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Effects of Diabetic Neuropathy on Body Sway and Slip Perturbation Detection in Older Population

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Postural control is a common mechanism to compensate for unexpected displacements of the body. In the older population, a slip or fall due to a failure of postural control is a common cause of morbidity and mortality. The ability of postural control decreases with aging or neuropathy. In this study, 2 groups, diabetics and non-diabetics in the older population, were compared to determine how patterns of postural sway during quiet standing were related to the detection of perturbation. The SLIP-FALLS system was applied to the measurement of sway and detection of perturbation. In phase 1 of the development of the predictive model, neural network algorithms were applied to find determinant variables for perturbation detection. In phase 2, a fuzzy logic inference system was developed to investigate the relationship between sway and perturbation detection. Results of this study may be applied to the design of floor mats or shoe insoles for preventing fatigue in workplaces.

sway   slip   perturbation detection   center of pressure

1. INTRODUCTION

Slips and falls are common causes of morbidity and mortality in the older population. Since the normal aging process diminishes the physical and psychological functions of humans, it is more likely for the elderly to be at risk from falls, especially after the age of 65 [1]. One study reports that one third to one half of the older population, aged 65 or over, experience falls every year [2]. The high possibility of falls in the elderly is due to the inability to maintain postural control when encountering unexpected displacements of the body [3]. Postural control requires an ability to keep the body's balance in space through visual, vestibular, and somatosensory systems while making an appropriate musculoskeletal response to perturbations. Keeping the balance is an ability to maintain the center of gravity of the body over the base of support; it requires capabilities of position maintenance, stabilization for voluntary movements, and reaction to external disturbances [4]. Maintaining and stabilizing the body's balance during voluntary movements require visual, vestibular, proprioceptive, kinesthetic, and somatic senses. These senses are expected to work in an integrated fashion to keep the balance. Reactions to external disturbances, such as a slip or a fall, require a process of detection and control of motion changes.

Even though sensing a disturbed balance is only one of the components necessary to control postural stability, the ability to detect a perturbation may be a critical measure for predicting the potential of failure to prevent a fall initiated by slipping. In the literature static and dynamic postural stability tests are introduced to the quantitative assessment for detecting fall initiation.

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As a static test, Graybie and Fregly [5] developed a Sharpened Rhomberg test to assess degrees of sway while placing the toe of the dominant foot against the heel of the non-dominant foot with the eyes closed. The Rhomberg test was originally considered as a test for detecting damage to the posterior columns of the spinal cord [6]. Woollacott, Shumway-Cook, and Nashner [7] found a positive correlation between the amount of sway, age, and muscular reaction time. Lord, Clark, and Webster [3] showed that the amount of sway tended to increase with declining joint position sense, tactile sensitivity, vibration sense, or visual acuity. These measures lack the common factor for all falls, which is failure to sense a perturbation and regain a balance. Falls in the older population are frequently the result of an accidental slip or trip caused by an unsteady gait [2]. According to Lord et al. [3] the lack of a stable gait might be due to deficiencies of postural control of short and unexpected displacements of the body. The ability to respond to transient perturbations can be considered as another measure for keeping balance and stability. Dynamic postural stability tests measure the response when a perturbation is applied to the body in order to examine some aspect of the complex postural mechanisms. Maki, Holliday, and Fernie [8] applied an external perturbation to the feet or ankles by translating or rotating a platform. Internally generated perturbations such as a reaching [9] or a weight-shifting task [10] are also used. Many different measures are used to quantify the response to various perturbations such as center-of-pressure [11], body segment movement [7], and patterns of muscle activation [12]. Pavol, Runta, Edwards, and Pai [13] investigated the effects of age on sit-to-stand slips and reported that older adults were more vulnerable to an unexpected perturbation even if it could be easily sensed. Balasubramanian [14] found a decreased fidelity in detecting small perturbations in the older population compared to younger population groups. Speers, Kuo, and Horak [15] hypothesized that increases in sway in older populations were due to decreased ability to detect small movements. These studies imply that there is a higher chance for older people not to detect slipping motions such as stepping on ice or walking on a wet floor, resulting in an increased risk of falling. Detection of smaller, less discernable perturbation can lead to further insights into postural control during slips.

Predicting the potential of slips or falls will be a difficult task. One of the possible reasons may be a complexity of factors including human and environmental aspects and the complicated relationships between them. Thus, it is unlikely for a predictive model to be successful if the analysis is based on a traditional set theory using binary memberships of set elements. Since it can be assumed that a postural control mechanism is based on a complex and uncertain procedure of cognitive, psychological, and behavioral processes, it will be very possible for set memberships to be indecisive, resulting in partial memberships. Zadeh [16] introduced a fuzzy set theory to the partial status of membership for a set and for measurements of membership on the basis of the possibility theory. Unlike conventional statistical methods, fuzzy logic approaches that mimic human capabilities of approximate reasoning can tolerate a possible imprecision, uncertainty, and partial truth of attributes for achieving a tractable, robust, and low cost analysis.

The objective of this study was to build a neural network-based fuzzy logic inference model to predict the perturbation detection capability on the basis of sway characteristics during quiet standing in an older population. Instead of large magnitude perturbations, this study employed a very small stimulus at the psychophysically detectable edge. It was based on the premise that postural instabilities or possibilities of slips and falls were related to the ability of detecting cues indicating that a margin of stability was exceeded and an abnormal motion was about to occur. In this study, the variables to be considered were treated as fuzzy sets to take vagueness of attributes into account. Two phases were used to build a prediction model that was a hybrid of a neural network algorithm and fuzzy logic inference. In phase 1, a supervised learning of neural network algorithm was used to select influential variables from the considered ones. In phase 2, a fuzzy logic rule-based inference system was developed with the variables identified from phase 1.

2. METHODS

2.1. Sway Measures

The following measures were considered as independent variables: the anterior-posterior center-of-pressure (AP-COP), media-lateral center-of-pressure (ML-COP), EMG from the medial segment of tibial anterior (TA) and gastrocnemius soleus (GS) muscle groups on both legs, and head acceleration. Each predictor variable was recorded with 250 readings per second during quiet standing. An average of the readings for a 20-ms window was calculated before the platform movement. Detection of platform movements at an average threshold of acceleration was considered as a dependent variable. It had a binary value 1 for detect and 0 for no-detect of perturbations.

The Sliding Linear Investigative Platform for Analyzing Lower Limb Stability (SLIP-FALLS) system at the Overton Brooks Veterans Administration Medical Center (VAMC) in Shreveport, LA, USA, was used to provide an intensity of perturbation stimulus that would elicit a dynamic response, but not a significant compensation or a fear reaction to the movements. The SLIP-FALLS system was designed to displace the platform at a precisely controlled movement without detectable vibratory cues [17]. The system measured the AP-COP and ML-COP using four load cells, platform acceleration, four channels of EMG data, and subjects' psychophysical response.

2.2. Determination of Threshold

Detection or discrimination of thresholds is a typical psychophysical test. The types of instructions for making a decision generally influence psychophysical responses. In conservative instructions, subjects are always asked to be so certain of the response that consequently they tend not to respond even to a detectable event. The opposite effect is observed when using liberal instructions, i.e., subjects can respond without any fear of punishment. When subjects are presented with a *Yes* or *No* (*Present* or *Absent*) question,

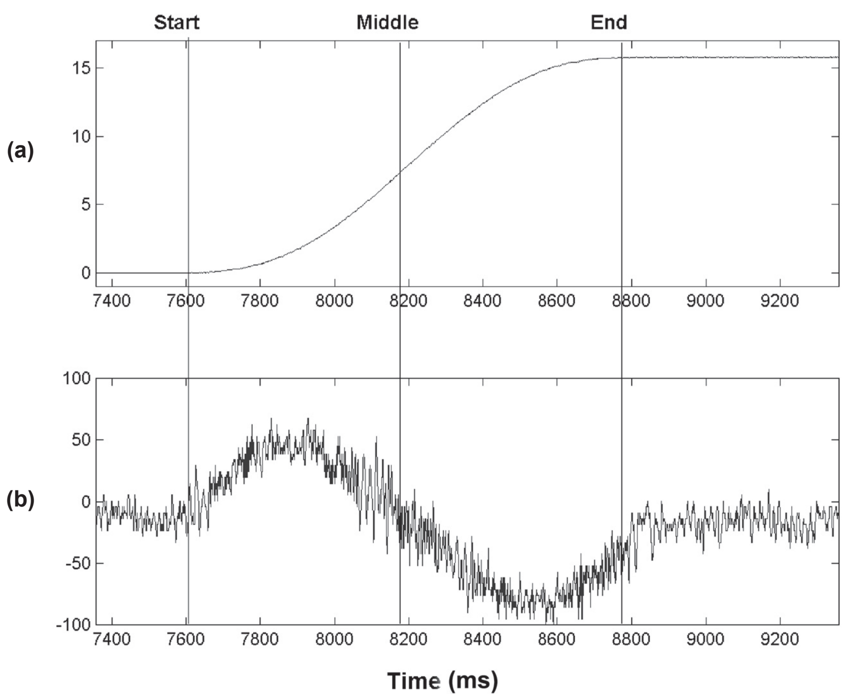

Figure 1. Acceleration profile during 16-mm perturbation (a) platform displacement, (b) acceleration of platform).

it is hard to determine a threshold because it is uncertain which judgment criterion—conservative or liberal—is adopted by the subjects.

The parameter estimation by sequential testing (PEST) was used with a two-alternative forced choice paradigm (*One* and *Two* in the test protocol) to determine thresholds of detection. The paradigm had subjects pick one alternative from two available choices presented sequentially. The PEST [18] is an adaptive psychophysical method where the intensity of stimulus is changed according to a previous response until a desired level of performance is obtained. The rule for changing stimulus intensity is analogous to the simple up-or-down rule. Stimulus intensity is not changed until a sequence of ups or downs has been observed. Levitt [19] reports probabilities of positive responses at convergence for different strategies of changing up-and-down sequences. After three true detections, the stimulus intensity decreased. When missing one true or one false, the stimulus intensity increased. To determine the threshold, the subjects were tested for a maximum of 30 trials after 10 practice trials using the SLIP-FALLS. Figure 1 shows a plot of the acceleration profiles of platform displacement.

2.3. Participants and Test Protocol

The Social Service Department at Overton Brooks VAMC recruited participants 50–80 years old. A total of 13 participants, 4 females and 9 males, participated in this study voluntarily. The ages ranged between 50 and 64 years old, and the mean age was 58. Six of them had Type 2 diabetes with neuropathy, and the rest of the participants were non-diabetic and neurologically intact. Tri-electrode EMG electrodes were attached to the medial segment of the GS and TA muscle groups bilaterally. The participants positioned their bare feet in a designated area on the platform of the SLIP-FALLS. In this study, the side-by-side stance position was used because the center-of-pressure could be measured more reliably from that stance [20]. A triaxial accelerometer from NGT Technology (USA) was used to provide a ±1.33 g acceleration range with 1.5 Volt per g conversion. The head accelerometer was placed on the left headphone ear-piece roughly in line with the horizon while the head was held in a 0^{o} tilt position. The acceleration line of force that was collected was related to the head perpendicular to the frontal plane. Figure 2 shows the graphical representation of possible ranges of the AP- and ML-COP and head acceleration. For testing a displacement perturbation, the subjects had headphones producing a constant masking white noise of 70 dB and a blindfold to cut off any auditory and visual cues. The following instructions were given over the headphones for the subjects to decide when the platform moved: *Ready*, *One*, *Two*, and *Decide*. Subjects were asked to press a wireless doorbell chime held in their hand once or twice if they detected a movement at *One* or *Two*, respectively, right after the *Decide* instruction. A 4-s interval was given between instructions.

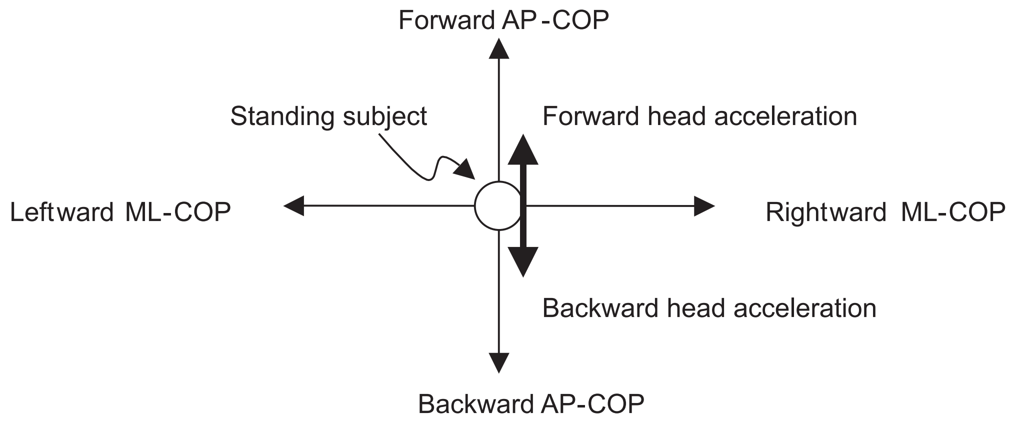

Figure 2. Directions of sway.

No feedback on the correctness of response was provided to participants. The length of translation for “smooth” acceleration perturbations was 16 mm because it was near the maximum sway range. The acceleration of the platform for testing was set at 125% of the average threshold found. After 5 practice trials, the test ran for at most 30 trials.

2.4. Data Analysis

2.4.1. Phase 1: selection of influential variables

In this study, a supervised learning neural network was used to find influential predictors according to the weights of neurons involved in the learning process. A supervised learning method is usually applied to tasks such as pattern classification and function approximation with a given data set [21].

The data set was divided into diabetics and non-diabetics. For each group, the selection process was performed using the following network architecture:

1. number of hidden layer: 1,
2. hidden layer size: 2,
3. learning parameter: 0.5,
4. momentum: 0.1,
5. initial weight on neurons: 0.5,
6. number of training cycle: 100.

Since the objective of the supervised learning neural network in this study was not to classify the responses into detect or no-detect, but to find influential variables for perturbation prediction, the binary dependent variable was treated as a continuous variable for function approximation.

2.4.2. Phase 2: construction of fuzzy logic inference

Linguistic variables defined

As an alternative approach to a precise model of system analysis, humans can articulate an imprecise linguistic description of the process or manner of system performance. The linguistic description generally has a vagueness or fuzziness. For instance, the detection of perturbation can be modeled using a rule:

- IF the AP-COP is backward,
- AND the ML-COP is rightward,
- AND the head acceleration is forward,
- THEN the Detection is high.

The terms *backward*, *rightward*, *forward*, and *high* are possible values of the variables AP-COP, MP-COP, head acceleration, and detection. The values are vague, but meaningful and qualitative. A fuzzy set can be associated with each of the vague linguistic terms. The variable that has a value of a linguistic term is defined as a linguistic variable. Zadeh [22, 23, 24] discussed advantages of the use of linguistic terms for describing variables. For each of the influential variables identified from phase 1, three linguistic variables were considered. For the dependent variable, two linguistic variables were used as shown in Table 1.

TABLE 1. Linguistic Variables for Independent and Dependent Variables

Independent/Dependent	Variables Considered	Linguistic Variables
Independent variables	AP-COP	backward, centered, forward
	ML-COP	leftward, centered, rightward
	EMG-right-TA	low, medium, high
	EMG-left-TA	low, medium, high
	EMG-right-GS	low, medium, high
	EMG-left-GS	low, medium, high
	head acceleration	backward, centered, forward
Dependent variable	detect	low, high

Notes. AP-COP—anterior-posterior center-of-pressure, ML-COP—media-lateral center-of-pressure, TA—tibial anterior, GS— gastrocnemius soleus.

Fuzzy rule-based inference

Fuzzy conjunction and disjunction operators were used to combine matching degrees of multiple conditions for each considered rule. In the inference step, each relevant rule derived a conclusion according to the matching degree that was calculated at phase 1. A conclusion was inferred by suppressing fuzzy membership functions of a rule's consequent. The clipping method was used for suppression in this study. In order to take any affecting rule into consideration, a combination of inference results of these rules was needed. This aggregation process was accomplished by superimposing all fuzzy conclusions about a considered output variable from phase 2. The centroid method was used for this process.

Adaptive neural network-based fuzzy inference

Generally, it is difficult to identify fuzzy rules and tune fuzzy membership functions in fuzzy inference systems. However, neural networks can apply their learning capability through training in this problem. Backpropagation learning, one of the most widely used learning methods of neural networks, was used to estimate membership function parameters and to identify fuzzy rules. For the urinalysis test classification, the backpropagation learning algorithm was derived from a cost function defined by a fuzzy predicted output and a corresponding target output that would be either detect (1) or no-detect (0) of an associated fuzzy input vector. The fuzzy membership functions and if–then rules in the developed fuzzy inference system were trained using the adaptive neural network-based fuzzy inference method [25] and tested with a sample data set. A detailed discussion of fuzzy logic and applications can be found in Yen and Langari [26]. In this study, an adaptive neural network-based fuzzy inference system was built using the *fuzzy*TECH™ (Inform Software Corporation, USA) software.

3. RESULTS

Two data sets of 170 and 169 observations were collected from diabetics and non-diabetics, respectively. Table 2 shows the observed values for the two groups between detect and no-detect. To find influential variables, each data set was randomly partitioned into training and testing data sets, almost equal in size. Table 3 shows selected variables with the weights of influence on the dependent variable and the mean squared error (*MSE*) of the function approximation during training and testing.

TABLE 2. Observed Measures for Each Group

	Diabetics			Non-Diabetics		
Measures	Range	Detect	No-Detect	Range	Detect	No-Detect
AP-COP (mm)	[–7.64, 2.66]	–2.20 ± 2.34	–1.27 ± 2.61	[–2.71, 2.22]	–0.47 ± 0.96	–0.39 ± 1.15
ML-COP (mm)	[–1.67, 1.14]	0.01 ± 0.72	0.03 ± 0.59	[–1.44, 1.86]	0 ± 0.49	–0.01 ± 0.42
EMG-right-TA (100 mV)	[0, 0.75]	0.06 ± 0.08	0.07 ± 0.18	[0.01, 0.30]	0.06 ± 0.06	0.06 ± 0.06
EMG-left-TA (100 mV)	[0, 0.15]	0.03 ± 0.03	0.03 ± 0.03	[0, 0.12]	0.03 ± 0.04	0.03 ± 0.03
EMG-right-GS (100 mV)	[0.01, 0.25]	0.09 ± 0.08	0.11 ± 0.09	[0.01, 0.36]	0.05 ± 0.06	0.05 ± 0.06
EMG-left-GS (100 mV)	[0.01, 0.42]	0.10 ± 0.08	0.12 ± 0.11	[0.01, 0.20]	0.05 ± 0.05	0.04 ± 0.03
Head acceleration (mm/s^2)	[–2.60, 0.56]	–0.65 ± 0.66	–0.54 ± 0.62	[–1.79, 1.55]	0.21 ± 0.72	0.22 ± 0.81

Notes. *M* ± *SD* was rounded up at the third decimal point. AP-COP—anterior-posterior center-of-pressure, ML-COP—media-lateral center-of-pressure, TA—tibial anterior, GS— gastrocnemius soleus.

TABLE 3. Selection of Influential Variables

	Weight of Variable	
Selected Variables	**Diabetics**	**Non-Diabetics**
AP-COP	0.742	0.751
ML-COP	0.595	0.343
Head acceleration	0.823	0.824
MSE (testing)	0.210	0.213
MSE (validation)	0.221	0.209

Notes. AP-COP—anterior-posterior center-of-pressure, ML-COP—media-lateral center-of-pressure, *MSE*—mean squared error.

The criterion of selecting influential variables was randomly set at the weight of 0.1. That is, variables with the weight greater than 0.1 were selected. The differences between diabetics and non-diabetics on the selected influential variables, i.e., AP-COP, ML-COP, and head acceleration, when detecting and not detecting the perturbation are shown in Figures 3, 4, and 5.

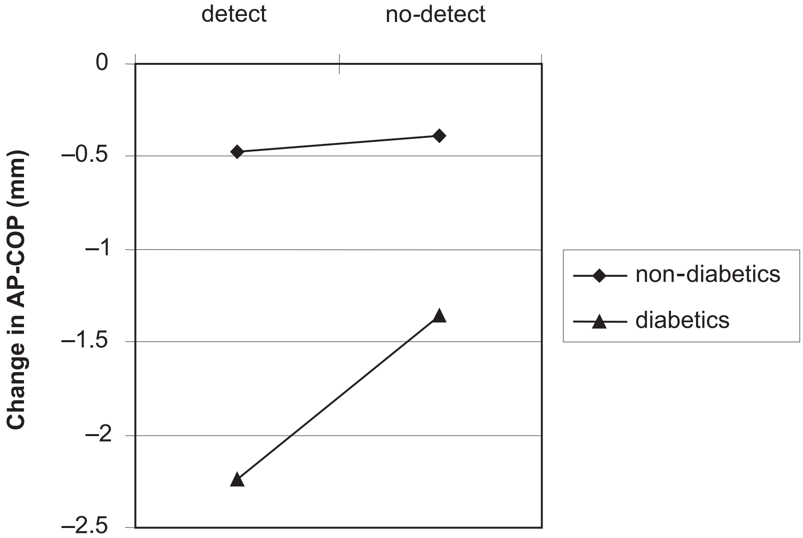

Figure 3. Change in AP-COP between detect and no-detect for each group. *Notes*. AP-COP—anterior-posterior center-of-pressure.

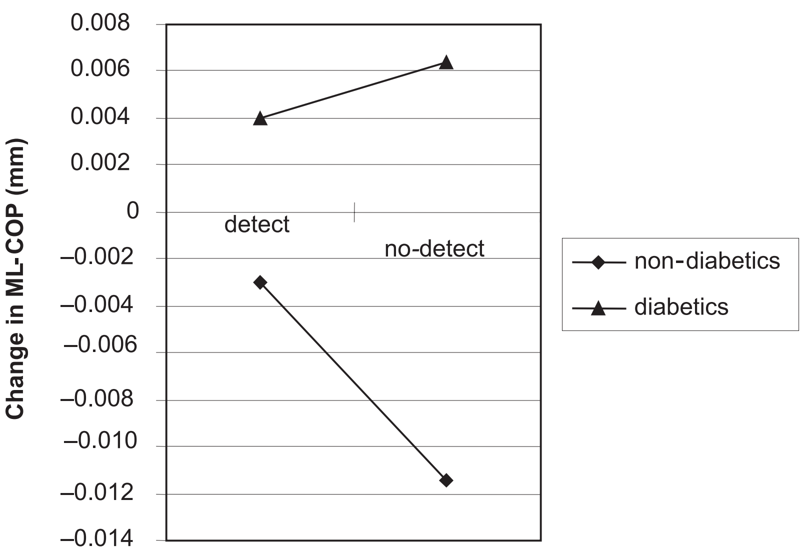

Figure 4. Change in ML-COP between detect and no-detect for each group. *Notes*. ML-COP—media-lateral center-of-pressure.

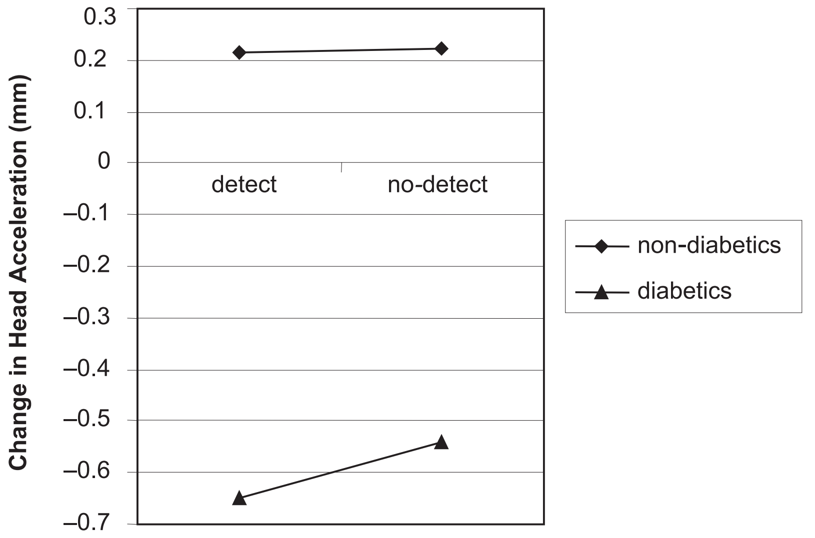

Figure 5. Change in head acceleration between detect and no-detect for each group.

Based on the selected influential variables, the fuzzy membership functions and rules were trained using the training data set to build the fuzzy logic inference system. Then, the fuzzy logic system was validated by comparing the inference from the system built and the actual response of detection of perturbation using the testing data set. The collected data sets were partitioned into the training and testing data sets. For training, 100 data points were used for each group. Table 4 shows the first five important fuzzy logics that were selected on the basis of the degree of support (DOS) for detect and no-detect. Here, the degree of support represents the individual weight ranging from 0 to 1 for firing the rule. The fuzzy rules for detect showed higher degrees of support than for no-detect for both groups.

TABLE 4. Fuzzy Logic for Perturbation Detection

Subjects	IF AP-COP	AND ML-COP	AND Head Acceleration	THEN Detect	DOS
Diabetics	backward	leftward	centered	low	0.16
	backward	rightward	centered	low	0.48
	centered	rightward	centered	low	0.30
	forward	leftward	centered	low	0.15
	forward	centered	forward	low	0.15
	backward	rightward	forward	high	0.95
	centered	leftward	forward	high	0.99
	centered	centered	centered	high	0.99
	centered	rightward	backward	high	0.96
	centered	rightward	forward	high	1.00
Non-diabetics	centered	centered	centered	low	0.16
	centered	centered	forward	low	0.16
	center	rightward	forward	low	1.00
	forward	leftward	forward	low	0.19
	forward	rightward	backward	low	0.36
	backward	leftward	forward	high	1.00
	centered	leftward	centered	high	1.00
	centered	centered	centered	high	0.91
	centered	centered	forward	high	0.92
	forward	centered	forward	high	0.99

Notes. AP-COP—anterior-posterior center-of-pressure, ML-COP—media-lateral center-of-pressure, DOS—degree of support.

When the AP-COP, ML-COP, and head acceleration were centered, both groups had a high DOS for detecting the perturbation. Meanwhile, it was difficult to find a common logic for the failure of detection between the two groups. When the AP-COP, ML-COP, and head acceleration were centered, rightward, and forward, respectively, the possibility of detection was high for diabetics, but low for non-diabetics. Contrastingly, when the measures were forward, centered, and forward, the trend was reversed. Figure 6 through Figure 13 show the trained fuzzy membership functions of the variables selected for the fuzzy rule inference system for diabetics and non-diabetics. The two groups showed similar patterns of membership functions for the considered variables except the ML-COP. To test the fuzzy rule inference system, 70 and 69 data points were used for diabetics and non-diabetics, respectively. Table 5 shows the comparison between the actual response and the prediction from the fuzzy rule inference. The fuzzy system showed a relatively high error rate when inferring no-detect during the training and testing for both groups.

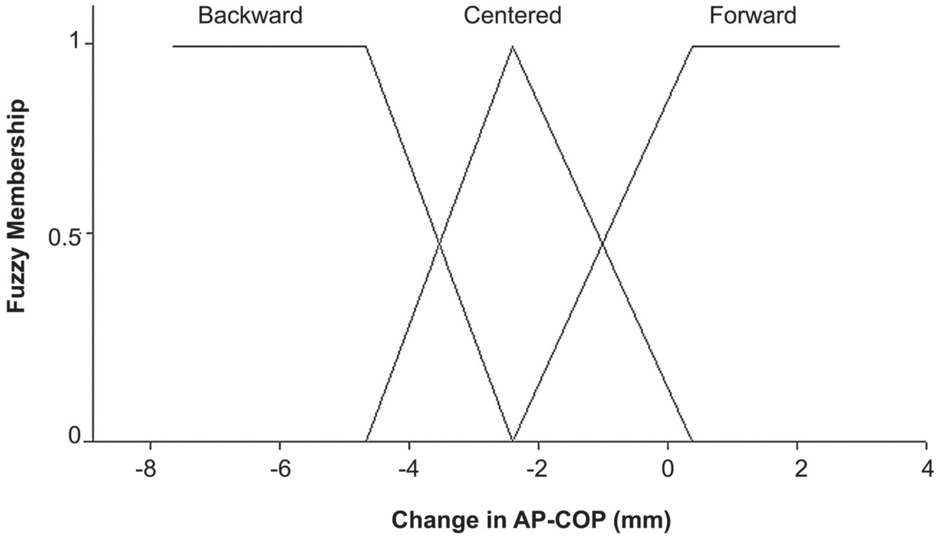

Figure 6. Membership function for AP-COP in diabetics. *Notes*. AP-COP—anterior-posterior center-of-pressure.

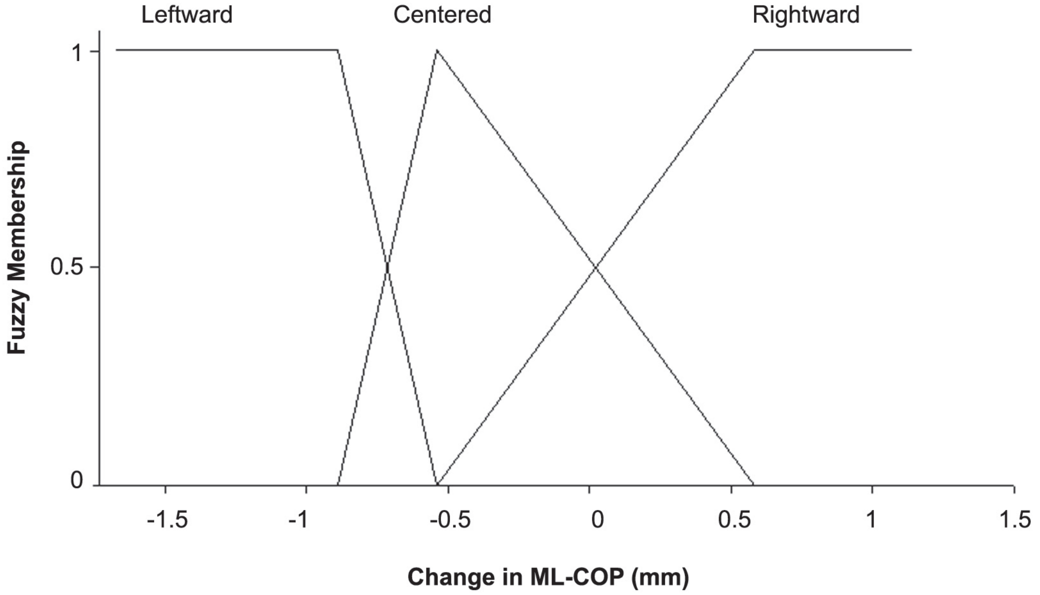

Figure 7. Membership function for ML-COP in diabetics. *Notes*. ML-COP—media-lateral center-of-pressure.

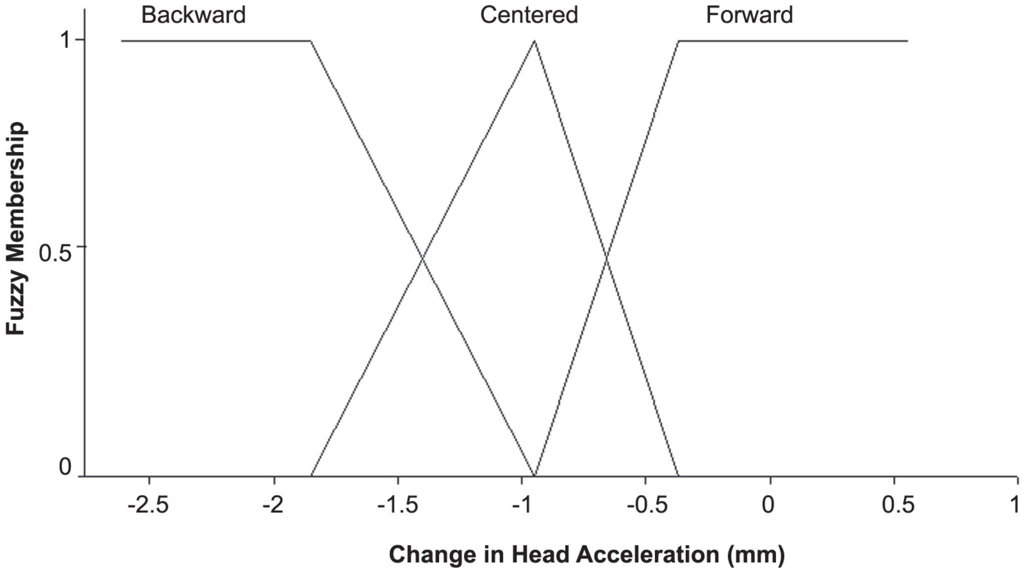

Figure 8. Membership function for head acceleration in diabetics.

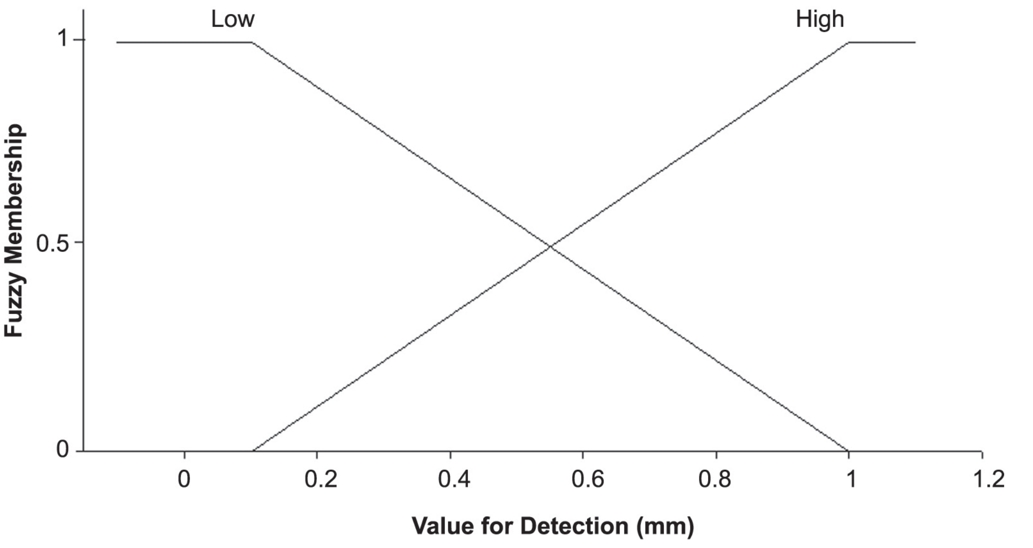

Figure 9. Membership function for detection in diabetics.

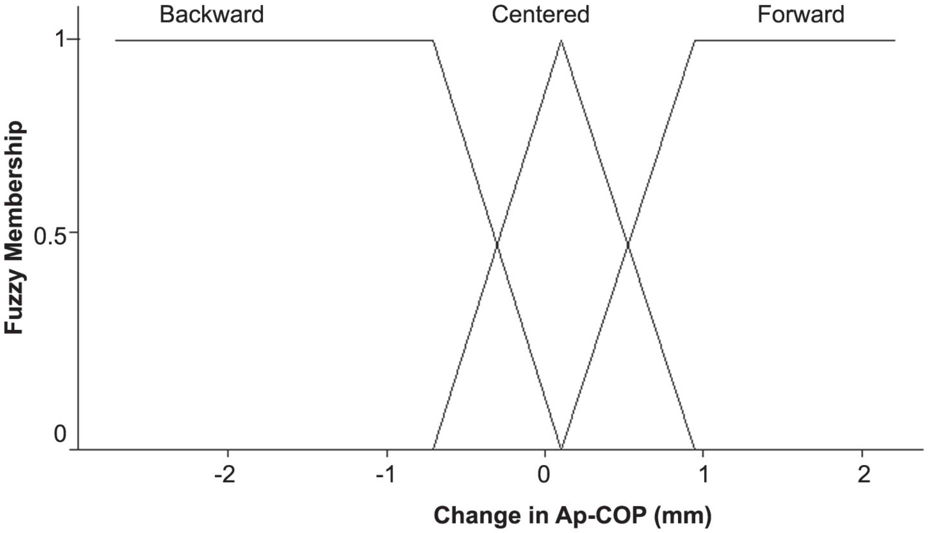

Figure 10. Membership function for AP-COP in non-diabetics. *Notes*. AP-COP—anterior-posterior center-of-pressure.

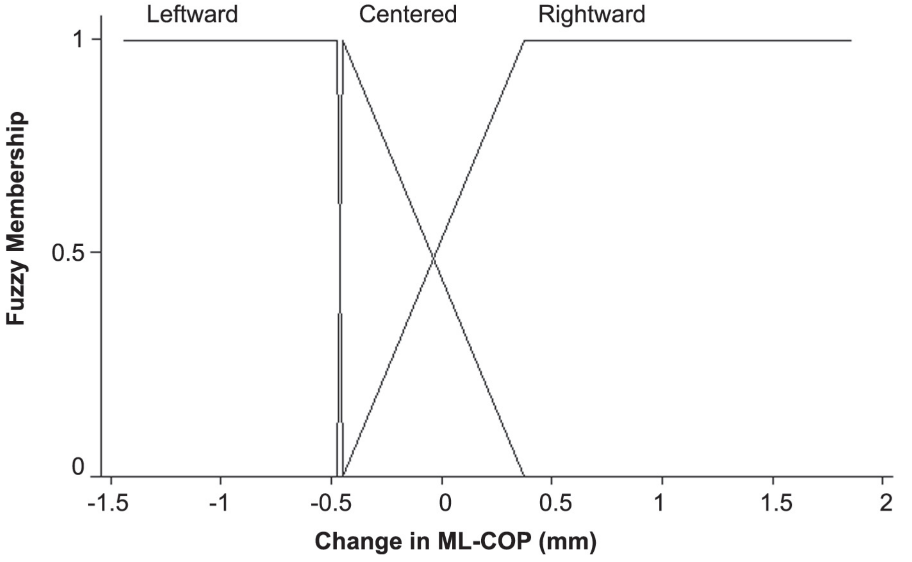

Figure 11. Membership function for ML-COP in non-diabetics. *Notes*. ML-COP—media-lateral center-of-pressure.

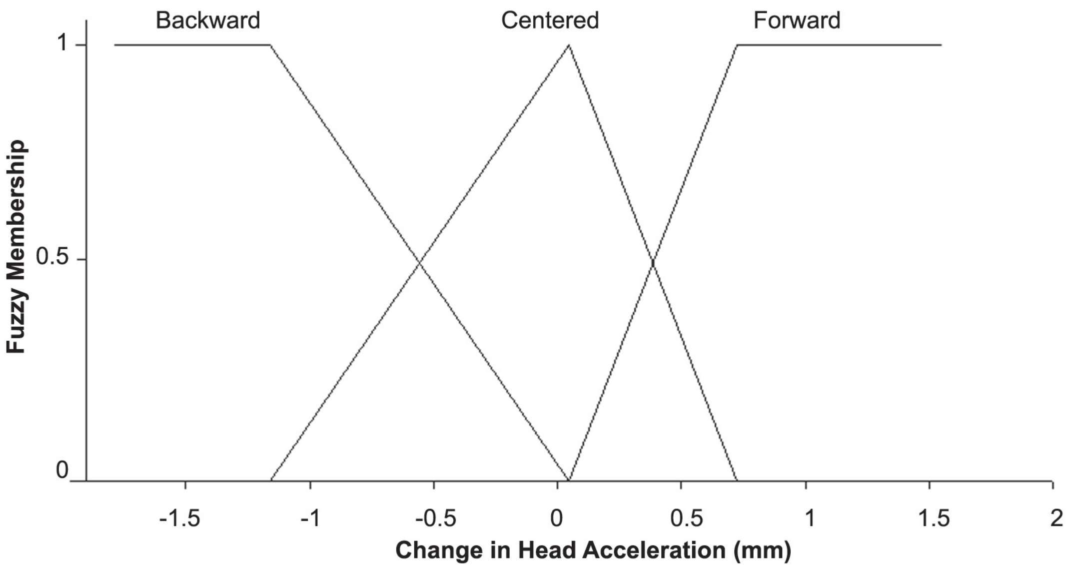

Figure 12. Membership function for head acceleration in non-diabetics.

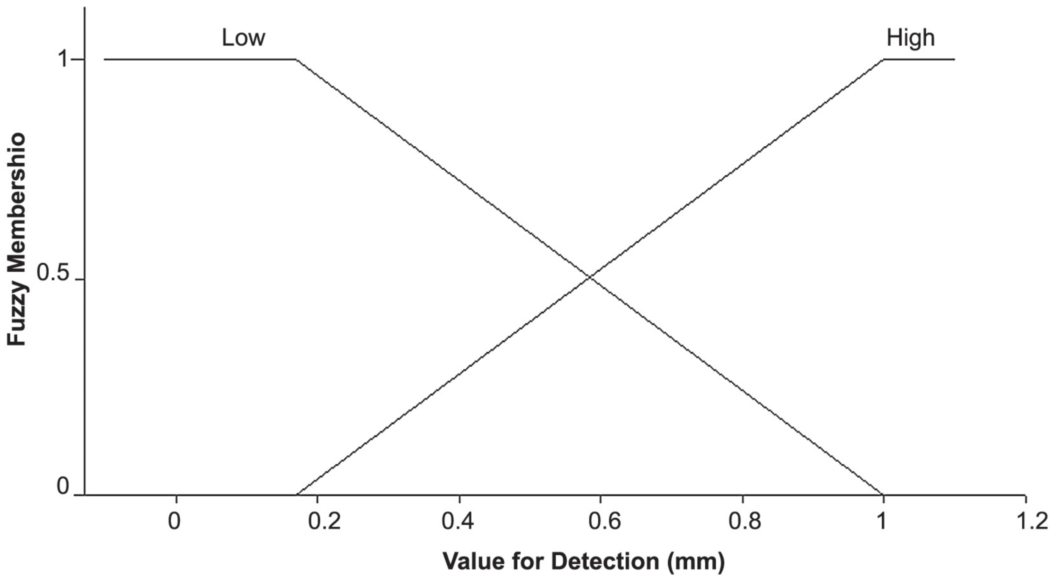

Figure 13. Membership function for detection in non-diabetics.

TABLE 5. Performance of Fuzzy Rule Inference System

Actual Response (Target)	Inference (Prediction)	Training		Testing	
		Diabetics	Non-Diabetics	Diabetics	Non-Diabetics
Detect	detect	64	76	37	40
	no-detect*	2	1	13	8
No-detect	detect*	18	14	18	18
	no-detect	16	9	2	3
Total data points		100	100	70	69

Notes. *—prediction error.

4. DISCUSSION

Sway patterns and detection of slip perturbation in the older populations was modeled using neural network-based fuzzy logic algorithms. Two groups, diabetics and non-diabetics, showed that the detection of slip perturbation was related to the AP-COP, ML-COP, and head acceleration during quiet standing. Both groups detected perturbation with a high possibility when the posture was stable. Prieto, Myklebust, Hoffmann, Lovett, and Myklebust [27] reported a difference of sway between young adults and older adults. Sparto, Robinson, and Faulkner [28] found a low detection threshold for young adults. The result of this study may support the relationship between postural steadiness and detection of perturbation. One interesting difference between the two groups is a pattern of sway with respect to perturbation detection. The diabetic group showed a high possibility of detection when the sway was oriented to the right in the media-lateral direction. Meanwhile, the non-diabetic group detected perturbation with a high possibility when the sway was in the anterior-posterior direction. Another point to be noticed is that the distributions of fuzzy membership functions for the AP-COP, head acceleration, and detection were not quite different between diabetics and non-diabetics. However, diabetics showed a wider and more backward sway pattern than non-diabetics. Also, the difference between the membership functions of the ML-COP for the two groups was noticeable. For the diabetic group, the positive relationship between the rightward ML-COP and the perturbation detection could indicate a different strategy for sensing stimuli from the non-diabetic group. The inference system was more successful for non-diabetics than for diabetics. It may indicate that the variations of measures are more uncertain in the diabetic group compared to the non-diabetic one. The success rate of inference was higher for detect than for no-detect. From this study, it is still unclear how people miss perturbation.

Results of this study can be applied to designing floor mats or safety boot insoles to prevent fatigue of the lower extremities or slips in workplaces. For instance, diabetics tend to sway more on an elastic pad than on a hard floor when compared with people with no diabetes [29]. Modifications of floor mats or shoe insoles, based upon the relationships between sway directions and perturbation detection, can reduce the intensity of changes of the center of pressure, resulting in more stable balance for diabetic workers.

It should be noted that the capability to detect perturbation investigated in this study is limited to static measures such as sway characteristics during quiet standing. The capability to detect a slip or fall initiation during gait will be quite different from that during quiet standing. The relationship between characteristics of postural sway and no-detect needs further research to find a deficiency of detection when people are exposed to slip or fall initiations.

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