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Real-Time Human Activity Recognition using Smartphone Inertial Sensors: A Review

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Abstract
Human Activity Recognition (HAR) has become an essential field of study for today's scenarios. Smartphone-enabled HAR is especially significant because of its practicality and affordability. In the modern world, the smartphones feature inertial sensors, including the gyroscope and accelerometer, which act as primary data inputs for HAR techniques. Smartphone-enabled HAR becomes common in applications related to health care, monitoring of physical activities, ambient assisted living, and context-aware mobile computing. This review will present some developments in HAR that utilize smartphone technologies, paying special attention to the accelerometer and gyroscope capable of sensing the body movements without hindering the user. This analysis will be focused on all stages of processing data collected by smartphones, including segmentation and motion pattern recognition. In this regard, we analyze two techniques: classical machine learning algorithms and advanced deep learning models. According to our findings, deep learning structures such as CNNs and LSTM networks provide greater recognition, accuracy and robustness than other approaches. However, some issues remain unresolved, including individual variations in human behavior and sensor noise. Several key factors such as computational complexity, latency, system robustness, and energy consumption are considered for their effect on the performance of mobile devices. Apart from discussing technical details of HAR using smartphones, this work considers practical applications of the discussed technique in unconstrained settings. Finally, the prospects in this field are discussed
Keywords Human Activity Recognition, Smartphone Sensors, Deep Learning, Real-Time Systems.

Introduction

Human Activity Recognition (HAR) has become a dominant research field now a days. Human Activity Recognition (HAR) can be used in controlled environments and as well as uncontrolled environments. Controlled environments are those in which specific parameters are strictly regulated, whereas uncontrolled environments are unregulated conditions where variables or conditions often changes. HAR systems are used as a medium of data regarding the behaviour of people. This data is collected from the signals of sensors. Har is widely used in healthcare monitoring, smart environments, and human-computer interaction. HAR systems are used to analyze human behaviors with data collected from sensors, particularly wearable and embedded devices [1].

Smartphones are included in the category of wearable computing and have emerged as a dominant assistant for HAR due to their ubiquitous availability, computational capabilities, and integration of multiple sensors such as accelerometers and gyroscopes [2]. Activity recognition with smartphones is more attractive due to sensitive and high acceptance in daily life. Moreover, these days smartphones are easily available at lower costs, so these are pocket-friendly also. Unlike vision-based systems, smartphone-based HAR preserves user privacy while enabling continuous monitoring in real-world (uncontrolled) environments [2].

The latest research works highlight HAR systems that recognize activities on a real-time basis; this means the activities can be recognized instantly, making fall detection, rehabilitation support, and other applications possible [3].

2. Review Method

This review was conducted through a comprehensive analysis of existing research articles focusing on real-time Human Activity Recognition (HAR) using smartphone inertial sensors. The purpose was to identify recent developments in sensing technologies, preprocessing techniques, feature extraction methods, classification methods, datasets, and application domains.

Based on their relevance to smartphone-based HAR systems employing inertial sensors, including accelerometers and gyroscopes, a total of twenty-one peer-reviewed research articles published between 2010 and 2024 were selected. Preference was given to studies that proposed novel algorithms, evaluated real-time recognition performance, or provided comprehensive surveys of smartphone-based HAR approaches. Publications unrelated to smartphone inertial sensing, purely vision-based activity recognition, or studies lacking sufficient methodological detail were not considered.

Each selected article was carefully examined to extract information regarding:

- smartphone sensing technologies and sensor configurations;
- data acquisition and preprocessing techniques;
- feature extraction and dimensionality reduction methods;
- machine learning and deep learning algorithms;
- transformer-based HAR approaches;
- benchmark datasets and evaluation metrics;
- recognition performance and computational efficiency;
- application domains and identified research challenges.

The extracted information was synthesized through thematic analysis, enabling comparison of existing approaches and identification of current research trends. Rather than statistically combining experimental results, this review qualitatively discusses the strengths, limitations, and future directions of smartphone-based real-time HAR systems.

Study Selection

The review included the following twenty-one representative publications:

Table 1: Representative Publications

Publication Reference	**Main Contribution**
Hassan et al. (2017)	Deep Belief Network-based smartphone HAR
Wang et al. (2016)	Feature selection using accelerometer and gyroscope
Wan et al. (2019)	CNN-based real-time HAR
Shweta et al. (2017)	Survey of HAR process
Lima et al. (2019)	Comprehensive overview of smartphone HAR
Attal et al. (2015)	Review of wearable sensor classification methods

Yu & Qin (2018)	Bidirectional LSTM for smartphone HAR
Chen et al. (2016)	Real-time sensor fusion for HAR
Moreira et al. (2021)	ConvLSTM for indoor localization HAR
Alanazi et al. (2024)	Machine learning comparison using KU-HAR dataset
Reyes-Ortiz et al. (2013)	Introduced the **UCI HAR** benchmark dataset for smartphone-based recognition of six daily human activities using accelerometer and gyroscope data.
Banos et al. (2014)	Presented the **MHEALTH** dataset for mobile health monitoring using multimodal body-worn inertial and physiological sensors.
Weiss (2019)	Released the **WISDM** dataset containing smartphone and smartwatch sensor data for activity recognition and biometric analysis.
Reiss (2012)	Developed the **PAMAP2** dataset for physical activity monitoring using multiple inertial sensors and heart rate measurements.
Roggen et al. (2010)	Introduced the **OPPORTUNITY** dataset for recognizing complex daily activities using multimodal wearable and ambient sensors.
Zhang & Sawchuk (2012)	Presented the **USC-HAD** dataset for daily activity recognition using wearable accelerometer and gyroscope sensors.
Gjoreski et al. (2018)	Developed the **SHL** dataset for multimodal locomotion and transportation activity recognition using smartphone sensors.
Sikder & Nahid (2021)	Introduced the **KU-HAR** dataset comprising 18 heterogeneous activities collected from smartphone inertial sensors.
Yin, Y et al. (2024)	Review of mobile-based HAR methodologies and emerging research trends.
Dentamaro et al. (2024)	Survey of smartphone sensor-based HAR with comparative analysis of techniques and datasets
Leite et al. (2024)	Evaluation of Transformer-based HAR models, highlighting their strengths and deployment challenges.

Data Synthesis

The selected studies were organized into following major themes:

1. Smartphone inertial sensing technologies
2. Data preprocessing and segmentation
3. Feature engineering

4. Machine learning and deep learning models
5. Transformer based approaches for HAR
6. Real-time HAR applications
7. Research challenges and future directions

Comparative tables were prepared to summarize different HAR datasets and representative studies for smartphone based HAR.

3. HAR Framework

HAR systems generally follow a structured process consisting of data acquisition, preprocessing, feature extraction, and classification [4].

3.1 Data Acquisition

Smartphones through inertial sensors collect motion data. These sensors primarily consist:

- Accelerometers (linear motion): These sensors are required for detecting linear movement, vibrations, tilt, and impact in smartphones, vehicles, and industrial machinery.
- Gyroscopes (angular motion): These sensors are required for angular momentum to maintain orientation and measure angular motion.

These sensors capture time-series data representing user movements in three-dimensional space [2].

3.2 Data Preprocessing

The raw data collected through sensors is often incomplete, inconsistent, and sometimes even contains noise and generally requires preprocessing. The preprocessing procedure includes the following tasks:

- Noise filtering: Elimination of non-informative or non-relevant data points from the raw dataset for improved classification accuracy.
- Data segmentation through sliding window approach: Segmentation of raw time series data collected by sensors into smaller chunks using a sliding window approach that could either be overlapping or non-overlapping.
- Normalization: Scaling numerical data points to a certain value range, which is usually 0 to 1 or -1 to 1. The process of segmentation is significant in determining the boundaries of activities in real-time systems [4].

3.3 Feature Extraction

Traditional HAR systems rely on handcrafted features such as:

- Mean, Variance, and Median: Fundamental characteristics of statistics used for recognizing the activities in sensor data analysis.
- Autoregressive Coefficients: Compact and effective characteristics used for modeling time series data collected by sensors.
- Fourier Transform Features (FFT): Transformation of time domain sensor data to the frequency domain, enabling the recognition of periodic human activities.

Feature transformation techniques like Kernel PCA and Linear Discriminant Analysis enhance robustness [1].

3.4 Classification

Classification refers to labelling an activity (for example walking, sitting, running) with pre-defined labels. The recognition of human activities can be formulated as a problem of classification where the task is to determine what activity a particular human being is doing [5].

4. Commonly used Smartphones HAR Datasets

Publicly available benchmark datasets play a crucial role in the development and evaluation of smartphone-based Human Activity Recognition (HAR) systems. These datasets offer consistent sensor recordings collected under various experimental conditions. Thus, enabling fair comparison of machine learning and deep learning algorithms. Table 2 summarizes the widely used datasets in smartphone inertial sensor-based HAR research.

Table 2: Comparison of Different HAR datasets

Dataset	Release Year	Subjects	Activities	Sensors	Sampling Rate	Primary Application
UCI HAR [6]	2012	30	6	Accelerometer, Gyroscope	50 Hz	Daily activity recognition
WISDM [7]	2010	51	18	Accelerometer	20 Hz	Smartphone HAR
PAMAP2 [8]	2012	9	12	IMU, Heart Rate	100 Hz	Physical activity monitoring
Opportunity [9]	2011	4	17	Multiple body-worn sensors	30 Hz	Gesture and activity recognition
MHEALTH [10]	2014	10	12	Accelerometer, Gyroscope, Magnetometer, ECG	50 Hz	Mobile health monitoring
USC-HAD [11]	2012	14	12	Accelerometer, Gyroscope	100 Hz	Daily activity recognition
SHL [12]	2018	3	8	Smartphone IMU, GPS	100 Hz	Transportation and locomotion recognition
KU-HAR [13]	2022	90	18	Smartphone IMU	100 Hz	Deep learning-based HAR

5. Machine Learning Approaches

5.1 Traditional Machine Learning Techniques

Traditional human activity recognition systems mainly rely on supervised learning algorithms based on classical machine learning algorithms, such as:

- Support Vector Machine (SVM): SVM is a fundamental algorithm used in human activity recognition applications to classify different activities (walking, sitting, running, etc.) based on the information extracted from sensors. This algorithm can be considered one of the best classifiers in dealing with multidimensional and nonlinear data collected from inertial sensors like accelerometers and gyroscopes.

- k-Nearest Neighbor (k-NN): k-NN is one of the simplest but most efficient supervised learning algorithms used for classifying new data in the training dataset based on their similarity to labelled data in the training dataset (for example, walking, sitting).
- Random Forest (RF): RF is a machine learning algorithm used for classifying complex human activities (walking, sitting, jogging, etc.) based on high dimensional data collected from inertial sensors.
- Gaussian Mixture Models (GMM): GMM is used as a model-based clustering algorithm to classify high dimensional data (accelerometers and gyroscopes) into different human physical activities.

From among all these algorithms, k-NN showed superior performance in some situations, and the Random Forest improved feature extraction and classification [14]. They are significantly dependent on feature engineering.

5.2 Deep Learning Approaches

Deep Learning has brought about a revolutionary change in Human Activity Recognition (HAR) since deep learning is capable of automatically and hierarchically extracting features from the data without the need for manually constructed features.

5.2.1 Convolutional Neural Networks (CNNs)

Convolutional neural network (CNN) is a type of artificial neural network that comprises many sequential layers, each layer consisting of multiple neurons. In the architecture of CNNs, different types of layers perform various tasks, including convolutional layers, pooling layers, and fully connected layers. CNNs are efficient in feature extraction and have proven better results than other algorithms on various benchmarks like UCI HAR [3].

5.2.2 Recurrent Neural Networks (RNNs) and LSTM

Recurrent neural networks (RNNs) have been devised specifically for dealing with sequences, and their design involves preserving information from previous inputs using feedback links. The Long Short-Term Memory (LSTM) network is a special type of RNN that is specifically designed to counteract the problem of losing information over time due to the vanishing gradient effect. Both LSTM and bidirectional LSTM can efficiently model temporal dependencies in sequence sensor data, achieving very high accuracies (nearly up to 93.79%) [15].

5.2.3 Deep Belief Networks (DBN)

Deep belief networks are part of deep learning technology that combines elements of unsupervised learning and neural network theory. Deep Boltzmann Networks have been utilized to increase recognition efficiency compared to conventional ANNs as well as SVM models [1]. The advantage of deep learning algorithms like Deep Boltzmann Networks is that they do not require manually constructed features.

6. Recent Transformer-Based Human Activity Recognition Approaches

Human Activity Recognition (HAR) have observed a gradual transition from recurrent neural network architectures, such as Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM), towards Transformer-based models. Even if CNN and LSTM architectures have proven an excellent performance in learning local spatial features and temporal dependencies from inertial sensor data, their sequential processing nature restricts computational efficiency and their ability to model long-range temporal relationships. Transformer architectures resolve these limitations by using self-attention mechanisms that capture both local and global dependencies simultaneously. Thus, enabling parallel processing of time-series data and improving scalability for complex activity recognition tasks [16].

Transformer-based HAR models have been increasingly adopted for wearable and smartphone sensor applications. They automatically learn contextual relationships among multi-sensor inertial signals without relying on handcrafted feature engineering. Recent studies have introduced several variants, including Vision Transformers (ViT), Time-Series Transformers, SensorFormer, ActivityFormer, and hybrid CNN–Transformer architectures. These approaches combine convolutional layers for low-level feature extraction with Transformer encoders for modelling long-range temporal dependencies, thus improving recognition accuracy for both simple and complex human activities. Such models have shown promising results on benchmark datasets while maintaining robustness across different sensing environments [17].

Although Transformer-based HAR models show excellent representative capability, but they introduce new challenges. Their computational complexity, memory requirements, and larger parameter sizes make deployment on resource-constrained smartphones and wearable devices difficult. Therefore, efficient deployment requires lightweight Transformer architectures, model compression, quantization, knowledge distillation, or integration with edge computing platforms. Recent comparative studies indicate that although Transformers achieve competitive performance under favorable conditions, they do not consistently outperform well-designed CNN-LSTM models when training data is limited or when implication must be performed on low-power mobile devices. Consequently, lightweight hybrid architectures that combine CNNs, temporal convolutional networks, recurrent networks, and attention mechanisms remain attractive alternatives for real-time smartphone-based HAR [17].

Further, future HAR research is expected to focus on efficient Transformer architectures specially designed for mobile and edge environments. Emerging directions include Tiny Transformers, hierarchical attention mechanisms, multimodal sensor fusion, federated learning, self-supervised representation learning, and explainable Transformer models. These advancements have the ability to improve personalization, robustness, and privacy while enabling real-time implication on resource-constrained smartphones. Thus, Transformer-based HAR is expected to play a significant role in next-generation intelligent healthcare, smart cities, and context-aware pervasive computing applications [16][18].

7. Real-Time HAR Systems

Real Several conditions need to be satisfied when building HAR systems in real time:

- Latency: Very important constraint especially when dealing with wearables where the delay between the actual physical action and the system reaction should be as low as possible.
- Computational efficiency: Should combine high classification efficiency with saving on power, memory usage, and latency.
- Energy consumption: Strives to decrease the amount of energy used by the wearable device or smartphone due to their limited power resources while maintaining high activity detection efficiency.

Feature selection lowers computational effort and enables real-time performance [2]. Inertial sensor fusion along with other sensors, including depth sensors, increases precision rates (above 97%), but still ensures real-time execution [19]. Mobile Edge Computing (MEC) technology improves real-time processing by shifting computationally intensive workloads from mobile phones onto edge servers [3].

8. Comparative Analysis of Representative Smartphone based HAR Studies

Table 3 compares representative studies with respect to their methodological approach, classification models, benchmark datasets, and key contributions to provide a consolidated overview. The comparison illustrates the transition from conventional machine learning techniques to deep learning architectures and, more recently, Transformer-based approaches for improving recognition accuracy and real-time performance.

Table 3: Comparison of representative smartphone based HAR studies

Reference	Approach	Model/Technique	Dataset(s)	Key Contribution
Hassan et al. (2017) [1]	Deep Learning	KPCA + LDA + DBN	Smartphone HAR	Proposed a robust deep belief network-based HAR framework with improved recognition accuracy.
Wang et al. (2016) [2]	Machine Learning	Feature Selection + SVM	UCI HAR	Compared accelerometer and gyroscope data and proposed an

				efficient feature selection method.
Wan et al. (2019) [3]	Deep Learning	CNN, LSTM, BLSTM	UCI HAR, PAMAP2	Evaluated deep learning models for real-time HAR and demonstrated CNN superiority.
Shweta et al. (2017) [4]	Survey	Literature Review	Multiple	Reviewed sensing technologies, preprocessing, feature extraction, and classification techniques for HAR.
Lima et al. (2019) [5]	Survey	Comprehensive Review	Multiple	Summarized smartphone-based HAR methodologies, datasets, challenges, and future directions.
Attal et al. (2015) [14]	Machine Learning	k-NN, SVM, RF, GMM, HMM	Wearable Sensor Dataset	Compared supervised and unsupervised classifiers for wearable sensor-based HAR.
Yu & Qin (2018) [15]	Deep Learning	Bidirectional LSTM	UCI HAR	Proposed BiLSTM for temporal modeling of smartphone inertial sensor data.
Chen et al. (2016) [19]	Sensor Fusion	Collaborative Representation	Depth + Inertial Dataset	Developed a real-time HAR system using depth and inertial sensor fusion.
Moreira et al. (2021) [20]	Deep Learning	ConvLSTM	Indoor Smartphone Dataset	Applied ConvLSTM to improve indoor localization through activity recognition.
Alanazi et al. (2024) [21]	Machine Learning	LightGBM, XGBoost, RF, KNN	KU-HAR	Compared seven ML algorithms and identified LightGBM as the best-performing classifier.
Yin et al. (2024) [16]	Systematic Review	Literature Synthesis	Multiple	Reviewed mobile-device HAR technologies, trends, challenges, and future research directions.
Dentamaro et al. (2024) [18]	Survey	Comparative Analysis	Multiple	Reviewed smartphone sensor-based HAR with emphasis on datasets, algorithms, and evaluation methods.
Leite et al. (2024) [17]	Review	Transformer-based HAR	Multiple	Evaluated Transformer architectures and discussed their opportunities and deployment challenges.

As shown in Table 3, early HAR studies primarily relied on handcrafted feature engineering combined with traditional machine learning classifiers such as Support Vector Machines and Random Forests. Now a days, HAR has increasingly adopted deep learning models, including CNNs, LSTMs, and BiLSTMs, to automatically learn different representations from raw data collected from inertial sensors. More recently, Transformer-based architectures have appeared as a capable alternate for modeling long-range temporal dependencies, although their deployment on resource-constrained smartphones remains an active research challenge. Survey articles published in 2024 further highlight trends toward lightweight models, edge intelligence, multimodal sensing, and privacy-preserving HAR systems.

9. Applications

Human Activity Recognition systems have a number of applications, including:

9.1 Healthcare and Assisted Living

Human activity recognition is essential for automated processes that use AI in identification, monitoring, and analysis of the human activities to improve patient care, safety, and rehabilitation. HAR is an integral part of current healthcare technology, as it uses data collected via wearable sensors to observe patients and older people, detect falls, and track rehabilitation processes. [14]

9.2 Smart Environments

This technology uses sensors, IoT, and cameras to detect and analyze human activities. In this way, it makes automation of personalized services possible within smart home and smart city settings. [1]

9.3 Transportation and Localization

HAR is important for connected solutions in modern transportation and logistics, as well as smart environment management. Indoor Positioning System provides data such as whether a person is walking, sitting, and climbing stairs, thus significantly increasing the precision of finding a person's location where GPS technology cannot be used. [20]

9.4 Fitness and Lifestyle Monitoring

The technology is applied to detect and analyze physical movements and exercises. [21]

10. Challenges

Despite significant progress in HAR, several challenges still persist, limiting the widespread deployment and scalability of current systems. These challenges are:

10.1 Variability in Human Behavior

Different individuals perform the same activity differently, which often lead to distribution shifts that degrade the performance. Thus, affecting model generalization [2].

10.2 Sensor Noise and Data Quality

The inaccuracy of sensors and their sensitivity to environmental effects can create noise in the data. This issue becomes a crucial factor affecting human activity recognition (HAR) algorithms.

10.3 Energy Consumption

With the increasing popularity of wearables, it is vital to conserve energy. The constant sensing and computing process consumes a lot of energy from a smartphone's battery.

10.4 Real-Time Constraints

The human activity recognition framework poses strict time requirements. In the context of HAR, the correctness of detecting actions does not only refer to logical correctness but includes generating information in a timely manner. To achieve real-time data processing, HAR needs to consider real-time constraints in use cases that can be deployed on wearables.

10.5 Complex Activity Recognition

Recognizing complex activities involves the identification of compound or high-level activities (e.g., cooking, studying, traveling). Identifying complex activities proves to be more difficult than detecting simple actions.

11. Future Directions

Future work in HAR should focus on:

- **Edge AI integration** for real-time processing: Edge AI integrates artificial intelligence directly onto local devices—such as IoT sensors, cameras, specialized accelerators. Thus, enable real-time processing and immediate decision-making without relying on cloud connectivity.
- **Multimodal sensor fusion** for improved accuracy: various types of input data and different types of sensors can be combined to improve accuracy in HAR.
- **Adaptive and personalized models**: HAR can improve accuracy by adapting generic, and sensor-based models for unique motion patterns, movement, and context of individual users.
- **Energy-efficient algorithms**: Energy-efficient algorithms are critical for battery-powered wearable devices, to reduce power consumption.
- **Explainable AI in HAR systems**: XAI can enhance transparency and trust by revealing how sensor data leads to activity classification.

Deep learning combined with edge computing is expected to dominate next-generation HAR systems.

12. Conclusion

This paper reviews real-time HAR using data collected from inertial sensors on mobile phones. It highlights the process improvements and challenges associated with it. From traditional machine learning to deep learning and transformers, there have been many breakthroughs in the effectiveness and reliability of HAR. However, even with these innovations, several challenges remain with real-time HAR implementations in terms of computing, energy efficiency, and differences in human behavior..

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