Samarra J. Engineering Sci. and Res. , 2024; 2 (3): 26-39

IRAQI Academic Scientific Journals

SAMARRA JOURNAL OF ENGINEERING SCIENCE AND RESEARCH

S.J.E.S.R

Software Defined Radio-based Human Activity Recognition: A Comprehensive Review

Zhraa Zuheir Yahya[1] and Dia M. Ali [2*]

1- Communication Engineering Department, College of Electronics Engineering, Ninevah University, Iraq
2- Biomedical Engineering Department, College of Electronics Engineering, Ninevah University, Iraq

Article Information
Received: 25/05/2024
Accepted: 05/07/2024
Keywords:
Human Activity Recognition, Software Defined Radio, USRP, Deep Learning, and Machine Learning.
Corresponding Author

E-mail: dia.ali@uoninevah.edu.iq
Mobile: 07701650111

Abstract

The Human Activity Recognition (HAR) systems have been recognized as one of central important components in numerous inevitable everyday-life applications, e.g. healthcare, security, search and rescue. In order to overcome the wearable sensor burden, RF-based HAR has become a promising technology candidate for many applications to save on privacy concern. The fundamental concept of this systems is achieved by the fact that human movement will affect the RF propagation path and characteristics, which will lead to reflected signals with distinctive fingerprint for different activities. In this research, a comprehensive review of RF-based HAR with the utilization of Software Defined (SDR) technology is presented for practical implementation by transmitting the RF signals towards the human and receiving signals from various scenarios through the utilization of several Universal Software Radio Peripheral (USRP) platforms. This research gives details about the types of HAR classifiers, human activities, type of the utilized waveforms and systems architectures. The High classification accuracies for different tasks have been achieved with the use of various deep learning, machine learning and model-based techniques. The efficacy of SDR technology has been demonstrated in real-time practical HAR systems.

1. Introduction

Recently, Human Activity Recognition (HAR) has been utilized for a wide applications, including military, academic, healthcare, surveillance, and others. Depending on the purposes, HAR aims to identify the physical duties performed by a specific person or group of people [1, 2]. Others defined HAR as the process of recognizing and classifying human actions as normal or abnormal and have greatly benefited global human safety and well-being [3, 4].

Regarding computer vision and pattern recognition, HAR is a prevalent issue, and it is used to detect diverse human activities [5]. Various aspects affected the effectiveness of HAR, including lighting, background, cluttered scenes, camera angle, and action complexity [6]. The emphasis nowadays, is focusing on using effective methods or systems for identifying anomalies in human behaviour, which can be utilized for prediction or decide the best course of action [7].

According to the information types, HAR can be divided into three categories: sensor-based, vision-based HAR [8, 9] and Radio Frequency (RF)-based HAR [10]. Sensor-based approach analyses information as time series from sensors like: accelerometers, gyroscopes, radars, and magnetometers. This approach includes sensor selection, data collection, feature extraction, model training and model testing [11].

Vision-based approach, on the other hand, uses camera data in video or picture format, then analysed, processed using image segmentation, filters and other image processing techniques to detect these activities [12-14]. Vision-based HAR has its own drawbacks, like susceptible to environmental factors, such as camera angles, illumination, and overlapping between individuals [15, 16]. While sensor-based HAR offers better convenience and privacy than vision-based HAR [6, 17]. The most up to date HAR is RF-based, the main idea of this type that the human activity causes changes in environmental RF signals, which in turn causes RF signals to reflect by human bodies in a unique manner caused a thumbprint [18]. Fig.1 illustrates the three categories of HAR process.

Constructing a transmitter and receiver for continual sending and receiving of RF signals is necessary for many RF-based devices [10, 18]. RF-based approach is suitable for identifying indoor activities in the healthcare system. These systems use radar, infrared, or Wi-Fi-based sensing modalities [19-21].

To Identify or classify the human activities, Deep Learning (DL) algorithms and conventional Machine Learning (ML) techniques can be used effectively. Support Vector Machines (SVM), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN) are the most often utilized supervised methods for HAR. DL approaches have gained popularity due to their ability to automatically extract features from vision or image data, as well as time-series data, making it simple to learn high-level and significant characteristics. Modern DL approaches like CNN and LSTM demand larger datasets than traditional ML algorithms like SVM [22-24].

Deep learning architecture-based recognition of human behavior generally has four phases. The first phase involves on selecting and implementing input devices, such as sensors and cameras or RF signal.

The second phase is data collecting, wherein an edge device is employed to interpret data from input devices and transmit it to the primary server via diverse communication techniques.

Edge computing, which combines edge servers for dependable real-time information processing and sensors for data perception, is utilized for data collecting and processing. DL algorithms are used at the feature extraction and selection to extract the required features from the raw signals as phase three. A notification mechanism that allows an agent a machine or a human to be informed is included in the last phase [25, 26].

In this article, a comprehensive review of RF-based HAR is presented. This work discusses the utilization of Software Defined Radio (SDR) development platforms for HAR with various transmission signals and environment. Also, various DL and ML classification algorithms for activity recognition are discussed.

The rest of the article is organized as the following: the RF-based HAR is discussed in section 2, Software Defined Radio (SDR) Technology in section 3, literature review in section 4, and comparison among the literature performances in section 5, and finally the conclusion in section 6.

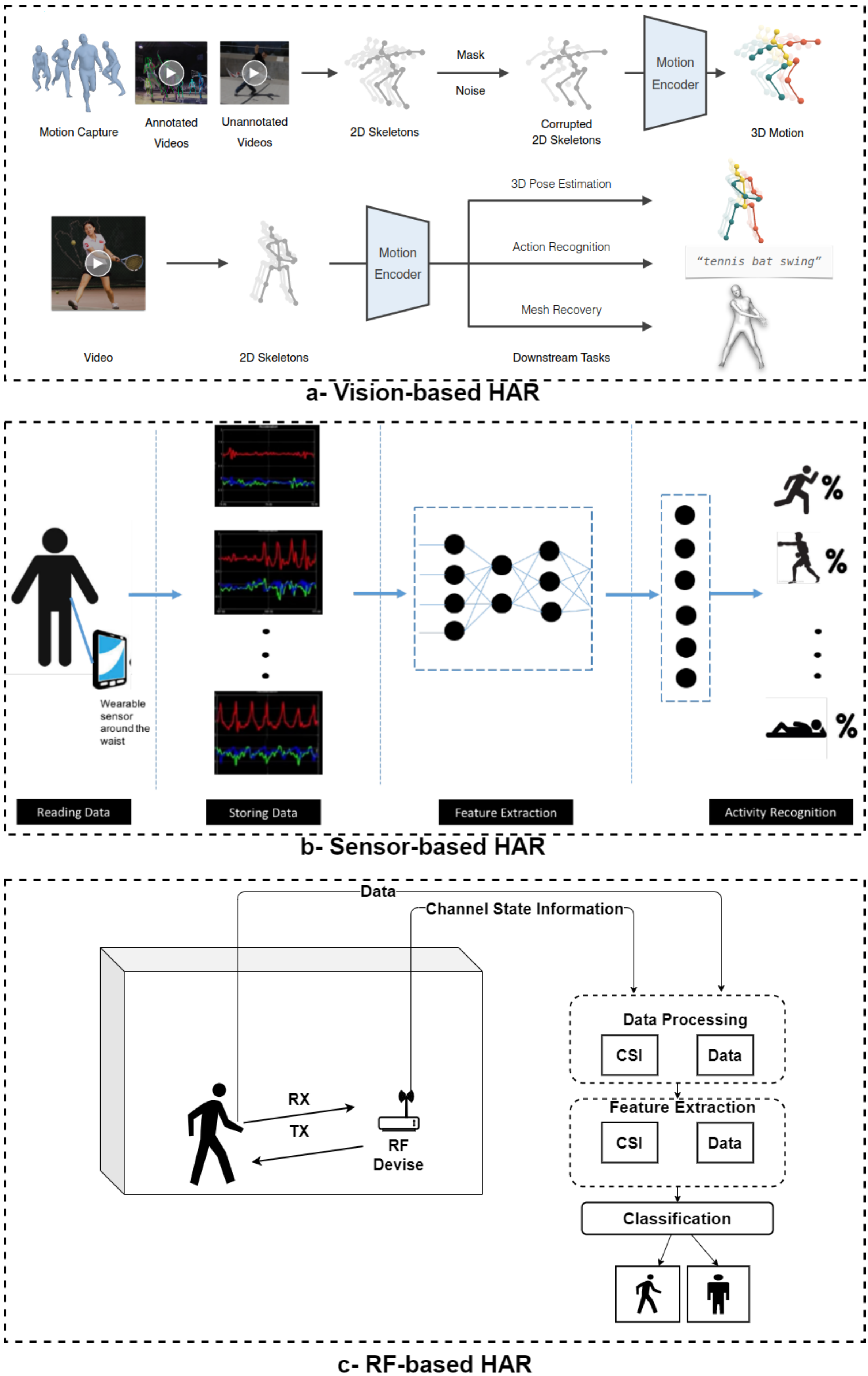

Fig. 1. General *HAR system process: a- Vision-based HAR b- Sensor-based HAR c- RF-based HAR*

2. Radio Frequency-Based Human Activity Recognition

For the elderly and those with physical disabilities, wearable sensors require humans to carry or wear sensors, which is intrusive, unpleasant, and uncomfortable. Vision-based systems have their own drawbacks [27]. RF-based HAR systems have several benefits over vision-based and wearable sensor-based techniques and can be defined as systems which recognize the activity of a person using analysis of radio signals while the person itself is not required to carry a wireless device. RF-based HAR systems are a more suitable option for smart homes and healthcare applications [28].

Radio systems can emit RF signals and receive reflected radio signals after colliding with objects, estimating the size, form, distance and motion. Radio signal-based sensing modalities employed in surveillance scenarios can thus detect stationary objects, persons, and human motions using the properties of the received signal to infer human activity [29].

Using RF Channel State Information (CSI)-based signals for activity detection has several advantages, including the ability to capture small scale multipath propagation, resolve battery issues, and provide wider coverage areas than wearable sensing devices or cameras-based systems. The CSI-based technology can detect human behavior even through barriers and difficult circumstances, surpassing other existing techniques [30].

For real-time implementation the Software Defined Radio (SDR) technology has been gained attention recently in an indoor and outdoor environments, wide range of frequencies that assist to detection the activity are available and the same device can be used for transmitting and receiving the RF signal [31]. Fig.2 illustrates the RF-based HAR process.

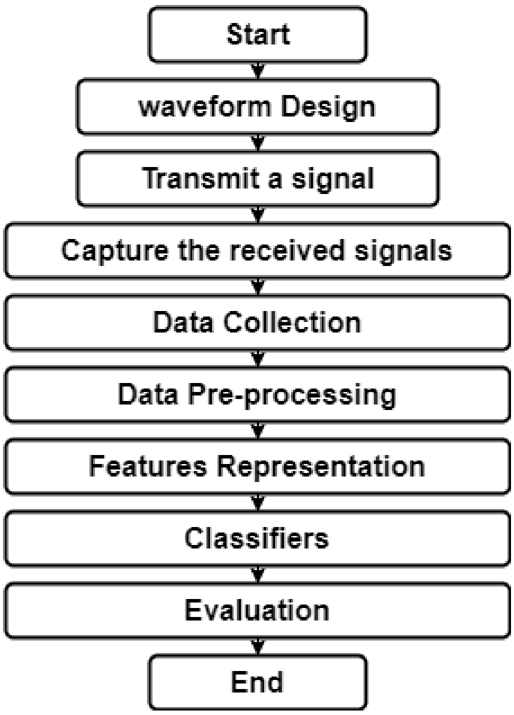

Fig. 2. RF-based *HAR system process*

3. Software Defined Radio (SDR) Technology

SDR is a communication device in which the radio can be controlled and run in software. SDR platforms can transmit and receive while the physical components (Filters, Amplifiers, Modulators, Coders, Detectors, and others) are implemented in software, unlike what is in traditional radio. SDRs can be utilized to test numerous waveforms, communication protocols and distinct algorithms in software. In addition, SDRs provide a wide degree of freedom for various transceiver applications and are also used for multichannel applications like passive radar systems and direction-of-arrival (DoA) measurement setups [32, 33].

Universal Software Radio Peripheral (USRP) is an SDR platform by Ettus Research which are designed for RF applications. USRP are ideal for developing and prototyping complex wireless designs. The USRP communication system can adapt to its environment owing to SDR instant configuration changes. The USRP can be used for RF-based HAR for CSI extraction and dataset collection [34]. Fig. 3 illustrates HAR system using USRP.

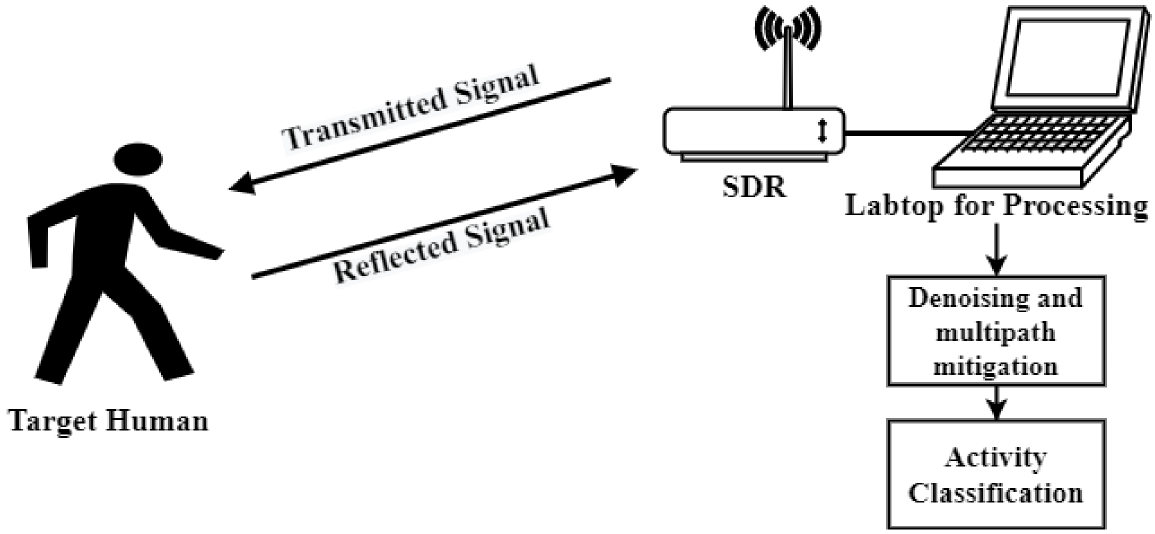

Fig. 3 *HAR system using USRP platform ensure traces are distinguishable in black and white*

4. Literature Review

Many researchers have investigated and presented models for HAR. The following are literatures that use SDR technology.

In [35], a wireless technology was proposed for sensing and recognition of human gesture using USRP-N210s platform. The proposed approach achieved an average accuracy of 94% in office environment and a two-bedroom apartment. The study of HAR utilized SDR platform and ML classifiers is shown in [36]. The researchers considered activity detection with one and two stages classifiers. Additionally, the results indicate that the localization of a detected activity can occur simultaneously within an area of less than 1 meter radius.

In [37], an SDR of two USRPs platform is utilized for HAR. Orthogonal Frequency Division Multiplexing signals are used to extract the channel state information. The results show that the amplitude fluctuated when activity was exist between the transmitter and receiver.

An SDR device with Doppler elaboration features presented in [38] for non-contact human respiration signals sensing. A quadrature receiver used to overcome the critical issues related to the occurrences of null detection points while the phase-locked loop components included in the software defined radio transceiver are successfully exploited to guarantee the phase correlation between I/Q signal components. Experimental results show that the proposed model has the ability to accurately detect human breath.

In [39], the authors suggested a WiGrus model for human gesture recognition. WiGrus utilized the CSI from the WiFi signals to recognize the hand gestures. The USRP and WiFi both utilized to obtain the signals information (amplitude and phase. The 2-stages RF algorithm is used for recognition and compared with ML algorithms SVM, KNN, Decision Tree, XGBoost, and CNN. The recognition accuracies achieved were 96% and 92% using the two scenarios Line of Site and Non Line of Site, respectively.

A HAR system proposed in a quasi-real time approach utilizing a non-invasive algorithm [40]. The wireless signals obtained using an SDR platform used as dataset. The ML algorithms are used for classification. The higher recognition accuracy achieved using Random Forest algorithm is 96.70%. In [41], DL-based CNN models used for detection mobility of the ankle in patients who have ankle fracture surgery. The USRP platform used to capture the CSI. The recognition accuracy achieved using ZFNet and AlexNet was 98.98% which is higher to that in ML classifiers.

In [42], a non-contact sensing environment utilizing artificial intelligence was proposed for recognition of post-surgery activities. The USRP platform was employed to obtain data from spinal cord operated patients throughout weight lifting activities. The OFDM scheme has been utilized for CSI extraction. The achievement accuracy using K-nearest neighbour, a ML algorithm was 99.6%.

In [43], the authors suggested deployable, non-invasive, flexible, and adaptable framework using SDR platform for HAR, where two USRPs used for CSI extraction. Various ML classifiers used (K-Nearest Neighbour, Decision Tree, Discriminant Analysis and Naïve Bayes) for the suggested framework performance assessment. The recognition accuracy achieved using K-nearest neighbour was 89.73%, which outperforms the other utilized algorithms.

For large and small scales human body movement recognition, a model was designed using the USRP to extract the channel state information (CSI) from the received signal in [44]. Based on CSI signature, the human activities were recognized.

In [45], a Matlab model was designed with USRP platform to track breathing rate and small scale body movement. The OFDM signal is used in the transmitter and receiver to capture the CSI. The USRP data used with ML algorithms for recognition and the performance compared with wearable sensor. The results show that K-Nearest Neighbour achieved highest accuracy of 91%, while 48.99%, 59.72% and 71.131% achieved using discriminant analysis, naive bayes and decision tree. In [46] a Deep Gated Recurrent Unit (DGRU) algorithm has been proposed for HAR. The USRP was used to implement IEEE 802.11a for CSI extraction and dataset collection. Also a LSTM algorithm used as an advanced DL technology. The suggested model achieved 95–99% recognition accuracy.

Intelligent wireless walls (IWW) was suggested for high precision HAR in complicated environment in [47]. The proposed model comprises the utilization of a reconfigurable intelligent surface (RIS) and ML algorithms. Two USRPs (X300) and (X310) used as a transmitter and receiver in two scenarios of environments. The maximum detection gain achieved compared with conventional intelligent surface were 28% and 25% using multi-floor and corridor junction scenarios respectively.

In [48], HAR system was proposed based on a distributed MIMO Radar with multiple antennas of millimeter wave MIMO Radar architecture (Ancortek SDR-KIT 2400T2R4) in an indoor environment. Two separate and identical monostatic radar subsystems were employed to detect and record the bidirectional movement of humans from two different angles. A feature extraction network extracts various features, then a multiclass classifier used to recognize five different types of human activity. The suggested system achieved 98.52% recognition accuracy, which outperforms the accuracy of SISO radar by almost 9%.

A HAR system is built in a multi-floor scenario where the transmitter and receiver were connected to a universal software radio peripheral platform in a non-line-of-site environment. The data was collected in two cases of Intelligent Reflecting Surface (IRS), turn off and turn on. The accuracy achieved using three different machines learning algorithms-support vector machine bagging, and decision tree were 31%, 23%, and 24%, respectively, improvement in the case of turn-on IRS [49].

A non-contact smart sensing through the wall system is proposed using USRP platform for HAR in [50]. An OFDM signal is used at the transmitter and receiver to extract CSI. ML algorithms have been utilized for classification the activities. The performance of the proposed approach archived 99.7% recognition accuracy using fine tree algorithm.

In [51], a distributed 2×2 MIMO system configured from the Ancortek SDR-KIT 2400T2R4 mm-Wave radar in a Single-Input-Single-Output (SISO) was used for HAR. The proposed system uses the dynamic time wrapping algorithm for gesture recognition and the performance outperform to that of SISO, where the capability to recognition in all direction is higher.

A smart monitoring for HAR framework was proposed in [52] using two USRPs platforms and ML algorithms. The proposed system, operates at 3.75 GHz, has the ability to recognize sixteen different activities based the learning technique using the obtained CSI. Up to 98% recognition accuracy was achieved using the proposed approach.

Wi-Fi CSI-based HAR is proposed in [53], with assessments and contrasts using CNN, LSTM, and combination (CNN+LSTM) approaches. The USRP used for CSI collection to recognize six different human activities. The accuracy achieved with LSTM was 95.3%, outperforming CNN and combining the combination. In [54], a USRPs-X300/X310 are utilized for human activities data collection. The CSI is used in ML classifiers for detection. The proposed techniques achieved up to 90% recognition accuracy.

A multi-sensing data fusion system was proposed in [55], for HAR. A neuromorphic computing was utilized to integrate distinct hardware devices (inertial measurement unit (IMU) sensors, software-defined radios, and radars). Feature selection, feature extraction, and hopfield neural network were used for one-shot learning. The results show that the proposed approach achieved 98.98% recognition accuracy.

A continuous wave radar was implemented at 2.4GHz for fall detection in [56]. The ML Decision Tree algorithm was used to classify an SDR signals for human fall detection. The maximum accuracy achieved of this proposed system is 99.4%.

An SDR was used to collect CSI, IQ samples, and received signal strength of WiFi and radar signals for HAR in [57]. The proposed system achieved 65.09% and 97.78% classification accuracy with CNN architecture using WiFi-based activity and Radar, respectively.

5. Literatures Performance Comparison

The design configuration and performance of the studied literatures using the SDR technology are listed in Table 1, where various classification techniques were used. Some studies used ML algorithms that comprises decision tree, k-nearest neighbor, fine K-nearest neighbor, support vector machine, Random Forest, Discriminant Analysis, Naive Bayes, Extra Tree, and bagging classifier). Other literatures utilized DL networks such as CNN and LSTM that have achieved higher recognition accuracy. Also, some literatures used the model-based classification algorithms.

Many literatures presented the transmitter and receiver sides in different positions, utilizing more than one USRP for transmitting and receiving with a distance between them, while others used a single USRP for transmitting and receiving as listed in Table 2.

The utilization of the USRP in such literatures can correct frequency and phase offsets using OFDM technique by desynchrony of local oscillators between the transmitter and receiver. Thus, CSI can be extracted which contains detailed amplitude and phase information and can be expressed as:

$$H(f_i) = H(f_i)e^{\angle H(f_i)} \quad (1)$$

where, $H(fi$)is the amplitude of CSI and $\angle H(f_i)$is the phase information of CSI. The information of the CSI can be extracted from the received OFDM subcarriers, which can be represented as:

$$H = (h_1, h_2, h_3, \ldots\ldots\ldots, h_N) \quad (2)$$

The measurement of the amplitude and phase of CSI performed using the Inverse Fast Fourier Transform block at the transmitter and Fast Fourier Transform block at the receiver. The channel response $H(f)$ can be expressed as:

$$H(f) = \frac{x(f)}{Y(f)} \quad (3)$$

where, $x(f)$ is the transmitted OFDM signal and $Y(f)$ is the received OFDM signal.

At the receiver, the OFDM signal used for extract the CSI, where the amplitude frequency response for each human activity obtained for several seconds. Each collected data consist of several OFDM symbols and subcarriers. After data collection, a preprocessing and classification techniques are used for activity recognition.

Some literatures used a Frequency Modulated Continuous Wave (FMCW) 2 × 2 MIMO radar chirp waveform to obtain the Doppler information of a moving human from different perspectives. Every transmitter broadcasts the chirp waveform on a regular basis during the specified timeslot. The human range and micro-Doppler information can be obtained from the phase and frequency fluctuations of the backscattered signal using the appropriate radar signal preprocessing techniques.

In [40], In-phase/Quadrature (I/Q) continuous wave signal has been used for transmitting as the following:

$$I_{TX}(t) = cos\left[2\pi f_{IF}t + \theta_{IF}[t]\right] \quad (4)$$

$$Q_{TX}(t) = s\,i\,n\left[2\pi f_{IF}t + \theta_{IF}[t]\right] \quad (5)$$

where, f_{IF} the intermediate frequency and θ_{IF} the phase noise.

The SDR device complete the transmitting processing and up converted the signal to the carrier frequency. The received I/Q components attenuated due to the propagation phenomena and delayed a period of time. By splitting the received signal and allocating it in parallel to the two demodulator branches, the received I/Q components are extracted. The down conversion procedure carried out by shifting the spectrum of the two signal components from the carrying frequency to the intermediate frequency once more by mixing and filtering operations.

Table 1. Studied Literatures Techniques and Performance.

Ref.	Year	Utilized Techniques	Activities	Accuracy
[35]	2013	Hidden Markov Models, Dynamic Time Warping	Push, pull, dodge, punch x2, circle, strike, kick, bowling, drag	94%
[36]	2014	ML Classifiers	Walking, standing, lying, empty, crawling	High to 70%
[37]	2019	Data for recognition only	Not mentioned	Not specified
[38]	2019	Radar signal processing	Not mentioned	Not specified
[39]	2019	Principal Component Analysis, Discrete Wavelet Transform , CNN, ML Classifiers	Hand Gestures (up, down, left, right, OTW, Boxing, Circle Slide)	96% in LOS, 92% in NLOS
[40]	2020	ML Classifiers	Standing Up, Sitting Down	90%
[41]	2020	CNN	Ankle Activities	98.98%
[42]	2020	ML Classifiers	Multi-Pose Complex Weight Lifting Activities	99.6%
[43]	2020	ML Classifiers	Standing UP, Walking, Sitting on a Chair, Bending Down, Exercise	89.73%
[44]	2020	Variances of CSI signatures	No activity, Walking, Sitting on a Chair	Not specified
[45]	2021	ML Classifiers	Elevated Breath, Normal Breath, Shallow Breath	91%
[46]	2021	DGRU, LSTM	Fall, Jump, Lay, Run, Sit, Walk, NA	95–99%
[47]	2022	ML Classifiers	Sitting, Standing, Walking	High accuracies, maximum 100%
[48]	2022	Feature extraction, CNN	Falling, Walking, Standing up, Sitting down, Picking an object	98.52%
[49]	2022	ML Classifiers	Sitting, Standing, Walking	86%
[50]	2022	ML Classifiers	Standing, Walking, Running, Bending Fall	99.7%
[51]	2022	ML, deep CNN Classifiers	Fall Detection	Not Specified
[52]	2022	ML Classifiers	Sitting, Standing, Walking	98%
[53]	2023	LSTM-CNN	No Activity, Sitting, Standing, Leaning, Walking	91%
[54]	2023	ML Classifiers	Leaning, walking, standing, Sitting	90%
[55]	2023	Hopfield Neural Network	Standing Up, Sitting Down	98.98%

[56]	2024	Decision Tree ML Classifiers	Walking, Fall	99.4%
[57]	2024	CNN	Run, fall, Walk, Lie down, Stand up, Sit down, Pick up	65.09%, 97.78%

Table 2. Studied Literatures Waveforms and SDR Utilization.

Reference	Waveform (Signal)	Number of the Utilized USRP	SDR Type
[35]	OFDM	2	USRP-N210
[36]	FM radio	2	USRP N200
[37]	OFDM	2	USRP
[38]	IQ Continuous Wave	1	USRP-2920
[39]	OFDM	1	USRP N210
[40]	OFDM	2	USRP X310/X300
[41]	OFDM	2	USRP B210
[42]	OFDM	2	USRP B210
[43]	OFDM	2	USRP X310/X300
[44]	OFDM	2	USRP X310/X300
[45]	OFDM	2	USRP X310/X300
[46]	OFDM	2	USRP
[47]	OFDM	2	USRP X310/X300
[48]	FMCW 2×2 MIMO	1	SDR-KIT 2400T2R4
[49]	OFDM	2	USRP X310/X300
[50]	OFDM	2	USRP B210
[51]	FMCW 2×2 MIMO	1	SDR-KIT 2400T2R4
[52]	OFDM	2	USRP X310/X300
[53]	OFDM	2	USRP X310/X300
[54]	OFDM	2	USRP X310/X300
[55]	OFDM	1	USRP X300
[56]	Digital signal	1	USRP B205-mini
[57]	FMCW	6	NI B205 mini, B201, X310, E312, RTL, HackRf

6. Conclusion

Over the last decade, researchers worldwide have concentrated on detecting human activities. HAR systems are classified into three types: sensor-based, vision-based, and RF-based HAR. This article provides an exhaustive review of the RF-based HAR systems using SDR. The RF-based HAR is chosen over the sensor-based and vision-based HARs because it does not require any wear sensor. It can be conclude that the majority used techniques of ML and CNN. Many researches focused on large scale activities regarding to the upper and lower limps, while other focused on small scale activities like breathing.

Regarding to the accuracy, the overall accuracy of various techniques were below the acceptable ratio (less than 90%). The utilizing SDR technology for HAR on the other hand is much better than other wireless products due to its flexibility and scalability to perform a wireless designs. Various SDR platforms have been utilized in the literatures for CSI and dataset collection with various system designs in various environments. The SDR-based HAR achieves higher recognition accuracies using various ML and DL algorithms.

References

1. Qiu, S., Zhao, H., Jiang, N., Wang, Z., Liu, L., An, Y., ... & Fortino, G. (2022). Multi-sensor information fusion based on machine learning for real applications in human activity recognition: State-of-the-art and research challenges. *Information Fusion*, 80, 241-265.
2. Gupta, N., & Agarwal, B. B. (2023). Recognition of Suspicious Human Activity in Video Surveillance: A Review. Engineering, *Technology & Applied Science Research*, 13(2), 10529-10534.
3. Tripathi, R. K., Jalal, A. S., & Agrawal, S. C. (2018). Suspicious human activity recognition: a review. *Artificial Intelligence Review*, 50, 283-339.
4. Zin, T. T., Htet, Y., Akagi, Y., Tamura, H., Kondo, K., Araki, S., & Chosa, E. (2021). Real-time action recognition system for elderly people using stereo depth camera. *Sensors*, 21(17), 5895.
5. Dang, L. M., Min, K., Wang, H., Piran, M. J., Lee, C. H., & Moon, H. (2020). Sensor-based and vision-based human activity recognition: A comprehensive survey. *Pattern Recognition*, 108, 107561.
6. Chen, K., Zhang, D., Yao, L., Guo, B., Yu, Z., & Liu, Y. (2021). Deep learning for sensor-based human activity recognition: Overview, challenges, and opportunities. *ACM Computing Surveys (CSUR)*, 54(4), 1-40.

7. Tripathi, R. K., Jalal, A. S., & Agrawal, S. C. (2018). Suspicious human activity recognition: a review. *Artificial Intelligence Review*, 50, 283-339.
8. Vrigkas, M., Nikou, C., & Kakadiaris, I. A. (2015). A review of human activity recognition methods. *Frontiers in Robotics and AI*, 2, 28.
9. Zheng, W., Yan, L., Gou, C., & Wang, F. Y. (2022). Meta-learning meets the Internet of Things: Graph prototypical models for sensor-based human activity recognition. *Information Fusion*, 80, 1-22.
10. Wang, W., Liu, A. X., Shahzad, M., Ling, K., & Lu, S. (2017). Device-free human activity recognition using commercial WiFi devices. *IEEE Journal on Selected Areas in Communications*, 35(5), 1118-1131.
11. Beddiar, D. R., Nini, B., Sabokrou, M., & Hadid, A. (2020). Vision-based human activity recognition: a survey. *Multimedia Tools and Applications*, 79(41), 30509-30555.
12. Mahmud, T., & Hasan, M. (2021). Vision-based human activity recognition. *Contactless Human Activity Analysis*, 1-42.
13. Wang, J., Chen, Y., Hao, S., Peng, X., & Hu, L. (2019). Deep learning for sensor-based activity recognition: A survey. *Pattern recognition letters*, 119, 3-11.
14. Wang, Y., Cang, S., & Yu, H. (2019). A survey on wearable sensor modality centred human activity recognition in health care. *Expert Systems with Applications*, 137, 167-190.
15. De-La-Hoz-Franco, E., Ariza-Colpas, P., Quero, J. M., & Espinilla, M. (2018). Sensor-based datasets for human activity recognition–a systematic review of literature. *IEEE Access*, 6, 59192-59210.
16. Zhang, H. B., Zhang, Y. X., Zhong, B., Lei, Q., Yang, L., Du, J. X., & Chen, D. S. (2019). A comprehensive survey of vision-based human action recognition methods. *Sensors*, 19(5), 1005.

17. Manaf, A., & Singh, S. (2021, May). Computer vision-based survey on human activity recognition system, challenges and applications. In *2021 3rd International Conference on Signal Processing and Communication (ICPSC)* (pp. 110-114). IEEE.
18. Boulila, W., Shah, S. A., Ahmad, J., Driss, M., Ghandorh, H., Alsaeedi, A., ... & Saeed, F. (2021). Noninvasive detection of respiratory disorder due to covid-19 at the early stages in saudi arabia. *Electronics*, 10(21), 2701.
19. Adib, F., Kabelac, Z., & Katabi, D. (2015). Multi-person motion tracking via RF body reflections. In *NSDI'15: Proceedings of the 12th USENIX Conference on Networked Systems Design and Implementation* (pp. 279–292).
20. Rehman, M. U., Najam, S., Khalid, S., Shafique, A., Alqahtani, F., Baothman, F., ... & Ahmad, J. (2021). Notice of Retraction: Infrared Sensing Based Non-Invasive Initial Diagnosis of Chronic Liver Disease Using Ensemble Learning. *IEEE Sensors Journal*, 21(17), 19395-19406.
21. Wei, B., Hu, W., Yang, M., & Chou, C. T. (2019). From real to complex: Enhancing radio-based activity recognition using complex-valued CSI. ACM *Transactions on Sensor Networks (TOSN)*, 15(3), 1-32.
22. Arshad, M. H., Bilal, M., & Gani, A. (2022). Human activity recognition: Review, taxonomy and open challenges. *Sensors*, 22(17), 6463.
23. Li, X., Zhao, P., Wu, M., Chen, Z., & Zhang, L. (2021). Deep learning for human activity recognition. *Neurocomputing*, 444, 214-216.
24. Abdel-Basset, M., Hawash, H., Chakrabortty, R. K., Ryan, M., Elhoseny, M., & Song, H. (2020). ST-DeepHAR: Deep learning model for human activity recognition in IoHT applications. *IEEE Internet of Things Journal*, 8(6), 4969-4979.
25. Alshehri, F., & Muhammad, G. (2020). A comprehensive survey of the Internet of Things (IoT) and AI-based smart healthcare. *IEEE access*, 9, 3660-3678.
26. Medhane, D. V., Sangaiah, A. K., Hossain, M. S., Muhammad, G., & Wang, J. (2020). Blockchain-enabled distributed security framework for next-generation IoT: An edge cloud and software-defined network-integrated approach. *IEEE Internet of Things Journal*, 7(7), 6143-6149.
27. Loncar-Turukalo, T., Zdravevski, E., da Silva, J. M., Chouvarda, I., & Trajkovik, V. (2019). Literature on wearable technology for connected health: scoping review of research trends, advances, and barriers. *Journal of medical Internet research*, 21(9), e14017.
28. Muaaz, M., Chelli, A., Gerdes, M. W., & Pätzold, M. (2022). Wi-Sense: A passive human activity recognition system using Wi-Fi and convolutional neural network and its integration in health information systems. *Annals of Telecommunications*, 77(3), 163-175.
29. Ye, W., Chen, H., & Li, B. (2019). Using an end-to-end convolutional network on radar signal for human activity classification. *IEEE Sensors Journal*, 19(24), 12244-12252.
30. Liu, J., Wang, L., Guo, L., Fang, J., Lu, B., & Zhou, W. (2017, October). A research on CSI-based human motion detection in complex scenarios. In *2017 IEEE 19th International Conference on e-Health Networking, Applications and Services (Healthcom)* (pp. 1-6). IEEE.
31. Zhang, J., Xu, W., Hu, W., & Kanhere, S. S. (2017, November). Wicare: Towards in-situ breath monitoring. In *Proceedings of the 14th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services* (pp. 126-135).

32. Krueckemeier, M., Schwartau, F., Monka-Ewe, C., & Technische, J. S. (2019, June). Synchronization of multiple USRP SDRs for coherent receiver applications. In *2019 Sixth International Conference on Software Defined Systems (SDS)* (pp. 11-16). IEEE.
33. Machado-Fernández, J. R. (2015). Software defined radio: Basic principles and applications. *Revista Facultad de Ingeniería*, 24(38), 79-96.
34. Ulversoy, T. (2010). Software defined radio: Challenges and opportunities. *IEEE Communications Surveys & Tutorials*, 12(4), 531-550.
35. Pu, Q., Gupta, S., Gollakota, S., & Patel, S. (2013, September). Whole-home gesture recognition using wireless signals. In *Proceedings of the 19th annual international conference on Mobile computing & networking* (pp. 27-38).
36. Sigg, S., Scholz, M., Shi, S., Ji, Y., & Beigl, M. (2013). RF-sensing of activities from non-cooperative subjects in device-free recognition systems using ambient and local signals. *IEEE Transactions on Mobile Computing*, 13(4), 907-920.
37. Khan, M. B., Yang, X., Ren, A., Al-Hababi, M. A. M., Zhao, N., Guan, L., ... & Shah, S. A. (2019). Design of software defined radios based platform for activity recognition. *IEEE Access*, 7, 31083-31088.
38. Costanzo, S. (2019). Software-defined doppler radar sensor for human breathing detection. *Sensors*, 19(14), 3085.
39. Zhang, T., Song, T., Chen, D., Zhang, T., & Zhuang, J. (2019). WiGrus: A WiFi-based gesture recognition system using software-defined radio. *IEEE Access*, 7, 131102-131113.
40. Taylor, W., Shah, S. A., Dashtipour, K., Zahid, A., Abbasi, Q. H., & Imran, M. A. (2020). An intelligent non-invasive real-time human activity recognition system for next-generation healthcare. *Sensors*, 20(9), 2653.
41. Barua, A., Zhang, Z. Y., Al-Turjman, F., & Yang, X. (2020). Cognitive intelligence for monitoring fractured post-surgery ankle activity using channel information. *IEEE Access*, 8, 112113-112129.
42. Al-hababi, M. A. M., Khan, M. B., Al-Turjman, F., Zhao, N., & Yang, X. (2020). Non-contact sensing testbed for post-surgery monitoring by exploiting artificial-intelligence. *Applied Sciences*, 10(14), 4886.
43. Ashleibta, A. M., Zahid, A., Shah, S. A., Abbasi, Q. H., & Imran, M. A. (2020). Flexible and scalable software defined radio based testbed for large scale body movement. *Electronics*, 9(9), 1354.
44. Ashleibta, A. M., Zahid, A., Shah, S. A., Imran, M. A., & Abbasi, Q. H. (2020, July). Software defined radio based testbed for large scale body movements. In *2020 IEEE International Symposium on Antennas and Propagation and North American Radio Science Meeting* (pp. 2079-2080). IEEE.
45. Ashleibta, A. M., Abbasi, Q. H., Shah, S. A., Khalid, M. A., AbuAli, N. A., & Imran, M. A. (2020). Non-invasive RF sensing for detecting breathing abnormalities using software defined radios. *IEEE Sensors Journal*, 21(4), 5111-5118.
46. Bokhari, S. M., Sohaib, S., Khan, A. R., & Shafi, M. (2021). DGRU based human activity recognition using channel state information. *Measurement*, 167, 108245.
47. Usman, M., Rains, J., Cui, T. J., Khan, M. Z., Kazim, J. U. R., Imran, M. A., & Abbasi, Q. H. (2022). Intelligent wireless walls for contactless in-home monitoring. *Light: Science & Applications*, 11(1), 212.

48. Waqar, S., Muaaz, M., & Pätzold, M. (2023). Direction-Independent Human Activity Recognition Using a Distributed MIMO Radar System and Deep Learning. *IEEE Sensors Journal*.
49. Saeed, U., Shah, S. A., Khan, M. Z., Alotaibi, A. A., Althobaiti, T., Ramzan, N., & Abbasi, Q. H. (2022). Intelligent reflecting surface-based non-LOS human activity recognition for next-generation 6G-enabled healthcare system. *Sensors*, 22(19), 7175.
50. Khan, M. B., Mustafa, A., Rehman, M., AbuAli, N. A., Yuan, C., Yang, X., ... & Abbasi, Q. H. (2022). Non-contact smart sensing of physical activities during quarantine period using SDR technology. *Sensors*, 22(4), 1348.
51. Waqar, S., Muaaz, M., & Pätzold, M. (2022). Human activity signatures captured under different directions using SISO and MIMO radar systems. *Applied Sciences*, 12(4), 1825.
52. Saeed, U., Yaseen Shah, S., Aziz Shah, S., Liu, H., Alhumaidi Alotaibi, A., Althobaiti, T., ... & Abbasi, Q. H. (2022). Multiple participants' discrete activity recognition in a well-controlled environment using universal software radio peripheral wireless sensing. *Sensors*, 22(3), 809.
53. Khan, M. Z., Ahmad, J., Boulila, W., Broadbent, M., Shah, S. A., Koubaa, A., & Abbasi, Q. H. (2023, June). Contactless Human Activity Recognition using Deep Learning with Flexible and Scalable Software Define Radio. In *2023 International Wireless Communications and Mobile Computing (IWCMC)* (pp. 126-131). IEEE.
54. Saeed, U., Shah, S. A., Khan, M. Z., Alotaibi, A. A., Althobaiti, T., Ramzan, N., ... & Abbasi, Q. H. (2023). Software-defined radio based contactless localization for diverse human activity recognition. *IEEE Sensors Journal*.
55. Yu, Z., Zahid, A., Taha, A., Taylor, W., Le Kernec, J., Heidari, H., ... & Abbasi, Q. H. (2022). An intelligent implementation of multi-sensing data fusion with neuromorphic computing for human activity recognition. *IEEE Internet of Things Journal*, 10(2), 1124-1133.
56. Alimisis, V., Arnaoutoglou, D. G., Serlis, E. A., Kamperi, A., Metaxas, K., Kyriacou, G. A., & Sotiriadis, P. P. (2024). A radar-based system for detection of human fall utilizing analog hardware architectures of decision tree model. *IEEE Open Journal of Circuits and Systems*, 5, 224-242.
57. Dahal, A. (2024). Software Defined Radio (SDR) based sensing, M. Sc Dissertation, James Worth Bagley College of Engineering, Mississippi State University.