A Methodology for Examining the Chaotic Behavior of the CoP Signal during the Quiet Standing Based on Empirical Mode Decomposition Method

Rahel Hajipour[1], Fateme Asadollahzadeh Shamkhal[2], HamidReza Kobravi[3*]

[1,3] Research Center of Biomedical Engineering, Mashhad Branch, Islamic Azad University, Mashhad, Iran

[2] Department of Electrical Engineering, Faculty of Engineering, Ferdowsi University of Mashhad, Iran

** Email: Hkobravi@mshdiau.ac.ir*

1 Email: hajipourr91@gmail.com,
Mobile Number: +98-9153009429,
Telephone: +98-51-36629467,
Postal Address: Department of Biomedical Engineering, Faculty of Engineering, Islamic Azad University (Mashhad Branch), Ostad Yusofi Street, Emamieh Boulevard, Ghasem Abad, Mashhad, Iran.
P.O. BOX: 91735-413

2 Email: Fateme_A_shamkhal@yahoo.com,
Mobile Number: +98-9158087487,
Telephone: +98-51-38806051,
Postal Address: Department of Electrical Engineering, Faculty of Engineering, Azadi Square, Mashhad, Razavi Khorasan Province, Iran.
P.O. BOX: 91775-1111
Fax numbers:+98-51-38763302

3 Email: Hkobravi@mshdiau.ac.ir,
Mobile Number: +989153173567,
Telephone: +98-51-36629467,
Postal Address: Department of Biomedical Engineering, Faculty of Engineering, Islamic Azad University (Mashhad Branch), Ostad Yusofi Street, Emamieh Boulevard, Ghasem Abad, Mashhad, Iran.
P.O. BOX: 91735-413

Running title: Examining the Chaotic Behavior of the CoP Signal

Abstract

A key parameter for analyzing the human balance dynamics during standing is the center of pressure (CoP). But, so far no conclusive idea has been posed with respect to elicited dynamics of the CoP signal during quiet standing. In this paper, a heuristic algorithm has been proposed to prove the chaotic behavior of the CoP signal with high confidence. In the proposed algorithm, at first the deterministic and non-deterministic (may be stochastic or may be chaotic) components of CoP signal are extracted using the empirical mode decomposition (EMD) method. Then the nonlinear features of the extracted components such as fractal dimension, Lyapunov exponent, correlation dimension, and alpha parameter are computed. Then according to the quantitative value of the computed features, the chaotic component is selected among the extracted components. Finally, using the recurrence quantitative analysis (RQA), the selected chaotic component is reanalyzed to give assurance of correct selecting the chaotic component. In this manner, the kind of CoP dynamics can be determined with high confidence. The analyzed CoP signals were recorded through some experiments on 12 healthy subjects being between 20 to 70 years old. The results of this study show that CoP is a chaotic signal whit high confidence.

Keywords: Quiet Standing, Center of Pressure (CoP), Empirical Mode Decomposition (EMD), Chaotic Dynamics, Recurrence Quantitative Analysis (RQA)

1. Introduction

The position of ground reaction force called CoP plays an important role in controlling the balance during standing [1-4]. It alone can be a criterion to measure stability during the quiet standing [1]. Not only may the magnitude of the CoP but also its direction of displacement, or heading, of the CoP provide further insight into the control of posture [2]. In other words, the CoP measurement is usually performed as an indicator of maintaining balance and postural control. Hence, in recent years, many researchers have investigated the behavior of CoP signal as a nonlinear signal [5-19]. The eminent conducted studies regarding this issue, are concentrated on two main axes: part of them focus on studying the complicated nature of the CoP signal and the process of standing balance [6-10], and the other part on the changes of the CoP features in different conditions [11-19]. In the first group of studies, researchers investigated whether the process of standing is a chaotic process or not. Some of them could not reach a definite conclusion about the chaotic or the stochastic behavior of the CoP signal [10]. Collins et al. considered the behavior of the CoP signal for the first time and suggested that this behavior has a sign of a random correlated noise [7]. Later, other researchers suggested that the complex and unpredictable behavior of the motor sensor control system can be indicative of the existence of chaos in controlling the status of the individual's body [8,9]. Ghomashchi et al. could not reach a definite conclusion about the chaotic or stochastic behavior of the CoP signal [10]. In the second group of studies, in order to analyze the changes in the nonlinear features of the CoP in different conditions, researchers used various methods. Kuznetsov et al. by using fractal analysis, and Gurses et al. by using correlation dimension estimation of CoP signal conducted some studies on the process of standing balance and body sway [13,14]. However, a controversial question has yet remained without a confident answer. Is the CoP a chaotic signal or not? The Langevin equation has been also used to model the CoP dynamics [15,16]. They analyzed the change of CoP dynamics with respect to excluding the visual feedback, age, and disease severity [15,16]. Through this approach, the change of the balance dynamics could be shown. But nothing can be claimed about the nature of the CoP during standing. In addition, the original Langevin equation describes a specific stochastic process called Brownian motion [17], while no conclusive evidence has been presented so far showing the Brownian nature of the CoP signal. Snoussi et al. studied the behavior of CoP by decomposing the signal into its components using the EMD method [18]. They emphasized that the presence of deterministic and stochastic component accompanied by chaotic components in CoP signal may result in mixing up the chaotic behavior of CoP with a stochastic behavior. Therefore, they used the EMD method to extract the chaotic component of the CoP signal based on the analysis of the Lyapunov exponent. Using the EMD, a time series is partitioned into the Intrinsic Mode Functions (IMF) without leaving the time domain. Such modes may provide insight into various signals within the data. In other words, the EMD can pave the way to extract the time components showing different behavioral aspects of the nonlinear and non-stationary signals. So, it could be useful for our study. But, the analysis based on the Lyapunov exponent alone may lead to some misleading results because of the presence of either discretization errors or measurement noise. Therefore, in this study, an analysis algorithm based on the EMD method has been proposed to select the chaotic component among the extracted components, with high confidence.

2. Methods and Materials

2.1 Data Collection

The experiments were conducted on 12 healthy subjects with no history of disease 6 males and 6 females aged between 20 and 70 years, participated in experiments. Though the range of the age range is wide, according to the received medical consultations, the balance quality in the subjected whose age was older than 50 was not affected significantly owing to the aging. Therefore, we did not categorize the subjects in terms of their age. The subjects were asked to stand quietly with barefoot on the Force Plate (9286A, KISTLER) and eyes open during experiments. Each trial lasted 2 minutes and sampling frequency was 100Hz. Individuals maintained their upright posture while CoP signal was recorded during each experiment. Fig. 1, shows the experimental setup.

2.2 The proposed analysis methodology

Fig. 2 shows the flowchart of the proposed analysis methodology. In this suggested algorithm, at first, the CoP data were decomposed into their components using a nonlinear preprocessing method called EMD. Then, the fractal dimension (FD) was computed for the extracted components. Since the presence of computational error may be raised owing to data discretization can result in obtaining a fractional number instead of an integer number. Since there is no trivial approach for reducing the quantization error, a heuristically simple approach was chosen. We used the Higuchi method for computing the fractal dimension [19]. According to this approach, the fractal dimension is computed through the following exponential relation [19]:

$$\langle L(k) \rangle \propto k^{-D} \tag{1}$$

Where D is the fractal dimension, k is the length of the time interval, and the $\langle L(k) \rangle$ is the average value of the lengths associated to the time series constructed using the raw data [19]. In this study, the computed fractal dimensions (D) were about 1. Therefore, 1±0.01 (or 1±less than 0.01) does not change significantly the L value, because 0.01 (or less) can be negligible in comparison with 1. But, this may be misleading. Because the L value will not be as outlier data as that one can recognize. Therefore, we regarded the 0.01 as a computational margin. In this manner, those components whose fractal dimension were fractional and were at least 0.01 more or less than an integer value, were selected as the candidate chaotic components. Next, the correlation dimension (CD) and Lyapunov exponent were computed for the candidate components [20]. The selected components should have fractional correlation dimension and positive Lyapunov exponent. Finally, by using another nonlinear analysis method called DFA, logarithmic diagrams related to the extracted components were plotted. The component whose logarithmic diagram had the enough expanded linear area and that did not mislead to estimate the scaling exponent was calculated as the slope of a straight line fit to the log-log graph. Therefore, the component whose logarithmic diagram had the most expanded linear area was selected as the component that was the chaotic component with high confidence.

2.2.1 EMD analysis

Empirical Mode Decomposition (EMD) is an experimental method for analyzing the natural signals that are usually non-linear and non-stationary [5,21]. It was first introduced by Huang in [21]. EMD decomposes a nonlinear non-stationary signal into a finite number of oscillatory functions that are called Intrinsic Mode Functions (IMF). IMFs of a signal are extracted during a process called screening process which includes the following stages:

1. Specifying all the local extrema of the signal
2. Obtaining the upper and lower envelope of the signal
3. Calculating the mean of the upper and lower envelope of the signal

$$e(t) = \frac{X_L(t) + X_U(t)}{2} \tag{2}$$

4. Subtracting the envelope mean from the entering signal

$$d(t) = X(t) - e(t) \tag{3}$$

Continuing the screening process for the remaining signal $d(t)$ until we get to the final specified conditions The extracted component will be IMF if it meets the following two conditions:

1. Throughout the dataset, the number of extremes and the number of crossing the zero should be equal or maximally have 1 unit of difference.
2. In each point, the envelope mean defined by the local maximums and the envelope defined by the local minimums should be zero. In other words, an IMF should be a symmetric function at about zero.

If these above conditions are met, the extracted component will be considered as IMF. Otherwise, the screening process is continued on the remaining signal until the first IMF is extracted.

The screening process can be stopped by any of the following predefined conditions:

1. When the remaining component is so small that it is smaller than a predefined significant amount.

2. When the remaining component changes into a monotonic function of which no other IMF can be extracted.

After termination of the screening process, the explained nonlinear analysis is carried out.

2.2.2 DFA analysis

Detrended Fluctuation Analysis (DFA) is a known approach to quantify the complexity of non-stationary signal based on analysis of short term and long term autocorrelation of a signal. DFA algorithm output is a parameter called a which is the slope of the logarithmic graph. It indicates statistical self-affinity of the signal. In this method, the signal squares least distance from the signal trend is analyzed as a function of the scale parameter [22-24]. For $X(i)$, DFA algorithm is applied in the following manner:

1. Calculation of the value of the $X(i)$ oscillation

$$y(k) = \sum_{i=1}^{k} \left(X(i) - X_{avg} \right)^{y} \tag{4}$$

2. Calculation of the average value of the signal oscillation relative to its trend

$$F(n) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} \left(y(k) - y_n(k) \right)^2} \tag{5}$$

3. Plotting $logF(n)$ logarithmic graph to $\log n$

$$F(n) \approx n^{a} \tag{6}$$

In the plotted logarithmic graph, the slope of the linear region is considered as parameter a. In fact, a is the slope of a region where $\log F$ has a linear relationship with $\log n$.

2.2.3 Calculating the Lyapunov Exponent

Since there was no differential equation model describing the raw data or IMFs, the Lyapunov exponents should be computed from the available signals. Therefore, the Wolf well-known method was applied [25]. According to the Wolf method, the Lyapunov exponent (LE), defined by long term evolution of nearby orbits in a reconstructed m-dimensional phase state, can be computed using Equation 7 [25].

$$\lambda_1 = \frac{1}{t_M - t_0} \sum_{k=1}^{M} log_2 \frac{L'(t_k)}{L(t_{k-1})} \tag{7}$$

Where λ_1 is the Lyapunov Exponent, $L(t_{k-1})$ is the Euclidian distance between a data point located at the nearest neighborhood of a point in the phase portrait related to a time instance (t_{k-1}), $L'(t_k)$ is Euclidian distance between the next replaced data point and the next point in the phase portrait related to a time instance (t_k), M is the total number of the replacement steps, and t_0 and t_M show the initial and the last time instances.

2.2.4 Analysis of IMF5 using RQA

At the last step of the proposed algorithm, the complexity of the selected IMF and raw CoP signal was compared to account for the achieved results. In other words, it is expected that the selected IMF is a more complex signal in comparison to the raw CoP signal. In this manner, it can be claimed that the selected IMF is the chaotic component of the CoP signal with high confidence. Here, the RQA (Recurrence Quantitative Analysis) has been utilized. The RQA is a nonlinear method for analyzing dynamic systems especially for measuring the complexity of a signal [26]. The method is established for quantifying the recursive plots (RP) on the basis of short-scale structures [27]. RQA is based on making a recurrence plot, in which some variables that measure different aspects of the dynamics of COP data are extracted [28]. Recursive plots include a graphic expression of the trajectories dynamic of system mode space [26,27,29]. The basic principle in RQA is that phase space of a single time series can only be reconstructed using time delay and The RQA is a relatively simple method, widely used in some past research [30]. The output of the RQA is a set of features for quantitative analysis of recursive graphs. In this study, we used a feature called determinism (DET). This measure is related to the predictability of the system dynamics. The DET is defined as the percentage of the recurrence points of diagonal lines to the total number of recurrence points. The DET can be calculated as below:

$$DET = \frac{\sum_{l=l_{min}}^{N} lP(l)}{\sum_{i,j=1}^{N} R(i,j)} \tag{8}$$

Where $P(l)$ is the distribution of the diagonal lines and l is the number of points forming the line. This measure is related to the predictability of the system dynamics.

3. **Results**

3.1 Analysis of the IMFs

Fig. 3 shows an example of CoP decomposition to 11 IMF components using the EMD algorithm. In The next step, the fractal dimension of obtained IMFs is calculated. In this stage, the components whose related fractal dimensions were fractional and were at least 0.01 more or less than an integer value was selected as the candidate chaotic components. The calculated values for selected IMFs related to a two sample participant are given in Table I. and Table II. As shown in Table I. and Table II, second to fifth components satisfied the mentioned conditions and were selected. The noteworthy point was the significant similarities between the computed fractal dimensions despite the considerable differences between the subjects' weight, height, and age. This claim is based on the calculated average and standard deviation of computed fractal dimensions among the participants. It was 1.02± 0.01, and this show that the computed standard deviation is very small in comparison to the computed mean. These similarities can show the presence of similar movement patterns during standing among the healthy subjects. In the next step, to verify the correctness of the chaotic nature of selected components, the correlation dimensions and Lyapunov exponent of the selected IMFs were calculated. According to Table I and Table II, the calculated correlation dimension for the second to fifth components is also a fractional number, and Lyapunov exponents of the second to fifth components are large and positive. These results can confirm the chaotic behavior of the selected component because these results can confirm that the impact of the measurement noise and computational error on the results is likely low. It is worth noting that the calculated Lyapunov exponents related to the second to fifth components are greater than calculated Lyapunov exponent related to the raw signal. This shows that analysis of the raw CoP signal can be misleading, due to the stochastic and deterministic components of CoP signal. The other interesting point is obtaining similar results among all participants. Tables (I, II) show the obtained results related to two sample subjects, yet we obtained similar results among the participants.

3.2 Selecting an IMF using DFA

Finally, using the DFA analysis, among the second to fifth components the component which had a wider linear range was selected as the chaotic component, because the limited linear range may elicit the calculation error related to calculating the value of a . . This may lead to inaccurate judgment about the nature and complexity of the signal. As Fig. 4 shows, among the second to the fifth components, the fifth component has a wider linear region. Therefore, IMF5 was selected as a component which gives us more precise information about the chaotic nature of the CoP signal. Apparently, the analysis of the complexity of the balance process using IMF5 is more suitable.

The calculated α parameter related to IMF5, in all subjects, is substantially larger than 0.5. Therefore, it can be claimed that the extracted IMF5 signal, in all subjects, is an anti-persistent signal. This could be indicative of emergent behaviors in the balance process.

3.3 Analysis of the Selected IMF Using RQA

As mentioned previously, at the last step of the proposed algorithm, the complexity of the selected IMF and raw CoP signal was compared to account for the achieved results. It was carried out using a quantitative feature (DET) extracted using RQA. Table III shows the computed DET values along with related mean and the mean of the standard deviation values. Accordingly,t can be deduced the calculated DET related to extracted IMF5 component (0.98±0.01) had larger value than the corresponding raw CoP signal (0.89±0.06). This proves that the IMF5 component has more complex nature in comparison to the raw CoP signal.

The small calculated standard deviation proves the closeness of the calculated DETs, related to all of the subjects. It is interesting because it can support the previously mentioned conclusion about the presence of a similar movement pattern during the balance process in the able-bodied subjects.

4. Discussion

4.1 Groups

In this study, the analysis was carried out on the acquired data related to healthy subjects with different ages. The reason for focusing on healthy subjects was identifying the nature of CoP during the quiet standing of able-bodied subjects. The CoP signal can be considered as the criterion for quantitative analysis of balance quality during the quiet standing. Therefore, identification of the nature of elicited CoP signal during the quiet standing can be an informative analysis approach for human dynamic balance analysis. Analysis of the balance dynamics using quantitative criteria can be useful for diagnosis of some balance disorders and quantifying the loss of balance in a class of patients suffering from balance disorders during the upright standing. In addition, designing an adequate control strategy utilized for motor rehabilitation needs acquiring deep knowledge about characteristics of balance dynamics during the quiet standing. According to the obtained results, it can be claimed, with high confidence, that the balance dynamics in the able-bodied subjects is chaotic.

4.2 Dynamic Similarity

Some evidence in recent years proves the presence of similarities between the characteristics of balance dynamics in different individuals [31]. Consequently, we expect to have an insignificant gap between the computed nonlinear qualitative features of the signal such as CoP, elicited by body sway during the quiet standing, related to different healthy subjects**.** The calculated average and standard deviation of computed fractal dimensions among the participants were 1.02 ± 0.01. The very small value of the calculated standard deviation in comparison to the calculated mean showed significant similarities between the computed fractal dimensions of extracted IMFs despite the considerable differences between the subjects' weight and height. Such observation can certify this hypothesis. In addition, IMF5 was selected as a component which gives us more precise information about the chaotic nature of the CoP signal related to all participants. It is interesting and meditating that calculated α parameter using DFA related to IMF5, in all subjects is substantially larger than 0.5 meaning that the extracted IMF5 signal, in all subjects, is an anti-correlated signal. More interestingly, analyses of complexity of IMF5 using RQA method showed the calculated DETs related to all of the subjects were close. The calculated average and standard deviation of computed DET among the participants were 0.98± 0.01. All these results not only are consistent with evidence proving the presence of similar movement pattern during the balance process in the able-bodied subjects, but also elucidate the presence of a specific nonlinear dynamic balance during the standing which according to our interpretations, is chaotic.

4.3 Chaotic nature of CoP and IMF5

Using the EMD method for decomposition of CoP signal has been proposed earlier [19], this method can decompose the signal to local oscillations composing the non-stationary signal. These components can bear valuable information about the nature of signal but analysis results obtained using some computed nonlinear features may be tricky, especially when the features such as Lyapunov exponents and fractal dimensions should be computed. Measurement noise and likely computational errors may jeopardize the correctness of computational results. In our proposed multi-stage algorithm, the result related to each stage ratifies the archived result related to the last stages. The positive Lyapunov exponent along with the fractional fractal and correlation dimension of CoP related to all subjects may prove the chaotic nature of CoP [32]. Nevertheless, the results elucidate that calculated Lyapunov exponents related to the second to fifth components are greater than calculated Lyapunov exponent related to the raw CoP signal. This shows that the analysis of the raw CoP signal can be misleading. In addition, at the end of the algorithm, IMF5 was selected as the chaotic component of the CoP bearing the most precise information about the CoP dynamic. The calculated DET measure, in all subjects, related to extracted IMF5 component had larger value than corresponding raw CoP proving that the IMF5 component has more complex nature in comparison to the raw CoP signal. This result also ratifies that analysis of the raw CoP signal can be misleading. According to results, we believe that the CoP signal contains the chaotic local oscillations and consequently has a chaotic nature. Nevertheless, for analyses of balance dynamics and its variations during the upright standing, scrutinizing the extracted IMF5 is more appropriate.

4.4 Comparison with the Other Methods

The previous works mostly extracted the nonlinear features from raw CoP signal for analyses of the CoP dynamics [5-19]. But, we believe that the presence of deterministic and stochastic components accompanied by chaotic components in CoP signal may result in mixing up the different behavior of CoP with each other. Therefore, the analyses based on feature extraction from the raw CoP can be misleading. Thus, in this study, the EMD method was used for the analysis of the CoP signals. It is worth noting that the EMD method has been used so far to analyze the CoP [5], but they only aimed to distinguish between eye open and eye closed conditions [5]. Some other researchers only analyzed the change of CoP dynamics with respect to age, and disease severity [12,16], or sought to show the relationship between a nonlinear feature and actual balance ability [6]. Overall, none of the previous works [6-10], have posed clear and confident claims with respect to the CoP signal dynamics. Using the algorithm proposed in our study, a clear and confident claim has been posed about CoP dynamics. According to the presented study, it is confidently claimed that CoP signal is a chaotic signal.

5. Conclusion

Identification of the nature of CoP signal is controversial and important. In this study, a new algorithm has been presented to scrutinize the nature of CoP based on some known nonlinear analysis. We agree with the idea that non-chaotic components of the CoP signal may lead to the wrong analysis of CoP, but the choice of a suitable decomposition approach is an important issue. The decomposition approach must be able to detect the obscured dynamic properties of the signal. Therefore, a conventional decomposition method based on orthogonal functions cannot be useful, because the extracted components must bear information about the nature of CoP. Therefore, inspired by the results of recent research, the EMD method was used to decompose the CoP signal. On the other side, the impact of the measurement noise and likely computational errors always jeopardize the correctness of computational results related to computation of the nonlinear features being usually used to identify the chaotic nature of signals. Therefore, in this work, a multistage algorithm was utilized. In each stage, some nonlinear features were computed. Then, using some criteria, in each stage, some extracted components were selected as the candidate chaotic component. At last, the fifth extracted component was recognized as the chaotic component of the CoP signal with high confidence. Afterward, using RQA, the complexity of the fifth extracted component was analyzed. The analysis result confirmed the obtained result. Therefore, it was concluded that CoP can be recognized as a chaotic signal with high confidence.

On the sidelines of the results, another noteworthy conclusion is that despite the considerable differences between the subjects' weight and height, there are significant similarities between the calculated quantitative features. These similarities suggest that there may be a similar movement pattern during the quiet standing. This can be consistent with the fundamental concept of muscle synergy.

Acknowledgement

This work was supported by Biomedical Research Center at Islamic Azad University of Mashhad. The authors declare that there is no conflict of interests.

References

1. Popović, M.R., Pappas, I.P.I., Nakazawa, K., et al. "Stability criterion for controlling standing in able-bodied subjects", *J. Biomech.*, **33**(11), pp. 1359–1368 (2000).
2. Rhea, C.K., Kiefer, A.W., Haran, F.J., et al. "A new measure of the CoP trajectory in postural sway: dynamics of heading change", *Med. Eng. Phys.*, **36**(11), pp. 1473–1479 (2014).
3. Caballero, C., Barbado, D., Moreno, F.J. "What COP and Kinematic Parameters Better Characterize Postural Control in Standing Balance Tasks?", *J. Mot. Behav.*, **47**(6), pp. 550–562 (2015).
4. Tan, A.M., Fuss, F.K., Weizman, Y., Azari, M.F. "Centre of Pressure Detection and Analysis with a High-resolution and Low-cost Smart Insole", *Procedia Eng.*, **112**, pp. 146–151 (2015).
5. Pachori, R.B., Hewson, D.J., Snoussi, H., et al. "Analysis of center of pressure signals using Empirical Mode Decomposition and Fourier-Bessel expansion", *2008 IEEE Region 10 Conference*', TENCON 2008, pp. 1–6 (2008).

6. Liu, K., Wang, H., Xiao, J., et al. "Analysis of human standing balance by largest lyapunov exponent", *Comput. Intell. Neurosci.*, **2015**, pp. 158478 (2015).
7. Collins, J.J., Luca, C.J.D. "Open-loop and closed-loop control of posture: A random-walk analysis of center-of-pressure trajectories", *Exp. Brain Res.*, **95**(2), pp. 308–318 (1993).
8. Pascolo, P.B., Marini, A., Carniel, R., et al. "Posture as a chaotic system and an application to the Parkinson's disease", *Chaos Solitons Fractals*, **24**(5), pp. 1343–1346 (2005).
9. Ladislao, L., Fioretti, S. "Nonlinear analysis of posturographic data", *Med. Biol. Eng. Comput.*, **45** (7), pp. 679–688 (2007).
10. Ghomashchi, H., Esteki, A., Sprott, J.C., et al. "Identification of Dynamic Patterns of Body sway during Quiet standing: is IT a Nonlinear Process?", *J Bifurc. Chaos*, **20**, pp. 1269–1278 (2010).
11. Błaszczyk, J.W., Klonowski, W. "Postural stability and fractal dynamics", *Acta Neurobiol. Exp. (Warsz.)*, **61** (2), pp. 105–112 (2001).
12. Doyle, T.L.A., Dugan, E.L., Humphries, B., et al. "Discriminating between elderly and young using a fractal dimension analysis of centre of pressure", *Int. J. Med. Sci.*, **1** (1), pp. 11–20 (2004).
13. Kuznetsov, N., Bonnette, S., Gao, J., et al. "Adaptive fractal analysis reveals limits to fractal scaling in center of pressure trajectories", *Ann. Biomed. Eng.*, **41**(8), pp. 1646–1660 (2013).
14. Gurses, S., Celik, H. "Correlation dimension estimates of human postural sway", *Hum. Mov. Sci.*, **32**(1), pp. 48–64 (2013).
15. Bosek, M., Grzegorzewski, B., and Kowalczyk, A. "Two-dimensional Langevin approach to the human stabilogram", *Hum Mov Sci*, **22**(6), pp. 649–660 (2004).
16. Bosek, M., Grzegorzewski, B., Kowalczyk, A. et al. "Degradation of postural control system as a consequence of Parkinson's disease and ageing", *Neurosci. Lett.*, **376**(3), pp. 215–220 (2005).
17. Lemons, D. S. and Gythiel, A., "Paul Langevin's 1908 paper 'On the Theory of Brownian Motion' ['Sur la théorie du mouvement brownien,' C. R. Acad. Sci. (Paris) 146, 530–533 (1908)]", *American Journal of Physics*, **65**(11), pp. 1079–1081 (1997).
18. Snoussi, H., Hewson, D., Duchêne, J. "Nonlinear chaotic component extraction for postural stability analysis", *Conf. Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. IEEE Eng. Med. Biol. Soc. Annu. Conf.*, **2009**, pp. 31–34 (2009).
19. F Cervantes-De la Torre, J I González-Trejo, et al. "Fractal dimension algorithms and their application to time series associated with natural phenomena," *J. Phys.: Conf. Ser.* **475**, pp. 1-10, (2013).
20. Ding, M., Grebogi, C., Ott, E., Sauer, T., et al. "Estimating correlation dimension from a chaotic time series: when does plateau onset occur?", *Phys. Nonlinear Phenom.*, **69**(3), pp. 404–424 (1993).
21. Wu, Z., Huang, N.E. "Ensemble empirical mode decomposition: a noise-assisted data analysis method", *Adv. Adapt. Data Anal.*, **01** (01), pp. 1–41 (2009).
22. Golińska, A.K. "Detrended fluctuation analysis (DFA) in biomedical signal processing: Selected examples", *Stud. Log. Gramm. Rhetor.*, **29**, pp. 107–115 (2012).

23. Minamisawa, T. Takakura, K., Yamaguchi, T. "Detrended Fluctuation Analysis of Temporal Variation of the Center of Pressure (COP) during Quiet Standing in Parkinsonian Patients", *J. Phys. Ther. Sci.*, **21**(3), pp. 287–292 (2009).

24. Bardet, J.M., Kammoun, I. "Asymptotic Properties of the Detrended Fluctuation Analysis of Long-Range-Dependent Processes", *IEEE Trans. Inf. Theory*, **54**(5), pp. 2041–2052 (2008).

25. Wolf, A., Swift, J. B., Swinney, H. L., et al. "Determining Lyapunov exponent from a time series", *Physica. **16D**,* pp. 285–317 (1984).

26. Zbilut, J.P., Webber, C.L. "Recurrence quantification analysis: introduction and historical context", *Int. J. Bifurc. Chaos*, **17**(10), pp. 3477–3481 (2007).

27. Iwaniec, J., Klepka, A., Uhl, T. "Recurrence Plots and RQA Analysis for Damage Detection in Mechanical Systems", in *'Proceedings of the 8th International Conference on Structural Dynamics'* EURODYN 2011 , pp. 2476–2482 (2011).

28. Negahban, H., Sanjari, M.A., Karimi, M., et al. "Complexity and variability of the center of pressure time series during quiet standing in patients with knee osteoarthritis", *Clin. Biomech.*, **32**, pp. 280–285 (2016).

29. Masia, M., Bastianoni, S., Rustici, M. "Recurrence quantification analysis of spatio-temporal chaotic transient in a closed unstirred Belousov–Zhabotinsky reaction", *Phys. Chem. Chem. Phys.*, **3** (24), pp. 5516–5520 (2001).

30. Apthorp, D., Nagle, F., Palmisano, S. "Chaos in Balance: Non-Linear Measures of Postural Control Predict Individual Variations in Visual Illusions of Motion", *PLOS ONE*, **9** (12), p. e113897 (2014).

31. Torres-Oviedo, G., Ting, L.H. "Muscle synergies characterizing human postural responses", *J. Neurophysiol.*,**98** (4), pp. 2144–2156 (2007).

32. Hosseini, S. "Chaos and Bifurcation in Nonlinear Inextensional Rotating Shafts", *Sci. Iran.*, **0** (0), pp. - (2018).

Running title: Examining the Chaotic Behavior of the CoP Signal

List of Figure captions:

List of Table captions:

Fig.1. The healthy subject has stood quietly on a force plate.

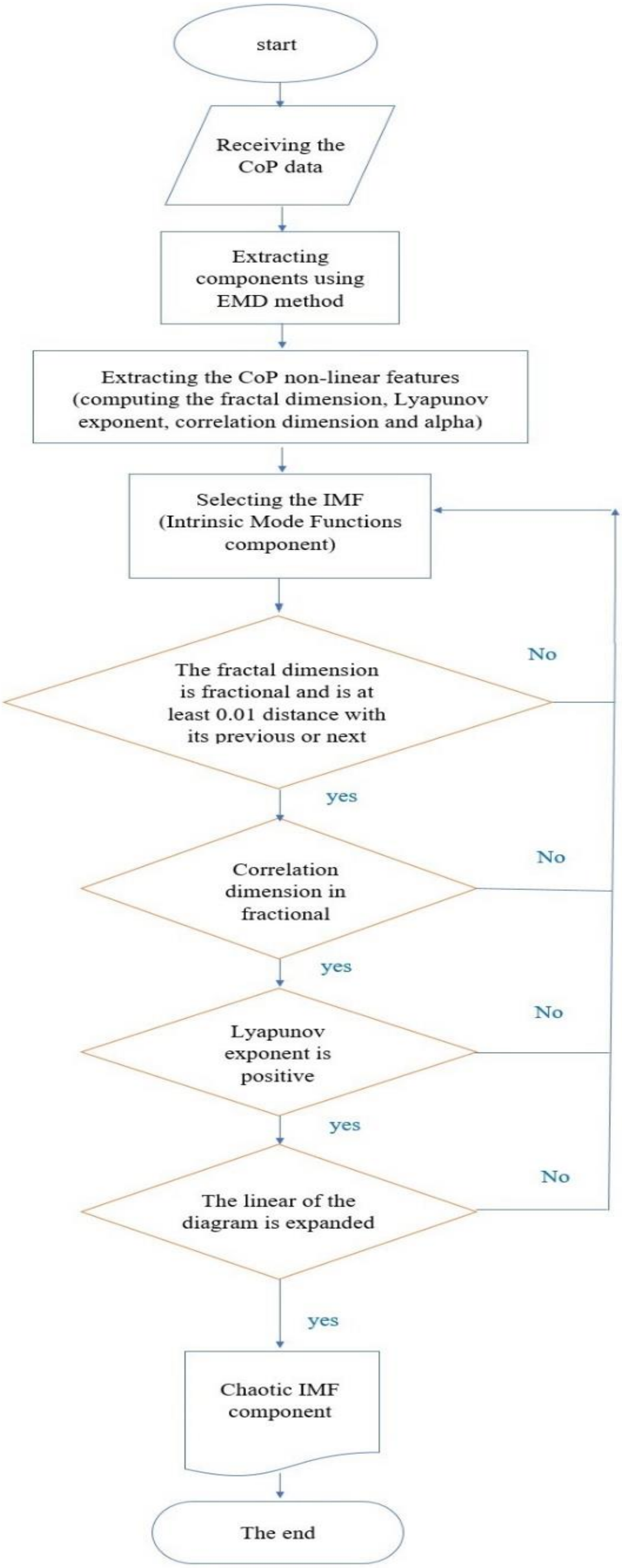

Fig.2. The flowchart of the CoP signal chaotic component selection algorithm.

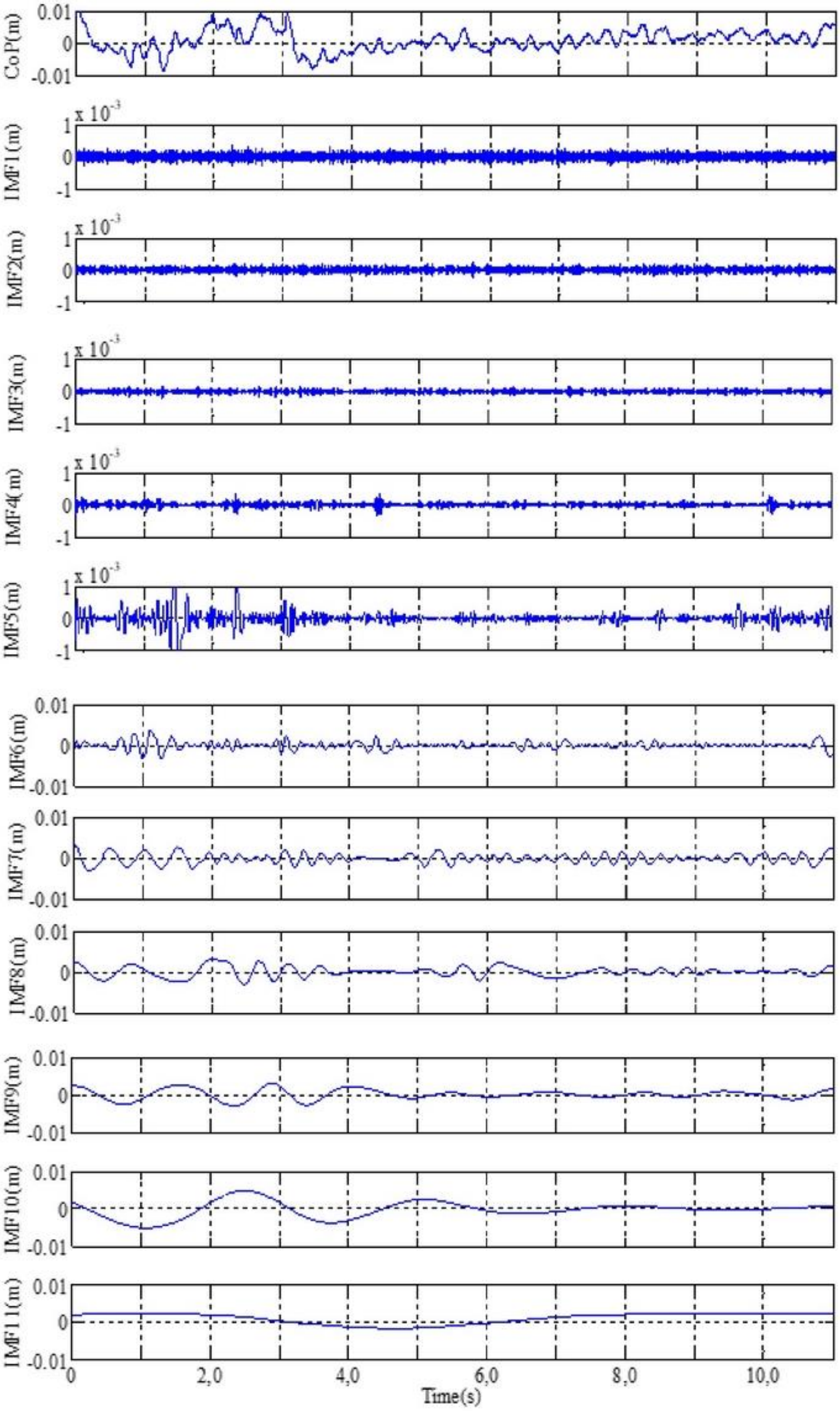

Fig.3. CoP signal taken from a healthy subject during quiet standing for 2 minutes and extracted IMFs from raw CoP signal using the EMD algorithm.

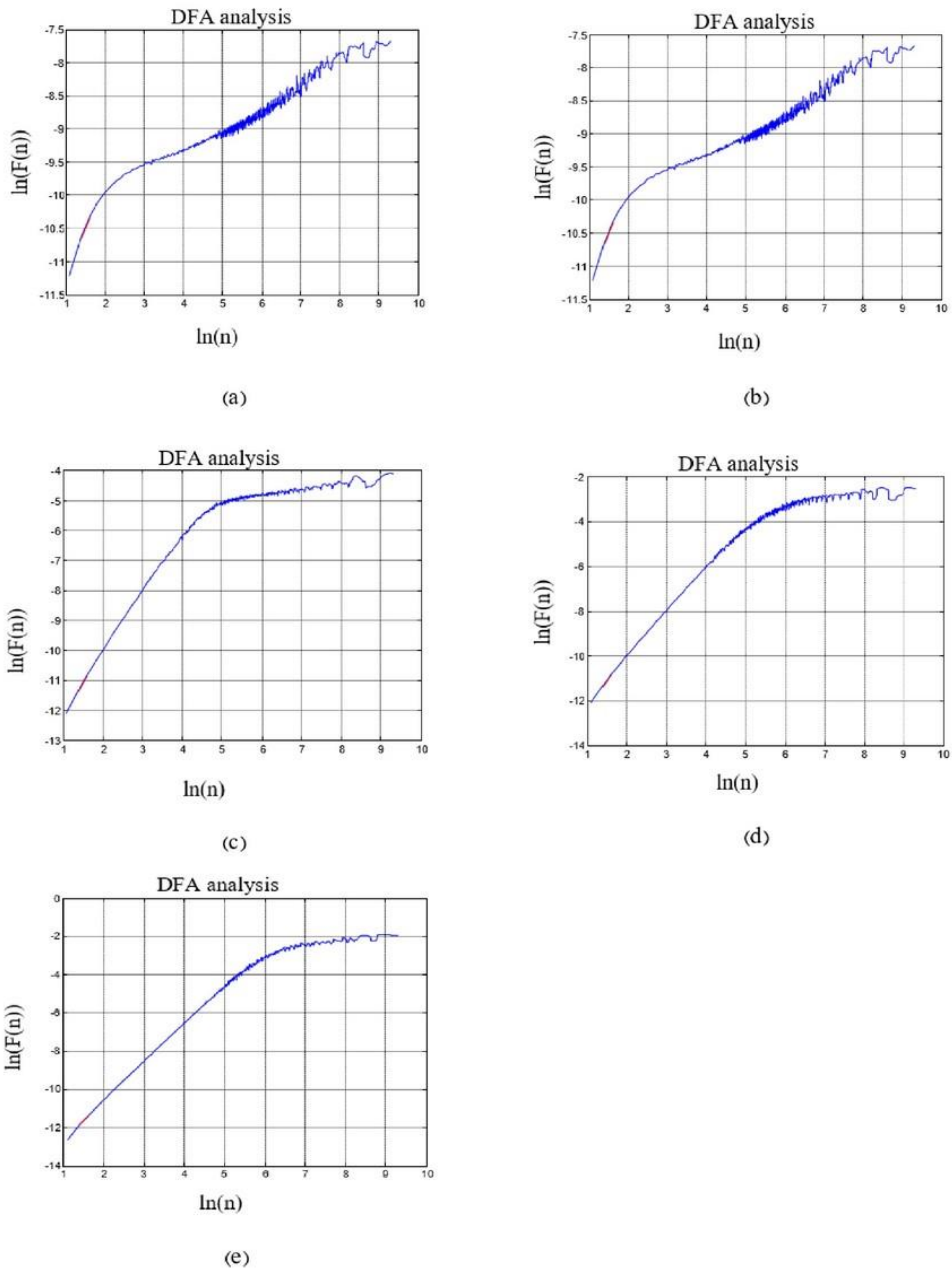

Fig.4. logarithmic graph of DFA analysis related to raw CoP signal (a), logarithmic graph of IMF2 to IMF5 (b-e).

Table I. Parameters of fractal dimension, correlation dimension, Lyapunov exponent and α parameter related to raw CoP signal and its extracted IMFs (related to subject 1).

Feature \ Signal	COP	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8	IMF9	IMF10	IMF11	IMF12
FD	1.64	2.00	1.96	1.67	1.18	1.02	1.00	1.00	1.00	0.99	0.99	1.00	0.99
CD	1.57	1.69	1.60	1.45	1.39	1.36	1.66	1.75	1.60	1.79	1.69	1.64	1.76
LE	0.56	8.85	8.72	8.30	7.43	6.51	5.71	5.19	4.40	3.60	2.85	2.32	-0.00
α (DFA)	1.04	0.41	1.44	2.03	2.24	2.30	2.30	2.31	2.31	2.31	2.30	2.31	2.31

Table II. Parameters of fractal dimension, correlation dimension, Lyapunov exponent and α parameter related to raw CoP signal and its extracted IMFs (related to subject 2).

Signal / Feature	COP	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8	IMF9	IMF10	IMF11	IMF12
FD	1.78	2.00	1.95	1.69	1.20	1.04	1.01	1.00	1.00	0.99	0.99	0.99	0.99
CD	1.62	1.64	1.64	1.58	1.52	1.24	1.40	1.55	1.68	1.81	1.80	1.72	1.73
LE	0.69	8.65	8.70	8.25	7.56	6.79	5.32	4.83	4.33	3.59	3.05	2.91	-0.00
α (DFA)	0.89	0.46	1.53	2.07	2.25	2.29	2.30	2.31	2.31	2.31	2.31	2.31	2.31

Table III. DET values of raw CoP signal and IMF5 component in all subjects.

Signal \ Subject	1	2	3	4	5	6	7	8	9	10	11	12	Mean±STD
Raw CoP	0.95	0.78	0.91	0.92	0.78	0.93	0.82	0.89	0.89	0.93	0.97	0.94	0.89±0.06
IMF5	0.99	0.98	0.99	0.99	0.95	0.99	0.97	0.99	0.99	0.99	0.99	0.99	0.98±0.01

Appendix

Biography

	**Rahel Hajipour** was born in 1983 in Mashad, Iran. She received her B.Sc. (2005) degree in Biomedical Engineering from Isfahan University, and M.Sc. (2014) degree in Biomedical Engineering from Islamic Azad University of Mashhad, Iran. Her main research interest is nonlinear analyses of human motions. Currently she is a teacher assistant in Islamic Azad University of Mashhad and medical devices expert in Mashhad University of Medical Science.
	**Fateme Asadollahzadeh Shamkhal** received the B.S. degree in Biomedical Engineering (Bioelectric) from Islamic Azad University of Mashhad, 2015, and the M.S. degree in Biomedical Engineering (Bioelectric) from Ferdowsi University of Mashhad, Iran, 2018, respectively. Her research interests concern the biomedical signal processing aimed to develop the new diagnosis methods, and rehabilitation technologies.
	**Hamid Reza Kobravi** received the B.S. degree in electrical engineering from Ferdowsi University, Mashhad, 2000, the M.S. and PhD degree in biomedical engineering from Iran University of Science and Technology, Tehran, 2004 and 2011, respectively. From 2001 to 2011, in cooperation with Neural Technology Center in Iran University of Science and Technology, he worked on design and development of variety of neural prostheses applicable to movement restoration in the patients with spinal cord injury. At present, he is assistant professor on biomedical engineering in Azad University of Mashhad (Iran). He is the head of Neuromuscular System Control Lab. in Azad University of Mashhad. His research interests concern the utilizing the artificial intelligence in control and modeling of the biological systems, biomedical signal processing and control of complex systems.