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AN ADVANCED REVIEW ON HUMAN ACTIVITY RECOGNITION USING ARTIFICIAL INTELLIGENCE

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ABSTRACT
Understanding human interactions and relationships requires human activity recognition (HAR). Extraction is difficult since it reveals a person's identity, personality, and mental state. Human activity movement forecasting is HAR. HAR is used in many applications since cellphones and video cameras can collect human activity data. Digital devices, apps, and AI advances have made deep learning data extraction for reliable detection and interpretation possible. This integration has strengthened our understanding of HAR's three pillars—acquisition devices, artificial intelligence, and their applications—which are expanding rapidly. While various review papers have covered the basics of HAR, few have compared all HAR devices and even fewer have examined the impact different AI designs. This assessment covers 2006–2021 and analyses HAR's three pillars. The study also suggests ways to improve HAR design for reliability and stability. Five main conclusions: (1) HAR is built on devices, AI, and apps; (2) HAR dominates the healthcare business; (3) hybrid AI models are still developing and require significant improvement to provide stable and reliable designs. Additionally, these models must have reliable predictions, high precision, effective generalisation, and the ability to achieve application objectives without bias; there has been little research on anomaly detection in human activities; and movement prediction has advanced little. The three core components of the HAR industry—electronic devices, apps, and artificial intelligence—will continue to evolve, and AI will shape the future of the sector. This paper summarises current human activity classification research. We classify human activity recognition methods and evaluate their pros and cons. Two main types of human activity classification techniques use one or more modalities. Subcategories within each category show how they represent human activities and which ones they highlight. We also exhaustively evaluate publically accessible human activity recognition datasets and ideal HAR dataset criteria. This paper highlights sensor-based and video-based human activity detection development, emphasizing on core technologies, identification systems, and applications from low-level to high-level representations.

Keywords: HAR, Artificial Intelligence, datasets, electronic devices, healthcare

INTRODUCTION

Human Human Activity Recognition (HAR) collects events and annotations to recognise behaviours and motions to understand the ecological context. Humans can comprehend a single movement. Humans naturally prefer dynamic over static stuff. Human movement research is a hot topic in machine learning. This article discusses human activity recognition machine learning methods and their difficulties. Real-time datasets are increasingly sought and analysed. The HAR activity chart follows.below

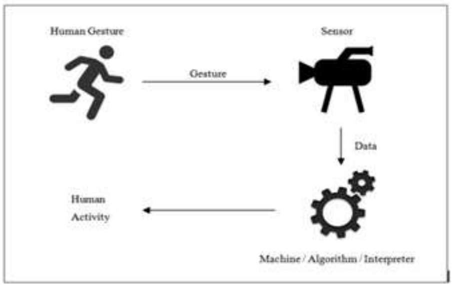

Fig.1: Activity chart of HAR (3)

Human HumanHuman Activity Recognition (HAR) uses AI to identify and classify actions from unprocessed data from multiple gadgets. Wearable sensors, smartphone inertial sensors, Kinect cameras, CCTV, and COTS equipment may be used. HAR is needed in healthcare, surveillance, remote care for elderly people, smart environments (homes, enterprises, cities), and sports and fitness tracking due to its diverse data sources.

The widespread use of HAR increases safety and quality of life. Sensors, video cameras, RFID, and Wi-Fi are not new, but their use in Human Activity Recognition (HAR) is. AI methods are improving rapidly, allowing HAR devices to be used in many fields. Thus, AI models and HAR devices work together. These models initially used single images or short sequences. AI advancements have opened new doors. Our results show that HAR expansion is intimately linked to AI advancement, expanding its application across numerous fields.

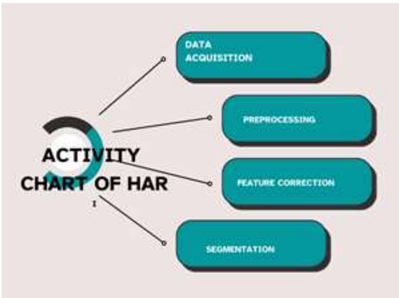

Fig.2 : Classification of HAR (5)

HAR applications using AI

In In recent decades Scholars from different fields have developed Human Activity Recognition (HAR) models in recent decades. A key question in HAR framework design is "Which HAR tool is suitable for which software domain, and what is the appropriate AI methodology". The review of numerous HAR applications, including their data sources and AI methodology, shows how HAR devices and AI approaches vary by application domain. The graphic below shows current research publications' application allocation. The following domains use HAR:

Crowd Surveillance (c-Surv): Detecting fear in a crowd.

Healthcare Monitoring (m-Healthcare): Supporting ICU patients and trauma resuscitation.

Smart Home (s-Home): Helping elderly or dementia patients and supervising youngsters.

Fall detection (f-Detect): Recognising movement abnormalities that may cause a fall.

Checking posture during exercise (e-Monitor).

G-Analysis: Assessing gait patterns for health issues.

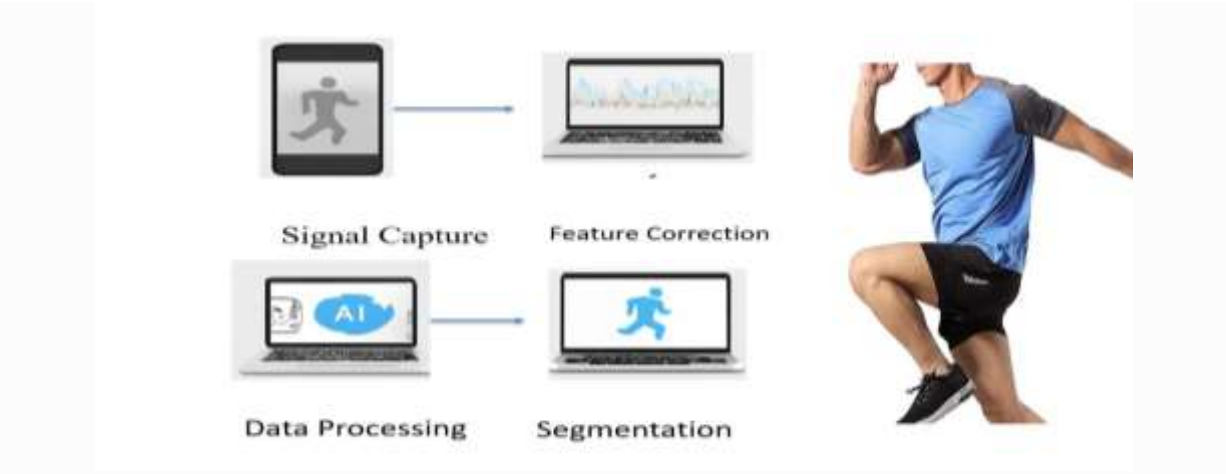

Fig.3 : Human activity recognition framework (63)

The Deep learning (DL) has greatly enhanced the extraction of useful characteristics from raw sensor data in Human Activity Recognition (HAR). Deep learning models, especially CNNs, have improved transfer learning, allowing a recognition model learnt on one dataset to be used on a different testing dataset. Inception, Residual Neural Networks (ResNets), and hybrid deep learning models like CNN-LSTM and Inception-ResNets are prominent in this arena.

Four phases are typical for HAR:

Capturing human-related sensor data.

Data pre-processing: Cleaning and arranging raw data for analysis.

Activity recognition using AI algorithms to classify human behaviours.

HAR managing user interfaces: Developing solutions for user interaction and management.

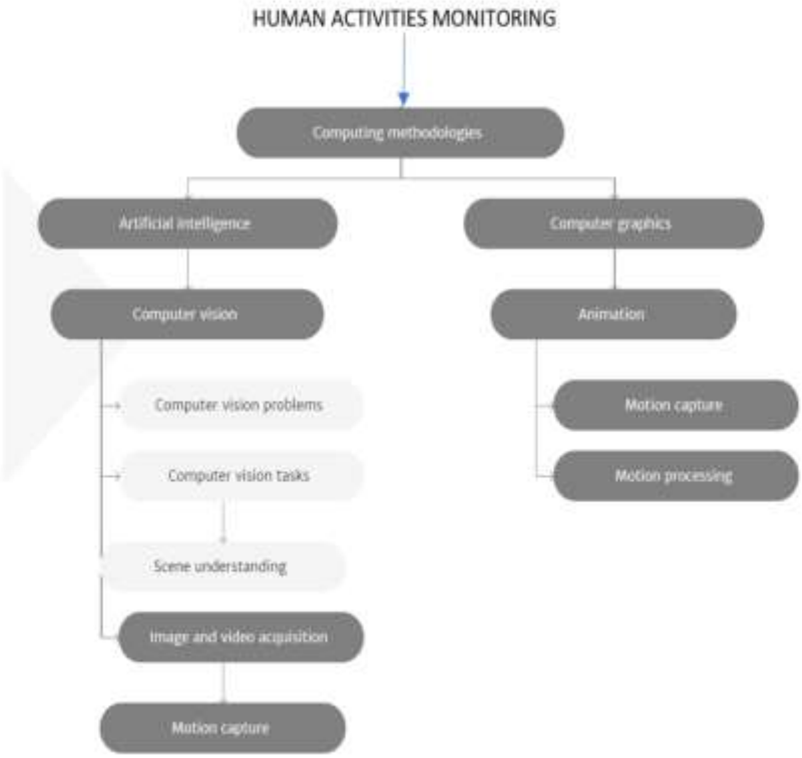

Fig.4: Human Activity Management flow chart (8)

Significantly, Advances in AI deep learning and machine learning have made it possible to extract deep, hidden information for effective detection and interpretation. Thus, understanding these developing paradigms that swiftly change HAR devices is crucial. We need a comprehensive investigation to compare AI and HAR device advancements. This study aims to improve understanding of the Human Activity (HI) framework by incorporating devices and application areas with specialist AI methods. Important questions include: Which peripherals suit different applications? When designing this framework, what AI traits should be considered?

This article categorises HAR devices and analyses knowledge-based infrastructure in the fast developing field of AI to explain how to choose the best device-AI combo.

Objectives

1. A reliable and accurate AI neural network prediction of human behaviour.
2. ResNet deep learning used in an Artificial Neural Network-based human event prediction model.
3. The model uses a collaborative artificial intelligence neural network to represent human behaviour based on assumptions.

RESEARCH GAP

Recent New mobility study demonstrates that human behaviour is statistically based. Behaviour is quite different, and common activities reflect average distance traversed. Despite their diversity, people are repetitious, visiting the same areas repeatedly. These dynamics allow precise human motion representation. The following publications include human mobility research and modelling.

Traditional behaviour recognition sensor data is expensive and difficult to collect, requiring specialised software. However, machine learning and personal tracking apps for health and well-being have made these technologies cheaper and more accessible. Thus, sensor data from these devices is easier to obtain and more abundant, making it a more commonly studied technique for identifying general behaviour. Predicting behaviour from a snapshot of sensor data from one or a few sensor types is the present challenge. This issue is generally a multivariate or univariate time series classification difficulty.

Fig.5: Categories of deep learning in human activity recognition (64)

Research Scope

In This study suggests primary research areas like:

Human Activity Recognition (HAR), mainstream sensors, and key public datasets in this field: what are their real-world applications?

Q2: What deep learning methods does HAR use and what are their pros and cons?

Q3: What issues does this sector face, and what remedies or possibilities may arise?

This study answers these questions by reviewing current findings. About sixty papers on HAR sensing technologies were examined between 2006 and 2021. Three types of technologies exist: RGB camera, intensity sensor, and wearable. The study shows that human activity recognition concentrates on Daily Living Activities (DLAs) to understand human behaviour in context and improve life quality.

Walking, running, lying, climbing stairs, sweeping, and cooking are daily activities. Data from many body sensors is pre-processed, characterised, and analysed to detect activities.

Many researchers have contributed to this topic, and this publication includes their main findings. We summarise HAR system research in sensors, video analysis, healthcare, CNN, RFID, and other disciplines.

Reviewing Research

Wang et al. (2011): Using feature density, we connected context to interest regions to study human activity identification.

Li and Zickler (2012) introduced a multiview activity identification method that enriches feature sets by connecting descriptors from diverse angles.

Rahmani and Mian (2015) suggested a deep learning-based non-linear model for action information transfer during multiview action detection. However, their method is computationally demanding.

Tian et al. (2013) recognised sports using 3D space-time volumes and a deformable part model.

Dynamic programming and temporal warping helped Kulkarni et al. (2015) identify action sequences in untrimmed video sequences.

A new spatiotemporal feature representation for human activities was introduced by Samanta and Chanda (2014) using 3D HAAR wavelet transforms and higher-order time derivatives.

Jiang et al. (2013) described mid-level video utilising optical flow characteristics and localised activity using hierarchical templates and tree search.

Rosh Khari and Levine (2013) created a spatiotemporal volume codebook-based hierarchical video representation for atomic activity recognition.

Unsupervised learning was used to categorise video activities by Le et al. (2011).

SVM classification matched action descriptions in Sadananda and Corso (2012)'s "action bank" for video sequences.

Wu et al. (2011) described video sequence interest points' spatiotemporal environment using Gaussian mixture models (GMM).

The "hankelet" function of Li et al. (2012) employs BoW to identify actions from different angles without camera calibration.

Vrigkas et al. (2014) identified activities using nearest-neighbor classification and grouped motion trajectories.

Yu et al. (2012) presented random projection tree-based propagative point-matching for unsupervised activity detection.

Jain et al. (2013) presented a divergence-curl-shear description for video flow patterns.

Wang et al. (2013) highlighted occlusion and missing data in dense optical flow channel motion patterns.

The discriminative groups of dense trajectories for human action analysis were weighted by Ni et al. (2015).

Hierarchical clustering was used by Gaidon et al. (2014) to learn human actions from brief video clips unsupervised.

Raptis et al. (2012) developed a mid-level spatiotemporal and trajectory cluster-based action detection method.

For overlapping candidates with maximal set coverage, Yu and Yuan (2015) estimated meaningful action pathways in video sequences using bounding box candidates.

A trajectory system by Li et al. (2011) gathers temporal data for similarity analysis and activity categorisation.

SVM was used to categorise features and provide trajectory snippets by Matikainen et al. (2009).

Messing et al. (2009) identified video segments using velocity-based motion features and a generative mixed model.

Tran et al. (2014) suggested a size- and shape-invariant spatiotemporal event localisation method for video sequences. A multi-camera system helped Holte et al. (2012) identify 3D activities and build a 4D interest point description.

Local spatiotemporal cuboids for action recognition using kernelized SVM classification are proposed by Zhou and Wang (2012).

Sanchez-Riera et al. (2012) used stereo cameras for action recognition with BoW and background clutter control.

Julieta et al. (2017) used RNN to study human mobility and compared it to other cutting-edge technologies.

End-to-end CNN system by Chao Li et al. (2018) learns co-occurrence characteristics from varied contextual data.

A symbiotic neural network utilising multi-scale CNN captured temporal and spatial motion recognition data by Maosen Li et al. (2021).

CONCLUSIONS

This study This study evaluates cutting-edge vision-based and sensor-based Human Activity Recognition (HAR) methods, highlighting their pros and cons. These methods have gained popularity due to their potential use in novel activity detection applications. Academics can understand activity recognition with detailed descriptions, analyses, and highlights of their qualities.

Work on handcrafted feature designs, models, deep structures, datasets, and assessment techniques was examined. The latest sensor-based and vision-based HAR developments were our emphasis. We examined many datasets that meet activity detection applications' main requirements: real-time operation with limited onboard processing resources and observational restrictions such camera quality. Classical machine learning and deep learning models used in HAR were also assessed for their strengths and weaknesses.

This evaluation also addressed HAR concerns and offered solutions. We found that hybrid deep learning models can automatically extract spatial-temporal information from raw sensor data to recognise complex human behaviours, surpassing models with more intricate architectures. CNN and GRU have been studied, but improved deep neural network models will come next.

Based on this review, the following research directions are suggested:

Real and Accurate Human Activity Prediction: AI neural networks for better human activity prediction.

This model predicts human events using ResNet deep learning.

Advanced Human Activity Model: Collaborative AI neural networks for more accurate human activity projections.

Future research may use deep Transformer models to categorise human behaviours across time, such as on the WISDM dataset. Transformers, which use self-attention, are great for learning raw sensor data sequence relationships. A larger WISDM dataset with more activities and participants can categorise new activities.

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