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Human Activity Recognition Using SVM-based on micro-Doppler Radar Data Classification

Claire Béranger[1], Alexandre Bordat[1,2], Petr Dobias[1], Ngoc-Son Vu[1],
Julien Le Kernec[1,3], David Guyard[2], Olivier Romain[1,3]
[1]*ETIS Laboratory UMR 8051, CY Cergy Paris Université, ENSEA, CNRS, F-95000 Cergy, France*
[2]*BlueLinea, 12 Parvis Colonel Arnaud Beltrame, 78000 Versailles, France*
[3]*James Watt School of Engineering, University of Glasgow, Glasgow, United Kingdom*
smartgaitlab@etis-lab.fr

Abstract—**In response to the challenges posed by an ageing population, radar-based fall detection is gaining attention as a valuable tool for clinical monitoring and teleassistance. Once the radar signals are processed, they can be visualised as spectrograms that capture the dynamic signatures of human activity. In this work, we propose an approach that leverages image processing techniques to extract descriptive features, such as *Area*, *Perimeter* or *Orientation* from these activity signatures. These features are then fed into a Support Vector Machine (SVM), a lightweight yet effective classification model. Our method achieves an accuracy of 88.85%, providing a resource-efficient alternative that matches or exceeds more complex state-of-the-art solutions.**

Keywords-Radar Spectrogram, Human Activity Recognition, Classification, SVM, Clinical Context

I. Introduction

Many developed countries face an ageing population, increasing the risk of motor impairments and falls. In France, 20% of the population is at risk, leading to 10,000 deaths and more than 136,000 hospital admissions each year [1]. In 2022, global recommendations were established for elderly fall prevention [2]. The standard approach involves physician referrals for clinical gait and balance assessments. However, overcrowded services often lack sufficient staff and time.

Wearable sensors, such as gyroscopes and accelerometers in necklaces or watches, can be used to recognise activities like "Walk" [3], but they are restrictive. Cameras offer alternatives, yet remain intrusive as well [4]. Radar provides a non-intrusive way to detect micro-movements without visual imaging. The resulting micro-Doppler spectrograms reflect activity-specific limb movements [5]. Classification models like Support Vector Machine (SVM), K-Nearest Neighbors (KNN) and GoogLeNet achieved recognition accuracies from 74% to 94%.

The study [6] achieved 87.10% accuracy with ResNet-18, without modifying the model or input data. This suggests potential for improvement using basic image processing and a lighter model. This paper proposes a lightweight classifier for human activity recognition based on spectrogram features, and explores simple image processing techniques.

Section II reviews radar pre-processing, classification methods, and image processing techniques used. Then, Section III presents the spectrogram generation, feature extraction, and classification applied. Section IV describes and compares results with [6], while Section V offers an overall analysis.

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II. Related Work

In this section, we present the radar data extraction method and the recognition techniques developed from it.

A. Radar Data Extraction

Radar (Radio Detection And Ranging) uses radio waves to detect and track objects. For activity recognition, its key advantage is analysing Doppler signatures [6]. Doppler signatures reflect frequency changes due to movement, while micro-Doppler are small variations caused by finer movements, such as arm motion during walking.

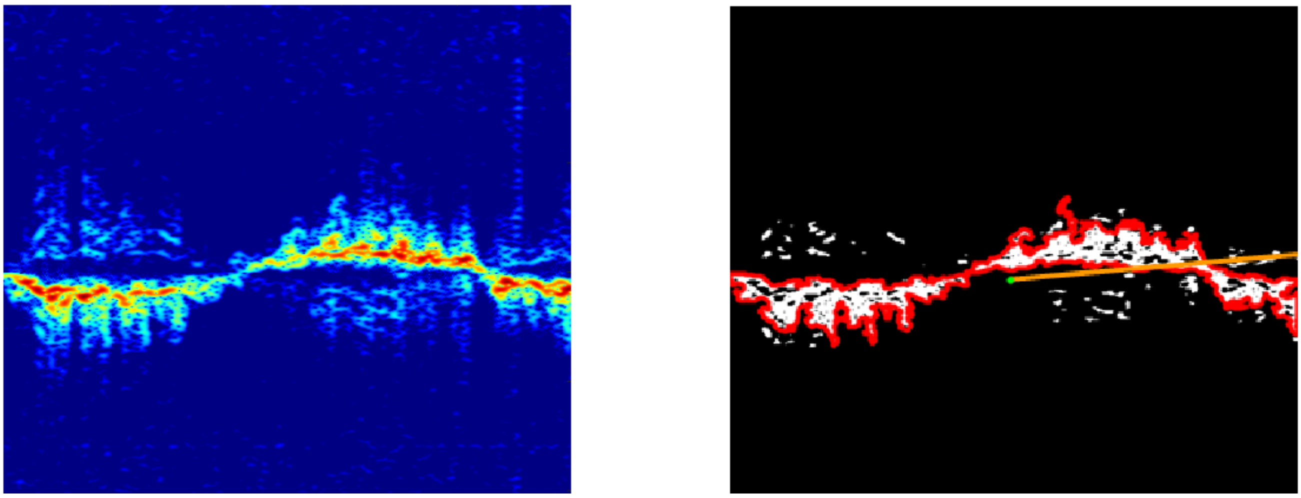
The radar emits signals and measures reflections. Most studies use Frequency Modulated Continuous Wave (FMCW) radars [7]. Analysis of the received signal provides Doppler frequency and time delay (beat frequency). Raw data undergoes Fast Fourier Transform (FFT) to extract distance and time, followed by filtering to remove static elements. Then, a Short Time Fourier Transform (STFT) generates velocity-time representations, highlighting Doppler variations.

The pre-processed data are spectrograms, visually representing movement speed over time. As shown in Figure 1a, spectrograms display signal energy distribution during an activity. These representations serve as the basis for recognition algorithms, which distinguish activities by their unique signatures.

For FMCW radar, range resolution depends on bandwidth, while Doppler resolution depends on observed signal duration in the STFT. In this study, we use a range resolution of 37.5 cm and Doppler resolution of 1.25 Hz (0.03 m/s), enabling accurate velocity analysis and classification. Using these parameters, spectrograms like Figure 1a are generated.

B. Activity Classification

Current research aims to improve image classification using radar data from animals or humans [9], [10]. Common models like SVM, KNN and ResNet-18 [6], [11], [12] require sufficient data for training. Experiments on the *Radar Signatures of Human Activities* dataset [8] show spectrograms are effective for recognition. Studies [11], [12] used AlexNet for feature extraction and transfer learning to SVM and KNN, achieving accuracies of 78.25% and 77.15%. Transfer learning uses knowledge from pre-trained models to solve related tasks.



(a) Spectrogram of "Walk" [8]

(b) Parameters Extraction (*Area*, *Perimeter*, *Orientation*, *Centroid*)

FIGURE I. Spectrogram Analysis, from the Original to the Parameters Extraction

ResNet-18, an 18-layer network, achieves 70% to 90% accuracy without optimisation, and suits resource-limited systems [6]. The study [6] reported 87.10% accuracy with unmodified ResNet-18. While deep learning models perform well, SVMs remain a viable lightweight alternative for embedded applications due to fast training and low resource needs.

SVMs are effective in human activity recognition by constructing optimal hyperplanes between classes. The study [13] showed SVMs can reach 92.8% accuracy on Continuous Wave (CW) radar and 95.4% on FMCW, though performance varies with pre-processing. Based solely on micro-Doppler data, the accuracy drops to around 80%. Kernel choice, hyperparameters, and pre-processing are critical. SVMs remain a strong option for balancing performance with hardware constraints, especially when combined with feature extraction.

C. Image Processing, Parameters Extraction & PCA

Studies [12], [13] on human activity recognition from spectrograms aim to improve performance by processing data. Some approaches [14] adjust parameters during data acquisition and pre-processing, like filters or biases. Others [15] modify the data before classification, with common classifiers including Convolutional Neural Network (CNN) or SVM.

Most datasets offer opportunities to enhance accuracy with different processing strategies. These datasets address human activity recognition in diverse contexts, based on spectrograms from radar or simulated sensors. The *Radar signatures of human activities* dataset [8], widely used with over 5,000 downloads, has been extensively tested in pre-processing, spectrogram manipulation, and classification. Techniques like binarisation and masks help extract relevant activity features.

Classical processing methods bring only slight improvements. Studies [16] show that Principal Component Analysis (PCA) effectively reduces dimensionality by selecting key spectrogram variables. This enhances model accuracy and lowers computational cost.

III. METHODOLOGY

This section describes the input data generation method and the classification model employed to improve accuracy.

A. Spectrogram Generation & Parameter Extraction

The *Radar signatures of human activities* [8] dataset, chosen for its completeness and relevance, contains 1,753 images across 6 activity classes. We follow the pre-processing chain of authors. After generating spectrograms, activity signatures are extracted by binarising the images, unlike [6], which used raw spectrograms. To reduce storage and computational costs, classical shape-based features are preferred.

We extract 8 shape features, *Area*, *Perimeter*, *Orientation*, *Major*, *Minor*, *Centroids X and Y*, and *Excentricity*, using mathematical methods and the *skimage*[1] Python library. Activity signatures are isolated by identifying connected regions in the binarised spectrograms. Morphological and geometric descriptors are computed via the *regionprops* function, while contours are extracted using *measure.find_contours* with a 0.9 threshold and *fully_connected* = ”*high*” option enabled to have full diagonal connectivity.

$$\theta = \begin{cases} \theta + 90, & \text{if } \theta < 0 \\ \theta - 90, & \text{else} \end{cases} \tag{1}$$

Contours oriented clockwise are reversed to counterclockwise to maintain geometric consistency. Orientation θ is converted to degrees and adjusted for the image coordinate system, where y increases downward, as described in Equation 1.

B. Hyperparameter & Parameter Selection

The *Radar signatures of human activities* [8] dataset contains two similar activities: "Pick" and "Drink". The paper [6] showed this confusion. To address this issue, we propose combining these activities under a single label, "Other". As a

[1] https://scikit-image.org/

result, we work with 5 activity classes: "Walk", "Sit", "Stand", "Other", "Fall".

The optimal SVM kernel was chosen based on the five highest classification accuracies from spectrogram parameters. Among common kernels (Linear, RBF, Sigmoid, Polynomial), Linear and Sigmoid were excluded due to the nonlinearity data. RBF and Polynomial kernels, which performed well in initial tests, were compared to identify the most suitable kernel and hyperparameters for human activity recognition.

For the Polynomial kernel, key hyperparameters include *C* (error penalty), *degree* (model complexity), and *coef0* (importance of lower *degree* terms, especially when *degree* > 1). Hyperparameter tuning was done using *GridSearchCV* (exhaustive search with cross-validation) and *Randomized-SearchCV* (random sampling within defined bounds), both ensuring model robustness and generalisation.

Finally, we apply PCA to reduce data dimensionality, capture key variations, and compare results with and without this technique. The goal is to optimise model parameters and hyperparameters by selecting the most relevant features from spectrogram signatures.

C. Classification Method

The study [6] has highlighted the feasibility of recognising activities using a simple and easily implementable recognition method. ResNet-18 performed initial training directly on the spectrograms obtained at the output of a radar recording. However, we are now exploring an alternative approach for interpreting the signatures, while still aiming to maintain a simple and lightweight solution.

An SVM is used to learn from spectrograms after feature extraction. It offers a lightweight, fast, and effective solution, especially for small datasets, and requires minimal storage. The *SVM implementation* from the Python library *sklearn*[2] is used, with the kernel type selected based on extracted data results. Hyperparameter tuning, detailed in Section III-B, identifies optimal settings.

Training is conducted on the *Radar signatures of human activities* dataset [8], using the same train and test splits as [6] for fair comparison with the ResNet-18 model. Despite the imbalance of the dataset, particularly fewer samples for the "Fall" activity, this does not hinder performance evaluation, as noted in [6]. The model is trained on features extracted from spectrograms stored in text files. From eight initial features, the most relevant ones are selected, as described in Section III-B, along with suitable kernels and hyperparameters.

IV. RESULTS & DISCUSSION

This section outlines the results, from parameter extraction to model training.

A. Hyperparameter Selection

The results presented here focus on the Polynomial kernel. To identify optimal hyperparameters, we applied two search techniques: *GridSearchCV*, which exhaustively explores a predefined set, and *RandomizedSearchCV*, which samples a fixed number of combinations randomly. We tuned the hyperparameters *C*, *degree*, and *coef0*. Both methods agreed on *coef0* = 1.0, but highlighted two promising values for *C* (100, 1000) and *degree* (3, 4).

TABLE I. ACCURACY FOR ALL HYPERPARAMETERS COMBINATIONS

	C=100	C=1000
degree=3	87.45%	87.45%
degree=4	87.80%	86.41%

All four combinations were tested, revealing up to a 10% accuracy difference between *degree* = 3 with *C* = 1000 and *degree* = 4 with *C* = 100. The highest accuracy was achieved with *degree* = 4 and *C* = 100, as shown in Table I. The next step involves extracting and selecting the most relevant features from the spectrogram data.

B. Parameter Extraction and Selection

To extract the characteristic data, the spectrogram image is first binarised as shown in Figure 1b, followed by contour extraction to recover the activity signature. This enables the computation of eight previously described parameters, including *Area*, *Perimeter*, and *Orientation*. In Figure 1b, the *Area* is outlined in red, the *Orientation* indicated by the orange line, and the *Centroid* marked by the green dot.

These parameters serve as SVM inputs, but their relevance must be assessed to determine whether the full set is necessary. PCA is then applied: the data are centred and standardised, and the explained variance of each principal component is calculated. As shown in Figure 2, at least 5 components are needed to preserve 90% of the total variance, indicating robust data representation.

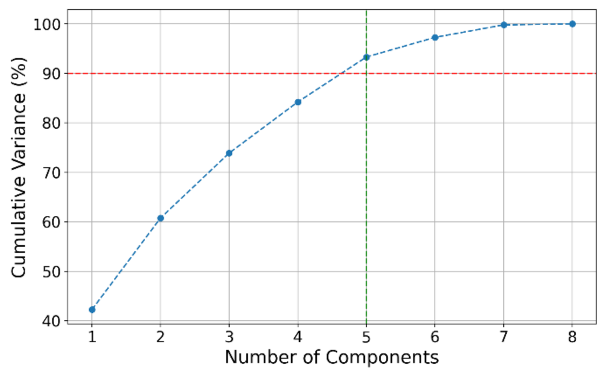


FIGURE II. Explained Variance per PCA

Subsequently, all parameter combinations were evaluated. Subsets of 5 to 6 features proved sufficient to achieve recognition rates of approximately 80% or higher. Among the top-performing subsets, the most consistently relevant features, identified using the polynomial kernel with tuned hyperparameters, are *Orientation*, *Major*, *Minor*, *Centroid X*, *Centroid Y*, and *Excentricity*.

C. SVM Application and Its Advantage over ResNet-18

Using the selected feature set, the SVM with a Polynomial kernel achieved an accuracy of 88.85%. This configuration

[2] https://scikit-learn.org/stable/

included the features *Orientation*, *Major*, *Minor*, *Centroid X*, *Centroid Y*, and *Excentricity*. The confusion matrix in Figure 3 confirms strong classification performance, with clear diagonals and minimal confusion between classes.

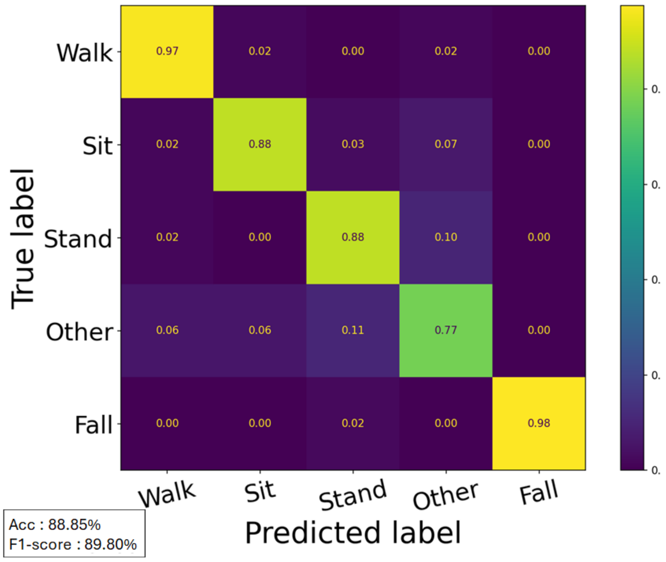


FIGURE III. SVM Normalised Confusion Matrix

The use of SVM improved activity recognition performance by 1.75% compared to the ResNet-18 of [6]. Grouping similar activities helped reduce confusion, while learning from image-extracted parameters led to further gains, exceeding a 1% improvement. These results emphasise the value of clearly defined spectrogram signatures, as more distinctive features allow for more accurate classification. In [6], an accuracy of 87.10% was achieved using dataset [8]. Our approach demonstrates that a lightweight, resource-efficient method focused on the most relevant features can still deliver strong performance.

V. CONCLUSION

This paper proposes a method for recognising human activity using Frequency Modulated Continuous Wave (FMCW) radar data. Spectrograms are generated through a preprocessing chain from an open-source dataset [8]. Key features such as *Area*, *Perimeter*, and *Orientation* are extracted from these spectrograms and used to train a Support Vector Machine (SVM). Using Principal Component Analysis (PCA), the approach achieved an accuracy of up to 88.85%, demonstrating that complex radar data can be effectively analysed with simple, informative features.

Future work will focus on exploring lightweight, efficient activity recognition methods and enhancing existing techniques. Once detection and recognition reach satisfactory performance, the next step will involve developing and evaluating a real-time solution for fall risk prediction. The long-term objective is to create a real-time embedded system suitable for real-world deployment.

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