Accuracy Improvement Using Conditional GAN in FMCW Radar-Based Fall Detection

Nayun Park
Dept. of Electrical and Electronics Engineering
Pusan National University
Busan, Republic of Korea
nayun_p@pusan.ac.kr

Do-Hyun Park
Dept. of Electrical and Electronics Engineering
Pusan National University
Busan, Republic of Korea
dohpark@pusan.ac.kr

Min-Wook Jeon
Dept. of Electrical and Electronics Engineering
Pusan National University
Busan, Republic of Korea
gow1128@pusan.ac.kr

Hyoung-Nam Kim
School of Electrical and Electronics Engineering
Pusan National University
Busan, Republic of Korea
hnkim@pusan.ac.kr

***Abstract*—As the number of elderly individuals living alone increases, these elderly individuals face significant challenges in responding quickly to falls. To address this issue, research on human activity recognition for fall detection is crucial. In this study, we utilize frequency-modulated continuous wave radar combined with deep learning to enhance fall detection. However, considering that deep learning models depend on large datasets, the lack of collected fall data poses a major obstacle. To overcome this, we propose a method that integrates a conditional generative adversarial network and transfer learning. This approach resulted in improved overall performance, with a notable increase in fall detection accuracy.**

***Index Terms*—human activity recognition, conditional generative adversarial network, transfer learning, fall detection**

I. Introduction

As low birth rates and an aging population persist in South Korea, the proportion of elderly individuals living alone has been increasing. The mortality rate due to falls among those aged 65 and older is also rising as age increases [1]. Elderly individuals living alone face difficulties in responding quickly to falls. This highlights the need for research in human activity recognition (HAR).

Traditionally, HAR involves attaching sensors to the body or using cameras [2], [3]. While sensor-based methods are adaptable, they are often inconvenient due to the need for wearable devices. Camera-based recognition offers high accuracy but raises privacy concerns. To address these challenges, frequency-modulated continuous wave (FMCW) radar is utilized as it does not require direct attachment to the body and avoids privacy issues. Additionally, deep learning is used for automatic activity recognition, leading to extensive research on applying it to FMCW radar data [4].

However, deep learning requires large amounts of data. Since the training data are usually collected by performing and measuring activities, generating large datasets is challenging. This has resulted in an imbalance in the number of samples between activities, with fall data being particularly limited due to the difficulty and risk of injury involved in performing falls. This data imbalance can degrade performance.

To address this issue, we implement a conditional generative adversarial network (CGAN) and transfer learning to improve classification accuracy. We then compare the results with those obtained without these techniques.

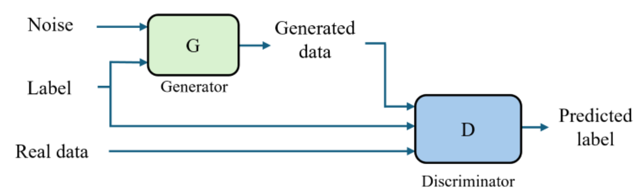

Fig. 1. The structure of CGAN

II. Recognition Enhancement Techniques

A. Data Generation using CGAN

CGAN is a model that conditions both the generator and discriminator on additional information [5]. By adding conditional information to the input, we can generate labeled data using CGAN. The overall structure of CGAN is shown in Fig. 1. The generative model G learns the distribution of measeured data and produces data that resembles real data. The discriminator model D distinguishes whether it is generated data or real data. Conditioning is performed by adding labels to both G and D as an additional input layer. The objective function is expressed as:

$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim p_{\text{data}}(x)}[\log D(x|y)] + \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z|y)))],$$

where $p_z(z)$ represents the prior noise distribution, $p_{\text{data}}(x)$ is the real data distribution, and y is the label that is applied to both models.

Fig. 2 shows the micro-Doppler spectrogram measured using FMCW radar, and Fig. 3 presents the results generated by CGAN when provided with the measured data and the activity type as labels. We can see that the spectrogram generated by the CGAN accurately captures the features present in the spectrogram generated from the measured signal.

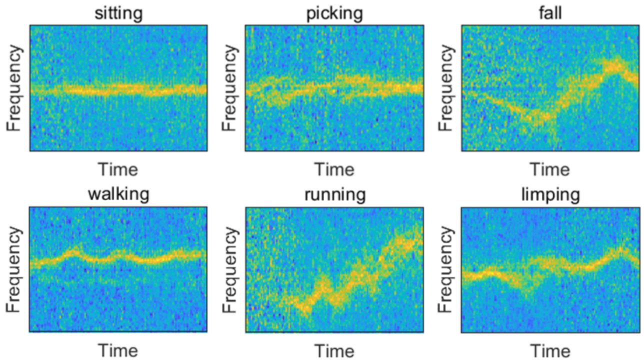

Fig. 2. The micro-Doppler spectrograms generated by CGAN.

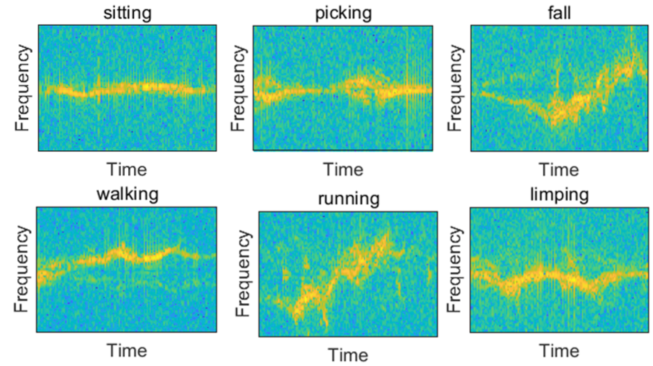

Fig. 3. The micro-Doppler spectrograms measured by FMCW radar.

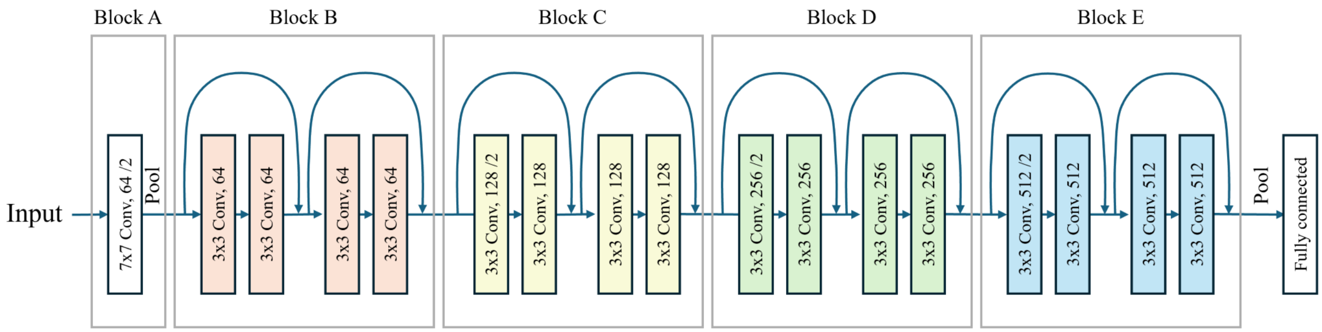

Fig. 4. The structure of ResNet18

TABLE I
MEASURED DATA SAMPLES PER ACTIVITY

activity	No. of Measured Data Samples
Fall	256
Limping	333
Picking	456
Running	330
Sitting	311
Walking	564

B. Transfer Learning

Transfer learning is a method of reusing pre-trained models for new problems and is widely applied across multiple domains [6]. In this paper, we transferred the neural network trained with images generated by CGAN to improve the accuracy of the classification network using real data.

III. DATA COLLECTION AND EXPERIMENT

We collected data for performance analysis using the AWR1642BOOST and DCA1000EVM. The activities were limited to six everyday activities: fall, limping, picking, running, sitting, and walking. Five participants performed these six activities repeatedly. Table I shows the number of measured data samples for each activity. Ten percent of the measured data was not used for training but only for performance comparison.

We trained CGAN using real data and generated 500 samples per activity using the trained CGAN. We used ResNet18 as the classification network [7]. The configuration of the neural network used is shown in Fig. 4. First, we pre-trained classification network using the data generated by CGAN and then applied it to the classification using only the real dataset. The final two layers of the pre-trained ResNet18 were partially reinitialized to adapt to the new dataset, which consists of real data.

We compared the classification performance of neural network pre-trained with CGAN and transferred, against neural network without transfer learning. The experimental results indicate that the overall classification performance increased from 94.7% to 96.9%. Figs. 5 and 6 show the classification accuracy in terms of a confusion matrix. The accuracy of fall detection increased from 84.6% in Fig. 5 to 92.3% in Fig. 6. This improvement highlights the effectiveness of using CGAN-generated data for pre-training, particularly in challenging cases like fall detection.

IV. CONCLUSION

This paper proposes a method to improve HAR classification performance using FMCW radar by applying CGAN and transfer learning. The experimental results show an increase in both overall accuracy and fall detection accuracy. This

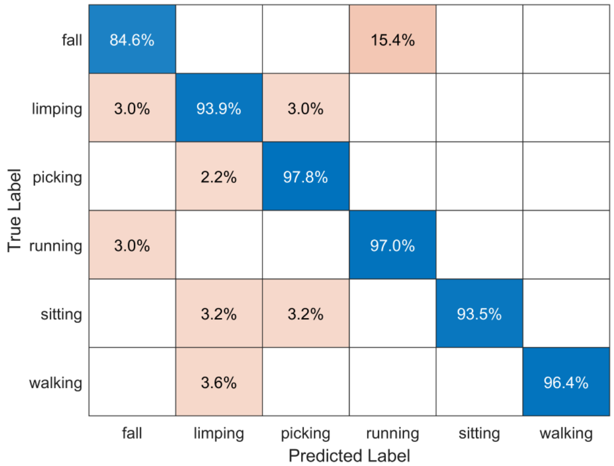

Fig. 5. Confusion matrix before transfer learning.

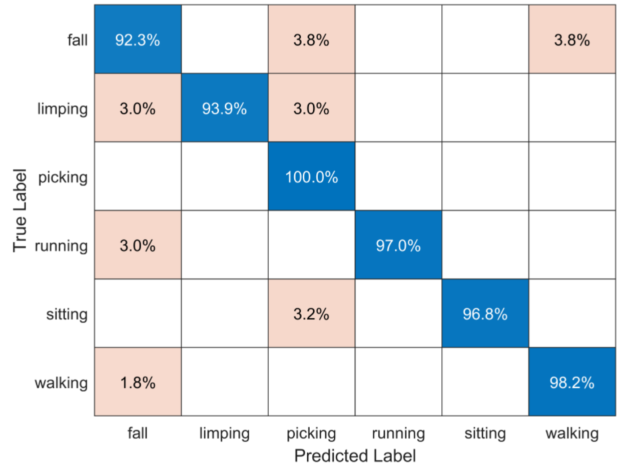

Fig. 6. Confusion matrix after transfer learning.

demonstrate that the proposed method is effective for HAR, particularly in improving fall detection.

REFERENCES

[1] Ministry of Health and Welfare, ”2020 Elderly Survey Report,” Korea Institute for Health and Social Affairs, 2020. [Online]. Available: https://www.mohw.go.kr/board.es?mid=a10411010100&bid=0019&act=view&list_no=366496.

[2] S. Gupta, ”Deep learning based human activity recognition (HAR) using wearable sensor data,” International Journal of Information Management Data Insights, vol. 1 n,o. 2, p. 100046, 2021.

[3] S. U. Park et al., ”A depth camera-based human activity recognition via deep learning recurrent neural network for health and social care services,” Procedia Computer Science, vol. 100, pp. 78-84, 2016.

[4] S. Z. Gurbuz and M. G. Amin, ”Radar-based human-motion recognition with deep learning: Promising applications for indoor monitoring,” IEEE Signal Processing Magazine, vol. 36, no. 4, pp. 16-28, Jul. 2019.

[5] M. Mirza and S. Osindero, ”Conditional generative adversarial nets,” arXiv preprint arXiv:1411.1784, Nov. 2014.

[6] S. J. Pan and Q. Yang, “A Survey on Transfer Learning,” IEEE Transactions on Knowledge and Data Engineering, vol. 22, no. 10, pp. 1345–1359, Oct. 2010, doi:https://doi.org/10.1109/tkde.2009.191.

[7] K. He, X. Zhang, S. Ren, and J. Sun, “Deep Residual Learning for Image recognition,” 2016 IEEE Conference on Computer Vision and Pattern recognition (CVPR), pp. 770–778, Jun. 2016, doi: https://doi.org/10.1109/cvpr.2016.90.