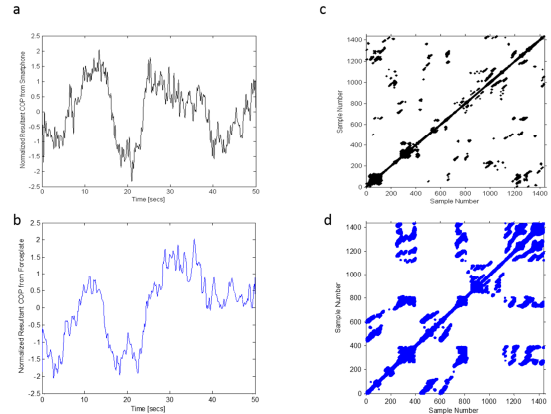


Figure 2. A representative data of a subject: COP_{res} time series for (a) smartphone and (b) force plate and recurrence plots of the same time series for (c) smartphone and (d) force plate.

The %REC, entropy, max line, percent laminarity, and trapping time between the two systems were found to be significantly different whereas the %DET and trend were not (Table 1).

Table 1. Mean and standard error of RQA variables for force plate and smartphone systems

	Force plate		Smartphone		p-value
	Mean	Std Err	Mean	Std Err	
%REC	0.53	0.12	3.92	0.8	0.0001
%DET	80.48	1.33	82.64	1.98	0.37
Entropy	2.5	0.09	3.26	0.19	0.001
Max Line	774.48	96.78	1321.52	54.22	<.0001
Trend	-0.9	0.19	-2.34	1.04	0.181
Percent Laminarity	40.71	6.27	84.64	2.76	<.0001
Trapping Time	4.15	0.31	7.95	1.1	0.0019

No significant difference of the percent determinism was observed between the two systems, whereas the smartphone had higher percent recurrence (Figure 3). Increase in the entropy and the max diagonal line length were also noted for the smartphone (Figure 4).

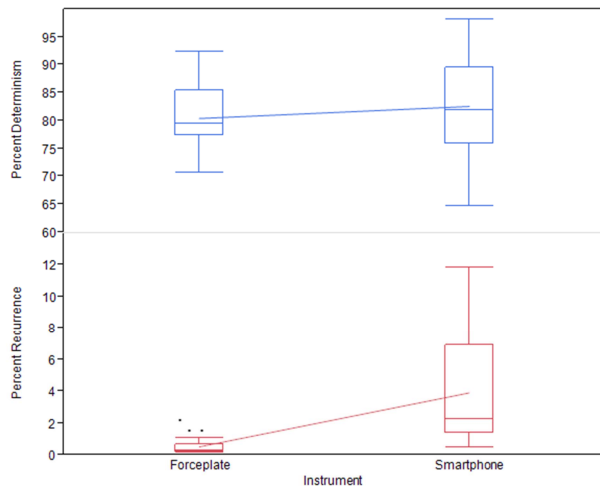


Figure 3. Percent determinism and percent recurrence comparison between the two systems

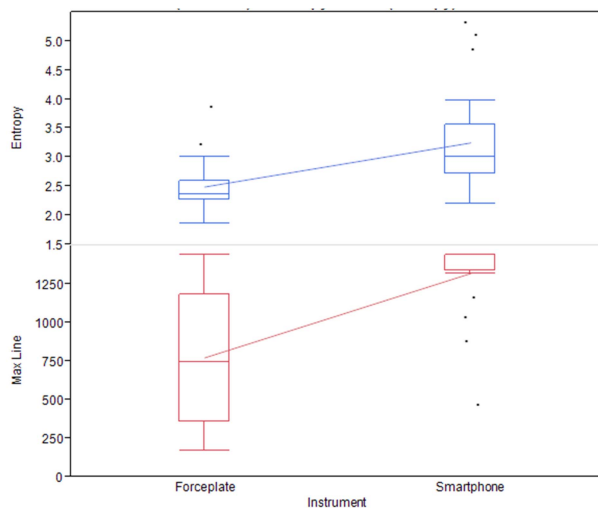


Figure 4. Entropy and Max Line comparison between the two systems

DISCUSSION

Smartphone is seen as an alternative to force plate for postural stability measurement. However, no study to our knowledge has been done until now to investigate non-linear physiological information using the smartphone system. The purpose of this study was to investigate if the non-linear information of postural sway captured by the smartphone is similar to that provided by the force plate. The dynamics of postural sway were investigated by means of RQA and most of RQA variables were significantly different between the force plate and the smartphone, which means that the two systems contain somewhat different information with exceptions.

Significantly higher %REC values were observed from the smartphone whereas no significant difference was observed on %DET values between the two systems. It means that the density of recurrence points is higher in smartphone data, but points that form diagonals of length is not significantly different between the two systems. It is the main finding of this study that proves the smartphone is capable of quantifying the predictability of the non-linear postural sway dynamics similar to the force plate.

Also, significantly higher entropy and max line values were observed in smartphone meaning that smartphone data has more complex diagonal line structure and higher longest diagonal line segment. Our results were consistent with previous finding that higher entropies were observed at trunk COP time series measured by inertial measurement unit when compared to COP time series measured by force plate (Soangra & Lockhart, 2013). A possible reason for this difference in this study is that the filter reduced noise in smartphone data, and it became less likely to break the diagonal structures (Ramdani et al., 2013). In result, diagonal lines may be shorter and length of the line segments may become more consistent, implying higher entropy.

This study could suffer several limitations. Direction information was lost with the resultant COP values, but it is not a crucial problem in this study since there was no comparison between groups (e.g. fallers vs. non-fallers, elderly vs. non-elderly). If the study involved comparison between groups, it could be a significant loss, since studies have reported a lower complexity in non-fallers compared to fallers (Costa et al., 2007). Also a lower complexity in the A/P direction of COP data was observed in frail compared to non-frail (Kang et al., 2009). If the smartphone was attached in frontal or sagittal plane, A/P and M/L directions of data could have matched that from the force plate. Also, it could have been strapped on sternum level rather than pelvic level since sway data from pelvic level may not observe sway of upper body. More independent variables (e.g. open/close eyes, with/without cognitive task, etc.) could be added to observe possible trend between the two systems. Also, this study was limited to only young healthy subjects; therefore further studies are required with elderly participants for external validity.

CONCLUSION

This study opens new prospects of using smartphone for easy clinical testing that may be relevant for assessing fall risks at home and patient environment. Our findings indicate that the dynamics of postural sway observed from the force plate and the smartphone contain somewhat different information, but most importantly the smartphone is capable of quantifying the predictability of the non-linear postural sway dynamics similar to the force plate. Addition of independent variables and more subjects such as elderly are needed in further research to determine an optimal position/direction of smartphone to capture complete movement artifacts of postural sway as that provided by force plate.

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