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Fall Detection Using Wearable Sensors in Loose-Fitted Clothing: A Survey

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ABSTRACT

Human activity monitoring is a crucial research area with diverse applications. Among the essential systems within this domain are fall detection systems, which are widely used in elderly care, sports performance analysis, and workplace safety. This study reviewed approximately 10 research papers focused on human activity monitoring and fall detection, revealing the challenge of limited studies in these fields. A significant issue arises when monitoring activities involving loose-fitting clothing, as the movement of such garments generates noise, complicating detection compared to tightly attached sensors. Fall detection is commonly achieved using wearable technologies equipped with various sensors, including inertial sensors, which are preferred for their affordability, simplicity, and privacy benefits. Despite their widespread application, most studies assume that sensors are firmly attached to the body, overlooking the noise caused by loose clothing. This research reviews advancements in fall detection systems and highlights methods for addressing loose clothing challenges. It identifies gaps in the literature and proposes approaches to enhance sensor accuracy in scenarios where loose-fitting garments are involved.

1. INTRODUCTION

Research into human activity tracking through wearable technology is vital across various applications including healthcare, senior care, fitness, and activity monitoring. Fall detection, particularly, plays a critical role in healthcare and fitness, addressing significant risks such as brain injuries and hip fractures in the elderly [1]. Following a fall, a substantial number of seniors remain on the ground for extended periods, increasing the risk of complications like pressure ulcers, pneumonia, and dehydration [2].

The field of Human Activity Recognition focuses on automatically identifying and assessing human actions through sensor data analysis [3]. This technology has proven successful in diverse domains such as home behavior analysis, gaming, military applications, sports training, remote health monitoring, and self-management of health.

Common home hazards contributing to falls include pets, clutter, poor lighting, unstable furniture, slippery surfaces, and narrow passageways. Besides home modifications, strategies to prevent falls include promoting regular exercise, monitoring medication side effects, and addressing vision impairments. Educating adults on risk factor management is crucial, challenging the misconception that falls are inevitable with age and beyond control.

This article is structured as follows: Section 2 presents recent datasets in fall detection research. Section 3 reviews recent surveys on activity monitoring and fall detection, highlighting their limitations, and current challenges. Section 4 examines recent studies in fall detection across sports, healthcare, and workplace applications. Section 5 Challenges and Research Gap. Section 6 presented the Common learning algorithms in fall detection. Section 7 explains loose-fitting clothes meaning and description. Finally, Section 8 concludes the paper.

2. RECENT DATA SETS IN FALL DETECTION RESEARCH

Many recent researchers provided experimental data sets for fall detection or prediction systems. This section lists the most recent and related data sets. In the study [4], the CAUCAFall dataset is introduced, featuring data from ten individuals that accurately categorizes five types of falls and five categories of activities of daily living (ADLs). Specifically, the dataset includes falls occurring while sitting, falls in opposite directions, lateral falls to the left and right. Participants performed various ADLs such as walking, jumping, object retrieval, sitting, and kneeling. The dataset encompasses a diverse group of individuals with unique characteristics such as age, weight, height, and dominant limb. Data collection took place in a domestic environment using an RGB camera, facilitating comprehensive training, validation, and testing of computer vision-based algorithms for human fall recognition. This dataset allows researchers to assess algorithm effectiveness under uncontrolled conditions. Primarily comprising photos and videos, the dataset is well-suited for training convolutional neural networks and other methods requiring feature extraction [4].

(a) (b)

Figure 1. Fall labeling with video. (a) Inertial sensor location, (b) simulated forward fall [5]

Table 1. Performance of three benchmark algorithms on the testing set as a whole [5]

Algorithm	FN	FB	Sensitivity %	Specificity %
Threshold	20/444	84/507	95.50	83.43
SVM	1/444	26/507	99.87	94.87
Conv-LSTM	3/444	5/507	99.32	99.01

In the research [5], the author introduced the "KFall" dataset, a comprehensive motion dataset designed for preemptive fall detection. This dataset was compiled by gathering data from 32 Korean volunteers who performed 21 distinct Activities of Daily Living (ADLs) and experienced 15 different types of falls (as depicted in Figure 1). The motion data includes measurements of acceleration, angular velocity, and Euler angles, captured using a nine-axis inertial sensor attached to the lower back of each participant.

This data set is characterized by the study [5]:

1). It includes activities and falls, hence depicting real-world scenarios.

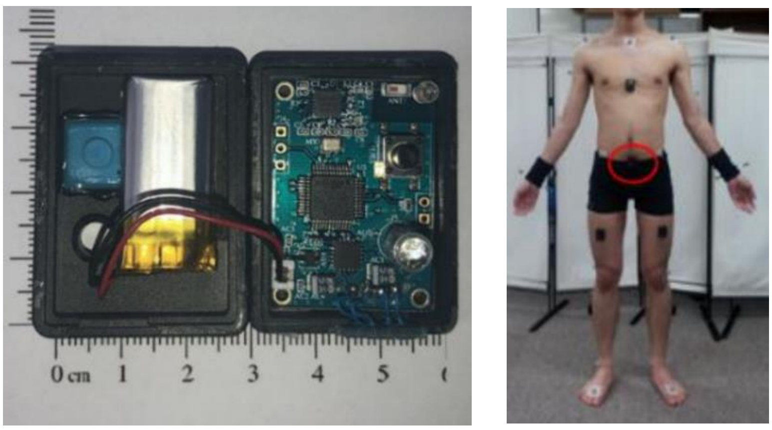
2). The data is acquired through the use of a synchronized video camera operating at a high frame rate of 90Hz.

3). The system utilizes three distinct algorithms: a threshold-based method, a support-vector machine technique, and a deep learning algorithm. The efficacy of these algorithms is demonstrated in Table 1.

Falls are defined as events that result in a person coming to rest accidently on the ground or another lower level. Falls are a substantial source of injury and death among the elderly [6], and they are defined as the events that result in a person falling [2]. Due to their decreased physical strength, elderly people have a greater likelihood of experiencing falls than younger people do [3]. When compared to younger individuals, the gait of elderly people is characterized by greater stiffness, less coordination, and an increased risk of injury. Both the ability to maintain posture, the ability to orient the body, the ability to manage reflexes, the ability to retain muscle strength and tone, and the ability to step at a higher height all decrease with age. In the event that an unanticipated trip or slide occurs, this drop makes it more difficult to avoid a fall from that happening [3]. As individuals age, their approach to maintaining balance after slipping changes. Initially, they rely on a quick adjustment known as the "hip strategy" which involves shifting their weight at the hip to avoid falling. However, as they continue to age, this strategy transitions to a "step strategy" where they attempt to prevent falls by taking a rapid step. Eventually, with further aging, individuals may lose the ability to make corrections in time to prevent a fall altogether [3]. The decline in vision, hearing, and memory that occurs with age often leads to an increase in the frequency of falls and accidents [3]. As per the World Health Organization (WHO) [7], there is a correlation between the occurrence of falls and the progression of age and frailty. On the other hand, the probability of fractures increases exponentially with age due to the reduction in bone density that occurs with time [8].

Given that falls cannot be entirely avoided, it is necessary to utilize protective equipment to minimize the consequences and prevent hip fractures in the event of a fall. Nevertheless, older individuals are unlikely to don them due to the impediment they pose to their activities [9]. There have been reports that these pads can shift within the clothing and fail to provide sufficient protection to the region of impact during a fall [10]. In order to address these issues and minimize the occurrence of injuries caused by falls, it is imperative to identify falls as they are happening (pre-impact fall detection show in Figure 2) and employ additional protective measures to minimize the impact [8] show in Figure 2.

We can use this dataset for training, validation, and testing any method for recognizing human fall motion using computer vision to evaluate the performance of methods in uncontrolled environments, as shown in Figure 3. Additionally, we primarily use the dataset consisting of images and videos to train convolutional neural networks or methods involving feature extraction, as shown in Table 2 [4].



(a) (b)

Figure 2. Wearable node a) IMU sensor; b) Sensor location [8]

Figure 3. Feature extraction fall recognition [4]

Table 2. Characteristics of the participants [4]

Sub	Age	Weight (kg)	Height (Meters)	Dominant
1	27	56	1.65	Right
2	34	70	1.73	Left
3	31	58	1.60	Left
4	38	75	1.68	Right
5	40	67	1.70	Right
6	33	77	1.65	Right
7	23	54	1.59	Right
8	25	59	1.63	Right
9	37	79	1.74	Left
10	28	61	1.62	Right

3. RELATED SURVEYS AND CURRENT CHALLENGES

Several categories are associated with loose clothing, including applications in health, posture and gesture detection, and automated explanations for human behavior modes. A study titled 'Human Activity Tracking Fall Detection Using Wearable Sensors in Loose Fitting Clothing: A Survey' in 2023 provided insights into these categories [11].

Another paper from 2018 titled 'A Survey of Wearable Sensor Networks in Health and Entertainment' also explores various divisions related to wearable sensing. These include activity monitoring and estimating energy expenditure, long-term health monitoring using wearable sensors, and applications in athletics and gait analysis [12].

Most of recent works in human activities monitoring field ignore the fitted and loose clothing topic. So, this topic is not addressed by recent surveys, which leaves a gap in the research, since most of our daily clothing are loose. In this paper we aim to shed some lights on recent work in fall detection application and especially the ones that address loose clothes or similar situation where the sensors are embedded within the object environment rather than being fixed directly on the him.

4. RELATED WORK

For the purpose of this survey we focused on researched within the last 10 years, not only in fall detection, but in the fields of human activity monitoring in general. These surveys address several papers with different sensor types. Also they addressed several embedding style such as: fixed to the object, embedded in the object clothes, or embedded int eh object environment.

Recent research projects have focused extensively on wearable sensors embedded in flexible clothing for monitoring human activity. This introduction aims to provide a comprehensive overview for both newcomers and researchers alike. Sensor-based human activity monitoring is widely recognized as a transformative technology across various applications [11], enhancing efficiency, applications, quality of life, and safety.

Several recent studies have concentrated on evaluating wearable sensors for specific applications such as Elderly Fall Detection [1], Sleep Condition Detection [13] shown in Figure 4, and Fall Detection using wrist-worn devices [9] show in Figure 5. Other studies have explored the use of multiple sensors placed on different parts of the body to investigate the accuracy of activity classification. Sensors have been positioned at various locations including the wrist, hip, neck, knee, chest, lower arm, lower back, upper arm, and ankle [10].

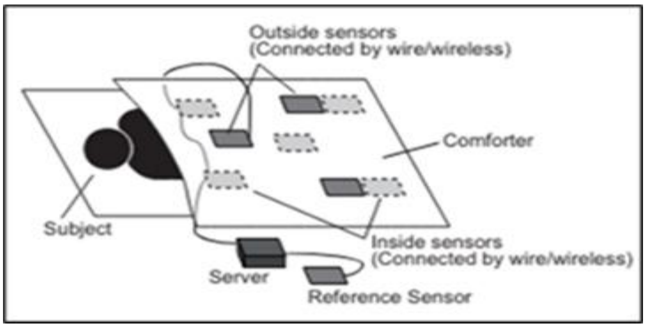


Figure 4. Multiple ambient sensor comforter measuring system overview [13]

Figure 5. Fall detection with Wrist-Worn Watch [9]

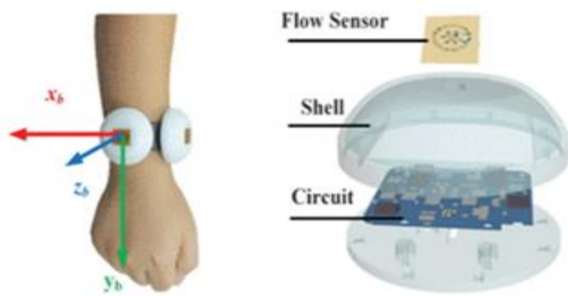


Figure 6. 3D velocity tracking device [14]

One study highlighted high accuracy in classifying three levels of physical activities-sedentary behavior (SB), light-intensity physical activity (LPA), and moderate-to-vigorous-intensity physical activity (MVPA)-using thigh data. Similarly, non-dominant wrist data showed high accuracy in classifying sedentary behavior. However, there was lower accuracy in classifying physical activities based on data from the dominant wrist and hip [10]. Consequently, the study suggested using thigh data or non-dominant wrist data for analyzing different levels of physical activity.

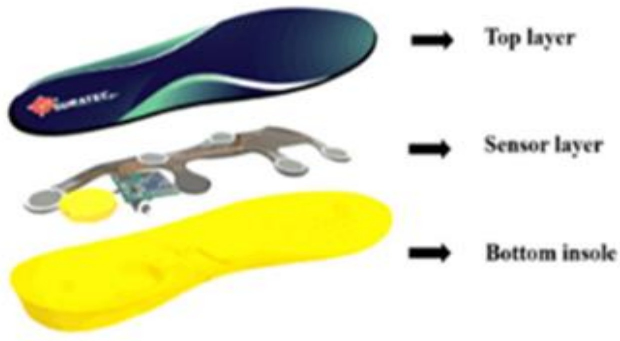


Figure 7. Smart insole layer and sensing spots [15]

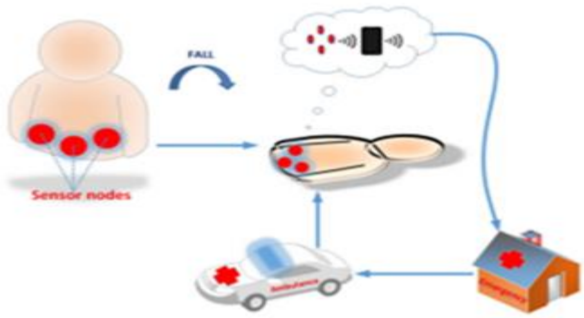


Figure 8. Escalation scheme simulation [16]

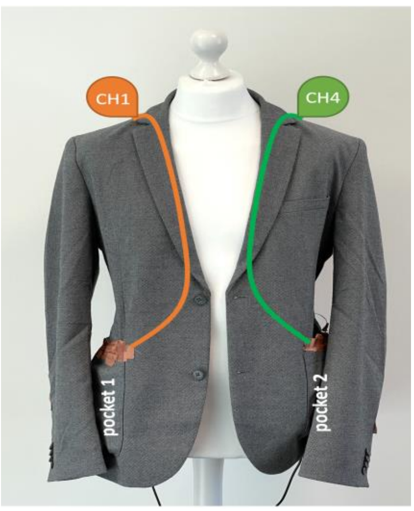


Figure 9. Smart blazer design [17]

The wearable system utilizes a typical man's blazer to detect body postures and gestures, particularly when the garment is loose-fitting, as shown in Figures 6 ,7 and 8. This approach addresses the challenge of monitoring movements in clothing that does not tightly adhere to the body. Experiments were conducted with 14 participants, and the results showed the system's high effectiveness, achieving an average recognition accuracy ranging from 86% to 97%. These findings demonstrate the system's ability to accurately identify gestures and postures, even when worn with looser clothing and shoe in Figure 9 [17].

In the next subsections we will review other recent work classified into three major applications: sport, healthcare, and workplace and show in Table 3 and Table 4.

4.1 Fall detection in sport application

The development of Internet of Things (IoT) and Microelectromechanical Systems (MEMS) has significantly enhanced the ability to detect falls promptly and automatically initiate emergency assistance. This paper focuses on a fall detection system that precisely targets patterns of walking, falling, and remaining motionless. The system utilizes an algorithm based on statistical observations of acceleration over one-second intervals to detect falls. Acceleration data is collected from the M5StickC-Plus watch worn on the wrist. The watch itself analyzes the data in real-time, as depicted in Figure 5. When a fall is detected, the system immediately sends an alarm signal to a remote healthcare system connected to the internet in real-time

This approach leverages the capabilities of wearable technology and real-time data processing to enhance safety and provide timely assistance in critical situations, particularly for individuals at risk of falling or in need of immediate medical attention. The integration of IoT and MEMS technologies enables continuous monitoring and rapid response, improving overall health management and emergency response systems [9].

There are various applications that require monitoring human motion, including movies, animation, sports training, physical rehabilitation, and human-robot coordination. To accurately detect limb and central body movements, a method is needed that is both simple and user-friendly. This study aims to propose a wearable velocity monitoring system design utilizing two micro flow sensors arranged orthogonally. This system is designed to be worn by the user depicted in Figure 6. In addition, a Functional Link Artificial Neural Network (FLANN) model has been developed to extract trunk velocity and relative limb velocity from absolute limb motion captured by the wearable device. This model can determine relative limb velocities by learning from the data, leveraging the unique dynamic properties of each limb position. Experimental validation was conducted to assess the effectiveness of the velocity tracking methodology. Results demonstrated that the proposed wearable device enables real-time measurement of limb and trunk motion velocities with high accuracy, free from cumulative errors. Moreover, the method proves reliable for dynamic activities like walking and running, while remaining user-friendly and easy to operate [14].

The objective of this project is to utilize wireless pressure sensors integrated into insoles (as shown in Figure 7) for training machine learning (ML) models capable of predicting the likelihood of an individual falling. A key innovative aspect of this research is the collection of dynamic walking data from 1101 individuals using smart pressure insoles. These sensors provide real-time pressure distribution information as individuals walk, which is crucial for developing accurate predictive models for fall risk assessment. The data gathered from these sensors will be instrumental in understanding patterns and indicators that precede falls, thereby enhancing preventive measures and intervention strategies. This approach represents a significant advancement in utilizing wearable technology for proactive healthcare applications, particularly in the context of fall prevention and elderly care [15].

4.2 Health care: Elderly care centers

A portable fall detection system is designed to provide prompt and effective assistance to individuals facing life-threatening situations due to falls, as depicted in Figure 9. The test measurements conducted with subjects yielded positive results in identifying fall events and in the acceptance of implementing this system. The use of ECG sensor in conjunction with inertial sensors combines physical (acceleration measurements) and medical (ECG measurements) to enhance the accuracy of fall detection and potentially predict falls when necessary. Regarding the acquisition of the ECG signal, we aim to improve the design of the ECG harness. Additionally, we are exploring alternative sites for ECG measurement, with one potential option being the use of a smartwatch. The effectiveness of this alternative will be evaluated in subsequent stages of development [16] show in Figure 8.

Individuals diagnosed with Parkinson's disease who experience freezing of gait (FOG) can suddenly lose their ability to move forward, leading to unexpected falls. To prevent accidents caused by FOG and reduce the risk of falling, it is essential to have a dependable and accurate system capable of detecting or predicting FOG in real-time. Such a system should have the capability to activate prompts or cues as required [18].

4.3 Fall detection in workplace

This section discusses fall detection research conducted in industrial regions or workplaces, specifically focusing on fall detection in human-machine shared workspaces.

In the studies [19, 20], the proposed technique leverages RF signal disruptions captured from wireless devices positioned near workstations to extract parameters associated with human mobility and posture. Furthermore, a sensor fusion strategy is proposed, integrating image-based sensors with RF devices to obtain oversampled data for precise operator localization purposes, as shown in Figures 10 and 11 and Table 3 and Table 4.

Figure 10. Helmet design (Left) Helmet view (side), (Right) Helmet view (inside) [20]

By strategically placing the EEG signal acquisition [21] and accompanying sensors within a standard worker's helmet, as shown in Figure 10, a new range of possibilities emerges for monitoring, detecting, and assisting workers on-site. This approach simplifies the process and effectively prevents unnecessary accidents or incidents through the use of an integrated alert system. There are numerous innovative possibilities for exploring this concept in various applications with minimal need for re-engineering. Several enhancements are currently under active consideration for future models, including the integration of conductive fabric EEG, the development of an algorithm for indoor localization, and the introduction of helmet-to-helmet communication rather than relying on a central access point [21].

Table 3. Summary of related work- part 1

#ref	Sensor Type	D/P	Data Collection	Algorithm
[1]	Inertial	D	S	ML
[14]	Inertial	D	S	ML
[15]	Pressure	P	R and S	ML
[18]	Camera, Pressure, Infrared, pulse sensor and Microphone	D	R and S	ML
[19]	Inertial	D	S	ML
[20]	Inertial	D	R	ML

R: Real, S: Simulated, ML: Machine Learning, D: Detection, P: Prediction

Table 4. Summary of related work part 2

#ref	Sensor Location	S_Rate	Data Size
[1]	on the waist	20Hz	~4000 sets
[14]	hand wrist	100Hz	___
[15]	Smart insoles	20Hz	2202 samples
[18]	lower body	___	___
[19]	___	___	___
[20]	fingerprinting	___	___

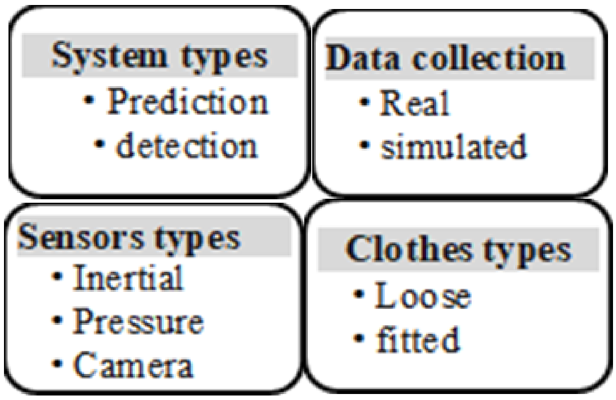


Figure 11. Fall detection systems classifications

In the study [22], authors utilized a radio frequency (RF) technology to assess received signal intensity for two main purposes: accurately locating individuals and detecting incidents of falling. The proposed detection method employs Hidden Markov Model techniques and leverages RF signal perturbations collected from a distributed network of wireless devices deployed in a workplace environment. This system gathers data on location, mobility, and key postural indicators relevant to human health. To enhance sensor coverage crucial for ensuring worker safety in industrial settings, the fall detection system integrates these sensors. Furthermore, it serves as a data source that can potentially be combined with other sensor inputs such as environmental cameras, if available. An experimental study was conducted to validate the accuracy of fall detection and target localization algorithms, assessing their overall performance. Preliminary findings suggest that the proposed approach effectively identifies falling incidents with high sensitivity and specificity.

5. CHALLENGES AND RESERCH GAP

To monitor everyday activities sensors are embedded in the subject clothes or accessories. In many ordinary situations these clothes and accessories are loose, which makes the sensors reading prone to error.

However, from the papers discussed in this survey, it is clear that the concept of loose cloths is not addressed properly in the field of activity monitoring. Even though some work [13, 17] tackled the idea of loose clothes or garments but not directly or didn't include falling activity [11]. This research gap is also evident in the papers that presents data sets for activity monitoring (as explained in Section 2). In these datasets, multiple factors are introduced e.g. subject age, weight, height dominant limb and even gender, but no mention of garment properties (show in Table 3 and Table 4) and (show in Figure 11).

6. COMMON LEARNING ALGORITHMS IN FALL DETECTION

Pattern recognition algorithms, such as decision trees, k-nearest neighbors (KNN), Support Vector Machine (SVM), Random Forest (RF), Naive Bayes (NB), and Bayesian methods, were commonly employed for activity classification based on sensor data analysis in these studies [1].

Overall, these research endeavors aim to uncover activity patterns and movement quality through the analysis of sensor data, contributing significantly to the field of wearable technology and human activity monitoring.

7. LOOSE-FITTING CLOTHES TERMINOLOGY

Typically, people wear loose-fitting clothing to improve their body's range of motion and flexibility. Without restrictive sleeves, arms and legs can move freely and comfortably, allowing for unhindered movement. Comfortable attire is essential in daily life, especially when tackling numerous tasks, ensuring no hindrance or disruption during work. Factors such as ventilation, support, and comfort are important considerations when selecting clothing. In the realm of fashion, various terms like "baggy," "voluminous," and "cozy" may be used interchangeably to describe similar concepts. Nonetheless, the majority of our garments are loosely fitted. This category includes not only work wear like overalls and jackets but also traditional attire, evening dresses, and casual wear.

The advancement of smart clothing with embedded sensors has introduced new possibilities. However, it's crucial to note that many sensors and applications benefit from close contact with the body. For instance, an acceleration sensor embedded in clothing can effectively detect body movements. Previous Studies have shown that tightly fitted clothing is often perceived as uncomfortable. Yet, recent experiments using loosely-fitting sensor-equipped garments have demonstrated the feasibility of identifying postures and activities, albeit with challenges in sensor placement and reduced accuracy [14].

8. CONCLUSION

In this paper, we presented a literature review focusing on wearable sensors that can be integrated into loose-fitting clothing f or activity tracking and monitoring purposes. Applications we explored included health monitoring, safety in workplace and activity tracking.

In term of sensor the majority of research use inertial sensors due to its availability and ease of use. These sensors are employed in either real or simulated experiment setup to detect or predict the fall. Typical with the help of machine learning algorithms for data analysis.

While there has been extensive research on wearable activity tracking and monitoring over the past decade, to the best of our knowledge, none specifically addressed the integration of wearable sensors in loose-fitting garments. This is likely due to the relatively recent recognition of this specific issue, resulting in limited research thus far. Despite this, it's noteworthy that many of our everyday garments are indeed loosely fitted according to personal preferences and definitions.

As future work, this paper presents three major recommendations: first, provision of human activity monitoring data sets that include sensors embedded loose clothes and accessories. Conduct of statistical analysis to quantify the noise levels in the sensor's measurements, especially inertial, pressure, and capacitance sensors, which affected its location on human body. Third, study the ability of machine learning algorithm to overcome the hurdles introduced this noise.

REFERENCES

[1] Yu, Z., Liu, J., Yang, M., Cheng, Y., Hu, J., Li, X. (2022). An elderly fall detection method based on federated learning and extreme learning machine (fed-elm). IEEE Access, 10: 130816-130824. https://doi.org/10.1109/ACCESS.2022.3229044

[2] Tinetti, M.E., Liu, W.L., Claus, E.B. (1993). Predictors and prognosis of inability to get up after falls among elderly persons. Jama, 269(1): 65-70. https://doi.org/10.1001/jama.1993.03500010075035

[3] Munoz-Organero, M. (2019). Outlier detection in wearable sensor data for human activity recognition (HAR) based on DRNNs. IEEE Access, 7: 74422-74436. https://doi.org/10.1109/ACCESS.2019.2921096

[4] Guerrero, J.C.E., España, E.M., Añasco, M.M., Lopera, J.E.P. (2022). Dataset for human fall recognition in an uncontrolled environment. Data in Brief, 45: 108610. https://doi.org/10.1016/j.dib.2022.108610

[5] Yu, X., Jang, J., Xiong, S. (2021). A large-Scale open motion dataset (KFall) and benchmark algorithms for detecting pre-impact fall of the elderly using wearable inertial sensors. Frontiers in Aging Neuroscience, 13: 692865. https://doi.org/10.3389/fnagi.2021.692865

[6] Todd C, Skelton D. (2004). What are the main risk factors for falls among older people and what are the most effective interventions to prevent these falls? Copenhagen, WHO Regional Office for Europe. Health Evidence Network Report. http://www.euro.who.int/document/E82552.pdf, accessed on 5 Apr., 2004.

[7] Aggarwal, J.K., Ryoo, M.S. (2011). Human activity analysis: A review. Acm Computing Surveys (Csur), 43(3): 1-43. https://doi.org/10.1145/1922649.1922653

[8] Ahn, S., Kim, J., Koo, B., Kim, Y. (2019). Evaluation of inertial sensor-Based pre-Impact fall detection

algorithms using public dataset. Sensors, 19(4): 774. https://doi.org/10.3390/s19040774

[9] Li, S. (2023). Fall detection with wrist-Worn watch by observations in statistics of acceleration. IEEE Access, 11: 19567-19578. https://doi.org/10.1109/ACCESS.2023.3249191

[10] Jayasinghe, U., Harwin, W.S., Hwang, F. (2019). Comparing clothing-Mounted sensors with wearable sensors for movement analysis and activity classification. Sensors, 20(1): 82. https://doi.org/10.3390/s20010082

[11] Fadhil, M.A., Shareef, W.F. (2023). Human activity tracking using wearable sensors in loose-Fitting clothes: Survey. TELKOMNIKA (Telecommunication Computing Electronics and Control), 21(6): 1382-1390. http://doi.org/10.12928/telkomnika.v21i6.24196

[12] Lord, S.R., Menz, H.B., Sherrington, C. (2006). Home environment risk factors for falls in older people and the efficacy of home modifications. Age and Ageing, 35(suppl_2): ii55-ii59. https://doi.org/10.1093/ageing/afl088

[13] Umetani, T., Ishii, M., Tamura, Y., Saiwaki, N., Yokoyama, K. (2018). Change detection of sleeping conditions based on multipoint ambient sensing of comforter on bed. In 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Honolulu, HI, USA, pp. 4997-5001. https://doi.org/10.1109/EMBC.2018.8513477

[14] Zhang, J., Liu, S., Zhang, Y., Zhu, R. (2020). A method to extract motion velocities of limb and trunk in human locomotion. IEEE Access, 8: 120553-120561. https://doi.org/10.1109/ACCESS.2020.3006336

[15] Agrawal, D.K., Usaha, W., Pojprapai, S., Wattanapan, P. (2023). Fall risk prediction using wireless sensor insoles with machine learning. IEEE Access, 11: 23119-23126. https://doi.org/10.1109/ACCESS.2023.3252886

[16] La Blunda, L., Gutierrez-Madronal, L., Wagner, M.F., Medina-Bulo, I. (2020). A wearable fall detection system based on body area networks. IEEE Access, 8: 193060-193074. https://doi.org/10.1109/ACCESS.2020.3032497

[17] Bello, H., Zhou, B., Suh, S., Lukowicz, P. (2021). Mocapaci: Posture and gesture detection in loose garments using textile cables as capacitive antennas. In Proceedings of the 2021 ACM International Symposium on Wearable Computers, pp. 78-83. https://doi.org/10.1145/3460421.3480418

[18] Wang, Y., Beuving, F., Nonnekes, J., Cohen, M.X., Long, X., Aarts, R.M., Van Wezel, R. (2020). Freezing of gait detection in Parkinson’s disease via multimodal analysis of EEG and accelerometer signals. In 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Montreal, QC, Canada, pp. 847-850. https://doi.org/10.1109/EMBC44109.2020.9175288

[19] Kianoush, S., Savazzi, S., Vicentini, F., Rampa, V., Giussani, M. (2015). Leveraging RF signals for human sensing: fall detection and localization in human-machine shared workspaces. In 2015 IEEE 13th International Conference on Industrial Informatics (INDIN), Cambridge, UK, pp. 1456-1462. https://doi.org/10.1109/INDIN.2015.7281947

[20] Dhole, S.R., Kashyap, A., Dangwal, A.N., Mohan, R. (2019). A novel helmet design and implementation for drowsiness and fall detection of workers on-Site using EEG and Random-Forest Classifier. Procedia Computer Science, 151: 947-952. https://doi.org/10.1016/j.procs.2019.04.132

[21] Kianoush, S., Savazzi, S., Vicentini, F., Rampa, V., Giussani, M. (2016). Device-Free RF human body fall detection and localization in industrial workplaces. IEEE Internet of Things Journal, 4(2): 351-362. https://doi.org/10.1109/JIOT.2016.2624800

[22] Konak, O., Liebe, L., Postnov, K., Sauerwald, F., Gjoreski, H., Luštrek, M., Arnrich, B. (2023). Overcoming data scarcity in human activity recognition. In 2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Sydney, Australia, pp. 1-7. https://doi.org/10.1109/EMBC40787.2023.10340387