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Article Paper

The Static Standing Postural Stability Measured by Average Entropy

Sung-Yang Wei [1], Chang Francis Hsu [1], Yun-Ju Lee[2], Long Hsu [1], and Sien Chi [3]*

[1] Department of Electrophyics, National Chiao Tung University, Hsinchu 30010, Taiwan; mejicomejico@yahoo.com.tw; francis-920@hotmail.com; pinky750619@hotmail.com; long@cc.nctu.edu.tw

[2] Department of Industrial Engineering and Engineering Management at National Tsing-Hua University, Hsinchu 30013, Taiwan;
yunjulee@ie.nthu.edu.tw

[3] Department of Photonics, National Chiao Tung University, Hsinchu 30010, Taiwan

* Correspondence: schi@mail.nctu.edu.tw; Tel.: +886-3-5731824

Abstract: Static standing postural stability has been measured by multiscale entropy (MSE), which is used to measure complexity. In this study, we used the average entropy (AE) to measure the static standing postural stability, as AE is a good measure of disorder. The center of pressure (COP) trajectories were collected from 11 subjects under four kinds of balance situation, from stable to unstable: bipedal with open eyes, bipedal with closed eyes, unipedal with open eyes, and unipedal with closed eyes. The AE, entropy of entropy (EoE), and MSE methods were used to analyze these COP data, and EoE was found to be a good measure of complexity. The AE of the 11 subjects sequentially increased by 100%as the balance situations progressed from stable to unstable, but the results of EoE and MSE did not follow this trend. Therefore, AE, rather than EoE or MSE, is a good measure of static standing postural stability. Furthermore, the comparison of EoE and AE plots exhibited an inverted U curve, which is another example of a complexity versus disorder inverted U curve.

Keywords: Center of pressure (COP); Average Entropy (AE); Entropy of Entropy (EoE); Multiscale Entropy (MSE), Inverted U curve; Biological Disorder; Biological Complexity

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1. Introduction

Postural stability is a major public health concern in modern society. Based on a WHO global report in 2015 [1], approximately 28%–35% of people aged of 65 years and over fall each year, and this rate increases to 32%–42% for those over 70 years of age. The average cost of hospitalization for instability-related injuries for people 65 years and older in the United States is projected to increase to US$240 billion by 2040. Accurate identification of individual postural instability factors, including impaired balance and poor vision, can greatly increase the likelihood of selecting an appropriate prevention or treatment strategy that is targeted to meet the needs of the individual person [1].

Maintaining postural stability involves a complex sensorimotor control system in the human body [2]. Any disturbance from the surroundings or subjects' breathing could cause an increase in static standing postural instability [3], and such a loss of static standing postural stability can be shown in the center of pressure (COP) or the center of foot pressure (CFP) trajectory [4, 5, 6]. Force platforms are simple devices that can be used to record subjects' COP trajectory over time in anteroposterior (AP) and mediolateral (ML) directions [7]. Open eyes (denoted here as "O") or closed eyes (denoted here as "C") are some of the simplest variables that influence subjects' static standing postural stability [8], since vision can provide a great amount of information regarding postural stability [9]. Further, unipedal (denoted here as "1") and bipedal (denoted here as "2") standing also influence subjects' postural stability [10]. Since leg muscles consume more energy in unipedal than in bipedal cases [11], postural stability shown by COP data in unipedal cases is lower. Combinations of these four variances (closed eyes, open eyes, unipedal, and bipedal) are also used for balance testing [12], assistive device evaluations [13], or balance control training [14]. The trend of postural

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instability, from the most stable to the most unstable cases, goes from bipedal with open eyes (O2), to bipedal with closed eyes (C2), to unipedal with open eyes (O1), and to unipedal with closed eyes (C1).

There are some entropy-based methods, such as the multiscale entropy (MSE) method, that can be used to distinguish these characteristics under different balance situations [15, 16]. In such studies, higher MSE values are thought to be more stable; for example, MSE complexity index (CI) values under open eyes cases are usually larger than those under closed eyes cases [16]. However, there are still some issues that require further discussion. For example, larger MSE CI values are not always more stable. Subjects who exhibit larger COP trajectory variances, which are more unstable, are generally associated with greater MSE CI values, and vice versa [17]. Further, due to the use of different data processes in these studies, the MSE CI values for the closed eyes groups are sometimes higher than those of open eyes groups [15, 18].

Recently, average entropy (AE) has been proposed to measure the disorder of biological time series [19]. Heart rate time series signals from atrial fibrillation (AF) groups, which are unhealthy, are more disordered than those from healthy groups. Therefore, the AE method can be used to measure the disorder of heart rate time series from different groups. The entropy of entropy (EoE) method has been proposed to measure the complexity of biological time series [20]. Heart rate signals from healthy groups are more complex or have larger EoE values than those from AF groups.

In this study, the AE, EoE, and MSE methods were used to individually measure the disorder and the complexity of 11 subjects' COP data collected under four different balance situations. The aim was to determine which method is suitable to measure static standing postural stability.

2. Materials and Methods

2.1 Materials and Experiment Setup

The force platform used in this studying was the AccuGait System with AMTI's powerful NetForce/BioAnalysis software package. The sampling rate was 1000 Hz, and the filter was a fixed 100 Hz third-order analogue.

The 11 subjects included 2 females and 9 males. Their average age ± standard deviation was 30.27 ± 10.76 years old, their average height ± standard deviation was 170.86 ± 4.93 cm, and their average mass ± standard deviation was 67.06 ± 8.34 kg. Subjects had no ankle or knee injuries; did not suffer from any neurological conditions that might affect their balance, such as vestibular disorders or diabetes; and did not take any medications that affected their balance. The project was approved by the National Tsing Hua University Institutional Review Board, and all subjects provided written informed consent before taking part in the experimental procedures.

Subjects were asked to stand on the force platform under four kinds of balance cases for 30 s, and the first and last 2 s of data were removed. Subjects were asked to stand as still as possible in the center of the force platform without locking their knee joints and with their arms relaxed at their sides [21]. For the bipedal tests, the spaces between subjects' two legs were as wide as their shoulders and symmetric to the center of the force platform. For the unipedal test, the subjects were asked to use the leg on the same side as their dominant hand and to stand on the center of the force platform. For the open eyes tests, subjects were asked to focus on a point 2 m in front of them. For the closed eyes tests, they were asked to close their eyes once they were standing on the force platform.

2.2 MSE Method

The MSE method was used to analyze the COP data under the four kinds of balance situations. These analyses were performed using MATLAB (v7, The Mathworks, Inc., Natick, MA) and LabVIEW (2017, National Instrument). Raw COP time series were downsampled from 1000 to 250 Hz [15] because the MSE method requires longer time series to be analyzed. To filter noise and to pick up the frequency intervals of interest, the COP time series were detrended with the ensemble

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empirical mode decomposition (EEMD) method before the MSE analysis [15]. The ensemble number for the EEMD was 100. All intrinsic mode functions (IMFs) were the averages of these 100 times EEMD results. Twelve unique IMF combinations were generated and IMFs 8–12 were removed, which exhibited frequencies below 0.2 Hz, to ensure a minimum number of dynamic patterns within the length of our time series. Additionally, IMFs 1 and 2 were also removed, as they exhibited frequencies above 20 Hz and were thus unlikely to reflect balance-related biological processes. The continuously sequenced combinations of IMFs 3–6 were used in the AP direction and IMFs 3–7 were used in the ML direction for the best distinguish in each sway direction [15]. The details of the characteristic frequencies of IMFs are shown in Table 1.

In this study, the two variables in the MSE method were the length m for calculating the sequences similarity, which was set to $m = 2$, and the amplitude percentage range r, which was set to $r = 0.15$. The MSE scales were chosen to be 1–25 in the AP direction and 1–35 in the ML direction [15]. These specific IMFs and MSE scale combinations were chosen since the literature shows that postural steadiness can be best discriminated using these.

Table 1. Details of the intrinsic mode functions (IMFs) and MSE scales used in this study.

COP Direction	IMFs	Characteristic IMF Frequencies (Hz)	MSE Scales
AP	3, 4, 5, and 6	19.43, 8.40, 3.49, and 1.36	1–25
ML	3, 4, 5, 6, and 7	19.36, 7.79, 3.26, 1.19, and 0.52	1–35

2.3 Average Entropy and Entropy of Entropy Methods

The AE and EoE methods were used to analyze the COP data under the four kinds of balance situations. These analyses were performed using MATLAB (v7, The Mathworks, Inc., Natick, MA) and LabVIEW (2017, National Instrument). Raw COP time series were downsampled from 1000 to 50 Hz for the best discrimination of the AE and EoE values under these the four kinds of balance situations.

The speed time series of the COP data were calculated from the COP trajectories under the four kinds of balance situations. For N COP trajectory data points, the instantaneous COP speed time series $v(N)$ was

$$v(N) = \sqrt{|x(N) - x(N-1)|^2 + |y(N) - y(N-1)|^2}.$$

where x and y denote the coordinates of the original COP trajectory in the ML and AP directions, respectively. Afterward, the speed time series $v(N)$ were analyzed by the AE and EoE methods. The plots of instantaneous speed $v(N)$ under the four kinds of balance situations (O2, C2, O1, and C1) are shown in Figure 1.

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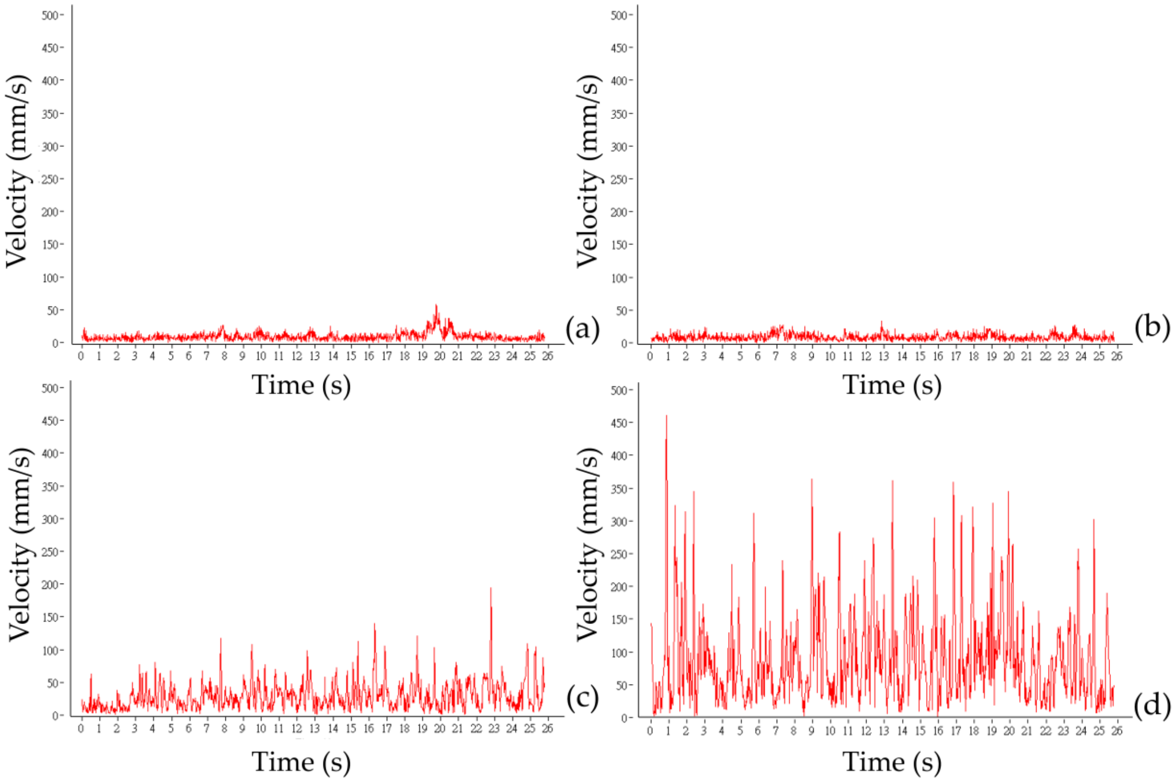

Figure 1. The example plots of COP speed time series of a subject under four kinds of balance situations. Every plot contains a 26 s COP speed time series. (a) The O2 case. (b) The C2 case. (c) The O1 case. (d) The C1 case.

The flowchart of the AE and the EoE methods is shown in Figure 2. The detailed algorithm of the AE method can be found in [19], and the detailed algorithm of the EoE method can be found in [20]. Both of these two methods contain the following two steps: First, the Shannon entropy is used to characterize the "state" of a COP displacement time series within a time window τ, which represents the "information" contained in that period of time. In this study, τ = 4 was used. Second, the average of all the Shannon entropies of each window for AE or the Shannon entropy of all the Shannon entropies of each window for EoE is used to characterize the degree of the "changing" of the states. The COP speed $v(N)$ ranged from v_{min} = 0 mm/s to v_{max} = 1000 mm/s and was divided into 75 slices of equal speed width, such that each slice represented an independently physiologic state of $v(N)$ intervals.

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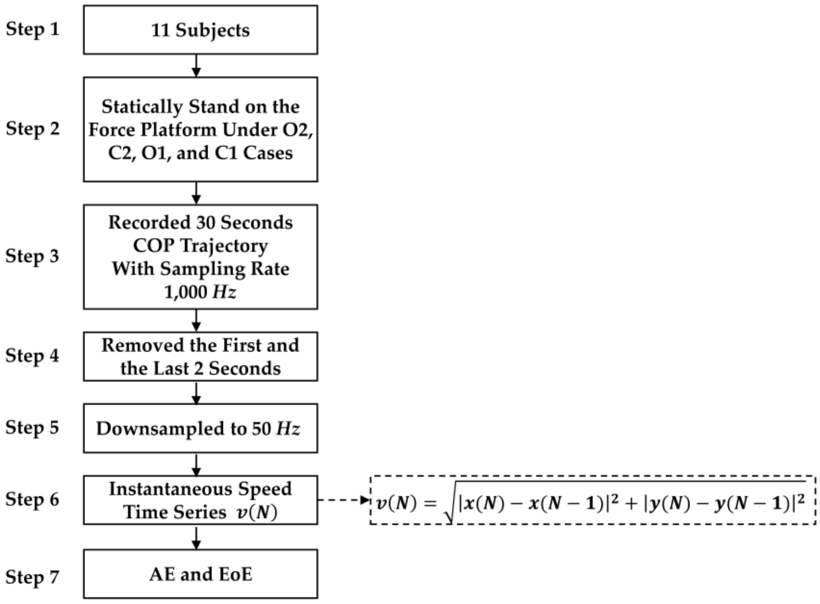

Figure 2. The flowchart of the AE and EoE methods.

3. Results

In this section, the COP data results of the 11 subjects under the four kinds of balance situations are described. The AE results are shown in Figure 3 and the EoE results are shown in Figure 4. The MSE CI results in the ML and AP directions are shown in Figure 5(a) and (b), respectively. The plot of the EoE values versus the AE values is shown in Figure 6. The color points in these graphs are as follows: the blue triangles show the O2 cases, the yellow star points show the C2 cases, the green triangles show the O1 cases, and the red points show the C1 cases.

Figure 3 shows the AE values for the 11 subjects. There are four points for each subject which represent the AE values under the four kinds of balance situations from stable to unstable: O2, C2, O1, and C1. As shown in Figure 3, 100% of the AE results had the following trend: AE (O2) < AE (C2) < AE (O1) < AE (C1); that is, the lower the AE values, the more stable the static standing.

In a previous study, AE was shown to be a measure of disorder [19]. In this study, disorder was considered to be the same as postural instability. Based on the trends of the subjects (Figure 3), the AE method was demonstrated to be a good measure of static standing postural instability of COP speed time series under different balance situations.

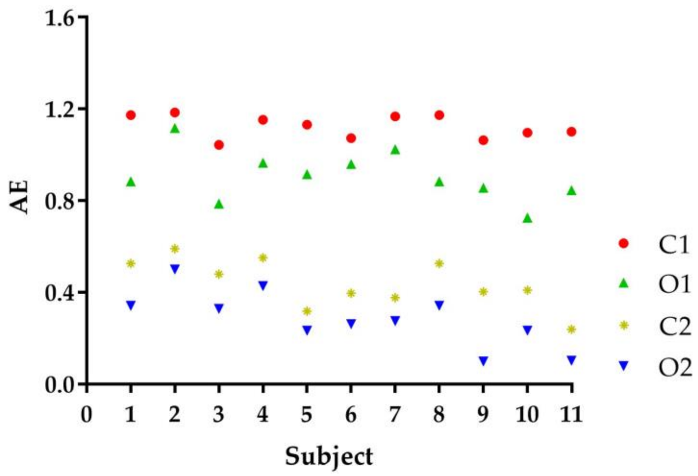

Figure 3. The AE values of the 11 subjects under four kinds of balance situations: O2, C2, O1, and C1.

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Figure 4 shows the EoE values for the 11 subjects. The O1 cases had the largest EoE values for most of the 11 subjects. The trends of the EoE values were different across subjects and did not follow the postural instability trend. EoE is a complexity measure [20]. In this study, complexity could not measure static standing postural stability. Based on the trends of the subjects (Figure 4), the EoE method cannot be considered a good measure of static standing postural instability of COP speed time series under different balance situations.

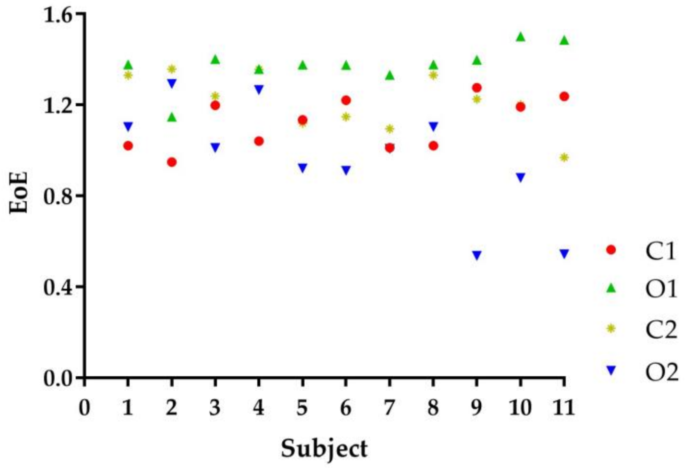

Figure 4. The EoE values of the 11 subjects under four kinds of balance situations: O2, C2, O1, and C1.

Figure 5(a) shows the MSE CI values in the ML direction of the 11 subjects and Figure 5(b) shows the MSE CI values in the AP direction of the 11 subjects. There are four points for each subject which represent the MSE CI values in the ML direction and the MSE CI values in the AP direction under the four kinds of balance situations: O2, C2, O1, and C1. Only 1 of the 11 subjects (subject 4) shown in Figure 5(a) followed the postural instability trend of MSE CI (O2) < MSE CI (C2) < MSE CI (O1) < MSE CI (C1). None of the 11 subjects shown in Figure 5(b) followed this trend.

MSE CI values are considered to be a measure of complexity [15, 16]. In this study, the MSE CI values could not measure static standing postural stability. Based on the trends of the subjects (Figure 5(a) and (b)), the MSE method cannot be considered a good measure of static standing postural instability of COP speed time series under different balance situations.

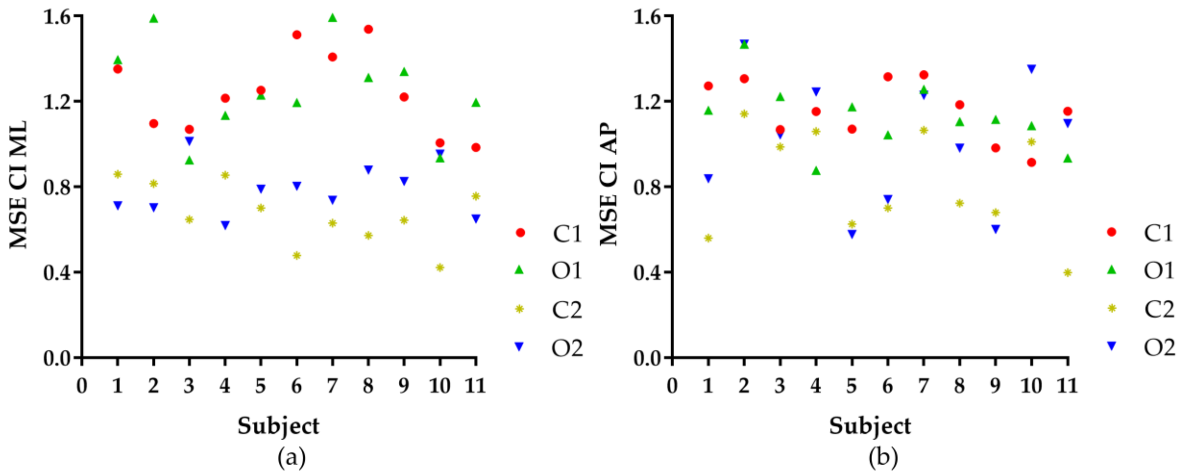

Figure 5. The MSE CI values in the ML direction and the MSE CI values in the AP direction of the 11 subjects under four kinds of balance situations: O2, C2, O1, and C1.

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(a) The MSE CI values in the ML direction of the 11 subjects. (b) The MSE CI values in the AP direction of the 11 subjects.

Figure 6 shows the plot of the EoE values versus the AE values of the 11 subjects under different balance situations: O2, C2, O1, and C1. The plot of the EoE values versus the AE values exhibits an inverted U curve, where the maximal complexity value appears in the O1 case, between the largest and smallest AE values.

This inverted U relation exhibited in the complexity (EoE value) versus the disorder (AE value) plot of the COP speed time series is another example of an inverted U relation, like what was found for heart rate time series signals in a previous paper [19].

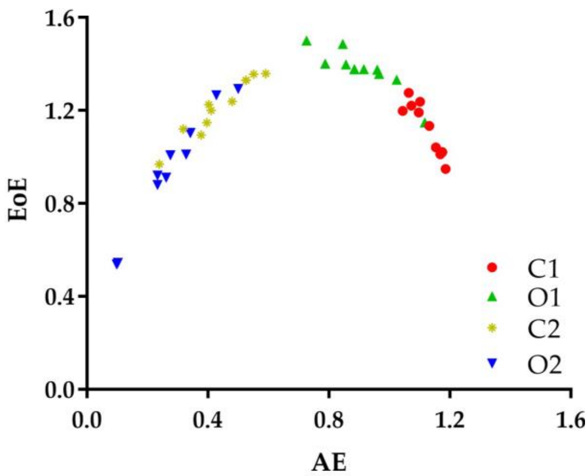

Figure 6. The plot of the EoE values versus the AE values of the 11 subjects.

4. Discussion

The health condition of the heart can be measured by the complexity of the time series of the heart beat rate, and this complexity is measured by MSE or EoE. Higher complexity indicates a healthier heart. Static standing postural stability can be measured by the disorder of the time series of the center of pressure of the body on a force platform, and this disorder is measured by AE. Greater disorder indicates unstable static standing. Heart beats are controlled by the autonomic nervous system, but static standing postural stability is controlled by the nonautonomic nervous systems (the somatic nervous system). These facts suggest that disorder measurement is useful in a nonautonomically controlled nervous system, and complexity measurement is useful in an autonomic system. We are conducting further experiments to support these claims.

5. Conclusions

We have shown that AE, a measure of disorder, can measure static standing postural stability. For the 11 subjects under four kinds of balance situations, the AE values of each individual subject increased from stable to unstable cases. On the other hand, MSE or EoE, as measures of complexity, could not measure static standing postural stability.

Furthermore, the plot of the complexity (EoE) value versus the disorder (AE) value of the COP speed time series of the 11 subjects under four kinds of balance situations exhibited an inverted U relation. This inverted U relation exhibited in the complexity versus disorder plot of the COP speed time series is another example of an inverted U relation, similar to that which was exhibited for heart rate time series signals.

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