Improving Human Balance with Wearable Devices

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ABSTRACT

This study investigates the use of an optical-based balance sensor and a muscle-mimetic wearable robot to evaluate and improve balance in elderly people with various health conditions. We analyzed data from 149 subjects to extract critical temporal and frequential features related to balance, such as center of pressure (CoP), center of gravity (CoG), and theta angles, to categorize them into five distinct levels (i.e., levels 0,1,2,3, and 4). A correlation analysis between balance sensor features and gastrocnemius lateralis (GL) muscle maximum voluntary contraction (MVC) confirmed our hypothesis that subjects with stronger GL muscles maintained better balance. Hence, we developed a wearable muscle-mimetic robot to compensate for the weakened GL muscle. The GL muscle-mimetic ankle robot, which mimics muscle mechanical properties and uses human intrinsic physiological signals for control, simultaneously relaxes and contracts with the GL muscle to enhance postural stability and balance. Furthermore, testing the wearable robot with the balance sensor demonstrated promising results in enhancing balance, as evidenced by the decreased variance of CoP when the robot was worn. Our findings suggest that the optical-based balance sensor and muscle-mimetic wearable robot provide an effective approach for assessing and improving balance in elderly individuals, with potential implications for reducing fall risk and improving postural stability in aging populations.

INTRODUCTION

Human balance ability is vital in various aspects of daily life, including walking [1],

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running [2] and maintaining an upright posture [3]. This fundamental skill is also essential for preventing falls [4], particularly in older adults [5] and individuals with balance or sensory impairments. A thorough understanding of the underlying mechanisms of human balance is crucial for developing effective interventions, improving overall mobility, and enhancing quality of life.

There are numerous subjective measures of balance, including the Berg Balance Scale [6] and the Timed-Up-and-Go test [7]. However, there is still a demand for quantitative, objective measures that accurately and reliably assess balance. Such measurements could elucidate the mechanisms underlying balance control and facilitate continuous monitoring of balance improvement when being compensated with wearable assistive devices. Force platforms [8] are widely used in laboratory settings to measure ground reaction forces [9] and compute the center of pressure (CoP) [10] during static and dynamic balance tasks. These devices provide quantitative data on postural sway, which can be used to evaluate balance ability. While certain risk factors for balance impairments, such as age and specific medical conditions, are well-established, other potential factors may be less recognized. Identifying these additional risk factors could enable targeted interventions for individuals at a heightened risk for balance impairments. It is evident that balance impairments contribute to fall risks. However, the precise factors connecting balance issues to falls remain incompletely understood. Consequently, enhancing our understanding of the relationship between balance and falls could result in more effective fall-prevention interventions and assistance through wearable devices. To attain a comprehensive understanding of multi-information and image-based assessment, a high-resolution balance sensor was developed in a previous study [11]. The sensor used in this study aims to address the aforementioned gaps and provide methods for the assessment of balance improvement by wearable devices.

Researchers have developed and employed robotic exoskeletons to enhance human balance capabilities [12-14]. When an exoskeleton is utilized to control joint movement or balance abilities, it generates control signals, thus necessitating a high degree of responsiveness. According to a study, in order to improve the standing balance of human users, exoskeletons must exhibit faster response times than physiological responses [15]. This finding aligns with the well-established principle that controlling a high-bandwidth system with a lower-bandwidth controller can be challenging, as the controller may not be able to adequately respond to the system's high-frequency dynamics. To effectively employ a robot or exoskeleton to improve human balance, two primary strategies can be pursued. The first approach entails enhancing the response speed of the robot or exoskeleton by developing faster robotic actuation technologies. The second strategy involves integrating hierarchical human and robot two-system control approaches by using a single controller, so as to avoid different motion information from the robot and human two control systems. For individuals with paralysis or disabilities, the robotic controller can concurrently actuate the human body and the exoskeleton. [16,17]. In other application scenarios, the robot serves as an assistance device, compensating for muscle strength to improve balance, which implies the by utilizing of the human body's inherent proprioceptive sensory information by the robot.

The human vestibular system, visual system, and somatosensory work together to process sensory information, enabling the central nervous system (CNS) to generate appropriate motor responses that maintain balance [18]. The CNS integrates the sensory information from these systems and generates motor commands to activate various muscles in a coordinated manner, maintaining balance and facilitating movement [19]. The motor commands are transmitted through the spinal cord to the peripheral nervous system, which innervates the muscles, modulating their force production and adjusting joint angles to stabilize the body [20]. The human body can maintain balance by controlling muscle activity through the nervous system. Therefore, an ideal robotic system should be able to match or surpass the response speed of human muscles. Furthermore, the system should be capable of receiving control signals from the human body, which would then be "translated" into control commands and relayed to the robot, thus facilitating the process of muscle compensation.

The gastrocnemius muscle plays a crucial role in human balance control by maintaining postural stability [1] and counteracting external disturbances by generating of appropriate forces at the ankle joint [21] in standing balance control. However, aging can result in decreased gastrocnemius lateralis (GL) muscle strength, which may adversely affect balance. In this study, we introduce a muscle-mimetic wearable robot designed to compensate for the diminished GL strength, along with an optical-based balance sensor for the objective, quantitative, and continuous evaluation of fall risk level and the effectiveness of the robotic compensation on human balance.

METHODOLOGY

Development of the balance sensor

The balance sensor is designed based on the principle of total internal reflection optics. Two glass plates are placed at an angle of 45 degrees inside the sensor to reduce its height. When a human foot touches the sensor surface, total internal reflection is achieved to generate an image that is reflected through the angled mirrors and captured by the camera. Although this arrangement does not affect the image clarity, it halves the required sensor height [22]. This angled glass plate configuration not only saves floor space but also minimizes the risk of subjects falling when standing on the sensor. Leveraging this compact design, the sensor can precisely detect human balance by analyzing the reflected foot image. The structure and appearance of the balance sensor are illustrated in Figure 1. The concept of utilizing total internal reflection is inspired by a previous texture sensor developed in our lab [23].

We developed a web interface for the balance sensor where there is a “Fill in information” button where users can input tester information and the required duration of the experiment. We typically set the video duration to 30 seconds. When the users click the “Take Video” button, the testers have 30 seconds or another set seconds to complete the test. This will record 30 seconds or more of video into the camera. Subsequently, the captured video can be transferred from the camera to the computer for further analysis. Given the frame rate of up to 30 frames per second, each video encompasses approximately 900 frames in total.

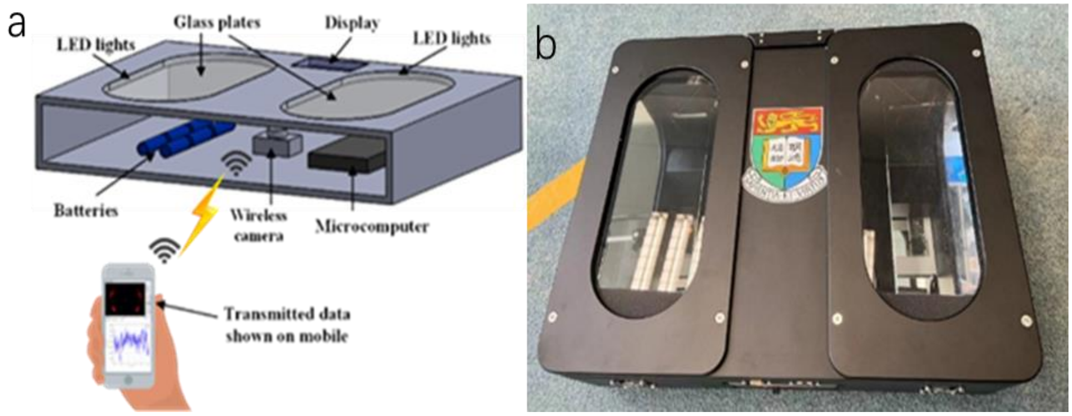

Figure 1. a. The structure [24] and b. The appearance of the balance sensor

Development of the muscle-mimetic wearable robot

To mimic the functionality of the GL muscle, a muscle-mimetic robot has been designed to emulate the mechanisms that are intrinsic to the GL muscle. The anchoring points of the robot are strategically positioned at the heel and knee, mirroring the attachment sites of the GL muscle. As illustrated in Figure 2, the orientation of the muscle-mimetic actuator aligns with the gastrocnemius muscle, situated at the posterior aspect of the lower leg. By emulating the mechanical properties of the GL muscle, the robot can synchronize its movements with the natural muscle contractions and effectively compensate for the deficiencies in GL muscle strength.

The robotic system is designed to interpret physiological signals from the human body and convert them into actionable robotic commands. Consequently, the GL robot leverages the individual's innate control signals to adopt the human body's neuromuscular control strategy for generating appropriate tension. Governed by electromyographic signals originating from intrinsic physiological data, the GL muscle-mimetic ankle robot concurrently engages in relaxation and contraction with the human gastrocnemius muscles. When the body experiences perturbations, causing it to sway forward or backward, the GL robot and other musculature surrounding the ankle joint collaboratively generate corrective torques to reestablish equilibrium.

Figure 2. Wearable gastrocnemius lateralis (GL) muscle-mimetic robot. a. subjects wore short pants and robots and b. robots wear underneath long pants.

EXPERIMENTAL RESULTS AND EVALUATION

Our balance sensor has been tested on 149 elderly subjects aged 65 and older with various health conditions. The experimental protocol involved subjects removing their shoes and socks and standing barefoot on the two glass plates on either side of the balance sensor. With handles provided on both sides for safety, the subjects were asked to stare straight ahead, keep their hands still by their sides, and maintain their balance for 30 seconds while the balance sensor recorded changes in their center of pressure.

We analyzed the plantar pressure data of 149 subjects to evaluate their balance ability, extracting important temporal and frequential features. The center of pressure (CoP), which indicates the position of the center of gravity on the plantar contact surface, reflects the body's balance state. We calculated 45 temporal features and 15 frequential features for CoP, including the mean velocity, amplitude, range of movement, and power spectral density at different frequencies. The center of gravity (CoG), which is defined as the geometric center of mass of all body parts, determines body balance together with CoP. We extracted the same sets of temporal and frequential features for CoG as for CoP. These features, allow us to make a preliminary distinction between the elderly people of different physical health statuses with risk levels 0,1,2,3 and 4, as shown in Figure 3.

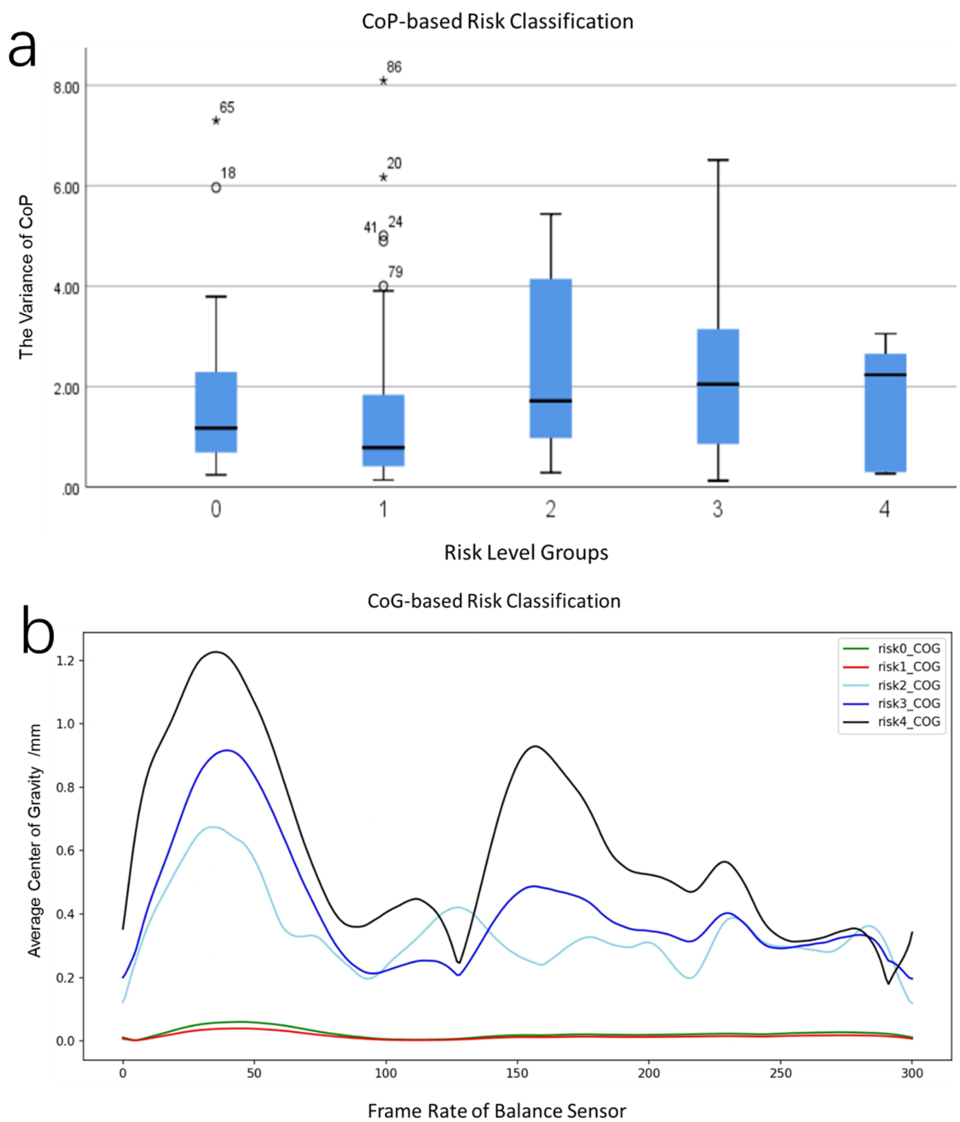

Figure 3. a. The center of pressure (CoP)-based risk classification and b. The center of gravity (CoG)-based risk classification for the elderly with different physical health statuses with risk levels 0,1,2,3 and 4.

We simultaneously measured the maximum voluntary contraction (MVC) of GL muscle in 29 subjects as shown in Figure 4. Our hypothesis was that subjects with larger GL muscle MVC would perform better in the balance test, which in the context of our balance sensor would mean that the center of pressure, the center of gravity, and theta angle features extracted would be smaller during the experiment.

In Figure 4., each row represents the extracted features over 30 seconds of the subject standing still and looking forward on the balance sensor, including the center of pressure, the center of gravity, and angle theta, totaling 58 features. The angle theta represents the angular tilt of the joints about the X and Y axes. We also derived corresponding temporal and frequential features for angle theta. Each column represents three separate MVC measurements and their averages for GL muscle. Red represents correlation coefficients greater than 0, indicating a positive correlation between the two, while blue represents coefficients less than 0 indicating a negative correlation. Values closer to 1/-1 indicate a stronger correlation. Evidently, the majority of the results from the balance sensor show a negative correlation with GL muscle MVC, confirming our hypothesis that subjects with stronger GL muscles maintained better balance.

Figure 4. Correlation between balance sensor data features and GL muscle MVC features.

We also conducted experiments using the wearable muscle-mimetic robot in conjunction with a balance sensor. The subject stood on the balance sensor without wearing the robot and swung their upper limbs with a specific amplitude, placing the body in an unbalanced state. This action caused the GL muscles and other lower limb muscle groups to activate in order to maintain balance. The center of pressure (CoP) data for the entire 30-second measurement process is illustrated in Figure 5. Subsequently, the subject donned the wearable muscle-mimetic robot and stood on the balance sensor while swinging their upper limbs at the same frequency and amplitude as before. This triggered the robot's activation alongside the GL muscles and other lower limb muscle groups to maintain balance after experiencing an imbalance. The CoP data for this 30-second measurement process is also depicted in Figure 5. The CoP variance relative to the mean CoP decreased from 0.533 (without robot condition) to 0.096 (wearing robot condition), showing promising results in improving balance when worn by subjects, both in active force front-back directions and passive left-right directions. However, for the healthy subject, the range of CoP did not exceed the yellow (average risk level 0,1) and red circles (average risk level 2,3,4).

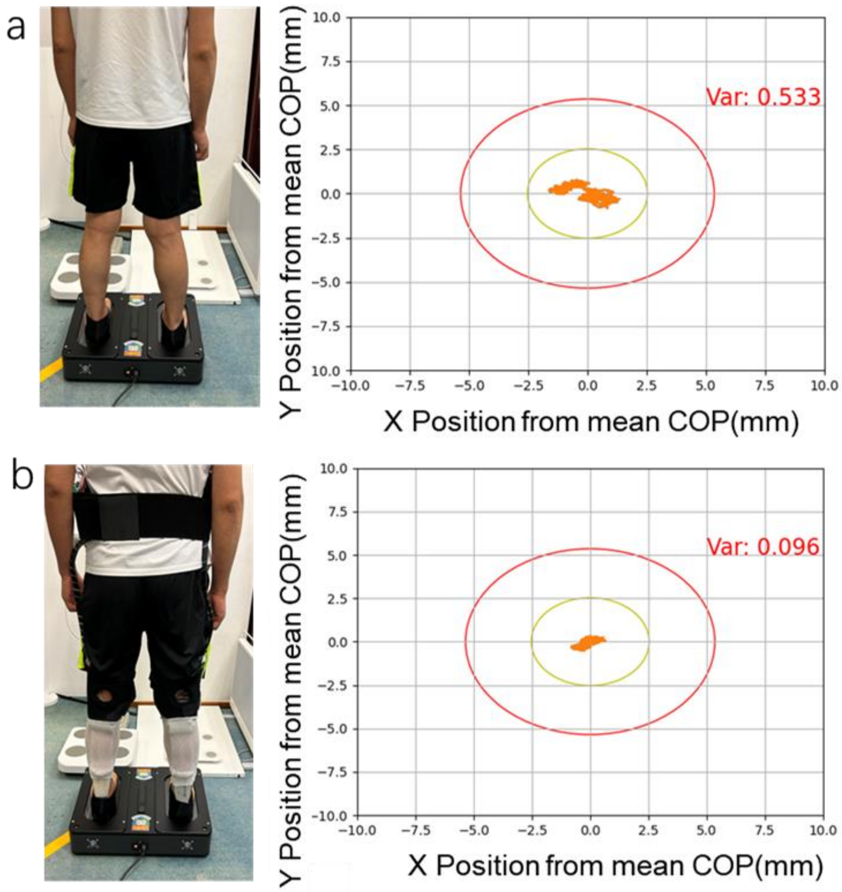

Figure 5. a. Experimental setup and deviation of CoP position from the mean CoP in the condition without the GL robot. b. Experimental setup and deviation of CoP position from the mean CoP in the condition with the GL robot. X and Y represent the left/right and front/back positions, respectively. The yellow circles indicate the average deviation of CoP for risk levels 0 and 1, while the red circles represent the average deviation of CoP for risk levels 2, 3, and 4.

CONCLUSION

Our study demonstrates the potential of utilizing an optical-based balance sensor and muscle-mimetic wearable robot for evaluating and improving balance in elderly individuals with various health conditions. Through the analyzing data from 149 subjects, we extracted essential temporal and frequential features of the center of pressure (CoP), center of gravity (CoG), and theta angles, enabling us to classify balance ability and fall risk in elderly individuals. By categorizing the participants into different risk groups, targeted interventions and personalized assistance can be provided to improve balance and reduce the likelihood of falls. We selected 29 subjects to complete the GL muscle maximal voluntary contraction (MVC) test and analyzed the correlations between MVC results and various CoP parameters. Our hypothesis that subjects with larger GL muscle maximum voluntary contraction (MVC) would perform better in the balance test was confirmed through a correlation analysis between balance sensor features and GL muscle MVC features. The majority of the balance sensor results exhibited a negative correlation with GL muscle MVC, indicating that subjects with stronger GL muscles maintained better balance.

Therefore, to compensate for the decline in the strength of the GL muscle, the muscle-mimetic wearable robot can be utilized as an assistive device. By mimicking mechanical properties and interpreting control signals from the human body, the wearable robot completes the process of muscle compensation, assisting in maintaining balance and stability by compensating for the weakened GL muscle. Integrating of the wearable muscle-mimetic robot with the balance sensor demonstrated promising results in enhancing balance. Comparative data from the subjects revealed a significant decrease from 0.533 (without robot condition) to 0.096 (wearing robot condition) in the variance of CoP relative to the mean CoP. This finding indicates that the wearable robot can effectively assist in maintaining balance, thus reducing the risk of falls and promoting overall postural stability.

In conclusion, the optical-based balance sensor and muscle-mimetic wearable robot offer an effective approach for assessing and enhancing balance in elderly individuals with various health conditions. The study suggests that this type of robotic assistance could serve as a valuable intervention for individuals with weakened balance, ultimately mitigating the risk of falls and enhancing the overall quality of life for elderly people. Future research should focus on refining the design and control of the robot, as well as exploring the long-term and dynamic effects of such interventions on balance and fall prevention.

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