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Visual-Balance Echo-Dispersal System (VBEDS): Measurement of Physical Signals for Postural Stability Prediction in the Elderly

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Abstract

Postural instability in the elderly is a leading contributor to falls, necessitating precise and non-invasive balance assessment systems. This study proposes the Visual-Balance Echo-Dispersal System (VBEDS), which evaluates postural fluctuations based on physical signal transitions under varying visual conditions. Data were collected from 25 elderly participants using a customized signal acquisition and processing setup. The system captures fluctuations across postural states—eyes open, eyes closed, head tilted directions—analyzing frequency variations within the 0.01 Hz to 2 Hz range. By comparing conditions such as VB-ΩEDNO-NC, VB-ΩEDPO-PC, VB-ΩEDHR-HL, and VB-ΩEDHB-HF, the model distinguishes between abnormal, normal, and optimal balance states. Results show significant variation in visual-balance fluctuation averages, identifying critical thresholds for fall-risk prediction. The VBEDS system demonstrates effective acquisition, signal separation, and analysis of human postural motion, making it a promising approach for clinical and home-based fall prevention monitoring. Future integration with real-time correction and feedback mechanisms may enhance its applicability in geriatric care and rehabilitation.

Introduction

The global increase in the elderly population brings an urgent need for improved health-monitoring systems that ensure quality of life and autonomy. Among the various age-related health issues, postural instability is a prominent cause of injury, often leading to falls, hospitalization, and long-term disability. Studies show that even mild impairments in balance mechanisms can significantly increase the risk of falls in older adults [1]. Balance control is inherently multisensory, integrating signals from the visual, vestibular, and proprioceptive systems. However, aging affects each of these components, especially visual acuity and vestibular function, which are critical for maintaining upright posture during motion and in static positions [2][3].

Traditional clinical assessments of balance, such as the Romberg or Berg Balance tests, are often subjective and limited to controlled environments. Recent advancements in sensor technology and computational modeling have paved the way for more objective and real-world postural assessments [4]. Incorporating force plates, inertial measurement units (IMUs), and signal-processing systems has enabled the development of low-cost, scalable diagnostic tools for posture analysis [5][6]. Furthermore, the need to transition from laboratory-based models to real-time, context-aware systems has led to the exploration of non-invasive methods that can capture physical signal fluctuations in naturalistic settings [7].

In this context, the Visual-Balance Echo-Dispersal System (VBEDS) offers an innovative approach to detect postural deviation through a signal fluctuation framework. The VBEDS model assesses transitions between open-eye and closed-eye conditions, as well as head tilt orientations, to capture variance in balance control. These vision-state-based transitions are essential in understanding how visual input modulates postural responses [8]. Notably, horizontal and vertical shifts under different vision conditions yield specific signal dispersions that are measurable and repeatable, offering insight into the subject's risk level for imbalance or fall [9].

This paper presents a comprehensive design, implementation, and evaluation of the VBEDS model using data from elderly participants. The goal is to identify fluctuating patterns in postural balance and relate them to abnormal, normal, and optimal conditions. This approach builds on existing models while integrating a novel physical signal acquisition and interpretation mechanism that is highly adaptable to clinical and home-care environments [10].

Existing Model

Existing models for postural balance evaluation in elderly individuals primarily rely on force-plate analysis, visual assessments, and sensor-based motion tracking systems. Traditional clinical tools like the Berg Balance Scale (BBS) or the Timed Up and Go (TUG) test provide basic insights but lack precision in capturing dynamic postural fluctuations [1]. To address this, researchers have introduced wearable sensors, such as inertial measurement units (IMUs), and non-wearable systems like pressure mats and depth cameras to track body motion and sway under various physical and visual conditions [2].

Force-plate systems, in particular, have been pivotal in quantifying center-of-pressure (CoP) trajectories under different visual constraints—eyes open (EO), eyes closed (EC), and head tilt variations. These systems record displacement and velocity of CoP and compute metrics like sway range, sway path, and frequency components [3]. However, despite their effectiveness, such systems are generally restricted to laboratory environments, limiting their applicability in real-world or home settings [4].

To bridge this gap, studies have focused on automated postural state recognition using machine learning and deep learning. Finite State Machines (FSMs) [5], Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs) have been proposed to classify postural states such as sitting, standing, walking, and turning using motion data from community-dwelling elderly [6][7]. These models achieve moderate success but require extensive training and validation datasets.

Another notable approach includes the application of signal fluctuation analysis to detect anomalies in balance behavior. For instance, Albites-Sanabria et al. developed a model leveraging frequency domain features from standing posture under natural conditions for fall prediction, outperforming lab-based measures [8]. Similarly, deep neural networks trained on force-plate time-series data have demonstrated near-perfect accuracy in classifying fall-risk levels [9].

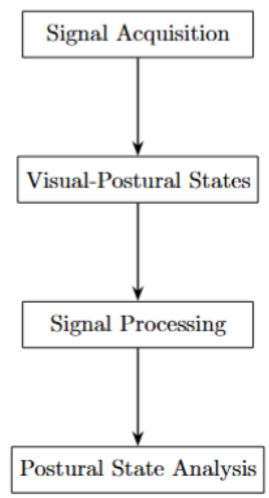

Figure 1: Block Diagram: Existing System

While promising, existing models often suffer from limited adaptability to multiple visual-postural states, lack real-time responsiveness, and require extensive computational resources. This study builds on such limitations by proposing the VBEDS model, which integrates visual-modulated signal fluctuation tracking in a compact, dual-system (acquisition and processing) architecture [10].

Proposed Model

The proposed Visual-Balance Echo-Dispersal System (VBEDS) is designed to address the challenges of conventional postural assessment techniques by capturing and analyzing physical signal fluctuations under various visual and postural conditions in elderly individuals. The system functions through a dual-layer structure comprising a data acquisition module and a signal processing and classification module. In the first stage, posture-related physical signals are gathered using a PXI-based data acquisition setup that records micro-movements and fluctuations across multiple states: eyes open (NO), eyes closed (NC), open eyes with extended arms (PO), eyes closed with extended arms (PC), and head tilts in right, left, forward, and backward directions (HR, HL, HF, HB). The data is sampled across a frequency range of 0.01 Hz to 2 Hz, which is particularly sensitive to postural micro-oscillations, enabling the identification of minute instability cues that often precede falls.

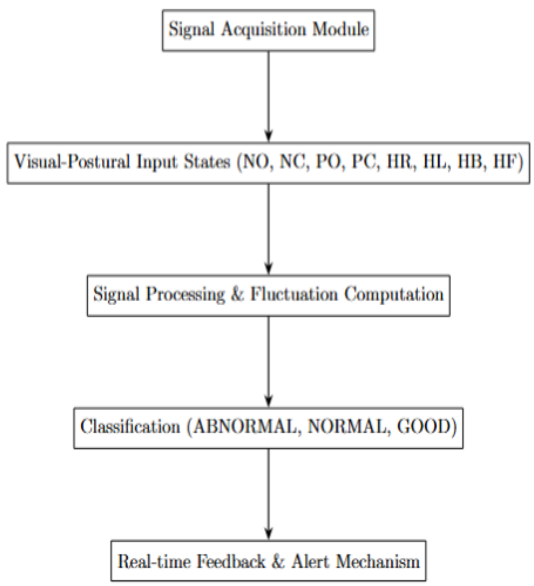

Figure 2: Block Diagram of Proposed VBEDS Model

These signals are then passed through a signal processing pipeline that includes filtering, Fourier transformation, and variance analysis to extract meaningful metrics. The system computes average dispersion values for each postural condition, denoted as VB-ΩAVG-NO, VB-ΩAVG-NC, and so on. These metrics are classified into three categories—VB-ΩABNORMAL, VB-ΩNORMAL, and VB-ΩGOOD—based on fluctuation thresholds derived from empirical observations of 25 elderly participants. The classification is achieved by comparing visual-paired states such as NO versus NC or HR versus HL. Greater fluctuation between paired states typically indicates impaired postural control and higher fall risk. The system is further enhanced with a real-time feedback mechanism that allows alerts to be issued if the fluctuation exceeds predefined safety thresholds, prompting corrective actions or clinical intervention. For example, if a participant's VB-ΩAVG exceeds 30 units, it signals an abnormal condition, triggering alerts or guidance through connected caregiver interfaces.

By integrating various visual-postural combinations, VBEDS goes beyond traditional systems that usually rely on singular EO/EC conditions. It provides a deeper understanding of how vision affects balance and how fluctuations can be tracked to evaluate postural stability. Its adaptability, personalized threshold settings, and real-time response capabilities make it suitable for deployment in clinics, rehabilitation centers, or even home-based eldercare environments. The model thus offers a comprehensive framework for both diagnosis and early intervention in fall-risk management, making it a significant contribution to elderly health monitoring.

Result & Discussions

The VBEDS model was evaluated using data collected from 25 elderly individuals (age 65–83 years) across multiple visual-postural conditions. The results were classified into three balance categories—abnormal, normal, and good—based on fluctuation values computed from physical signal transitions. As presented in Table 1, abnormal conditions exhibited significantly higher average fluctuations, notably 33.98 ± 18.58 units in NO-NC state, compared to 19.52 ± 4.81 units for normal and 13.64 ± 3.32 units for good conditions. Similar patterns were observed across PO-PC, HR-HL, and HB-HF comparisons. These consistent trends validate the system's capability in detecting instability across varied head and eye orientations.

Table 1: Average Fluctuation Values by Risk Category Across Postural Conditions

Postural Condition	Abnormal (Mean ± SD)	Normal (Mean ± SD)	Good (Mean ± SD)
VB ΩBENO-NC	33.98 ± 18.58	19.52 ± 4.81	13.64 ± 3.32
VB ΩBEPO-PC	33.77 ± 22.63	17.48 ± 4.84	11.80 ± 3.35
VB ΩBEHR-HL	42.46 ± 4.44	20.56 ± 2.33	15.23 ± 0.79
VB ΩBEHB-HF	46.33 ± 16.66	20.67 ± 3.31	13.14 ± 3.87

Table 2 highlights average fluctuation values across different vision conditions, showing that vision impacts posture dispersal significantly. For example, VB-ΩAVG-HB-HF recorded the highest variance (26.72 ± 7.94), indicating instability when the head tilts backward or forward. This underlines the importance of vision-state inclusion in postural analysis, especially in dynamic conditions. Overall, vision-modulated posture fluctuations were reliably captured, showing the system's sensitivity to subtle balance shifts.

Table 2: Average Fluctuation Values Across Vision-Based Postural Conditions

Vision Condition	Average Fluctuation (Mean ± SD)
VB ΩAVG-NO-NC	22.38 ± 8.91
VB ΩAVG-PO-PC	21.04 ± 10.27
VB ΩAVG-HR-HL	26.08 ± 2.52
VB ΩAVG-HB-HF	26.72 ± 7.94

Figure 3 displays the signal dispersion profile of subjects under different posture states. Each waveform shows increasing fluctuation as the postural condition deteriorates, with pronounced peaks during abnormal vision-balance combinations.

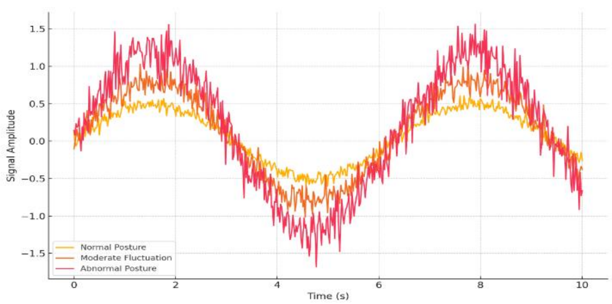

Figure 3: Signal dispersion profile of subjects under different postural conditions

Figure 4 illustrates the comparison between VB-ΩABNORMAL, VB-ΩNORMAL, and VB-ΩGOOD categories across postural states. The visual trend line suggests that VBEDS effectively segregates fall-risk categories based on signal thresholds.

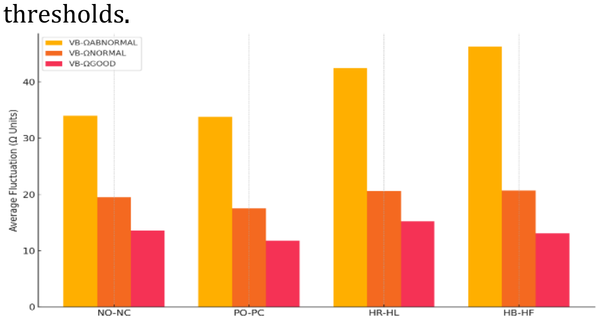

Figure 4: Comparison between VB-ΩABNORMAL, VB-ΩNORMAL, and VB-ΩGOOD categories across postural states

The discussion reveals that VBEDS can distinguish early signs of postural instability. Its frequency-domain approach provides a deeper understanding of balance behavior, especially in complex states like head tilts. By quantifying the dispersion and relating them to known risk levels, this system offers a predictive and preventive solution for elderly fall-risk assessment. Its integration with feedback mechanisms enhances clinical applicability for real-time monitoring and intervention.

Conclusion & Future Scope

This study presented the Visual-Balance Echo-Dispersal System (VBEDS), a novel approach to assessing postural stability in elderly individuals by analyzing physical signal fluctuations under varying visual conditions. Through detailed experimentation and analysis, the system successfully identified and categorized balance states into abnormal, normal, and good based on frequency-domain signal variations. The model's sensitivity to vision-induced postural changes, especially in eye and head orientation states, demonstrates its potential for early fall-risk detection. Its dual-module design—integrating real-time data acquisition and advanced signal processing—offers a promising solution for both clinical assessments and home-based monitoring.

Future research will focus on enhancing the system's portability, integrating wearable sensors, and developing mobile applications for remote monitoring. Additionally, expanding the dataset with more diverse participant groups and incorporating AI-based adaptive learning models can further refine classification accuracy. VBEDS thus holds significant potential in preventive healthcare, rehabilitation, and elderly well-being.

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