

2nd International Conference on Innovative Solutions in Software Engineering

nov 29, 30 2023 : Ivano-Frankivsk, Ukraine



MULTIMODAL RADAR DATA FUSION FOR HUMAN ACTIVITY RECOGNITION

Djazila Souhila KORTI¹ & Zohra SLIMANE¹

¹ Belhadj BOUCHAIB University, Ain Temouchent, Algeria

OUTLINE		
	Introduction	
	Radar based HAR	
	Multi-Sensor Radar System for HAR	
	Main objectives	
	Materiels and mathod	
	Results	
	Conclusion	

Introduction

Human Activity Recognition or HAR, is the process of using technology to automatically identify and classify human activities.

* HAR plays a pivotal role in applications ranging from healthcare and sports to security and smart environments.

HAR can be achieved based on data from various sensors and sources.



Radar-based Human Activity Recognition offers a distinct advantage due to its ability to operate in various environmental conditions, including low light, darkness, and adverse weather, which can be challenging for cameras.

* Radars can passively detect activities without user intervention.

Radar systems can provide a wide field of view and capture activities across a larger area, making them well-suited for applications in smart environments and security where comprehensive coverage is essential.

Multi-Sensor Radar System for HAR

Multi-sensor setups capture a more comprehensive and accurate picture of human activities by collecting data from various radar sources.

The combination of data from multiple sensors enables a more robust analysis of human movements, reducing the risk of false positives or inaccuracies.

Multi-sensor systems provide redundancy, making them more resilient to sensor failures or inaccuracies, ensuring continuous and reliable monitoring.

Main objectives

The present work aims to :



Focus on data fusion techniques in radar-based multimodal Human Activity Recognition (HAR) systems.



Consider three key approaches: early fusion, mid-fusion, and late fusion.



Introduce a hybrid model for multi sensor systems.



Determine the most effective way to fuse data from multiple radar sources for accurate human activity recognition.

Data base: The multi-frequency RF sensor network's human activity database

Proposed by	Data acquisition	Participants	N° of samples	Number of gesture classes
Gurbuz et al. (2020)	 frequency-modulated continuous waves (FMCW) at 77 GHz. frequency-modulated continuous waves at 24 GHz. ultra-wideband radio pulses (IR- UWB) at 10 GHz. 	6 volunteers	60 image for each class/radar	



Fig. 1 Micro-Doppler signature for each radar/activity

Multi Input-Multi Output Convolutional Extra Trees (MIMO-CxT)

- MIMO-CxT is a combination between a convolutional neural network and Extra Tress classifier
- Consists of a multi input architecture each on fed with the data of a specific radar.
- A light weight architecture with fewer parameters.
- Detect different patterns.
- Extract more diverse features from the same activity.
- Provide the final classifier with more information to make a decision.



Fig. 2 MIMO-CxT architecture [14]

[14] D.S. Korti, Z. Slimane, "Unobtrusive hand gesture recognition for post stroke patient rehabilitation using ultra-wide band radar and deep learning," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 13, no 6, pp. 6872-6881,2023. available: https://ijece.iaescore.com/index.php/IJECE/article/view/32272.

Fusion strategy

• **Early Fusion:** We combine the sensor data from different frequencies at the beginning of the processing pipeline.

 Late Fusion: data integration takes place after the individual processing of each sensor's output.

 Halfway Fusion: Merging data from multiple sensors at an intermediate stage of the processing.





Performance measures

Accuracy =
$$\frac{T_P + T_N}{T_P + F_P + F_N + T_N}$$

$$Precision = \frac{T_P}{T_P + F_P}$$

Recall =
$$\frac{T_P}{T_P + F_N}$$

True Positives
$$(T_p)$$

True Negatives (T_N)
False Positives (F_p)
False Negatives (F_N)

$$FI\text{-score} = \frac{2T_P}{2T_P + F_P + F_N}$$

Implementation details

- The model is implemented in Python using Keras framework with Tensorflow backend.
- The model's performance are visualized using Yellowbrick package.

Hardware configuration :

Intel (R) Core (TM) i5@2.40 GHz CPU			
I6GBs of RAM			
ITo of hard disk and Windows 10.			

RESULTS



 Replace depth separable convolutional layers with conventional convolutional layers and changing the number of units in the last dense layer to 150, all the preset model configurations remain unchanged.

• The three-input CNN-Softmax is trained with 100 epochs by the back-propagation algorithm using a batch size of 16,

• Softmax is replaced by the Extra Trees classifier.

RESULTS

Evaluation process



 Table 1. Comparative analysis of performance for fusion strategy

Fusion strategy	Train acc (%)	Test acc (%)	Runtime prediction (s)	CNN N° of parameters
Early fusion	100	94.65	0.230664	79459
Halfway fusion	100	95.41	0.264935	233699
Late fusion	100	90.83	0.443204	234899

Fig. 5 Classification report: (a) early, (b) halfway, (c) late, fusion



Halfway fusion has consistently demonstrated superior performance in HAR models, producing the most accurate results compared to other fusion methods, making it an indispensable approach in this field.



The combination of Convolutional Neural Networks (CNN) with Extra Trees has proven to be a highly effective strategy for achieving enhanced performance in HAR systems. This fusion of deep learning and ensemble methods significantly boosts accuracy and robustness.

3 Not only the model structure but also the choice of fusion strategy plays a pivotal role in the development of accurate HAR models. The synergy between model architecture and fusion techniques is a critical factor in achieving reliable and precise human activity recognition.

Thank you !