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DOI
10.1109/RadarConf2147009.2021.9455218

Publication date
2021

Document Version
Final published version

Published in
2021 IEEE Radar Conference (RadarConf21)

Citation (APA)
Li, Z., Le Kernec, J., Fioranelli, F., Romain, O., Zhang, L., & Yang, S. (2021). An LSTM Approach to Short-range personnel recognition using Radar Signals. In *2021 IEEE Radar Conference (RadarConf21)* Article 9455218 IEEE. https://doi.org/10.1109/RadarConf2147009.2021.9455218

An LSTM Approach to Short-range personnel recognition using Radar Signals

Zhenghui Li
James Watt School of Engineering
University of Glasgow
Glasgow, UK
2227284L@student.gla.ac.uk

Julien Le Kernec
James Watt School of Engineering
University of Glasgow
Glasgow, UK
julien.lekernec@glasgow.ac.uk

Francesco Fioranelli
MS3, Department of Microelectronics
TU Delft
Delft, The Netherlands
F.Fioranelli@tudelft.nl

Olivier Romain
ETIS lab
CY University
Cergy Pontoise, France
olivier.

Lei Zhang
James Watt School of Engineering
University of Glasgow
Glasgow, UK
lei.zhang@glasgow.ac.uk

Shufan Yang
James Watt School of Engineering
University of Glasgow
Glasgow, UK
shufan.yang@glasgow.ac.uk

2021 IEEE Radar Conference (RadarConf21) | 978-1-7281-7609-3/20/$31.00 ©2021 IEEE | DOI: 10.1109/RadarConf2147009.2021.9455218

***Abstract*—In personnel recognition based on radar, significant research exists on statistical features extracted from the micro-Doppler signatures, whereas research considering other domains and information such as phase is less developed. This paper presents the use of deep learning methods to integrate both phase and magnitude features from range profiles and spectrogram. The temporal features of both domains are separately extracted using a stack of Long Short Term Memory (LSTM) layers. Then, the extracted features are aggregated in the corresponding domains and pass through a series of dense layers with SoftMax classifier. Finally, the information from the two domains is fused with a soft fusion approach to improve the performance further. Preliminary results show that the proposed network with soft fusion can achieve 85.5% accuracy in personnel recognition with six subjects.**

Keywords—Radar sensing, Personnel Recognition, LSTM network, Phase information, Micro-Doppler signatures, Range-time information

I. INTRODUCTION

In the past few years, a series of techniques have been proposed for personnel recognition in order to enhance public security, where most of the approaches are based on optical devices [1] and biometric technology [2]. However, vision-based method and biological features have their own limitations. For optical devices, there are possible invasion of privacy and disputes over image rights. People may feel violated when their whereabouts are monitored by a camera all the time. Also, the performance degrades highly when the field of view is narrow, and in adverse lighting conditions. On the other hand, biological features, such as fingerprint or retina scans, are also highly private and require the compliance of people, which cannot always be taken for granted. Radar has potential advantages over the sensors mentioned above, making it a relevant technology in personnel recognition.

Typically, radar-based personnel recognition uses gait analysis from spectrograms [3, 4, 5, 6]. Human gait can provide clear and detailed micro-Doppler signatures [7, 8] of different people. The recognition and classification based on the micro-Doppler signatures are generally performed by extracting hand-crafted features, such as bandwidth and Doppler mean speed. However, the performance of classification or recognition based on the features are highly dependent on the robustness of those features. In [9], it is stated that personnel recognition based on radar signal requires more robust features than human activity recognition. Thus, the centroid features and mathematical features based on singular value decomposition (SVD) were proposed for personnel recognition. The best results achieved by the authors were the accuracy of 88.5% for centroid features and the accuracy of 99.0% for SVD matrix features, on a limited set of three subjects. However, the traditional feature extraction methods based on experience and statistical characteristics still have many limitations in capability and flexibility, which limits the achievable accuracy with the spectrogram. Deep learning methods are therefore introduced to address the issues.

Deep learning has become a popular research topic in radar fields because it can automatically extract salient features from radar data [10, 11]. It aims to find the mapping relationship between the training data and labels through supervised and testing of a large number of samples. Compared with the traditional hand-picked features, using deep learning technologies can achieve a higher accuracy of classification.

Vandersmissen et al. [12] proposed a deep convolutional neural network (DCNN) to identify persons based on their gait characteristics. They also compared its result with traditional techniques which were the principal component analysis (PCA) in combination with a support vector machine (SVM) and a random forest (RF) classifier. The DCNN achieved average classification error rates of 24.7% and 21.5% on the validation set and the test set, respectively, where both error rates were lower than the PCA with RF and the PCA with SVM.

Huang, Ding, Liang and Wen [13] focused on multi-person recognition using a separation method, which splits the Micro-Doppler signature of multi-person up to their individual components. The separated micro-Doppler signatures were then used with a separation convolution neural network (SCNN) and a residual dense network (RDN), achieving an average accuracy of 95.40%.

The radar spectrogram can be treated not only as an optical image but also as a temporal sequence. Hence, Long Short-Term Memory (LSTM) networks have been adopted in [14,15]. In [14], J. Zhu et al. proposed a deep learning model that consists of a 1-D convolutional neural network (1D-CNN) and an LSTM network. The proposed method can extract spatial characteristics with CNN and temporal characteristics with LSTM thus achieving the best accuracy of 98.28%, with

The authors would like to thank the British Council 515095884 and Campus France 44764WK – PHC Alliance France-UK for their financial support.

relatively low complexity compared with the existing 2D-CNN methods. In [15], Wang, Zhang and Cui developed a stacked recurrent neural network (RNN) with two 36-cell LSTM layers to extract features from six different human motions and then classify the motion types, which achieved an overall accuracy of 92.65%.

Although the methods with both hand-crafted features and deep learning in personnel recognition are emerging, most of the researchers still focus on the radar spectrogram [10]. In this paper, we explore the use of phase information and high range resolution profile (range resolution δr = 37.5cm) in personnel recognition, which are less investigated in the current open literature. This paper proposes a novel hybrid information fusion algorithm based on the Long Short-Term Memory (LSTM) units in the recurrent neural network (RNN) that fuses the magnitude and phase information from both the spectrogram and the range profile for improving the performance. To summarize, the main contributions of our research are as follow:

- We evaluate the performance of phase information and range profile compared with the traditional methods which only uses the magnitude information of spectrogram.
- We propose a novel and robust human recognition approach using the combination of spectrogram and range-time domain with both magnitude and phase information.

According to the domain of the input data of the LSTM, the networks investigated in the paper are named as Doppler-LSTM and Range-LSTM [16, 17]. In this paper, we not only consider the spectrogram and high resolution range profile, but the phase information extracted from both sources. Besides, a hybrid information fusion solution is also given to improve the performance further. The input of the Doppler-LSTM network is the spectrogram, which contains the micro-Doppler signature magnitude and phase information of the spectrogram. The Range-LSTM uses the range-time information and phase of the high range resolution profile as the input. Range profiles do not illustrate the differences in features in an easily perceptible way, compared to the spectrogram. However, the fact that it is difficult to interpret visually for a human does not mean that it is a limitation for neural networks such as LSTMs investigated in this paper.

This paper is organized as follows: in Section II, the radar system used to collect dataset and methodology are presented. Section III illustrates and discusses the initial results. Section IV concludes this paper and points out some possible future works.

II. METHODS

A. Radar Data and Pre-Processing

The University of Glasgow Radar Signature dataset [18, 19] was collected using an off-the-shelf Frequency Modulated Continuous Wave (FMCW) radar system from Ancortek, which operates at a carrier frequency of 5.8 GHz, with 1 ms pulse repetition period and 400 MHz bandwidth. The output power of the transmitting amplifier is approximately +18 dBm. The radar is connected to two Yagi antennas, one for transmission and the other for reception, with a gain of about +17 dB. The database is collected from 72 participants aged from 21 to 98 years old containing six types of daily activities, which are walking, sitting, standing, picking up an object, drinking, and fall. In this paper, we only consider walking activity for the personnel recognition problem. Each walking data is a 10 seconds long recording, and each participant repeats it three times. We randomly choose five adults (labelled C1 to C5 and aged between 21 to 60) from the participants' pool to compose the dataset for this paper. An additional older person (labelled C6 and aged over 60) is also considered to increase the diversity of the dataset.

The motivation of the pre-processing of the raw signal data is to generate essentially low noise data for further application. For the raw radar signal, the processing steps are followed. Firstly, a 128-point Hamming-window is proposed to reduce the sidelobes in range-bin. Then, a Fast Fourier Transform (FFT) method is applied to the raw data matrix to convert it into Range-Time domain, which is also known as the high range resolution profile. Next, a high-pass Butterworth notch filter with cut-off frequencies at 0.0075Hz is utilized to remove static clutter caused by stationary objects such as furniture and walls. After that, Short-Time Fourier Transform (STFT) is implemented with a 0.2s Hamming window with 95% overlap on the Range-Time data to generate micro-Doppler signatures.

B. LSTM Recurrent Neural Networks

CNN-based architectures do not include the memory unit. Hence, the network processes each window of the spectrogram as independent inputs. This may cause much overlap when the time interval is small. The response of RNN-based structure to new data is decided by the current and the past input, which acts on the memory of the network. When the time interval is small, it can feed small pieces of the spectrogram into the network saving on computational load compared to CNN.

LSTM uses a gate structure to achieve its function, which contains three types of gates: input gate *i*, output gate *o*, and forget gate *f* [20]. By controlling the gates, the cell can determine the storing, writing and reading operation of information. For each time step t, x_t is the input to the memory cell layer, and the updated states of each parameter are shown in the following equations:

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i) \tag{1}$$

$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + b_f) \tag{2}$$

$$c_t = f_t c_{t-1} + i_t tanh(W_{xc}h_{t-1} + W_{xc}x_t + b_c) \tag{3}$$

$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o) \tag{4}$$

$$h_t = o_t tanh(c_t) \tag{5}$$

Where σ(x), W and b represents the sigmoid function, weight and bias factor, respectively. For the input x_t, the input gate i_t (1) can accumulate new value flowing into the memory cell. The forget gate f_t (2) determines what needs to be discarded from the memory of a cell, which means it can force the memory cell to forget things that are not significant. Equation (3) demonstrates how the memory of cell updates in terms of the new input and the previous value. The output gate o_t (4) determines what should be output to the next cell from the current memory cell and h_t (5) is the hidden output of the current cell.

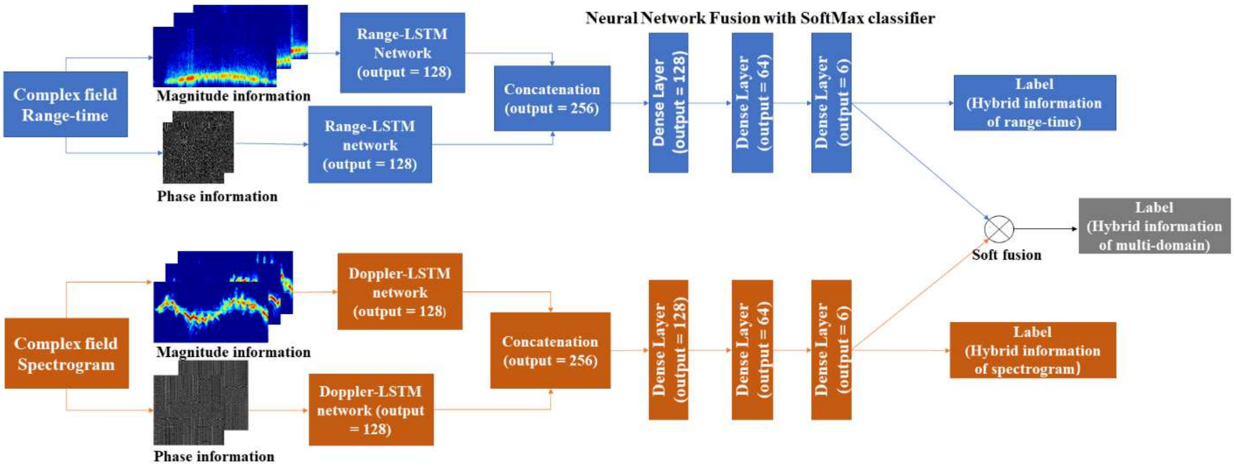

Fig. 1. Overview of the hybrid solution with Doppler-LSTM and Range-LSTM.

Overfitting is a problem that often happens in deep learning applications due to the robust learning ability of neural networks which only focus on training data. This negatively impacts the result when the network processes new or unseen testing data. This problem usually occurs when the database is small, or the model is complex, which is the case here.

Different methods have been proposed to prevent overfitting problems [21]. For example, the early-stop method can stop the learning process when the performance begins to degrade on the validation set. In this paper, the dropout [22] method is proposed to address the overfitting problem. Dropout means dropping out units, which abandons a part of the output randomly in one layer, yielding to improved generalization.

C. A Hybrid information fusion method using LSTM

To improve the performance, a hybrid information fusion method, which is the combination of neural network fusion and a soft fusion at the decision level, is then considered. The architecture of the network is shown in Fig. 1. It consists of two parts, a feature extraction network and a fusion network including a deep fusion part and a soft fusion part. The feature extraction network contains the Range-LSTM and the Doppler-LSTM, which are both composed of two LSTM layers extracting temporal features from magnitude and phase separately. Afterwards, the temporal features from both magnitude and phase information in the same domain are aggregated, and then a series of dense layers are integrated with a SoftMax classifier to generate the prediction of class for each domain. Finally, a soft fusion method is employed to combine the outputs of the previous networks to improve performances.

Soft fusion [23, 24, 25] aims at generating the new prediction of classes by combining the scores which are generated in the last layer of network with SoftMax activation. In the SoftMax layer, the classifier generates a scoring matrix with regard to the posterior probability, which represents the confidence level. The class with the highest probability will be chosen as the output class. The following equation illustrates how the combination works mathematically, where W_D is the weight of the fused Doppler network, and W_R is the weight of the fused range network. S_D and S_R are the score matrix of the fused Doppler network and fused range network, respectively.

$$S_F = W_D \bullet S_D + W_R \bullet S_R \qquad (6)$$

III. RESULTS

Due to the limitation of the number of samples, the original samples are processed with data augmentation to expand the size. The original data is cut using a sliding window with a fixed duration of 1 second. It starts from 0s to 1s, and then shifts in time of 0.1s each step. For instance, the second cut is 0.1s to 1.1s, and the third cut is 0.2s to 1.2s. By using the approach, the total number of samples expands from 18 to 1638.

In the first experiment, we investigate the performance of both networks using magnitude and phase separately. The Range-LSTM and the Doppler-LSTM networks are investigated with a 1310 samples training set (80%) and a 328 samples validation set (20%), where those datasets are randomly picking data from the entire database, as mentioned before. The network structure used in this experiment is a two-layers LSTM, with 128 neurons in each hidden layer, and the dropout probability between two LSTM layers is 0.6 for the Doppler-LSTM and 0.5 for the Range-LSTM. The output of LSTM layers is passed to fully connected (FC) layers. The first FC layer uses ReLU as the activation function due to its low computational cost. The second FC layer uses the same activation function. Then, a softmax layer is connected to the second FC layer since it can output the final labels. The block diagram of the network is shown in Fig. 2.

The networks are trained in 200 epochs using magnitude and phase separately, with the Adam optimizer and fixed initial learning rate of 0.001. Fig. 3 and Fig. 4 demonstrate the loss curves as a function of epochs. The validation accuracy is illustrated in Table I and the training time consumption is shown in Table II.

The result shows that, in both the spectrogram and range-time domain, using phase information can accelerate the convergence of the network compared with traditional methods using amplitudes. In Doppler-LSTM, both training and validation of phase information converge within 50 epochs. To the magnitude information, both training and validation converge at around 100 epochs, which is approximately twice longer than for the phase. In range-LSTM, the convergence finishes in a short time, which is ~40 epochs for phase and ~75 epochs for magnitude. In addition, the loss of both remains at an acceptable range at the end of the process, which means the dropout method succeeds, and the network limits overfitting problems.

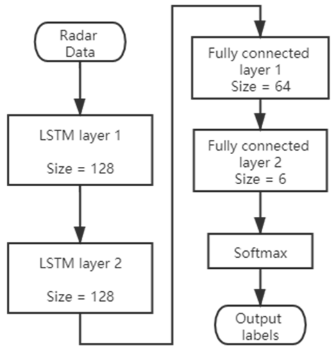

Fig. 2. The LSTM architecture for the recognition.

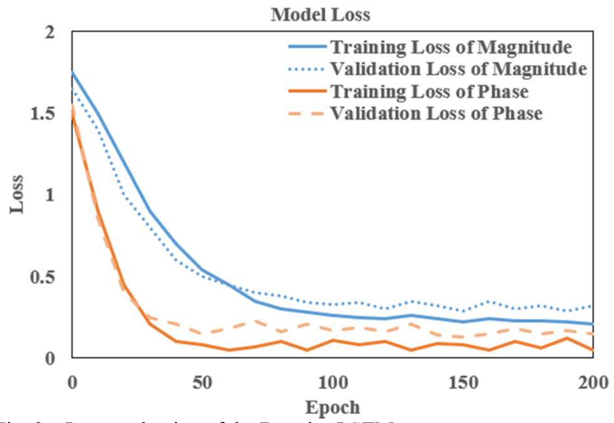

Fig. 3. Loss evaluation of the Doppler-LSTM.

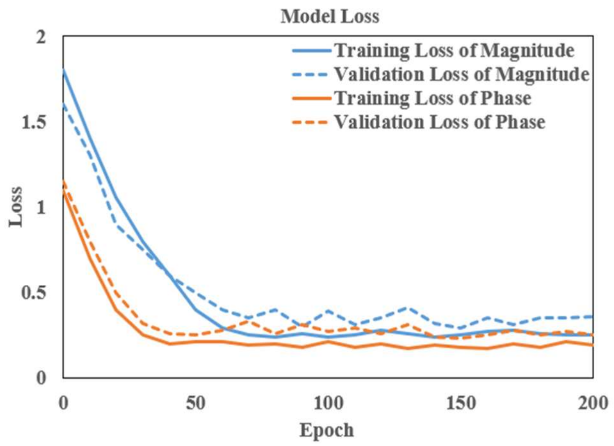

Fig. 4. Loss evaluation of the Range-LSTM.

In the second experiment, a stratified ten-fold cross-validation approach is used to assess our approach. Compared with the normal k-fold cross-validation, the stratified one extracts the validation set in terms of the ratio of class, which makes the validation more comprehensive. To further improve the accuracy of the recognition, the hybrid information fusion method is employed, where the phase and magnitude information from the same domain are fused using deep fusion methods at the first stage, and then the results are used for the second stage with soft fusion. The hyperparameters of the networks remain the same as the first experiment, and the network is still trained with 200 epochs. The weight ratio between the Doppler-LSTM and Range-LSTM sets from 1:5 to 5:1, to appraise the performance of this method. The result is shown in Fig. 5.

The Fig. 5 shows that the accuracy reaches 85.5% for the hybrid information fusion methods when the weight ratios ($W_D : W_R$) are 2:1.

To further analyze the influence caused by the phase information and the differences between the two domains, the neural network fusions of Range-LSTM and Doppler LSTM are independently used. The results are shown in Table I and the time consumption is demonstrated in the Table II.

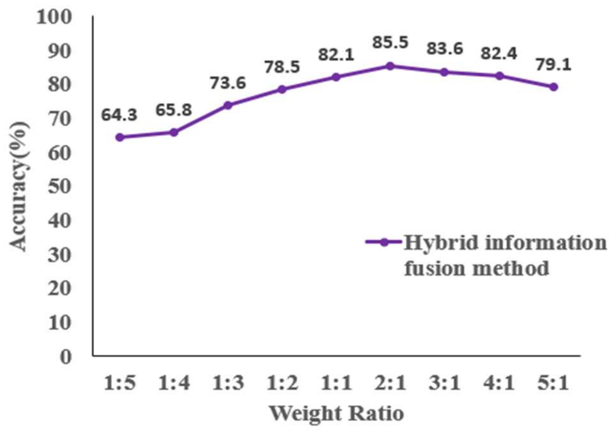

Fig. 5. Hybrid solution evaluation with different weight ratios.

The experiment shows the Doppler-LSTM performs better than the Range-LSTM, with both higher average accuracy (76.0% for the Doppler and 64.7% the for range-time) and better results in the fusion performance (81.9% and 71.0%, respectively). Generally, both networks achieve outstanding results in distinguishing C6. One possible reason is that the cycle of walking of the oldest person is longer than the younger adults, which means they have a smaller and slower pace. In addition, the extent of the body motion for the aged person is smaller than for younger adults, which results in an easily distinguishable micro-Doppler signature, leading to the recognition of that person easier. The performance of the Range-LSTM is not satisfying. In our perspective, the information contained in the range-time domain, which is the relative location from the target to radar, is not adequate for personnel recognition. Besides, the poor performance of the range-LSTM is possibly due to the low radar bandwidth. A higher bandwidth could result in a more satisfactory range resolution (range resolution < 10cm), which gives rise to the better performance. Another possible reason for the unsatisfactory result is that the size of the database is too limited to provide satisfactory performance. The recording of each subject is only 30s, which is not enough to provide an adequate number of samples. The performance could be better with a more extensive database in terms of longer recording for each subject.

Time consumption is shown in Table II. It is obvious that phase information improves on computation time by ~35.0% in Doppler and ~32.4% in Range profile compared to the magnitude information. Besides, the time consumption of the Range-LSTM is generally lower than the computation time of Doppler-LSTM, which is lower by ~30.0% using magnitude information and ~27.2% using phase information. To both the spectrogram and range-time domain, the training time is improved when the phase information is fused with magnitude

TABLE I. COMPARISON OF ACCURACY FOR HUMAN RECOGNITION USING DOPPLER-LSTM, RANGE-LSTM AND HYBRID INFORMATION

Accuracy (%)	C1	C2	C3	C4	C5	C6	Overall Performance
Magnitude of spectrogram	75.4	73.5	76.9	77.3	71.2	95.7	78.3%
Phase of spectrogram	67.5	72.4	68.6	73.8	74.3	85.2	73.6%
Magnitude of range-time	70.5	62.7	55.8	61.4	67.9	87.1	67.6%
Phase of range-time	64.8	51.5	62.9	70.4	53.8	66.7	61.7%
Hybrid information of spectrogram	80.7	78.1	77.5	81.5	79.3	94.1	81.9%
Hybrid information of range-time	64.1	74.7	73.1	70.5	65.5	78.3	71.0%
Hybrid information of two domains fusion	81.6	79.7	84.2	87.8	83.2	96.5	85.5%

information, compared with the independent use of magnitude information. The hybrid information fusion improves the performance of the recognition, which achieves the best result with the accuracy of 85.5%. However, in the multi-domain fusion, the computation time increases. One possible reason is that two deep fusion networks are implemented at the same time, which largely increase the computational load of the processor, leading to the degradation in computing speed.

TABLE II. TOTAL TRAINING TIME CONSUMPTION

Network	Time Consumption for 200 epochs (second)
Doppler-LSTM with magnitude	1483
Doppler-LSTM with phase	964
Range-LSTM with magnitude	1038
Range-LSTM with phase	702
Hybrid information of spectrogram	1221
Hybrid information of range-time	865
Hybrid information of two domains fusion	1892

IV. CONCLUSION

In this paper, we proposed the use of the recurrent neural network on both the spectrogram and range-time domain of radar signal for the identification of individual subjects. The preliminary experiment results show that without a hybrid information fusion, the Doppler-LSTM and Range-LSTM can achieve accuracy of approximately 78.3% and 67.6%, respectively. When the hybrid information fusion is applied in each domain, whereby the magnitude information is fused with the phase information, the accuracy can reach up to 81.9% and 71.0%. Meanwhile, the computational speeds are also improved by ~17.7% and ~16.7% compared with using magnitude information alone in Doppler-LSTM and Range-LSTM, respectively. This suggests that the phase information of radar signal is as effective as the magnitude information, with better convergence rate. On the other hand, the combination of phase information and magnitude information can reduce the rate of abnormal prediction and improve accuracy. When the Hybrid information fusion continues to be applied in multi-domain level, the performance improves to 85.5%, but the computational time increases largely. This might be caused by the simultaneous running of two neural network fusion, which places additional computing burden to the processor.

For future work, further advanced Range-LSTM and Doppler-LSTM scheme will be carried out, with other types of the layer such as Bi-LSTM layer. Besides, the phase information used in this paper is wrapped. The performance of the algorithm with wrapped vs unwrapped phase information should be investigated to determine whether this can improve accuracy. Also, designing an adaptive algorithm for fusing Range-LSTM and Doppler-LSTM could have the potential to improve performance. Furthermore, the complex number can be directly used as input in the neural network, and thus we can use one network with complex numbers of radar signal instead of two separate networks. Additionally, a thresholding method is proposed to upgrade the performance of phase information, which would facilitate network training by focusing more on regions of interest in the phase data. The dataset in this experiment is still limited, and thus more data from different participants repeating the same action should be collected, including different aspect angles with respect to radar and various measurement environments.

REFERENCES

[1] D. T. Nguyen, H. G. Hong, K. W. Kim, K. R. Park, "Person Recognition System Based on a Combination of Body Images from Visible Light and Thermal Cameras," Sensors, vol. 17, pp. 605, 2017.

[2] S. Yang, S. Hoque and F. Deravi, "Improved Time-Frequency Features and Electrode Placement for EEG-Based Biometric Person Recognition," in IEEE Access, vol. 7, pp. 49604-49613, 2019.

[3] L. Yang, G. Li, M. Ritchie, F. Fioranelli and H. Griffiths, "Gait classification based on micro-Doppler features," 2016 CIE International Conference on Radar (RADAR), Guangzhou, 2016, pp. 1-4.

[4] X. Li, Z. Li, F. Fioranelli, S. Yang, O. Romain, J. Le Kernec, "Hierarchical Radar Data Analysis for Activity and Personnel Recognition," in Remote Sens, vol. 12, no.14, pp. 2237, 2020.

[5] Y. Yang, C. Hou, Y. Lang, G. Yue, Y. He and W. Xiang, "Person Identification Using Micro-Doppler Signatures of Human Motions and UWB Radar," in IEEE Microwave and Wireless Components Letters, vol. 29, no. 5, pp. 366-368, May. 2019.

[6] R. Ricci and A. Balleri, "Recognition of humans based on radar micro-Doppler shape spectrum features," in IET Radar, Sonar & Navigation, vol. 9, no. 9, pp. 1216-1223, Dce. 2015.

[7] V. C. Chen, F. Li, S. -. Ho and H. Wechsler, "Micro-Doppler effect in radar: phenomenon, model, and simulation study," in IEEE Transactions on Aerospace and Electronic Systems, vol. 42, no. 1, pp. 2-21, Jan. 2006.

[8] V. C. Chen, The Micro-doppler effect in radar, Boston:Artech House, 2011.

[9] F. Fioranelli, M. Ritchie and H. Griffiths, "Performance analysis of centroid and SVD features for personnel recognition using multistatic micro-Doppler", IEEE Geosci. Remote Sens. Lett., vol. 13, no. 5, pp. 725-729, May. 2016.

[10] J. Le. Kernec, F. Fioranelli, D. Chuanwei, Z. Heng, S. Li, H. Hong, J. Lorandel and O. Romain, "Radar Signal Processing for Sensing in Assisted Living: The Challenges Associated With Real-Time Implementation of Emerging Algorithms," IEEE Signal Processing Magazine, vol. 36, no. 4, pp. 29-41, 2019.

[11] S. Z. Gurbuz and M. G. Amin, "Radar-Based Human-Motion Recognition With Deep Learning: Promising Applications for Indoor Monitoring," in IEEE Signal Processing Magazine, vol. 36, no. 4, pp. 16-28, July 2019.

[12] B. Vandersmissen et al., "Indoor Person Identification Using a Low-Power FMCW Radar," in IEEE Transactions on Geoscience and Remote Sensing, vol. 56, no. 7, pp. 3941-3952, July 2018.

[13] X. Huang, J. Ding, D. Liang and L. Wen, "Multi-Person Recognition Using Separated Micro-Doppler Signatures," in IEEE Sensors Journal, vol. 20, no. 12, pp. 6605-6611, June 2020.

[14] J. Zhu, H. Chen and W. Ye, "A hybrid CNN–LSTM network for the classification of human activities based on Micro-Doppler radar," IEEE Access, vol. 8, pp. 24713-24720, 2020.

[15] M. Wang, Y. D. Zhang, and G. Cui, "Human motion recognition exploiting radar with stacked recurrent neural network," Digital Signal Processing, vol. 87, pp. 125-131, April 2019.

[16] A. Shrestha, H. Li, J. Le Kernec and F. Fioranelli, "Continuous Human Activity Classification From FMCW Radar With Bi-LSTM Networks," in IEEE Sensors Journal, vol. 20, no. 22, pp. 13607-13619, Nov. 2020.

[17] H. Li, A. Mehul, J. Le Kernec, S. Z. Gurbuz and F. Fioranelli, "Sequential Human Gait Classification With Distributed Radar Sensor Fusion," in IEEE Sensors Journal, vol. 21, no. 6, pp. 7590-7603, 15 March, 2021

[18] F. Fioranelli, S.A. Shah, H. Li, A. Shrestha, S. Yang, J. Le Kernec, "Radar sensing for healthcare," IET Electronic Letters, 55(19), pp. 1022-1024, 2019.

[19] F. Fioranelli, S. A. Shah, H. Li, A. Shrestha, S. Yang, J. Le. Kernec, "Radar signatures of human activities," URL: http://researchdata.gla.ac.uk/id/eprint/848, University of Glasgow, 2019.

[20] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," Neural Computation, vol. 9, no. 8, pp. 1735-1780, 1997.

[21] J. Liang and R. Liu, "Stacked denoising autoencoder and dropout together to prevent overfitting in deep neural network," 2015 8th International Congress on Image and Signal Processing (CISP), Shenyang, 2015, pp. 697-701.

[22] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Dropout: a simple way to prevent neural networks from overfitting," J. Mach. Learn. Res. Vol. 15, no. 1, pp. 1929–1958, January. 2014.

[23] H. Li, A. Shrestha, H. Heidari, J. Le Kernec and F. Fioranelli, "Bi-LSTM Network for Multimodal Continuous Human Activity Recognition and Fall Detection," in IEEE Sensors Journal, vol. 20, no. 3, pp. 1191-1201, 1 Feb.1, 2020.

[24] C. Chen, R. Jafari and N. Kehtarnavaz, "A real-time human action recognition system using depth and inertial sensor fusion," in IEEE Sensors J., vol. 16, no. 3, pp. 773-781, Feb. 2016.

[25] H. Li, A. Shrestha, H. Heidari, J. Le Kernec, and F. Fioranelli, "A multisensory approach for remote health monitoring of older people, " IEEE J. Electromagn., RF Microw. Med. Biol., vol. 2, no. 2, pp. 102–108, Jun. 2018.