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Human Activity Recognition: Evolution, Techniques, Applications, and Future Challenges

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Abstract: *Human Activity Recognition (HAR) is becoming a hot topic for research at the intersection of artificial intelligence, computer vision, and sensor analysis. It analyses and classifies different human behaviors from diverse data inputs in an automated way. This paper provides a thorough study of Human Activity Recognition (HAR), following its development from early machine learning models which were handcrafted feature-based systems to modern deep learning models which process multimodal inputs. A number of methods such as wearable sensor-based techniques, vision-based approaches, radar and non-contact sensing, transfer learning techniques and domain adaptation are surveyed. An overview of real-world applications which include healthcare, sports, surveillance, and human-computer interaction is provided. These real-world applications reveal HAR's visible impact on society. Lastly, we discuss important future challenges such as robustness and generalizability, explainability and interpretability, multi-activity and complex behavior recognition, privacy concerns, and real-world & open-world recognition. This overview focuses on the current advancements and recognizes open research directions mandatory for reliable, interpretable, and ethically responsible HAR systems.*

Key Words: *Human Activity Recognition, Wearable Sensors, Vision-Based HAR, Radar Sensing, Deep Learning, Transfer Learning, Multimodal Fusion, Explainability, Open-World Recognition, Privacy, Robustness, Multi-Activity Localization.*

I. INTRODUCTION

Human Activity Recognition (HAR) is a rapidly growing research area focused on the automatic identification and classification of human physical actions by analyzing data. This data is captured using multiple sensing devices such as wearable sensors, cameras, radars and other non-contacting devices. The ability enables intelligent devices to understand and act in response to human behaviors, by assisting in a number of applications. These applications include healthcare monitoring, sports analytics, smart homes, security surveillance, workplace safety and human-computer interaction. HAR is gaining importance with the production of ubiquitous sensors and increased demand for context-aware, personalized systems.

In the early days, HAR research started with traditional feature engineering. Traditional feature engineering includes rule-based and handcrafted feature extraction methods applied to the data gathered from wearable inertial sensors such as accelerometers and gyroscopes. These traditional approaches depend upon expertise in the domain. Therefore, to design features that captures the temporal and spatial characteristics of human actions, classical machine learning classifiers are used to perform recognition tasks. Though, these methods make great efforts with generalizability and robustness in real-world and unconstrained environments.

With the introduction of deep learning, HAR is getting a transformation. Deep learning end-to-end learning frameworks are capable of temporal and spatial feature extraction from raw sensor data automatically. Vision-based HAR evolved from simple motion detection techniques to advanced convolutional neural networks (CNNs), recurrent neural networks (RNNs). Recently, transformer-based architectures are also available that model long-range dependencies and multimodal data inputs very effectively. Along with, radar and non-contact sensing techniques have developed. In sensitive scenarios, these techniques contribute to maintaining privacy in activity monitoring.

Additionally, the field of HAR has gradually embraced multimodal approaches. These approaches combine data from different sources to overcome the limitations integral to individual modalities, and improve recognition accuracy and contextual awareness. Identification of different activities and interpretability of complex models is very important for real-world deployment and user trust. Therefore, recent theories like open-world recognition and explainability have been introduced to tackle these challenges effectively.

This paper aims to provide a comprehensive survey of HAR, its historical evolution, current techniques, its practical applications, and evolving research challenges. By creating advancements within wearable sensor-based methods, vision-based approaches, radar and non-sensing techniques, and transfer learning frameworks, this study is focused on the multidisciplinary nature of HAR and identifies key directions for future research to understand robust, interpretable, and ethically responsible human activity recognition systems.

II. EVOLUTION OF HUMAN ACTIVITY RECOGNITION

At its early stage, HAR research was primarily focused on wearable sensor data, using handcrafted features. These features include statistical measures, frequency domain attributes, and time-domain descriptors obtained from accelerometers and gyroscopes. To categorize activities, classical machine learning algorithms, including Support Vector Machines (SVM), Decision Trees, and k-Nearest Neighbors (k-NN), were commonly employed[1]. As computational power and data availability increased, deep learning approaches gained importance by enabling comprehensive learning of features directly from raw sensor data without manual or handcrafted feature engineering [2].

Similar to sensor-based HAR, vision-based approaches developed from simple motion detection and handcrafted descriptors. Histogram of Oriented Gradients (HOG) and Optical Flow to sophisticated convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are capable of capturing spatial and temporal motions from video sequences [3][4]. Additionally, transformer-based architectures and attention mechanisms have enhanced the capability to model long-range dependencies and multimodal blend of inputs [5][6].

The integration of multimodal data sources, including wearable sensors, vision, and radar, has grown to overcome the limitations of individual modalities. Additionally, emerging paradigms such as open-world recognition, which enable systems to identify previously unseen activities, and explainability techniques to interpret complex models, have been introduced to address real-world deployment challenges [7].

III. TECHNIQUES FOR HUMAN ACTIVITY RECOGNITION

3.1 Wearable Sensor-Based Methods

Wearable sensors, like Inertial Measurement Units (IMUs), continue to be an essential part of Human Activity Recognition (HAR). The traditional methodologies relied on the extraction of features using machine learning techniques like Random Forests and SVM. However, with the advent of deep learning, new models have revolutionized the way the traditional process of feature extraction takes place in HAR. Convolutional Neural Networks are successful in extracting spatial features, while Recurrent Neural Networks, like LSTM, are successful in extracting temporal features of the data [2] [8].

Two of the challenges that arise with the use of wearable sensors are the orientation of the devices, which may affect the overall accuracy of the system. Recent advancements in the field of HAR propose models that are independent of the position of the devices, thereby increasing the overall accuracy of the system using data augmentation, sensor fusion, and invariant features [9]. Furthermore, the use of attention mechanisms has also been successful in highlighting the most important segments of the data, thereby increasing the accuracy of recognizing multiple activities within weakly labeled data sets.

3.2 Vision-Based Approaches

Vision-based human action recognition (HAR) uses video data to extract detailed spatial and temporal information about human actions. Although initial approaches used handcrafted features, modern approaches mainly use deep learning models, with 3D convolutional neural networks (3D CNNs) being prominent due to their potential for learning hierarchical spatiotemporal representations [10]. To address the issue of long-range dependencies and the need for more explainability, Transformer networks have also been introduced [5].

Despite the success of vision-based human action recognition, many challenges remain, including issues of occlusions, different viewing angles, and computational issues for real-time processing. Multimodal fusion, which includes combining vision with other data sources like inertial sensors, has also shown potential for improving human action recognition accuracy [11]. The development of benchmarks for human action recognition has also seen the development of datasets like NTU RGB+D and Kinetics.

3.3 Radar and Non-Contact Sensing

Radar-based non-contact human activity recognition (HAR) solutions provide the necessary tools for a privacy-preserving solution that can be used in indoor settings, especially for healthcare purposes. This is because the radar echo can be used to extract micro-Doppler signatures that relate to human movements, which can be interpreted by deep learning models, especially CNNs with attention mechanisms, to perform human activity recognition tasks [12][13].

Radar-based non-contact human activity recognition has several challenges, especially with regard to signal noise, multipath, and environmental factors. Recent research has focused on improving the preprocessing of the signals, especially with regard to feature extraction, to improve the overall performance of radar-based non-contact human activity recognition [14].

3.4 Transfer Learning and Domain Adaptation

Domain discrepancy occurs due to differences in sensor modalities, user sets, and environmental settings. The above differences restrict the generalization of human activity recognition (HAR) models. Transfer learning methods allow knowledge sharing from source domains with sufficient labeled data to target domains with limited labeled data [15]. Cross-modal transfer learning helps to share knowledge among various sensor modalities to deal with data scarcity.

Open world recognition models extend human activity recognition systems to recognize novel human activities not seen during training. This extends the applicability of human activity recognition systems to real-world scenarios. Open world recognition models include novelty detection, incremental learning, and uncertainty estimation [7].

IV. APPLICATIONS OF HUMAN ACTIVITY RECOGNITION

4.1 Healthcare and Assisted Living

HAR technologies allow for the continuous monitoring of the elderly and patients suffering from chronic diseases. They also aid in the detection of falls, rehabilitation, and lifestyle monitoring. When combined with other sensors such as radars and vision-based sensors, wearables can offer complete information on the level of activity of the patient or the elderly, thus aiding in preventative measures [16].

4.2 Sports and Fitness

For sports or fitness, Human Activity Recognition (HAR) can provide real-time feedback on the characteristics of human activity or intensity of movements. In modern times, Human Activity Recognition models can help in differentiating complex sports drills, thus leading to better coaching or training [17].

4.3 Surveillance and Security

HAR contributes to the security of public areas and critical infrastructure by automatically recognizing suspicious or abnormal behaviors. When combined with vision-based systems and radar systems, HAR can be used to enable proactive threat detection and response. These systems improve situational awareness and safety [18].

4.4 Human-Computer Interaction

HAR facilitates physical and intrinsic interaction models with gesture recognition and context computing capabilities. The application areas of HAR include virtual reality, home automation, and assistive technology, which offer an immersive user experience through intrinsic interaction models, as proposed by [19].

V. FUTURE CHALLENGES AND RESEARCH DIRECTIONS

5.1 Robustness and Generalizability

The development of robust human activity recognition systems is critical to the proliferation of the technology. The systems need to be robust against noise, sensor locations, and user differences. Data augmentation, domain adaptation, and continuous learning are preferred approaches, but these need to be augmented with large-scale, real-world data, as advocated by [20].

5.2 Explainability and Interpretability

This complexity associated with deep learning models makes it important to increase transparency to build trust and deploy these models in security-relevant domains. Explainable AI models that offer activity recognition outputs and their associated rationales are one of the most prominent areas of current research [21].

5.3 Multi-Activity and Complex Behavior Recognition

Recognition of concurrent and long-duration activities still remains a challenge. Developments in attention mechanisms, weakly supervised learning, and temporal localization are needed to accurately model overlapping and subtle behaviors [22].

5.4 Privacy and Ethical Considerations

It is also important to ensure that a proper balance is maintained between human activity recognition systems and users' privacy. Federated learning, on-device processing, and data representations that ensure privacy preservation are some of the techniques that have been put in place for this purpose, and this is an area that requires further consideration [23].

5.5 Real-World Deployment and Open-World Recognition

The challenge of bridging the gap between the controlled environment of experiments and the dynamic environment of the real world is significant. The ability of the open world recognition model to recognize new activities and adapt to environmental changes is critical for its deployment [7].

VI.CONCLUSION

Human Activity Recognition (HAR) is defined as an interdisciplinary research domain, combining sensor analytics, computer vision, and artificial intelligence. It includes the contributions of these areas to the analysis and interpretation of human activities with different forms of data and computation modalities. Some of the major achievements in the field of human activity recognition (HAR) include the shift from conventional approaches to modern approaches, which include deep learning and multi-modal approaches. The areas of application of HAR include healthcare, sports, security, and human-computer interaction, which reflect the potential for a positive impact on society in the near future. Overcoming the challenges associated with HAR is vital for the development of this field.

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