Comfort Prediction Method for Wearable Devices: Current Progress and Future Direction

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Abstract. Falls constitute a significant health risk, particularly among the elderly, thus prompting the introduction of various wearable devices capable of fall detection. However, the majority of these devices prioritize accuracy over wearer comfort, which significantly influences user adherence and, by extension, the broader development of wearable technologies. Addressing this oversight, this review first summarizes the current methods for predicting the comfort of wearable devices, evaluating them in terms of feasibility and accuracy, reliability and effectiveness, as well as safety and privacy. Subsequently, building upon the evaluation of existing methods, this review proposes a predictive solution based on the XGBoost algorithm.

Keywords: Machine learning; XGBoost algorithm; Wearable Devices; Comfort Prediction.

1. Introduction

Falls represent a sudden, unintended descent to the ground and pose a significant health hazard, notably among the elderly. Statistics reveal that approximately 30% of individuals aged 65 and over residing in communities experience falls annually [1][2]. Globally, falls are the predominant cause of accidental injuries and fatalities in seniors and the second leading cause of accidental death[3]. These issues underscore the necessity for reliable fall detection systems in real-world scenarios. Prevailing research highlights several mainstream methodologies for fall detection, including intelligent cameras [4][5] and wireless sensors [6][7]. However, such technologies are often impractical in private spaces (like bathrooms), posing significant installation challenges and privacy concerns. These limitations highlight the appeal of wearable detection systems as an optimal solution, evidenced by their growing popularity [8][9].

Recent years have witnessed a surge in wearable device research, concentrating primarily on the devices' fall detection accuracy. Most studies have assessed comfort through questionnaire surveys, theoretical data, or fabricated wearable devices. We contend that questionnaire surveys and other methods may introduce uncertainties and objective factors that can influence survey results, potentially leading to unreliable final collected data. Therefore, this review summarizes the current research progress and proposes more suitable prediction methods based on this foundation

This review is structured as follows: Section II overviews current research, achievements, and gaps within related works. Section III details the design the future solutions for comfort centered ensemble learning algorithms. The concluding section encapsulates the article's primary contributions, and potential avenues for future exploration.

2. Comfort Prediction Method

2.1 Current Algorithm Analysis

The realm of wearable technology has witnessed substantial growth, evolving rapidly to encompass a broader range of functions including human recognition and health monitoring. This expansion has propelled their usage in diverse sectors, notably in healthcare, military, and industrial spheres. One significant application emerging amidst the healthcare concerns of today is fall monitoring, necessitated by the prevalent health risks associated with falls.

Advancements in sensing technologies—accelerometers, gyroscopes, and infrared sensors, to name a few—have enhanced these devices' capabilities in human posture recognition. Furthermore, the refinement of machine learning algorithms, including K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and eXtreme Gradient Boosting (XGBoost), has been integral in minimizing both false negatives and false positives. This progress aims not only to boost the accuracy of wearable devices but also to address user comfort, ensuring the devices are lightweight and convenient, thereby fostering broader acceptance and adherence, especially in fall monitoring scenarios.

In contemporary society, wearable devices are garnering popularity across various everyday applications, from healthcare to education. A survey of existing machine learning algorithms employed in these contexts reveals impressive efficacy, with accuracy rates in experimental setups generally ranging from 90% to 99%. Specific studies[10][11], such as those by Chandak, have introduced novel fall detection methodologies, leveraging sensor placements on experimenters' wrists and pockets and utilizing diverse machine learning models, including SVM, Random Forest (RF), Multilayer Perceptron (MLP), and One-Dimensional Convolutional Neural Network (1D CNN). These studies have consistently reported accuracy surpassing 93%.

Presently, these fall monitoring systems offer significant promise in elderly care, providing robust tools to mitigate the dangers of falls and subsequently enhancing the quality of life for older adults and other at-risk demographics. Anticipated technological advancements are expected to further diminish fall-related risks, ushering in safer living environments and spearheading innovation in this health sector[12].

This realization underscores the necessity for a more nuanced approach in wearable design, factoring in both the quantity and placement of devices to enhance overall wearability[13]. Ergonomic considerations and social acceptability also emerge as crucial elements in this discourse, potentially serving as catalysts in advancing wearability research[14].

Despite the availability of commercial fall detection units, their practical effectiveness has been underwhelming, plagued by issues of high false alarm rates, exorbitant initial and upkeep costs, and lack of ergonomic design. Researchers have highlighted these challenges, emphasizing that the discomfort associated with wearing these devices significantly deters usage among elderly individuals[15]. Consequently, enhancing wearability—encompassing comfort, scalability, and flexibility—has emerged as a research priority in this domain.

However, a gap in the research landscape is apparent: studies seldom address the interplay between the comfort and accuracy of wearable devices. The focus predominantly remains on precision, often overshadowing the importance of user comfort during wear. Investigations into user comfort have been largely observational, centering on wearers' physical responses to the device's positioning[16][17]. Certain insights suggest that devices positioned near the body's center of gravity, such as at the waist, strike a balance between accuracy and comfort[11][18]. Nonetheless, the societal tendency, particularly among the elderly, veers towards minimal reliance on technologically advanced wearables, attributable perhaps to the discomfort or unfamiliarity they engender.

In summary, as wearable technology continues to advance, its applications are broadening, marked by increased sophistication. The comfort prediction methods for the major wearable devices are shown in Table 1.This is particularly evident in the field of fall monitoring, where the evolution of device accuracy and user comfort is ongoing. Nevertheless, achieving the optimal balance between these aspects necessitates further exploration, inviting comprehensive strategies that consider ergonomics, user preference, and social acceptability in the quest to elevate wearable device comfort.

Table. 1 Summary of comfort prediction methods for major wearable devices

Method	Algorithm	Feasibility and accuracy	Effectiveness of comfort	Reliability	Security and privacy	Reference
Fuzzy set theory to assign weights	Fuzzy Functions, Minimum Spanning Trees	Qualitative, quantitative design	Assigned weights intuitively	Increase the number of devices; questionnaire surveys		[14]
Fuzzy measures and the Choquet integral	Chouquet integral theory, fuzzy set function, least squares method	Qualitative, quantitative design	Multi objective modeling	Validated using a training set and a test set	Quantified over multiple criteria	[17]
SmartStep and Wrist Sensor	Multinomial Logistic Discrimination	Questionnaire survey		Comfort Rating Scales (CRS)		[16]
PERFORM System	Body Area Network (BAN) of sensors	Questionnaire survey	Personal feelings	Comfort Rating Scales (CRS)		[20]

2.2 XGBoost Algorithm Assessment

(1) Feasibility and accuracy of XGBoost algorithm

XGBoost is a highly optimized, distributed gradient-boosting library crafted for efficiency, flexibility, and portability. It embodies an extensible tree-boosting algorithm that accelerates model training and enhances efficiency, swiftly and precisely addressing a multitude of data science challenges. The applicability of XGBoost across various domains, including medical diagnosis and network security, has been substantiated by numerous studies [21][22]. Particularly, reference [23] attests to XGBoost's remarkable predictive accuracy, showcasing its superior performance and precision across diverse datasets. Moreover, it offers considerable interpretability and scalability.

(2) Effectiveness of comfort parameters

This study successfully analyzed accelerations at various points on the body, including the front of the waist, wrists, soles of the feet, and knees, utilizing them as inputs [23]. Uniquely, this article suggests the incorporation of comfort-related parameters for input analysis. These parameters encompass device appearance, device size, the coordinates of the device's wearing position, device weight, and device material. Due to the fact that these five comfort parameters can to some extent affect body acceleration, and these factors are intrinsically tied to acceleration and remain critical indicators in pertinent research, the use of comfort parameters as inputs is deemed compatible with the overarching algorithmic model design, effectively facilitating comfort research.

(3) Reliability of investigation experiments

In this study, we opted for an experimental approach to gather comfort-related data. This method, compared to traditional questionnaire surveys, enables direct observation and quantification of participants' physiological and behavioral responses under defined conditions, yielding data that is both more precise and objective. A further merit of the experimental method is its capacity to control human factors' influence, thereby diminishing biases in experimental outcomes and guaranteeing the reliability of the data collected. Consequently, it can be utilized with greater confidence for subsequent analyses and decision-making processes. However, due to the lack of related dataset, it is not feasible to conduct the actual experiment.

(4) Investigating experimental security and privacy

In this article, data acquisition occurs through investigative experiments. Consequently, to encourage broader participation and effectively build trust, it's imperative to guarantee the confidentiality of participants' personal details (such as age, gender, etc.), safeguarding their privacy – a moral and legal imperative. Simultaneously, participants will be briefed on the experiment's purpose, along with the nature and significance of this study, to foster deeper trust. Additionally, pertinent institutions will scrutinize the experiment, ensuring its security and privacy measures are robust. As such, this investigative experiment maintains a level of security and poses no privacy threats to the participants.

3. Future Direction for Comfort Prediction Method of Wearable Devices

For future directions, we could augment the investigation duration and participant count —for instance, extending the study period to a week and increasing the participants to 500—to bolster the data's reliability.

Except refining survey experiments, XGBoost's predictive prowess can be extended to ascertain the significance of the comfort parameters discussed in this study, in tandem with rigorous survey experiments, to further validate the precision and dependability of these parameters' weight values.

In addition, adjusting the weights of algorithm parameters might enhance the algorithm's predictive accuracy, fortifying the reliability and precision of the forecasts.

4. Conclusions

In this review, we evaluated existing comfort research methods，summarized the current methods for predicting the comfort of wearable devices, and proposed a future direction based on the XGBoost algorithm. The future direction we suggests is enhancing research reliability by extending the study period to longer time with more participants, ascertaining the significance of the comfort parameters and adjusting the weights of algorithm parameters.

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