A Survey On Fall Detection Systems Using Wearable Devices

Dharmitha Ajerla

Seattle, United States
dharmitha.ajerla@gmail.com

Abstract

Falls represent a significant concern in healthcare, particularly for elderly individuals, as they often lead to severe injuries, hospitalizations, and fatalities. The growing prevalence of falls among older adults underscores the need for effective fall detection systems. Wearable devices equipped with sensors such as accelerometers and gyroscopes have emerged as promising solutions due to their affordability, portability, and ability to provide continuous monitoring. This survey systematically reviews existing fall detection systems utilizing wearable devices, categorizing them into threshold-based and machine learning-based approaches. Each technique is critically analyzed in terms of methodology, strengths, limitations, and performance metrics. Furthermore, this paper identifies key research gaps, including the need for adaptive sampling techniques, age-specific models, lightweight fusion algorithms for multi-sensor data integration, and hybrid approaches that combine threshold-based methods with machine learning. By synthesizing existing knowledge and highlighting future directions, this study aims to contribute to the development of more reliable, energy-efficient, and accessible fall detection technologies tailored for elderly care applications.

Keywords: fall detection, elderly care, wearable devices, machine learning, threshold-based methods, sensor data analytics.

I. INTRODUCTION

Elderly individuals face heightened risks associated with falls, which often result in severe injuries or even fatalities. The increasing frequency of falls among older adults presents significant challenges to healthcare systems worldwide. [1] Recent advancements in sensor technology integrated into wearable devices have enabled continuous tracking of human motion patterns, providing valuable data streams for real-time fall detection. By identifying abrupt changes in movement, wearable sensors can help with timely interventions and significantly reduce injury severity.

Although various commercial solutions exist for fall detection, economic barriers such as initial investment costs and ongoing subscription fees limit their accessibility and adoption among elderly populations.[2] Consequently, there is growing interest in developing affordable fall detection systems that utilize basic wearable sensors without compromising accuracy or reliability.

This survey comprehensively analyzes existing fall detection methods using wearable sensor data. Specifically, it categorizes current approaches into threshold-based techniques—which rely on predefined thresholds—and machine learning-based techniques—which leverage data-driven algorithms for classification. Each category is critically evaluated based on methodology strengths, limitations, accuracy metrics, and practical usability.

The primary objective of this survey is to synthesize existing knowledge clearly and systematically while highlighting critical research gaps and future directions in wearable-device-based fall detection systems. Section II provides background on fall detection research methodologies and frameworks utilizing wearable sensors. Section III offers comparative analysis, highlighting significant findings across different studies, Section IV has suggestions for future research directions. Finally, Section V concludes by summarizing insights gained from this comprehensive review.

II. Background

Fall detection is usually performed using three types of devices: vision, ambient and wearable sensor based. In vision-based sensors, mainly cameras are used to detect the body shape change, posture, inactivity, spatial temporal and 3D head change analysis. They are less intrusive and can detect multiple events at a time. They are increasingly in use now-a-days as in-house assistive care systems. The main disadvantage is that they are costly to setup and computationally hard. In ambient devices mainly audio and video data are collected, which is time sensed to vibrational data. The vibrational data collected is less intrusive as the sensor is placed on the floor. This approach assumes that when a person falls certain vibrations can be felt on ground. In case of audio and video sensors a fall is detected through the event functions and when such event is detected it sets up an audio medium. It continuously monitors the person till a fall is detected. This would require a lot of computational power and storage capacity as stated by Muhammad Mubashir et al [3]. In the wearable devices different sensors are used to measure the accelerations. Even though they monitor the environment continuously they would need lesser computational power and storage capacity than the other two. They are cheap and popular. They are more intrusive when compared to the others but can be easily integrated into day-to-day life. In this survey report we will concentrate on detecting a fall using these wearable devices.

Type of sensor	Metrics	Features
Accelerometer	Linear acceleration	Steps, Distance, Fall
Gyroscope	Orientation	More accurate acceleration
Altimeter	Altitude	Floors climbed
Bio impedance	Electrical resistance	Heartrate
Optical	Pulse	Heartrate
Pulse Oximetry	LED facing photodiode	Oxygen levels
3D Accelerometer + heart rate monitor	Small body movements	Sleep
Actigraph	Sleep patterns	Sleep

TABLE I. Different types of Sensors in wearable devices

Wearable devices have become very popular in the last few years. They measure different biometrics and play a major role in maintaining fitness. Different sensors are used to measure different metrics like accelerometers are used to measure the change in velocity i.e. linear acceleration. It gives us information like the steps we have taken, distance we travelled, etc. Table 1 shows the sensors usually used in some of the popular wearable devices.

Accelerometer and gyroscope are the most common and basic sensors present in the wearable devices. Accelerometers are used to measure inertial measurements of velocity and position i.e. movement in every direction. And a gyroscope is used to measure the orientation and maintain the angular velocity. When a 3-axis accelerometer and a 3-axis gyroscope are combined full 3D movement can be measured. All the wearable devices which measure distance and steps use these sensors.

Williamst et al (G. Williamst, 1998) [4] is the first one who used accelerometer data to detect fall. They developed a sensor which detects fall and sends alarm to the caregiver when the activity of the person exceeds a predefined threshold value. They categorized different type of falls and activities so that health practitioners can have more insight into the type of injury experienced by the older adult. When a fall is detected the device gives the person who fell 15 seconds of time to switch the device off. If it doesn't receive any such negative response it sends an alarm to the caregiver and notifies the person with a beep that help is on its way. They have categorized fall into categories. Fall event i.e a minor fall and the person can get up after it and Fall alarm i.e a major fall where the person experiences a serious injury and needs help. This system reduces the alarms raised for near-fall events.

A typical fall detection mechanism is as follows (Fig.1). Firstly, the data is collected from sensors placed on a human body. From the extracted raw data values features with high variance are extracted. Then a fall detection algorithm is used to classify if it's a fall or not. If it's a fall, an alarm is raised to inform the caregivers. If not, it continues analyzing the data collected. In this section all the steps in the framework are thoroughly discussed.

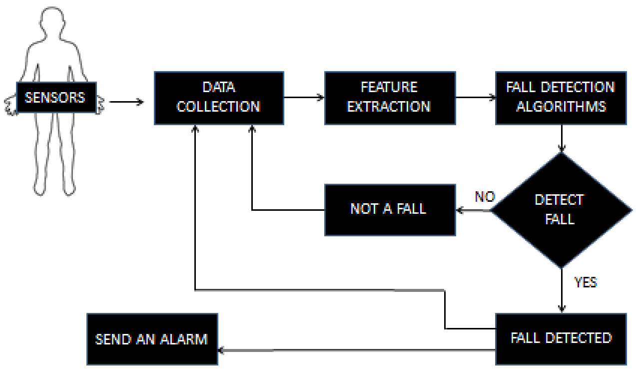

Fig.1 Framework of a fall detection system

III. Comparative Analysis of Fall Detection Techniques

The comprehensive comparison of fall detection techniques presented in Table III reveals several key insights that can guide future research and development in wearable fall detection systems.

A. Sensor Configurations and Placement Trends

The waist is one of the most frequently chosen locations for sensor placement due to its proximity to the body's center of mass, enabling the collection of stable and reliable data. In contrast, wrist-based sensors are more prone to false positives but are favored for their non-intrusive and easily adaptable design. Although waist and wrist placements dominate existing studies, there is considerable variation in sensor placement strategies. For example, Sorvala et al [8] demonstrated exceptional performance, achieving 95.6% sensitivity and 99.6% specificity, by utilizing a dual-sensor configuration at the waist and ankle with a sampling frequency of just 50 Hz. This highlights that carefully planned multi-sensor setups can deliver high accuracy while mitigating battery life concerns, making them ideal for practical applications.

B. Sampling Frequency Variations

The table demonstrates dramatic variations in sampling frequencies across studies (20Hz to 1000Hz). Interestingly, Bourke et al. (2007) used 1000Hz and achieved 100% specificity, while Yuwono et al [13] used just 20Hz and still achieved 100% sensitivity for in-group falls. This highlights an important trade-off between data resolution, fall detection algorithms and energy efficiency that warrants further investigation for real-world applications.

Paper	Subjects & Age	Sensors used	Sensor placement	Sampling Frequency	Feature Selection	Activities	Algorithms	Performance
Bourke et al(2007) [5]	10 subjects (21-29) 10subjects (70-83)	Two 3-axis accelerometers	Thigh and trunk	1000Hz	Upper & Lower fall threshold	8 falls and ADL's	Threshold based technique	UFT-trunk 100% SP
Kangas et al [6]	3 subjects (38-48) 2 subjects (22-38)	Three 3-axis accelerometers	Waist, wrist and head	400Hz	Falling Index, Vertical accelerometer, Total sum vector	9 Falls and dynamic ADL's	Threshold based algorithms	100% SP 97% SE
Bourke et al(2010) [7]	10 subjects(24-35) 10 subjects(>65)	One 3-axis accelerometer	Waist	200Hz	Impact, Velocity and Posture	8 Falls, 10 ADL's and dynamic ADL's	Threshold based algorithms	V+I+P- 100% SP and SE
Sorvala et al [8]	2 subjects (26)	Two 3-axis accelerometer and 3D gyroscope	Waist and ankle	50Hz	Impact and posture	4 Falls and 4 ADL's	Two threshold based algorithms	SE – 95.6% SP – 99.6%
Ahmed et al [9]	140 people Between 31-40,41-50 and above 51	One 3-axis accelerometer, One 3-axis gyroscope	Waist, chest and hand	-	Raw values of accelerometer and gyroscope	Fall Left, Fall right, Sit, Stand and Walk	SVM, k-NN, ANN	k-NN SP - 96.23%, SE – 94%
Chia-Yeh et al [10]	10 healthy young subjects	One 3-axis accelerometer	-	200Hz	Magnitude of 3 axis and features from each axis	8 Falls and & ADL's	SVM – linear, quadratic and polynomial functions, k-NN	k-NN ACC – 96.2%
Vallabh et al [11]	11 subjects (MobiFall dataset)	One 3-axis accelerometer	Pocket	100Hz	Rank based feature selection from 38 features	4 Falls and ADL's	k-NN, ANN, SVM, NB, LSM	k-NN SP-83.78% SE-90.7%
Theodoridis et al [12]	UR Fall detection dataset	One 3-axis accelerometer and 2 kinect cameras	Pelvis	-	Raw and rotated accelerometer values	30 falls and 40 ADL's	LSTM	SP – 100% SE – 96.67%
Yuwono et al [13]	7 subjects for fall 5 subjects for ADL	One 3-axis accelerometer	Right pocket of vest	20Hz	Raw accelerometer values	293 falls and 1831 ADL's	ARBF, MLP, Ensemble of ARBF and MLP	ARBF SE of 100% for ingroup falls, 97.65% for outgroup

SP- Specificity, SN- Sensitivity, ACC- Accuracy, ADL- Activities of Daily Life, V+I+P – Velocity + Impact + Posture, ANN – Artificial Neural Network, SVM – Support Vector Machine, k-NN – k-Nearest Neighbours, NB- Naïve Bayes, MLP- Multi Layer Perceptron, ARBF – Augmented Radial Basis Function, LSTM- Long Short Term Memory networks.

Table III: Comparison of different fall detection techniques

C. *Feature Selection Approaches*

Feature selection plays a critical role in improving the accuracy and efficiency of fall detection systems by identifying the most relevant features from raw sensor data. Various approaches have been employed across studies to extract and select features that effectively characterize falls:

1) *Threshold-Based Features*

- Upper and Lower Fall Thresholds: Bourke et al [5] used predefined thresholds for accelerometer signals (e.g., upper and lower thresholds) to detect falls, achieving 100% specificity in controlled environments. However, this approach often struggles with false positives in real-world scenarios due to overlaps with non-fall activities.

- Composite Metrics: Kangas et al [6] used features like the Falling Index and Total Sum Vector to combine multiple signal parameters, improving robustness in fall detection.

- Advanced studies incorporate features like Impact Velocity which captures the speed at which a fall occurs and Posture Analysis which identifies body orientation before and after the impact, aiding in differentiating between fall types. Bourke et al [7] and Sorvala et al [8] used these features and were able to achieve high performance even with threshold-based algorithms.

2) *Machine Learning-Based Feature Selection*

- Rank-Based Selection: Vallabh et al [11] applied rank-based selection to identify optimal features from a pool of 38 extracted features, achieving high sensitivity and specificity with machine learning models like k-NN and SVM.
- Techniques such as Principal Component Analysis (PCA) are employed to reduce feature redundancy while retaining critical information for classification tasks.
- Feature normalization methods like Min-Max scaling ensure compatibility between datasets from different sources.

Some studies like Ajerla et al [14] used widely popular ReliefF algorithm to identify most important features to identify high variance and relevance to fall events.

D. *Algorithm Performance Across Demographics*

Studies that included older subjects (e.g., Bourke et al. [5] with subjects >65) faced different challenges than those with only younger subjects. This demographic variation highlights the importance of age-appropriate training data, as fall patterns differ significantly between young and elderly populations.

IV. RESEARCH GAPS

Based on the insights from this survey and the comparative analysis of existing fall detection systems, several critical research gaps have been identified. Addressing these gaps can significantly enhance the reliability, usability, and practicality of fall detection technologies, particularly for elderly care applications. Future research should focus on the following areas:

- Developing adaptive sampling techniques that balance energy efficiency and detection accuracy

- Creating age-specific models that account for demographic variations in fall patterns
- Exploring lightweight fusion algorithms for multi-sensor data
- Investigating hybrid approaches that combine the computational efficiency of threshold-based methods with the adaptability of machine learning techniques

This comparative analysis underscores the need for innovative approaches that address existing challenges while enhancing fall detection reliability and usability for elderly care applications.

V. Conclusion

Falls remain a critical issue in elderly care, often leading to severe injuries or fatalities. Despite decades of research, real-time fall detection systems that are universally applicable and reliable have yet to be fully realized. This survey has provided a comprehensive analysis of fall detection systems utilizing wearable devices, categorizing them into threshold-based and machine learning-based approaches. While threshold-based techniques offer simplicity and computational efficiency, they are prone to false positives. Conversely, machine learning-based methods demonstrate adaptability but often require high computational resources and extensive training data.

The survey highlights that future advancements in fall detection systems should focus on addressing key challenges such as energy efficiency, demographic-specific variations in fall patterns, and the integration of multi-sensor data using lightweight fusion algorithms. Hybrid approaches combining the strengths of threshold-based techniques with the flexibility of machine learning models hold significant promise for improving accuracy and usability. Additionally, ensemble classifiers and adaptive sampling techniques should be tested on real-world data to ensure practical applicability.

By synthesizing existing knowledge and identifying research gaps, this study aims to guide the development of innovative fall detection systems that are reliable, energy-efficient, and accessible for elderly care applications. Continued research in this domain will not only enhance healthcare outcomes but also promote independent living among older adults.

References

[1] World Heath Organization Falls," January 2025. [Online]. Available: http://www.who.int/mediacentre/factsheets/fs344/en/.

[2] Fernandes JB, Fernandes SB, Almeida AS, Vareta DA, Miller CA. Older Adults' Perceived Barriers to Participation in a Falls Prevention Strategy. J Pers Med. 2021 May 23;11(6):450. doi: 10.3390/jpm11060450. PMID: 34070987; PMCID: PMC8224773.

[3] M. Muhammad, S. Ling and S. Luke, "A survey on fall detection: Principles and approaches," *Neurocomputing,* vol. 100, pp. 144-152, 2013.

[4] G. Williamst, K. Doughtyt, K. Cameront and D. A. Bradley, "A smart fall & activity monitor for telecare applications," *Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. Vol.20 Biomedical Engineering Towards the Year 2000 and Beyond (Cat. No.98CH36286), Hong Kong,* pp. pp. 1151-1154 vol.3, 1998.

[5] A. K. Bourke, J. O'Brien and G. Lyons, "Evaluation of threshold- based tri-axial acceleromter fall detection algorithm," *Gait and Posture Volume 26 Issue 2,* pp. 194-199, 2007.

[6] M. Kangas, A. Konttila, P. Lindgren, I. Winblad and T. Jamsa, "Comparison of low-complexity fall detection algorithms for body attached accelerometers," *Gait Posture ,* vol. 28, no. 2, p. 285–291, 2008.

[7] Bourke A K van de Ven P, Gamble M, O'Connor R, Murphy K, Bogan E, McQuade E, Finucane P, Olaighin G,Nelson, J, "Evaluation of waist-mounted tri-axial accelerometer based fall-detection algorithms during scripted and continuous unscripted activities.," *Journal of biomechanics,* vol. 43, no. 15, pp. 3051-3057, 2010.

[8] A. Sorvala, E. Alasaarela, H. Sorvoja and R. Myllyla, "A two-threshold fall detection algorithm for reducing false alarms," *2012 6th International Symposium on Medical Information and Communication Technology, ISMICT 2012,* 2012.

[9] Ahmed M, Mehmood N, Nadeem A, Mehmood A, Rizwan K. Fall Detection System for the Elderly Based on the Classification of Shimmer Sensor Prototype Data. Healthc Inform Res. 2017 Jul;23(3):147-158. doi: 10.4258/hir.2017.23.3.147. Epub 2017 Jul 31. PMID: 28875049; PMCID: PMC5572518.

[10] Hsieh Chia-Yeh, Huang Chih-Ning,Liu Kai-Chun, Chu Woei-Chyn Chan, Chia-Tai, "A machine learning approach to fall detection algorithm using wearable sensor," *Advanced Materials for Science and Engineering (ICAMSE), International Conference on,* 2016.

[11] Vallabh Pranesh, Malekian Reza,Ye Ning,Bogatinoska Dijana Capeska, "Fall detection using machine learning algorithms," *24th International Conference on Software, Telecommunications and Computer Networks,* pp. 1-9, 2016.

[12] Theodoridis T,Solachidis V,Vretos N, Daras P, "Human fall detection from acceleration measurements using a recurrent neural network," *IFMBE Proceedings Volume 66,* pp. 145-149, 2017.

[13] M. Yuwono, W. S. Steven and B. Moulton, "Fall detection using a Gaussian distribution of clustered knowledge, augmented radial basis neural-network, and multilayer perceptron," *IB2COM 2011 - 6th International Conference on Broadband Communications and Biomedical Applications,* pp. 145-150, 2011.

[14] Ajerla, Dharmitha & Mahfuz, Sazia & Zulkernine, Farhana. (2019). A Real-Time Patient Monitoring Framework for Fall Detection. Wireless Communications and Mobile Computing. 2019. 1-13. 10.1155/2019/9507938.