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Towards the Application of Hearables for Near-Fall Detection

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Abstract:

Introduction: Falls and gait disorders often result in hospitalization and immobilization. Near-falls may be one of the earliest signs of increased fall risk. In the literature, several sensor positions are used for fall detection, but few studies include the head as a sensor position. Hearables and hearing aids are increasingly equipped with inertial measurement units (IMUs) and are therefore of particular interest for measuring the risk of falling in everyday life.

Methods: Therefore, we investigate the suitability of the ear as a sensor position for near-fall detection in comparison to the standard sensor positions. The motion data of one study participant (female, 63 years) was exemplary analyzed. The participant walked at her individually preferred gait speed on a perturbation treadmill while nine different perturbations (anterior-posterior, medio-lateral and pitch) were applied with a time interval of 20-30 seconds. We used seven IMUs during the measurement at the positions ear, sternum, lumbar, wrist (left/right), foot (left/right).

Results: The absolute acceleration signals at the seven different positions show the periodicity of the normal gait before the perturbation. During and after the perturbation changes in the motion pattern can be seen, whereby the response to the perturbation occurs with a slight time lag. The Pearson correlations show that the sensor positions sternum, lumbar and ear correlate well with each other and thus show similar signal characteristics in the reaction to this perturbation.

Conclusion: This provides evidence that the ear sensor position is at least comparable to the preferred sensor positions in the literature on the torso. However, these results were obtained under laboratory conditions. Further research is needed to investigate the sensor position at the ear in everyday life.

Keywords: hearables, mobile health, fall risk, near-falls, gait assessment

1 Introduction

Gait disorders and fall events are one of the major risk factors for hospitalization and immobilization especially in older age. Their early identification increases the success of preventive measures. Inertial measurement units (IMUs) are widely used for gait analysis and determination of gait parameters [1-3]. It has been shown that sensor-based determination of fall risk has similar predictive value compared to clinical tests, such as the Timed Up and Go Test [4]. Machine learning has already been used in the area of fall detection [5], as well as for the identification of neurological and neuromuscular diseases [6] or different types of mild cognitive impairment [7]. In fall detection, often simulated falls are used and evaluated threshold-based or using supervised and unsupervised machine learning algorithms [8]. For gait analyses different IMU positions are used in the literature [9, 10]. Thereby it should be mentioned that IMU signals vary depending on their position. In most studies a single IMU, located on the lower back (lumbar) or in some cases on the sternum (chest) or foot [10], was used. A sensor at the head position was used in very few studies so far. However this is an interesting sensor position for, among other things, estimating the fall risk in everyday life. More and more hearing aids as well as hearables are equipped with IMUs. This together with further investigations could provide the ability to identify gait anomalies at an early stage and to estimate the fall risk especially for older people who wear a hearing aid more often. Since near-falls are frequent in everyday life and may precede actual falls [11], we want to primarily consider these type of events. Near-falls describe gait disturbances such as trips, slips or missteps without an actual fall and may represent one of the earliest signs of an increased fall risk.

The research question of this article is therefore: Is the head and especially the ear position suitable to detect near-falls?

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Fig. 1: Experimental setup with a MGait perturbation treadmill. The treadmill can introduce perturbations in anterior-posterior, medio-lateral and pitch direction (blue arrows)

2 Methods

To answer the suitability of the ear as sensor position, we examined the motion sensor data exemplary for one study participant (female, 63 years, 6 vertigo attacks and one near-fall event in the last four weeks). In our study a perturbation treadmill induced standardized gait disturbances, which can provoke near-falls. The perturbation treadmill can provide a link between laboratory and real data, since the systematic error, which is often introduced by the simulated falls, can be reduced.

The perturbation treadmill (MGait Motek Medical B.V., Amsterdam, the Netherlands) induced a total of nine different disturbances in addition to the normal gait mode (see Figure 1). The perturbations include anterior-posterior, medio-lateral and pitch perturbations. The integrated split-belt of the treadmill with separate force plates (sampling rate: 300 Hz) allows to perturb either both legs or just one leg during walking. The perturbations were designed to simulate typical near-fall situations whereby we measured the subjects' reactions. During the recordings, the subjects were secured with a harness to prevent them from falling to the ground. Motion sensor data were collected by seven synchronized inertial measurement units (Opal V1, Mobility Lab™ (ML), APDM, Inc., Portland, OR, USA) with a sampling rate of 128 Hz. Figure 2 shows the positioning of the sensors during the measurements: ear, sternum, lumbar, wrist (left/right), foot (left/right). Once the sensors were in place, first the individually preferred treadmill walking speed (3.8 km/h) was determined. The participants then completed the perturbation protocol with a duration of about 4 min and 30 s. The perturbation protocol started with 30 s of the preferred treadmill walking speed, followed by 9 perturbations



Fig. 2: APDM motion sensor and used sensor positions (ear, sternum, lumbar, right/left wrist and right/left foot).

randomly presented to the participants and mostly triggered on the dominant leg (right), whereby the time between perturbations varied between 20–30 s. A detailed description of the protocol can be found in [12]. The test procedures were approved by the local ethics committee (ethical vote: Carl von Ossietzky University Oldenburg No. 2021-093 and conducted in accordance with the Declaration of Helsinki.

3 Results

Figure 3 shows exemplary the absolute acceleration during a negative pitch perturbation. In this case, the treadmill suddenly tilts down by 5°. This disturbance can be imagined as going down a previously unseen incline (e.g., a ramp). The tilt of the treadmill before, during and after the negative pitch, can be seen in the lowest graph (pink line) of Figure 3. The perturbation starts at second 143.3 and ends at second 145. The signals before the perturbation show the periodicity of the normal gait. For example in the lumbar position, each peak can be interpreted as one step, which can be seen when comparing the signal with the signals of the right and left foot. The perturbation induces changes in the motion pattern. Of course, the response to the perturbation occurs with a slight time lag. In the case of the lumbar sensor, for example, there are clearly increased peaks directly after the begin of the perturbation until the gait returns to normal at second 146.

In order to investigate the differences in the sensor positions, correlation analyses were also conducted. The results for the negative pitch perturbation are presented in Table 1. All results with a Pearson correlation coefficient greater than 0.7 have been marked in bold. The results show that the sensor positions sternum, lumbar and ear correlate well with each other and thus show similar signal characteristics in the reaction to this perturbation. Table 2 shows the results for the correlation

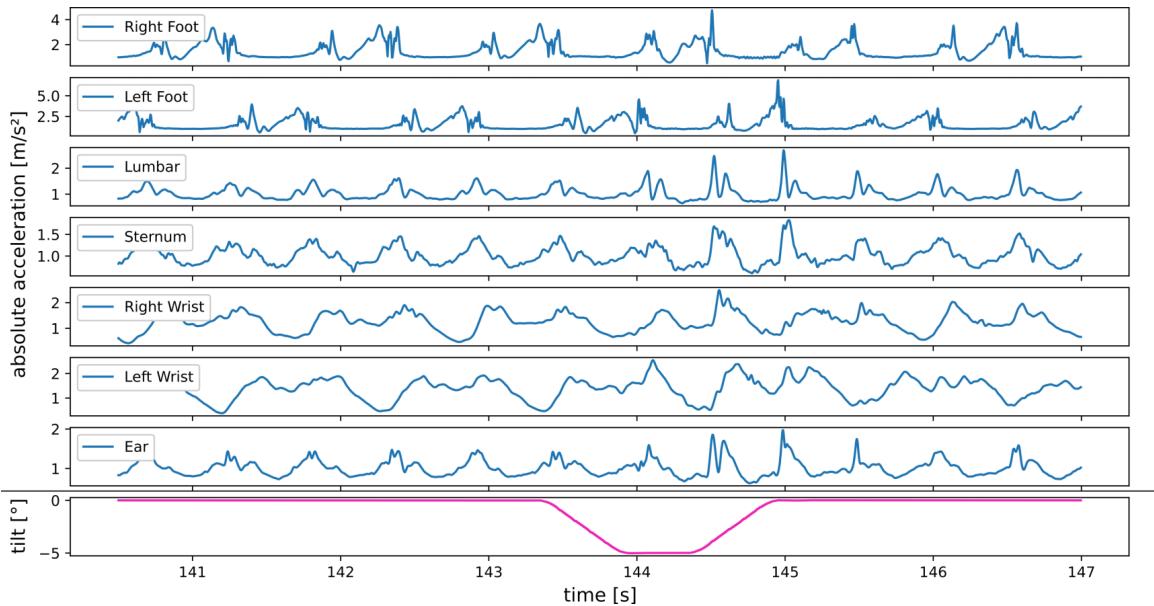


Fig. 3: Recorded absolute acceleration measured with IMUs at seven different body positions during a negative pitch perturbation, shown in the lowest picture (pink line). The signals show the periodicity of the normal gait before the perturbation and changes in the motion pattern during and after the perturbation.

coefficient for another perturbation, the slip left perturbation. Hereby the left treadmill belt is accelerated to 180% of the chosen preferred gait speed. From the correlations for this disturbance the same conclusions can be drawn as for the negative pitch perturbation. Therefore, the ear position could be suitable as a sensor position for future near-fall detection. It should be noted, however, that the correlations for the sensor positions sternum, lumbar and ear are lower than 0.7 for the perturbations trip both (deceleration of both belts to 0 km/h) and trip right (deceleration of the right belt to 40% of the baseline speed), which needs further investigation.

4 Discussion & Conclusion

The research question of this paper was whether the sensor position at the ear is generally suitable for near-fall detection. The background is that in the literature, positions on the sternum or lumbar are preferred as sensor positions. However, more and more hearing aids or hearables contain IMUs, so there is a good opportunity to detect an increased risk of falling early in everyday life and to take preventive measures at an early stage. The occurrence of near-falls, such as tripping or slipping, can be an indicator of an increased fall risk. In order to measure standardized perturbations, study participants were perturbed on a treadmill. We analyzed exemplary the reactions to the negative pitch disturbance for one study participant. The analyses showed that the sensor signals at

the ear have a high correlation to the signals at sternum and lumbar. This may arise from the fact that the head movement can only partially compensate for any irregular or unforeseen movement of the trunk. Some perturbations might even induce larger movements of the head than the corresponding movements of the trunk. Since the distance of the head to the hip joint is larger than the distance between sternum and hip joint, the relative motion of the head would be expected to be larger than the motion of the sternum if no compensatory head movement effect would occur. This all contributes to the assumption, that the ear position has in principle a comparable utility for recording gait instabilities as the preferred sensor positions on the trunk of the body. However, it must be noted that currently only a limited data set for one subject was evaluated and the measurements were performed under laboratory conditions [13]. In real life data, more disturbances through other head movements are expected. Therefore, further research is needed to investigate the sensor position on the ear under real conditions. However, our results provides evidence that the sensor position is, in principle, suitable for near-fall detection.

Author Statement

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Tab. 1: Correlation analyses for the negative pitch perturbation. The sensor positions sternum, lumbar and ear correlate well with each other.

	R. Foot	L. Foot	Lumbar	Sternum	R. Wrist	L. Wrist	Ear
R. Foot	1	-0.259	0.235	0.233	0.068	-0.523	0.292
L. Foot	-0.259	1	0.224	0.226	-0.374	0.066	0.241
Lumbar	0.235	0.224	1	0.781	0.195	-0.027	0.869
Sternum	0.233	0.226	0.781	1	0.240	-0.028	0.898
R. Wrist	0.068	-0.374	0.195	0.240	1	0.058	0.162
L. Wrist	-0.523	0.066	-0.027	-0.028	0.058	1	-0.032
Ear	0.292	0.241	0.869	0.898	0.162	-0.032	1

Tab. 2: Correlation analyses for slip left perturbation. The sensor positions sternum, lumbar and ear correlate well with each other.

	R. Foot	L. Foot	Lumbar	Sternum	R. Wrist	L. Wrist	Ear
R. Foot	1	-0.089	0.145	0.134	0.147	-0.243	0.136
L. Foot	-0.089	1	0.204	0.245	-0.013	0.057	0.222
Lumbar	0.145	0.204	1	0.772	0.280	0.181	0.792
Sternum	0.134	0.245	0.772	1	0.426	0.301	0.871
Right Wrist	0.147	-0.013	0.280	0.426	1	0.309	0.389
Left Wrist	-0.243	0.057	0.181	0.301	0.309	1	0.243
Ear	0.136	0.222	0.792	0.871	0.389	0.243	1

research related to human use complies with all the relevant national regulations, institutional policies and was performed in accordance with the tenets of the Helsinki Declaration, and has been approved by the authors' institutional review board or equivalent committee.

- [6] Joyseeree R, Abou Sabha R, Mueller H. Applying machine learning to gait analysis data for disease identification. In Digital Healthcare Empowering Europeans. IOS Press 2015;850-854.
- [7] Chen PH, Lien CW, Wu WC, Lee LS, Shaw, JS. Gait-based machine learning for classifying patients with different types of mild cognitive impairment. Journal of medical systems 2020;44:1-6.
- [8] Wang X, Ellul J, Azzopardi G. Elderly fall detection systems: A literature survey. Frontiers in Robotics and AI 2020;7:71.
- [9] Patterson MR, Johnston W, O'Mahony N, O'Mahony S, Nolan E, Caulfield B. Validation of temporal gait metrics from three IMU locations to the gold standard force plate. In 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE. 2016;667-671.
- [10] Ruiz-Ruiz L, Jimenez AR, Garcia-Villamil G, Seco F. Detecting fall risk and frailty in elders with inertial motion sensors: A survey of significant gait parameters. Sensors 2021;21(20):6918.
- [11] Maidan I, Freedman T, Tzemah R, Giladi N, Mirelman A, Hausdorff J M. Introducing a new definition of a near fall: intra-rater and inter-rater reliability. Gait & posture 2014;39(1):645-647.
- [12] Stuckenschneider T, Koschate J, Dunker E, Reeck N, Hackbarth M, Hellmers S, Kwiecien R, Lau S, Levke Brütt A, Hein A, Zieschang T. Sentinel fall presenting to the emergency department (SeFallIED) - protocol of a complex study including long-term observation of functional trajectories after a fall, exploration of specific fall risk factors, and patients' views on falls prevention. BMC Geriatrics 2022;22(1):594.
- [13] Schmitt AC, Baudendistel ST, Lipat AL, White TA, Raffegeau TE, Hass CJ. Walking indoors, outdoors, and on a treadmill: Gait differences in healthy young and older adults. Gait & Posture 2021;90:468-474.

References

- [1] Gietzelt M, Nemitz G, Wolf KH, Meyer Zu Schwabedissen H, Haux R, Marschollek M. A clinical study to assess fall risk using a single waist accelerometer. Informatics for health and social care 2009;34(4):181-188.
- [2] Schwenk M, Mohler J, Wendel C, Fain M, Taylor-Piliae R, Najafi B. Wearable sensor-based in-home assessment of gait, balance, and physical activity for discrimination of frailty status: baseline results of the Arizona frailty cohort study. Gerontology 2015; 61(3):258-267.
- [3] Hannink J, Kautz T, Pasluosta CF, Gaßmann K, Klucken J, Eskofier BM. Sensor-based gait parameter extraction with deep convolutional neural networks. IEEE Journal of biomedical and health informatics 2017; 21(1):85-93.
- [4] Marschollek M, Rehwald A, Wolf KH, Gietzelt M, Nemitz G, Meyer zu Schwabedissen H, Schulze M. Sensors vs. experts-A performance comparison of sensor-based fall risk assessment vs. conventional assessment in a sample of geriatric patients. BMC medical informatics and decision making 2011; 11:1-7.
- [5] Zurbuchen N, Wilde A, Bruegger P. A machine learning multi-class approach for fall detection systems based on wearable sensors with a study on sampling rates selection. Sensors 2021;21(3):938.