# Radar Sensing in Assisted Living: an Overview

J. Le Kernec, F. Fioranelli
University of Glasgow
University Avenue
G12 8QQ Glasgow, UK

C. Ding, H. Zhao, L. Sun, H. Hong
Nanjing University of Science and Technology
200 Xiaolingwei Street,
210094, Nanjing, Jiangsu, China.

O. Romain, J. Lorandel
University Cergy Pontoise, ETIS
6 av du ponceau
95000 Cergy-Pontoise, France

***Abstract*-This paper gives an overview of trends in radar sensing for assisted living. It focuses on signal processing and classification, looking at conventional approaches, deep learning and fusion techniques. The last section shows examples of classification in human activity recognition and medical applications, e.g. breathing disorder and sleep stages recognition.**

**Keywords: Radar, signal processing, human activity recognition, vital signs.**

## I. INTRODUCTION

In recent years, radar sensing for vital sign monitoring and human activity in the context of assisted living has attracted a lot of attention [1, 2]. Radar has grown quite popular as a sensing modality to support innovation in healthcare services (e.g. fall events, breathing disorder recognition) [1, 3].

Aging population is increasing rapidly worldwide, with more of them living on their own and at high risk of falling. 30% of people aged over 65 experience a serious fall event each year, with serious consequences [2]. The World Health Organization aims to democratize access to technologies providing older people with integrated care and increased autonomy, hence the interest in assisted living technologies as 30% of the world population will be over 65 by 2050. Societies will have to adapt rapidly to the health challenges related to ageing, from managing chronical and cognitive diseases, to the need of technologies for rehabilitation and preservation of mobility, for instance after strokes [2].

Many different sensing technologies have been proposed and investigated to address different needs in the assisted living context [4], ranging from wearable sensors such as accelerometers, gyroscopes, and magnetometers, to sensors embedded in the built environment such as pressure, acoustic, or infrared sensors, as well as cameras based on visible or infrared light, or depth perception. Radar is attractive for assisted living because it is wireless and seamless integration in the person's environment while preserving privacy [5].

This paper gives an overview of radar sensing developments in assisted living. In section II, we discuss radar signal processing going from conventional to deep learning techniques and exploring information fusion: multi-domains and multi-sensors. In section III, we describe recent applications of radar for assisted living. Finally, section IV concludes the paper.

## II. SIGNAL PROCESSING

The use of radar in the assisted living and healthcare context had initially focused on fall detection of the elderly [1]. Recent research shows many emerging additional applications, supported by innovative signal processing solutions. Figure 1 provides a compact sketch summarizing them, with the more conventional approaches (black), and emerging ones such as multi-domain radar analysis (green), multimodal sensing with information fusion (blue), and deep learning (orange).

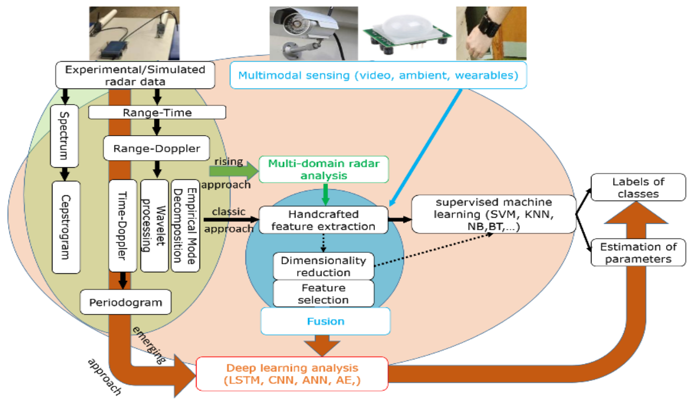


Figure 1. State of the art in radar signal processing for healthcare applications in assisted living, with conventional approach for fall detection in black color, and recent innovations highlighted in different colors.

### A. *Conventional Approach*

Signal processing will start from the raw data, which may be directly digitized as complex IQ samples, or reconstructed with a Hilbert transform. The transmitted radar signal $s(t)$ can be CW, FMCW, a modulated pulse, or waveforms derived from telecommunications. The received signal $s_r(t)$ can be modelled as the sum of the backscattered radar echoes from $N$ targets multiplied by the radar cross section $\sigma_n$ and delayed by the delay $\tau_n$ to and from a target at range $R_n$.

The conventional approach will then apply time-frequency (TF) distributions to the received signals (very often Short Time Fourier Transform (STFT) [1]) to extract Doppler-time signatures, that is to characterize patterns of movements over time which are specific to each activity. Historically, those measurements were done with CW radar or such narrow bandwidth that range did not provide extra information. Nowadays, radar systems also provide sub-metric range information, with emerging mm-wave radar as FMCW or pulsed Ultra-Wide Band systems. This additional information can be exploited with Range-Time plots (sequences of received radar signals accumulated over time and stacked in matrix format) and Range-Doppler plots. STFT applies a FT with sliding window *w(t)* across the range bins *r(t)*, as shown in equation (1) to obtain a Range-Doppler plot that is then summed to get a slice of the spectrogram. STFT is well known to be a trade-off between resolution in time or frequency. More generalized forms of TF distributions were proposed to address this issue [6].

$$STFT(t,\omega) = \int r(t')w(t'-t)\exp\{-j\omega t'\}dt' \quad (1)$$

Wavelets transformations (WT) have also been proposed [1] to capture both short-timed and long-timed changes in the received radar signal through different positions and scaling of the mother wavelet function, as shown in equation (2) where $\psi(\cdot)$ is the wavelet, $\frac{\omega}{\omega_0}$ is a scale parameter.

$$WT(t,\omega) = \left(\frac{\omega}{\omega_0}\right)^{1/2} \int s(t')\,\psi^*\left(\frac{\omega}{\omega_0}(t'-t)\right)dt' \qquad (2)$$

Other domains of representation include the Periodogram or Cadence Velocity Diagram (CVD), obtained by performing a further FFT on the output of the STFT along the time dimension as indicated in equation (3), the Cepstrogram shown in equation (4), and the Empirical Mode Decomposition (EMD).

$$CVD(\omega_{cad},\omega) = \int STFT(t,\omega)\exp\{-j\omega_{cad}t\}dt \qquad (3)$$

$$C(t,t') = \left|\int \left(\log\left(\left|\mathcal{F}\left(s_r(t)\right)\right|^2\right)\right)\exp\{j\omega t'\}d\omega\right|^2 \qquad (4)$$

These are summarized on the left-hand side of Figure 1 and are conventionally followed by feature extraction, i.e. the generation of numerical parameters' values describing relevant information in the radar signatures based on a supervised learning classification framework (e.g. K Nearest Neighbors, Bayesian classifiers, Support Vector Machines, Ensemble methods). Numerous different features have been proposed for classification of radar data in the assisted living context, ranging from physical features, textural features, features based on Singular Value Decomposition and Discrete Cosine Transformation, and data-driven features extracted from adaptation of typical audio/speech processing [7]. Significant research focused on optimizing the feature extraction algorithms to maximize performances for specific applications and datasets, demonstrating that the choice of the most salient features have often more impact than the choice of a specific classifier [7].

Dimensionality reduction and feature selection techniques can help reduce the feature space to identify the most relevant and informative features, with gain in terms of lighter computational load and increased performance. Several approaches exist [7], including Principal Component Analysis (PCA), "wrapper" approaches testing all combinations of features for a set classifiers, and "filter" approaches ranking features based on information metrics. The majority of research in the literature selects features for a given application and dataset. However, the selection of such subset for different operational conditions [7] such as radar parameters (e.g. Pulse Repetition Period, aspect angle) remains an open question especially as these could be dynamic and the radar also needs to adapt accordingly [8].

### B. *Deep Learning for Radar*

Deep learning has been recently proposed for radar data classification, including in the assisted living context, to leverage the breakthrough its adoption had in image classification. This opens the possibility to shunt convoluted feature extraction and selection algorithms, and the need of inputs from "expert human operators", to let neural networks (NNs) decide automatically the best features. This "bypassing leap" is highlighted in orange in Figure 1, whereas Figure 2 shows conventional signal processing radar data domains, with the corresponding applied deep/machine learning algorithms [2].

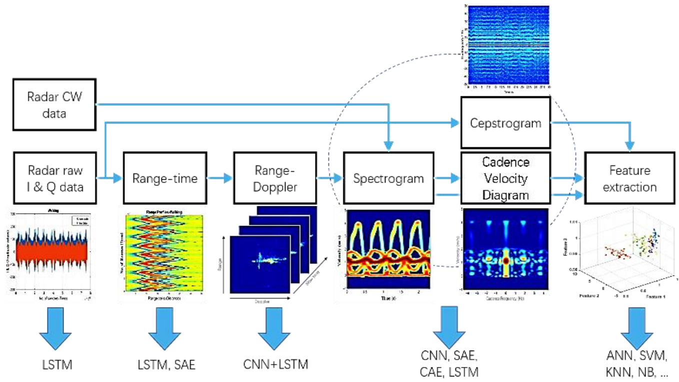


Figure 2. Typical radar signal processing chain and associated machine/deep learning method from the state of the art (SAE: stacked AutoEncoders, CAE: Convolutional AutoEncoders, LSTM: Long Short-Term Memory, CNN: Convolutional Neural Network), ANN: Artificial Neural Network.

Convolutional Neural Networks (CNN) consist of layers of convolutional filters and subsampling pooling layers, followed by fully connected layers and a decision block (very often Softmax classifier). Stacked Auto-Encoders (SAE) are NNs that attempt to learn a non-linear representation of the input at their outputs, often through a compression process as the output has reduced dimensionality compared with the input [9]. Convolutional AE (CAE) can combine the previous 2 architectures, in particular the unsupervised pre-training of the AE with the convolutional filters of CNNs [10]. These NN architectures were proposed to process radar data formatted as images, e.g. range-time and spectrograms (Figure 2).

Recurrent NNs (RNN) and in particular the Long Short Term Memory (LSTM) variant, have also been proposed to process radar data, in particular the time dependencies between samples, as these networks have been primarily designed for sequences of data such as speech or audio processing. These RNNs can be applied on spectrograms [11], combined with CNN on short series of spectrograms or range-Doppler plots [12], or directly applied on sequences of range profiles and even raw IQ data [2].

As deep learning algorithms and their underpinning technology progress, there is significant potential to transform the classification approaches in radar data. However, there are outstanding issues and questions related to the application of deep learning to radar data, such as identifying the most effective preparation strategy of training sets, choosing the best NN architecture for a given application, avoiding overfitting, and establishing a fair assessment and comparison procedure with limited datasets. Deep learning requires a large amount of training data, which, albeit easy to gather for optical images and audio, becomes unfeasible for experimental radar data. Proposed solutions include resorting to transfer learning techniques that can minimize the need of input training data and/or learn from simulated data and models, as well as the usage of Generative Adversarial Networks to augment the limited experimental data available (which is emerging in Synthetic Aperture Radar). Furthermore, there is the issue of establishing the best formats to provide radar data to NNs. These are often derived from research in computer science research and designed to process optical images/videos, and real-life audio samples. Radar data can be represented as images or sequences of samples, but they have physical meaning that may go beyond this apparent representation. A spectrogram can be seen as a matrix of pixels, but contains velocity information on targets' moving parts that may not be captured in the best way by networks designed to look for edges, surfaces, and other features of optical images. Hence, there is scope for innovative research on how to properly package and pre-process radar data for NNs, and conversely on which NN architectures are best suited to process them.

### C. *Multi-Domain Analysis*

The democratization of UWB radar chips and mm-wave radar hardware driven by the automotive sector enables the use of "range" information, as finer spatial resolution brings a wealth of supplemental information. This enables fusing information from multiple radar domains [13, 14], not just spectrograms, but also range-time and temporal sequences of range-Doppler images. In [13], a combination of range-time, spectrogram and integrated range-Doppler (IRD) information (see Figure 2 – when the range-Doppler images are integrated over slow time) goes through an SAEs to extract features from each domain followed by a Softmax layer for classification using features from all the domains combined. The most likely activity is then labeled: walk, fall, sit or bend. This method displays an overall of 95 % which is 3% higher than any of the standalone domains.

In [14], a binary classification between in-situ and non-in-situ activities in the range domain yielding 99.9% accuracy. 2 distinct algorithms are then tested on the weighted range time frequency transform. PCA-based features performed better for non-in-situ activities with bagged trees classifier with 95.3% accuracy and physical features for in-situ with subspace K-NN classifier with 94.4% accuracy.

### D. *Multi-Modal Sensing*

Every sensing technology has advantages and disadvantages, not only in terms of technical capabilities and limitations, but also for costs and perception from the end-users, patients, carers, and medical professionals if we consider the assisted living context. We argue that as technology progresses in areas such as Internet of Things (IoT) and smart homes, radar engineers will have to work with radar as "a sensor in a suite of sensors", developing signal processing methods that can combine and fuse multimodal information from heterogeneous sensors (video, acoustic, wearable, ambient sensors), as shown in blue in Figure 1. This poses additional challenges to identify which information from each sensor is the most salient for different scenarios and problems to address, and at which level fusion needs to be implemented, that is at signal, feature, or decision level [15]. Signal level fusion takes place when different sensors record similar quantities or commensurate data to combine. Feature level fusion combines all features' samples from different sources available into a single feature space, which can then be processed using feature selection and classification methods described in section II.A. Decision level fusion combines the partial decisions and levels of confidence of separate classification algorithms working independently on data from each sensor, in order to form a final decision.

Although radar in multimodal sensing has been investigated for a long time in the remote sensing community (radar data at different frequency bands and hyperspectral images) and recently for autonomous vehicles (radar plus video and Lidar data), it can still be considered an emerging approach for the assisted living and healthcare context. There is wide scope for radar researchers to investigate what additional and valuable information radar systems can provide, and what the best way is to exploit this in conjunction with other sensing modalities. As an example, Figure 3 reports results from [15] showing how combining radar and wearable data can improve the accuracy for a 10-class classification problem which included simulated falls among various indoor activities. Different approaches were considered, namely radar and wearable data on their own without feature selection, radar and wearable data with Sequential Forward Feature Selection (SFS), and fusion at feature and decision level through a voting approach. There is considerable improvement in sensitivity and specificity using fusion compared to stand-alone sensors.

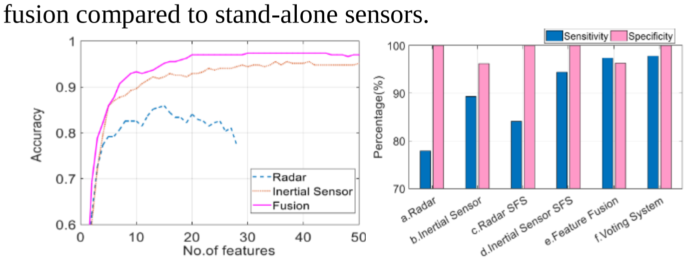


Figure 3. Classification accuracy using SFS for radar features, inertial sensor features, and feature fusion of radar + inertial data with an SVM classifier (left); sensitivity and fall specificity for different classification approaches (right) [15]

## III. Applications of Radar in Assisted Living

Radar can be used the complex challenge of in-home activity monitoring and mapping, including their location and frequency [10, 14]. Monitoring the repeatability of activities enables the detection of anomalies/changes, which may be correlated with declining health. The problem becomes more challenging than binary fall vs not-fall recognition (e.g. [10, 13, 15]), to include finer classification of activities whose intra-class variance in feature space may be limited. Classifying between different types of gait, e.g. unaided or aided walking has also been investigated using information from spectrograms [10, 16].

As further research is performed in activity recognition for assisted living, potential gaps are related to classification of continuous activities and classification over different time-scales. Current radar research tends to record different activities as separated, individual "snapshots" or datasets, whereas in realistic environments they would be performed in a continuum. It is necessary to develop methods to detect and characterize the transitions between activities of interest. Activities of daily living (macro-activities) are sequences of micro-activities (walking, carrying objects, and so on) performed for a certain duration and in a sensible order. How this can be achieved accurately and effectively with radar remains an open problem. Moreover, a challenge lies in handling multi-occupancy and its variability while identifying and discriminating pets for example as current research mainly focus on single user classification.

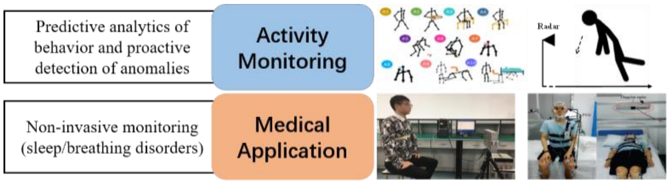

Figure 4. Overview of some of the most recent innovations in radar sensing and signal processing for healthcare applications.

Radar can provide rich information on many health parameters useful for medical applications. They include respiration/heartbeat rate estimation [17-19], breathing disorders and sleep stages monitoring [3, 20] among other things.

A fundamental medical application based on radar is the respiration/heartbeat rate estimation. It is vital for patients' status evaluation, healthcare monitoring at home, and search & rescue of victims after disasters. Conventional signal processing approaches including Fourier analysis and spectral estimation algorithm (e.g. MUSIC and RELAX) are used to process radar echo signals modulated by the periodic movement of the chest and heart, to estimate respiration and heartbeat rates. Recently, more accurate and quicker approaches have been proposed to estimate those from radar data such as stepwise atomic norm minimization and synchro-squeezing transformation for an accurate estimation of respiration and heart rate [18, 19].

Breathing is an important vital sign, and breathing disorders and alterations can be an important indicator for diagnosis and prognosis of different diseases, such as stroke, heart failures, metabolic diseases, injuries of respiratory centers. In [3], the system is a 2.4 GHz CW radar for breathing disorder monitoring. It works in conjunction with a recognition module based on supervised learning signal processing which can select the most salient features out of 13 with Relief-F, followed by a SVM classifier. It was validated with clinical experiments with 3 patients to recognize 6 patterns corresponding to diseases.

Poor sleep quality is correlated with adverse effects on health. Polysomnography, albeit accurate, requires dedicated lab facilities and staff, whereas radar sensors can monitor sleep by observing physiological signs including respiration, heart rate and body movements. A sleep stage estimation system based on radar from [20]. The baseband IQ signals from the radar are processed through a demodulation stage to extract physiological signs used to extract 11 features for classification with K-NN algorithm into sleep stages: wake, light/deep sleep, and dreaming stage. The system was validated on a 6h-sleep experiment with 1 volunteer, with over 80% classification accuracy compared with a gold standard device as ground truth.

## IV. Conclusion

This paper provided an overview of radar sensing in assisted living, capturing the latest trends such as deep learning, fusion of information from multiple radar domains and heterogeneous sensors, and innovative systems and processing for estimation of medical parameters (breathing and heart rate). Trends and challenges for each application have been highlighted. We believe that radar will be a 'corner stone' in assisted living and aging in place for smart homes in the future.

## Acknowledgment

This work was partly supported support by UK EPSRC grant EP/R041679/1 INSHEP, Campus France PHC Cai Yuanpei 41457UK, Horse Betting Levy Board SP006, and the National Science Foundation China under grant 61871224.

## References

[1] M. G. Amin *et al.*, "Radar signal processing for elderly fall detection: The future for in-home monitoring," *IEEE Signal Process. Mag.*, vol. 33, no. 2, pp. 71-80, 2016.

[2] J. Le Kernec *et al.*, "Radar for Assisted Living in the Context of Internet of Things for Health and Beyond," *26th IFIP/IEEE Int. Conf. Very Large Scale Integr. VLSI-SOC*, Verona, 2018, pp. 1-5.

[3] H. Zhao *et al.*, "A Noncontact Breathing Disorder Recognition System Using 2.4-GHz Digital-IF Doppler Radar," *IEEE J. of Biomed. and Health Informat.*, 2018.

[4] V. Nathan *et al.*, "A Survey on Smart Homes for Aging in Place: Toward Solutions to the Specific Needs of the Elderly," *IEEE Signal Process. Mag.*, vol. 35, no. 5, pp. 111-119, 2018.

[5] E. Cippitelli *et al.*, "Radar and RGB-depth sensors for fall detection: A review," *IEEE Sensors J.*, vol. 17, no. 12, pp. 3585-3604, 2017.

[6] V. Chen,H. Ling, *Time-Frequency Transforms for Radar Imaging and Signal Analysis*. Boston-London: Artech House, 2002, pp. 234-234.

[7] S. Z. Gürbüz *et al.*, "Operational assessment and adaptive selection of micro-Doppler features," *IET Radar, Sonar & Navigation*, vol. 9, no. 9, pp. 1196-1204, 2015.

[8] F. Fioranelli *et al.*, "Feature Diversity for Optimized Human Micro-Doppler Classification Using Multistatic Radar," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 53, no. 2, pp. 640-654, 2017.

[9] B. Jokanović,M. Amin, "Fall Detection Using Deep Learning in Range-Doppler Radars," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 54, no. 1, pp. 180-189, 2018.

[10] M. S. Seyfioğlu *et al.*, "Deep Convolutional Autoencoder for Radar-Based Classification of Similar Aided and Unaided Human Activities," *IEEE Transactions on Aerospace and Electronic Systems*, pp. 1-1, 2018.

[11] R. I. A. Harmanny *et al.*, "Radar micro-Doppler feature extraction using the spectrogram and the cepstrogram," *11th Eur. Radar Conf.*, 2014, pp. 165-168.

[12] Z. Zhang *et al.*, "Latern: Dynamic Continuous Hand Gesture Recognition Using FMCW Radar Sensor," *IEEE Sensors J.*, vol. 18, no. 8, pp. 3278-3289, 2018.

[13] B. Jokanovic *et al.*, "Multiple joint-variable domains recognition of human motion," *IEEE Radar Conf.*, Seattle, USA, 2017, pp. 0948-0952.

[14] C. Ding *et al.*, "Non-contact Human Motion Recognition based on UWB Radar," in *IEEE J. on Emerging and Sel. Topics in Circuits and Syst.*, ed, 2018.

[15] H. Li *et al.*, "A Multisensory Approach for Remote Health Monitoring of Older People," *IEEE J. of Electromagn., RF and Microw. in Med. and Biol.*, vol. 2, no. 2, pp. 102-108, 2018.

[16] A. K. Seifert *et al.*, "Radar-based human gait recognition in cane-assisted walks," pp. 1428-1433.

[17] T. Sakamoto *et al.*, "Noncontact Measurement of the Instantaneous Heart Rate in a Multi-person Scenario Using X-band Array Radar and Adaptive Array Processing," *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, pp. 1-1, 2018.

[18] L. Sun *et al.*, "Noncontact Vital Sign Detection based on Stepwise Atomic Norm Minimization," *IEEE Signal Process. Lett.*, vol. 22, no. 12, pp. 2479-2483, 2015.

[19] H. Zhao *et al.*, "Noncontact Physiological Dynamics Detection Using Low-power Digital-IF Doppler Radar," *IEEE Trans. Instrum. Meas.*, vol. 66, no. 7, pp. 1780-1788, 2017.

[20] H. Hong *et al.*, "Noncontact Sleep Stage Estimation Using a CW Doppler Radar," in *IEEE J. on Emerging and Sel. Topics in Circuits and Syst.*, ed, 2018.