Int Clin Neurosci J. 2022;9:e3

Original Article

doi:10.34172/icnj.2022.03

A Hidden Markov Model Based Detecting Solution for Detecting the Situation of Balance During Unsupported Standing Using the Electromyography of Ankle Muscles

Rashin Abdolhossein Harisi[1], **Hamid Reza Kobravi**[1*]

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

***Correspondence to**
Hamid Reza Kobravi:
Research Center of Biomedical Engineering, Islamic Azad University, Mashhad, Iran, Tel: 0098-915317-3567, E-mail: hkobravi@mshdiau.ac.ir

Published online January 17, 2022

Abstract

Background: In this study, three detecting approaches have been proposed and evaluated for online detection of balance situations during quiet standing. The applied methods were based on electromyography of the gastrocnemius muscles adopting the hidden Markov models.

Methods: The levels of postural stability during quiet standing were regarded as the hidden states of the Markov models while the zones in which the center of pressure lies within determines the level of stability. The Markov models were trained by using the well-known Baum-Welch algorithm. The performance of a single hidden Markov model, the multiple hidden Markov model, and the multiple hidden Markov model alongside an adaptive neuro-fuzzy inference system (ANFIS), were compared as three different detecting methods.

Results: The obtained results show the better and more promising performance of the method designed based on a combination of the hidden Markov models and optimized neuro-fuzzy system.

Conclusion: According to the results, using the combined detecting method yielded promising results.

Keywords: Quiet Standing; Hidden Markov Model; Electromyography; Dynamic Balance.

Citation: Abdolhossein Harisi R, Kobravi HR. A hidden markov model based detecting solution for detecting the situation of balance during unsupported standing using the electromyography of ankle muscles. Clin Neurosci J. 2022;9:e3. doi:10.34172/icnj.2022.03.

Introduction

Balance during upright standing describes the dynamics of body posture to prevent falling.[1] Furthermore, balance preservation during upright standing means keeping the center of pressure (CoP) within a specific zone[2]. Therefore, the quantitative assessment of the quality of standing balance based on CoP signals analysis has been addressed by some researchers.[2-4] Adopting such approaches can pave the way for objective evaluation of standing balance. Nevertheless, a real-time detection of the stability level has not been addressed profoundly in the literature. Implementing an efficient rehabilitation system or self-care system implies exploiting a real-time detecting method for monitoring the postural stability during unsupported standing. Even though the information content of the CoP signal is enough for analyzing the situation of stability during quiet standing, online measurement of the CoP requires large size devices or numerous insole shoe sensors. Therefore, using other biomedical signals and substituting them for CoP signals, can be an attractive research issue. Unless the net moment generated by the ankle muscles does not suffice for prevailing the gravity force, the excursion of CoP in anteroposterior (A/P) direction is controlled by ankle-strategy.[2] Since the ankle plantar-flexors/dorsiflexion muscles control the net ankle moment,[2] adopting the electromyography of the ankle muscles might be an eligible surrogate for the CoP processing. The electromyogram (EMG) signals can bear useful information related to the situation of upright stance. The surface EMG can be used for answering the questions related to the human standing control.[5] Thus, during recent years, many researchers have sought to discover the dynamical relation between the EMG signals and the situation of balance.[6,7] Some researchers analyzed the EMG-activity and swaying data concurrently.[6-11] Combining force plate measurements and surface EMG recorded during quiet and perturbed standing have been addressed.[6] Along this aim, the average EMG-COP time shift was estimated.[6] Another study aimed to assess the neuromuscular control of the ankle joint and the postural stability through analyzing the ankle EMG and CoP signals.[8] In the mentioned study, the relationship between activity onset of the tibialis anterior and soleus muscles with COP onset latency, during translating in an anterior or posterior direction, was examined.[9] The possible correlation between lower-limb muscles and postural stability has also been investigated based on analyzing the simultaneous recorded COP and EMG signals.[10] Moreover, the effects of surface stability and sway frequency on the muscle activation of the lower limb have been studied by some researchers.[11] And the correlation between optic flow and muscle activity has been assessed in the other studies.[12] Alongside the aforementioned research, in some reported studies, the electromyography was used for scrutinizing the role of muscle activation and co-activation dynamics, the contribution of different muscles on maintaining balance during the upright standing, and the postural control system[7, 13-16]. Also, it has been shown that incorporating the electromyography of lower-limb muscles could boost the accuracy and reliability of closed-loop system identification being used to elucidate the contribution of underlying systems involved in standing balance.[17] Electromyography along with *electroencephalography* (EEG) was also used for assessing the proprioception.[18] Furthermore, electromyography has been used for examining the effect of postural sway, the difficulty of the postural control tasks, paralysis, augmented visual feedback of the CoP, balance exercises, muscle fatigue, and wearing the prosthesis during standing on muscle activation dynamics.[16,19-28]

Despite valuable studies done, using electromyography for the real-time detection of stability level during unsupported standing has not been addressed profoundly. Therefore, in the current research, a hidden Markov model-based detecting solution has been proposed and evaluated for online determination of standing balance situation based on electromyography of ankle gastrocnemius muscles.

Materials and Methods

Data Collection

Participants

Five individuals aged 22-29 years participated in this research. The four healthy participants suffered from no balance disorders and one participant suffered from balance problems because of a stroke. Since the parameters of models describing the CoP stability zones were related to foot length, their foot lengths were measured before data collection. Table 1 shows the subjects' specifications.

Recording Protocol and Experimental Setup

According to the aim of the study, the ankle muscle EMG signals emerged during swaying, had to be recorded. Because these signals could bear information related to the posture control process performed during quiet standing. During the recording process, the subjects were asked to stand on a force plate (Kistler, 9286B) and start to sway voluntarily in the anterior-posterior plane ten times. In this way, adequate EMG data necessary for processing, could be gathered. The participant took a short rest between two consecutive trials to prevent the occurrence of muscle fatigue. During performing each trial, the CoP signals were recorded through the force plate. The sampling frequency was 100 Hz. Moreover, the frequency bandwidth of the surface EMG signal lies between 0 to 400 Hz.[29] Therefore, according to the Nyquist's theorem, the sampling frequency must be at least twice the highest frequency component of the signal. Thus, the EMG signal of gastrocnemius muscles was recorded simultaneously with a 1000 Hz sampling frequency. The surface Ag/AgCl electrodes were used for EMG recording. Figure 1 shows the experimental setup.

The raw EMG data were filtered by 10th order Butterworth band-pass filter with 10-500 Hz cut-off frequencies. Then the envelope of the filtered signal was extracted using a 10th order Butterworth low-pass filter with 0-5 Hz cut-off frequencies. The extracted envelope was considered as the muscle activation pattern.

Table 1. Subjects Specifications

Foot Length	Age	Patient
28.6 cm	25	E.S
23.8 cm	29	E.S
24.3 cm	25	H.R
23.7 cm	24	M.R

Proposed Detecting Solution

The main underlying idea of this study is using the HMM for determining the quality of balance during upright standing by analyzing the GA EMG signals, while the level of balance quality is determined according to the zone in which the CoP signals lie within. Therefore, the features extracted from the muscle activation pattern accounted for the observation vector, and levels of balance quality were considered as the hidden states. A sliding window with a length of 2 ms was selected and applied. At first, the time sliding window is moved forward in time in an offline manner. If the CoP time samples lying within the time window show that the CoP signals lie within the high preference zone (HPZ),[2] that time window is labeled "HPZ window". Also, if the data lying within the time

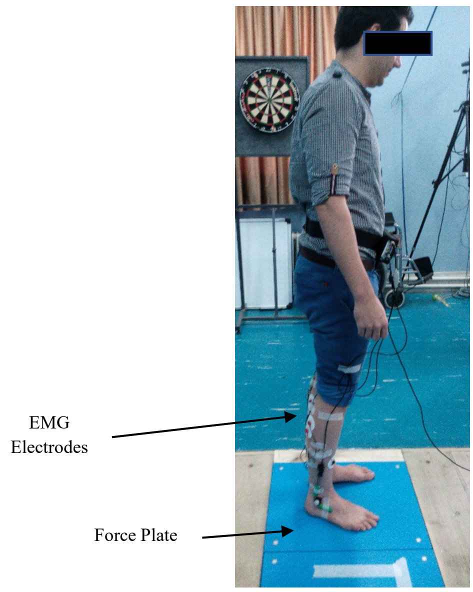

Figure 1. The Experimental Setup.

window show that the CoP time samples lie within the low preference zone (LPZ),[2] that time window is labeled "LPZ window". At last, if the CoP time samples lying within the time window show that the CoP signals lie within the unstable zone (UZ),[2] that time window is labeled "UZ window". The label of each window ("HPZ", "LPZ", "UZ") is considered as a hidden state. In this manner, the envisioned HMM has three hidden states. Furthermore, the extracted features from each corresponding time window of muscle activation pattern are the observations used for training and testing the designed HMM. In this manner, the continuous data was converted to a discrete sequence of observations. After considering the events as hidden states and observations, the HMM can be designed.[30] Figure 2 describes the structure of the designed HMM.

The feature selection was carried out based on the k-nearest neighbors (KNN) algorithm. The designed HMM was used under two different structures after training by using the Baum-Welch algorithm. The details of the proposed detecting method will be explained.

Feature Selection Method

As mentioned previously, the features extracted from each time window of the muscle activation pattern accounted for the observation vector. Thus, 22 time and frequency features were initially extracted[31]. Then, the most appropriate features were selected based on analyzing the receiver operating characteristic curve (ROC) obtained through performing the KNN algorithm. In other words, the features on which the KNN are performed and yield maximum ROC, were selected.

Applied Detecting Structures Based on HMM

Single HMM-Based Structure

Figure 3 shows the block diagram of the single HMM-based structure. Using this method, a single HMM is trained for detecting three different levels of balance quality.

Multi HMM-Based Structure

Figure 4 shows the block diagram of the Multi HMM-based structure. In this method, three separate Markov models were used for detecting each distinct level of balance quality during standing. In other words, each HMM was trained in a manner that could detect a specific level. During the online detection process, the maximum likelihood state (level of balance quality) was regarded as the detected level of balance quality. It is expected that the interference of learning is prevented by using this approach. Since interference of learning might degrade the performance of HMM, it is expected that using multi-HMM improves performance.

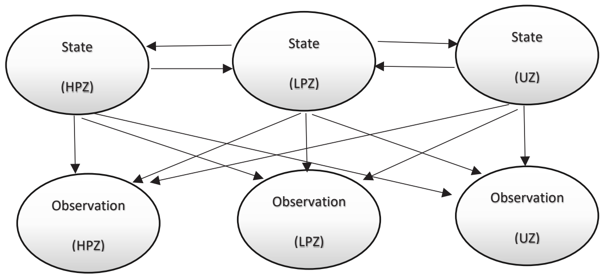

Figure 2. The Structure of the Proposed Markov Model.

Multi-HMM Alongside an ANFIS

As explained previously, it is expected that the interference of learning is prevented through using this multi-HMM-based structure. Nevertheless, detecting based on probabilistic parameters (transition probabilities) could undermine the detection accuracy. Thus, utilizing an intelligent fusion mechanism alongside three Markov models may boost the detecting accuracy. Therefore, the above combination was the other structure used in this study. Figure 5 shows this structure. In this approach, the maximum transition probabilities of each HMM account for the input vector of an adaptive neuro-fuzzy inference system (ANFIS) while ANFIS output determines the level of balance quality. The adopted ANFIS was designed based on Takagi-Sugeno fuzzy system with 8 rules. The number of the inputs and the input membership functions was 3, while the membership functions were Gaussian functions. The ANFIS was trained using *Levenberg–Marquardt* algorithm.

Training the HMM Using Baum -Welch Algorithm

In this research, the designed Markov models were trained using the well-known Baum-Welch algorithm.[30] In the used HMM, the initial probability functions were a combination of some Gaussian functions. The number of Gaussian probability functions starts from one and gradually increases until the output reaches its maximum value. The Baum-Welch algorithm is performed iteratively. Figure 5 describes the Baum-Welch algorithm briefly.[30] Figure 6, "$\xi_t(i.j)$" shows the probability of going to state "S_j" at time t+1 and observing the "O_{t+1}", while the state at time "t" is "S_j". Also, the "$O = O_1.O_2.\ldots.O_T$" is the observation. In addition, the "β_{t+1} (j)" is a probability of the observation of $O_{t+1}O_{t+2}\ldots O_T$, a_{ij} is transition probability and π_i is initial state distribution.

Results

Result of Feature Selection

As explained previously, feature selection was done based on analyzing the ROC curve obtained through performing the KNN algorithm. After analyzing the ROC the selected features were as follows[31]:

Simple Square Integral and Variance

Simple square integral (SSI) is a summation of square

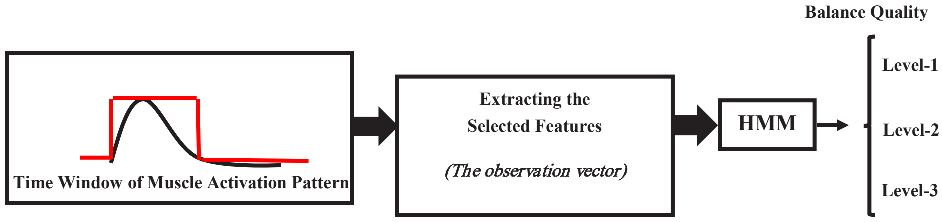

Figure 3. The Block Diagram Describing the Single HMM Based Detecting Structure. The features are extracted from the EMG signals lie within 2 ms sliding window.

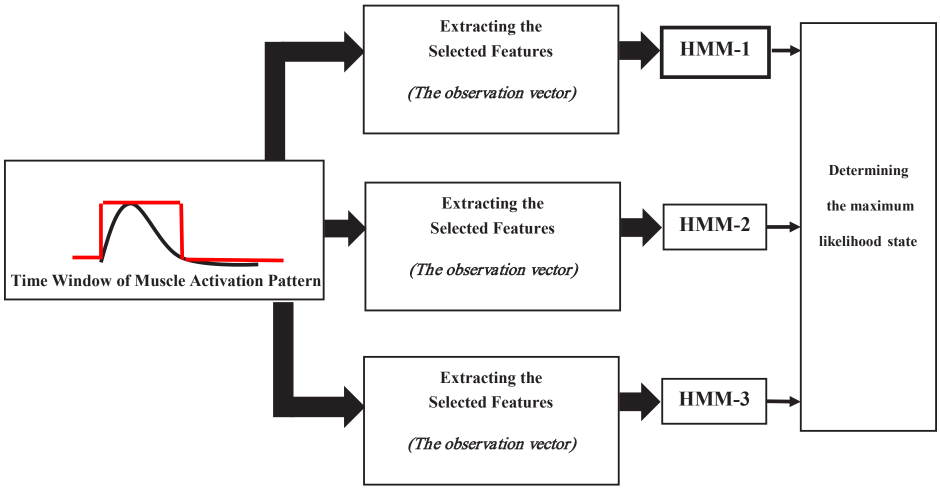

Figure 4. The block diagram describing the multi-HMM based detecting structure. The features are extracted from the EMG signals lie within 2 ms sliding window.

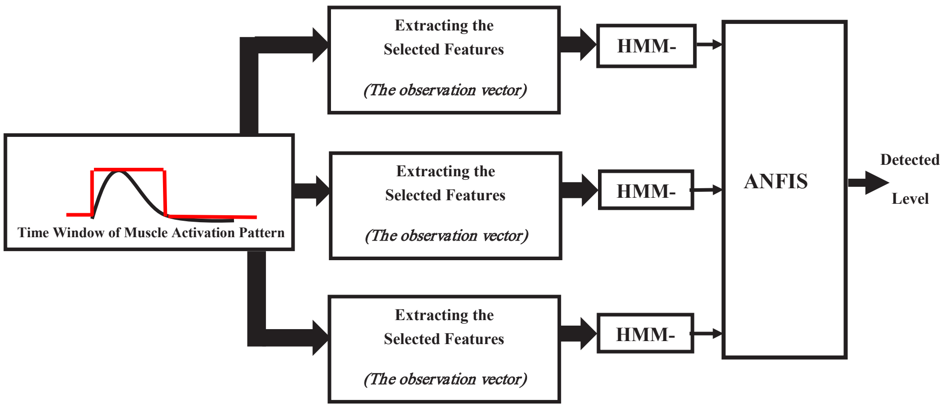

Figure 5. The Block Diagram Describing the Detecting Method Based on Combining Three Hidden Markov Models and an ANFIS as a Fusion Mechanism. The features are extracted from the EMG signals lie within 2 ms sliding window.

values of the EMG sample values. Also, the average of the calculated SSI is known as the other feature called variance (V). The aforementioned features can be calculated as follows[31]:

$$SSI = \sum_{i=1}^{N} X_i^2 \tag{1}$$

$$V = \left(\frac{1}{N}\sum_{i=1}^{N} X_i^2\right)^{\frac{1}{2}} \tag{2}$$

Where Xi is ith time sample of EMG signal, and N is the number of EMG samples.

Waveform Length and Average Amplitude Change

Waveform length (WL) is a measure of the complexity of a signal. It is defined as the cumulative summation of *signal difference values* between pairs of subsequent EMG signal sample values computed over the time segment. Also, the average of the calculated differences is known as the other feature called average amplitude change. The aforementioned features can be calculated as follows[31]:

$$WL = \sum_{i=1}^{N-1} |X_{i+1} - X_i| \tag{3}$$

Algorithm 1: The Baum-Welch algorithm

Initialization: $\theta_0, \{O_{1:T}\}$

Looping:

for $l = 1, \dots, l_{max}$ **do**

1. Forward-Backward calculations:

$$\alpha_1(i) = \pi_i b_i(O_1), \beta_T(i) = 1,$$

$$\alpha_t(i) = [\textstyle\sum_{j=1}^{*} \alpha_{t-1}(j) a_{ji}] b_j(O_t), \beta_t(i) = \sum_{j=1}^{K} a_{ij} b_j(O_{t+1}) \beta_{t+1}(j)$$

$$\text{for } 1 \leq i \leq K, 1 \leq t \leq T-1$$

2. E-step:

$$\gamma_t(i) = \frac{\alpha_t(i)\beta_t(i)}{\sum_{j=1}^{K} \alpha_t(j)\beta_t(j)}, \xi_t(i,j) = \frac{\alpha_{t}(i) a_{ij} b_j(O_{t+1}) \beta_{t+1}(j)}{\sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_t(i) a_{ji} b_j(O_{t+1}\beta_t(j))}$$

$$\text{for } 1 \leq i \leq K, 1 \leq j \leq K, 1 \leq t \leq T-1$$

3. M-step:

$$\pi_i = \frac{\gamma_1(i)}{\sum_{j=1}^{K} \gamma_1(j)}, a_{ij} = \frac{\sum_{t=1}^{T} \varepsilon_t(i,j)}{\sum_{k=1}^{K}\sum_{t=1}^{T} \varepsilon_t(i,k)}, \omega_{kd} = \frac{\sum_{t=1}^{T} \gamma_t(k,d)}{\sum_{t=1}^{T}\sum_{r=1}^{D} \gamma_t(k,r)}$$

$$\text{for } 1 \leq i \leq K, 1 \leq j \leq K, 1 \leq k \leq K, 1 \leq d \leq D$$

end

Result: $\{\boldsymbol{\theta}_t\}_{t=0}^{l_{max}}$

Figure 6. A Brief Description of the Baum-Welch Algorithm.

$$\mathrm{AAC} = \frac{1}{N}\sum_{i=1}^{N-1} |X_{i+1} - X_i| \tag{4}$$

Where *Xi* is ith time sample of EMG signal, and N is the number of EMG samples.

Difference Absolute Standard Deviation Value

Difference absolute standard deviation value (DASDV) is the root mean square value of *signal difference values* between pairs of subsequent EMG signal sample values. It is defined as follows[31]:

$$\mathrm{DASDV} = \sqrt{\frac{1}{N}\sum_{i=1}^{N-1} (X_{i+1} - X_i)^2} \tag{5}$$

Where *Xi* is ith time sample of EMG signal, and N is the number of EMG samples.

The 1rd, 2rd and 3rd Spectral Moments

Spectral moments are the features computed using the signal power spectrum. The 2rd (SM2) and 3rd (SM3) spectral moments are calculated as follows[31]:

$$\mathrm{SM1} = \sum_{j=1}^{M} P_j f_j$$

$$\mathrm{SM2} = \sum_{j=1}^{M} P_j f_j^2 \tag{6}$$

$$\mathrm{SM3} = \sum_{j=1}^{M} P_j f_j^3$$

Where P_j is the value of the EMG power spectrum at the frequency bin j (f_j), and M is the length of the frequency bin.

Absolute Value of the 4th and 5th Temporal Moments

The temporal moment is a statistical measure that is computed based on an averaging approach. The 4th and 5th moments of EMG signal are calculated as follows[31]:

$$\mathrm{TM4} = \left| \frac{1}{N}\sum_{i=1}^{N} X_i^4 \right|$$

$$\mathrm{TM5} = \left| \frac{1}{N}\sum_{i=1}^{N} X_i^5 \right| \tag{7}$$

Where *Xi* is ith time sample of EMG signal, and N is the number of EMG samples.

The Results of Detecting Approaches

As explained previously, the most appropriate features were selected according to the ROC. Since this curve (ROC) shows the true positive (TP) rate versus the false negative (FN) rate, the values of accuracy and sensitivity measures were computed and analyzed as the quantitative evaluating measures. The reason is that accuracy is a measure for an overall assessment of the detecting approach ($\frac{TP+TN}{TP+TN+FP+FN}$) and the sensitivity measure is a function of TP. Meanwhile, the TP is the determinant of not only the nominator but also the denominator of sensitivity measure ($\frac{TP}{TP+FP}$). Table 2 shows the achieved results. The mean and standard deviation (SD) values of accuracy and sensitivity were computed. In this study, the 10-fold cross-validation method was also used for the quantitative assessment of the detecting solutions.

As mentioned previously, using the single HMM-based method, a single HMM is trained for detecting three different levels of balance quality while each level of balance is determined according to the zone in which the CoP lies within (HPZ, LPZ, and UZ). Clearly, the related achieved results are not acceptable (Table 2). Such unacceptable results can be attributed to the existence of interference of learning.

It was expected that the multi-HMM-based method could eliminate the effect of interference of learning. In this method, three separate single Markov models are trained for detecting three different levels of balance quality. Each level of balance is determined according to the zone in which the CoP lies within (HPZ, LPZ, and UZ). Each Markov model was trained using the Baum-Welch algorithm, separately. The computed measures

Table 2. The Mean and SD Values of Computed Accuracy and Sensitivity Measures, While Single HMM, Multi-HMM, and Multi-HMM Along With an ANFIS Based Fusion Mechanism Adopted for Detecting the Level of Balance Quality

HMM based Detecting Approach	Accuracy (Mean±SD)	Sensitivity (Mean±SD)
Single HMM	43.90±8.99%	14.31%±31.25
Multi-HMM	78.75±0.67%	0.87%±81.05
Multi-HMM & ANFIS	87.81±0.88%	0.78%±98.20

SD, standard deviation.

increased significantly compared with the case in which a single HMM was adopted (Table 2). Such improvement may ensure eliminating the effect of interference of learning. Furthermore, increasing the accuracy and sensitivity measures means that not only the true positive and true negative values increased but also false positive and false negative values decreased. It shows that the number of times that the CoP signal entered a specific zone and was detected correctly, increased significantly. It is an intriguing improvement. Because boosting the number of correctly detected zones which the CoP signal entered within, is vital for the design of efficient rehabilitation systems or accurate self-care systems based on online quantifying the level of balance quality.

In this study, improving the performance of the probabilistic model was the underlying idea of incorporating the ANFIS based on fusion mechanism. As explained previously, the maximum transition probabilities of each HMM were the ANFIS inputs, while ANFIS output determined the level of balance quality. Each level of balance was determined according to the zone in which the CoP lies within (HPZ, LPZ, and UZ). The used ANFIS is a type of artificial neural network implemented based on the structure of a Takagi–Sugeno fuzzy inference system. Each Markov model was trained using the Baum-Welch algorithm, separately. The ANFIS was also trained using *Levenberg–Marquardt* algorithm. According to Table 2, adopting the above combination could boost two quantitative evaluation measures compared with the multi-HMM-based detecting method. Such acceptable results confirm the effective role of incorporating ANFIS. In addition, such improvement certifies that utilizing an inference-based fusion mechanism could pave the way for coping with the inaccuracies induced owing to the probabilistic identity of HMM.

Discussion

Detecting the level of stability during unsupported standing based on electromyography of ankle plantar flexor muscles (gastrocnemius muscles) was the main underlying idea of this research. Even though the CoP signal alone can determine the situation of stability during quiet standing, online measurement of the CoP signals implies using either the large size instruments (force plate) or plenty of insole shoe sensors (force sensing resistors or strain gages). None of them are feasible and affordable for implementing portable systems such as self-care systems. Therefore, in the current research, electromyography was used for determining the level of stability based on unveiling the information content of the CoP data. In addition, the HMM was used because this model can unveil the hidden states through analyzing the observation. In the proposed approach, a single HMM, a multi-HMM, and combining a multi-HMM and ANFIS were utilized for implementing the detecting solution. Furthermore, the zones (HPZ, LPZ, and UZ) in which the CoP lies within, determined the level of stability and were regarded as the hidden states. Using the single HMM yielded low accuracy (43.9 ± 8.99) and low sensitivity (31.25 ± 14.31). Such low values confirm the unacceptable high value of FP. This issue could undermine the applicability of the detection method for online processing of balance situation. Adopting the multi-HMM could boost the performance (Accuracy: $78.75 \pm 0.66\%$, Sensitivity: $81.05 \pm 0.78\%$). It elucidates that the inference of learning may undermine the performance seriously. It can be justifiable, because the ankle muscle activation pattern alters according to *tilt angle* along whole *body* tilts and this directly changes the CoP position. In other words, the ankle muscle activation pattern alters significantly according to the zone which the CoP lies in. Therefore, a single HMM must learn fully different dynamics for detecting the level of balance, and this could give rise to an inference of learning during HMM training. However, the accuracy value is not yet acceptable because it is less than 80%. While, using the multi-HMM and ANFIS yielded the best performance which was acceptable (Accuracy: $87.81 \pm 0.88\%$, Sensitivity: $98.20 \pm 0.78\%$). It means that not only accuracy but also sensitivity has increased. This could prove that incorporating the ANFIS based fusion method could lead to decreased FP and increased TP. Such improvements could be promising in terms of applicability of the method for acceptable online monitoring of balance situation. This could be attributed to the role of ANFIS to cope with unpredicted signal dynamics which could not be described using probabilistic models. Because the ANFIS works based on an inference-based approach, it could be able to detect more accurately in the condition that the signal dynamics deviate from the signal dynamics observed during the training process. Such dynamical deviation during a complex biological process such as balance preservation is inevitable. Therefore, boosting the accuracy due to using an inference-based fusion method, could be justifiable. In addition, according to the values of evaluated measures, the computed standard deviations (0.88 and 0.78) were less than one-tenth of the mean values (87.81 and 98.20). This shows that the detecting performance was not dependent on individuals. Even though more individuals have to be analyzed, this could prove that the proposed detecting method is partly generalizable.

Overall, utilizing the multi-HMM could improve the performance. Nevertheless, the probabilistic identity of HMM might undermine the detection accuracy because adopting the probabilistic mechanism could entail imprecisions. According to the results, incorporating an optimized ANFIS as a fusion mechanism accompanying multi-HMM improved the detecting performance.

The inference-based approach of the ANFIS system could compensate for the impediments ensuing from the probabilistic identity of hidden Markov models. Nevertheless, in future works, the proposed method has to be assessed under the condition that external disturbances are exerted. In addition, this study was designed based on electromyography of the gastrocnemius muscles because the gastrocnemius muscles have a key role in annihilating the gravity force vector in the sagittal plane. The effectiveness of the electromyography of the other ankle muscles along with the gastrocnemius muscles can be evaluated as future research work. Overall, this study can expand research on postural stability analysis based on electromyography.

Conclusion

In the present research, an HMM-based detecting solution was proposed for detecting the situation of stability during quiet standing. The proposed method was designed based on the electromyography of the gastrocnemius muscles. The level of stability was determined according to the zone in which the CoP signal was fluctuating. Three levels of stability were envisioned corresponding to three zones in which the CoP signal could enter. Three levels of stability accounted for the hidden states of HMM, while the features were extracted from the gastrocnemius muscle activation pattern. A single HMM, a multi-HMM, and a multi-HMM accompanied by an ANFIS were adopted and compared for detecting the situation of stability. According to the results, using the combinational detecting method yielded promising results.

Conflict of Interest Disclosures

The authors declare that they have no conflict of interests.

Ethical Statement

In this research, five adult individuals participated. Before data collection, their permissions were obtained, and they were fully aware of the procedure and its possible hazards. Also, safety procedures were followed to avoid falling during the process. A local ethics committee entitled "Theses Committee" certified the study in terms of ethical considerations.

Funding

Not applicable.

Acknowledgement

This research work was conducted in Biomedical Research Center at Islamic Azad University of Mashhad.

References

1. Winter DA. Human balance and posture control during standing and walking. Gait Posture. 1995;3(4):193-214. doi: 10.1016/0966-6362(96)82849-9.
2. Popovic M, Pappas IP, Nakazawa K, Keller T, Morari M, Dietz V. Stability criterion for controlling standing in able-bodied subjects. J Biomech. 2000;33(11):1359-68. doi: 10.1016/s0021-9290(00)00123-8.
3. Dozza M, Chiari L, Horak FB. Audio-biofeedback improves balance in patients with bilateral vestibular loss. Arch Phys Med Rehabil. 2005;86(7):1401-3. doi: 10.1016/j.apmr.2004.12.036.
4. de Haart M, Geurts AC, Huidekoper SC, Fasotti L, van Limbeek J. Recovery of standing balance in postacute stroke patients: a rehabilitation cohort study. Arch Phys Med Rehabil. 2004;85(6):886-95. doi: 10.1016/j.apmr.2003.05.012.
5. Vieira TM, Farina D, Loram ID. EMG and posture in its narrowest sense. In: Merletti R, Farina D, eds. Surface Electromyography: Physiology, Engineering and Applications. John Wiley & Sons; 2016. p. 408-39.
6. Borg F, Finell M, Hakala I, Herrala M. Analyzing gastrocnemius EMG-activity and sway data from quiet and perturbed standing. J Electromyogr Kinesiol. 2007;17(5):622-34. doi: 10.1016/j.jelekin.2006.06.004.
7. Vijayvargiya A, Prakash C, Kumar R, Bansal S, Tavares JM. Human knee abnormality detection from imbalanced sEMG data. Biomed Signal Process Control. 2021;66:102406. doi: 10.1016/j.bspc.2021.102406.
8. Karagiannakis DN, Iatridou KI, Mandalidis DG. Ankle muscles activation and postural stability with Star Excursion Balance Test in healthy individuals. Hum Mov Sci. 2020;69:102563. doi: 10.1016/j.humov.2019.102563.
9. Müller ML, Redfern MS. Correlation between EMG and COP onset latency in response to a horizontal platform translation. J Biomech. 2004;37(10):1573-81. doi: 10.1016/j.jbiomech.2004.01.004.
10. Wang CC, Jiang BC, Huang PM. The relationship between postural stability and lower-limb muscle activity using an entropy-based similarity index. Entropy. 2018;20(5):320. doi: 10.3390/e20050320.
11. Patikas DA, Papavasileiou A, Ekizos A, Hatzitaki V, Arampatzis A. Swaying slower reduces the destabilizing effects of a compliant surface on voluntary sway dynamics. PLoS One. 2019;14(12):e0226263. doi: 10.1371/journal.pone.0226263.
12. Raffi M, Piras A, Persiani M, Squatrito S. Importance of optic flow for postural stability of male and female young adults. Eur J Appl Physiol. 2014;114(1):71-83. doi: 10.1007/s00421-013-2750-4.
13. Cattagni T, Scaglioni G, Laroche D, Gremeaux V, Martin A. The involvement of ankle muscles in maintaining balance in the upright posture is higher in elderly fallers. Exp Gerontol. 2016;77:38-45. doi: 10.1016/j.exger.2016.02.010.
14. Pasluosta C, Lauck TB, Krauskopf T, Klein L, Mueller M, Herget GW, et al. Intermuscular coupling and postural control in unilateral transfemoral amputees-a pilot study. Annu Int Conf IEEE Eng Med Biol Soc. 2020;2020:3815-8. doi: 10.1109/embc44109.2020.9176850.
15. McCrumb D. Analysis of Connectivity in EMG Signals to Examine Neural Correlations in Muscular Activation of Lower Leg Muscles for Postural Stability [thesis]. Grand Valley State University; 2019.
16. Tanabe H, Fujii K, Kouzaki M. Intermittent muscle activity in the feedback loop of postural control system during natural quiet standing. Sci Rep. 2017;7(1):10631. doi: 10.1038/s41598-017-10015-8.
17. Pasma JH, van Kordelaar J, de Kam D, Weerdesteyn V, Schouten AC, van der Kooij H. Assessment of the underlying systems involved in standing balance: the additional value of electromyography in system identification and parameter estimation. J Neuroeng Rehabil. 2017;14(1):97. doi: 10.1186/s12984-017-0299-x.
18. Northrup TF. EEG and EMG Sensorimotor Measurements to Assess Proprioception Following ACL Reconstruction

[dissertation]. University of New Hampshire; 2019. p. 93.
19. Kouzaki M, Fukunaga T. Frequency features of mechanomyographic signals of human soleus muscle during quiet standing. J Neurosci Methods. 2008;173(2):241-8. doi: 10.1016/j.jneumeth.2008.06.008.
20. García-Massó X, Pellicer-Chenoll M, Gonzalez LM, Toca-Herrera JL. The difficulty of the postural control task affects multi-muscle control during quiet standing. Exp Brain Res. 2016;234(7):1977-86. doi: 10.1007/s00221-016-4602-z.
21. Huber J, Lisiński P, Ciesielska J, Kulczyk A, Lipiec J, Bandosz A. Surface electromyography studies in standing position confirm that ankle strategy remains disturbed even following successful treatment of patients with a history of sciatica. J Phys Ther Sci. 2016;28(2):563-8. doi: 10.1589/jpts.28.563.
22. Wang W, Xiao Y, Yue S, Wei N, Li K. Analysis of center of mass acceleration and muscle activation in hemiplegic paralysis during quiet standing. PLoS One. 2019;14(12):e0226944. doi: 10.1371/journal.pone.0226944.
23. Watanabe T, Saito K, Ishida K, Tanabe S, Nojima I. Fatigue-induced decline in low-frequency common input to bilateral and unilateral plantar flexors during quiet standing. Neurosci Lett. 2018;686:193-7. doi: 10.1016/j.neulet.2018.09.019.
24. Mansfield A, Aqui A, Fraser JE, Rajachandrakumar R, Lakhani B, Patterson KK. Can augmented feedback facilitate learning a reactive balance task among older adults? Exp Brain Res. 2017;235(1):293-304. doi: 10.1007/s00221-016-4790-6.
25. Florence Tse YY, Petrofsky J, Berk L, Daher N, Lohman E, Cavalcanti P, et al. Postural sway and EMG analysis of hip and ankle muscles during balance tasks. Int J Ther Rehabil. 2013;20(6):280-8. doi: 10.12968/ijtr.2013.20.6.280.
26. Alfuth M, Gomoll M. Electromyographic analysis of balance exercises in single-leg stance using different instability modalities of the forefoot and rearfoot. Phys Ther Sport. 2018;31:75-82. doi: 10.1016/j.ptsp.2018.01.002.
27. Wakasa M, Seki K, Fukuda A, Sasaki K, Izumi SI. Muscle activity and postural control during standing of healthy adults wearing a simulated trans-femoral prosthesis. J Phys Ther Sci. 2010;22(3):233-8. doi: 10.1589/jpts.22.233.
28. Gebel A, Lüder B, Granacher U. Effects of increasing balance task difficulty on postural sway and muscle activity in healthy adolescents. Front Physiol. 2019;10:1135. doi: 10.3389/fphys.2019.01135.
29. De Luca CJ, Gilmore LD, Kuznetsov M, Roy SH. Filtering the surface EMG signal: movement artifact and baseline noise contamination. J Biomech. 2010;43(8):1573-9. doi: 10.1016/j.jbiomech.2010.01.027.
30. Samaee S, Kobravi HR. Predicting the occurrence of wrist tremor based on electromyography using a hidden Markov model and entropy based learning algorithm. Biomed Signal Process Control. 2020;57:101739. doi: https://doi.org/10.1016/j.bspc.2019.101739.
31. Phinyomark A, Phukpattaranont P, Limsakul C. Feature reduction and selection for EMG signal classification. Expert Syst Appl. 2012;39(8):7420-31. doi: 10.1016/j.eswa.2012.01.102.