# User Activity Detection for mmWave Grant-free IoT Networks

Shanai Wu
*School of Electronic Engineering*
*Soongsil University*
Seoul, Korea
sunae0814@soongsil.ac.kr

Yoan Shin†
*School of Electronic Engineering*
*Soongsil University*
Seoul, Korea
yashin@ssu.ac.kr

***Abstract*—Considering sporadic traffic in IoT networks, grant-free random access is inevitable. In a grant-free random access system, channel estimation and activity detection are crucial to enable data transmission. In this paper, we propose a deep learning-based activity detection scheme for mmWave grant-free IoT networks, and the detection accuracy is validated by the simulation result.**

***Index Terms*—grant-free IoT, mmWave, channel virtual representation, activity detection, variational autoencoder**

## I. Introduction

Massive machine-type communication (mMTC) based on mmWave technology is receiving tremendous interest from academia and industry. Sporadic transmission is the most important characteristic of massive IoTs or mMTC systems. Considering sporadic traffic in IoT networks, grant-free random access is inevitable [1]. Channel estimation and activity detection are crucial to enable data transmission for a grant-free random access system. Due to massive machine connections and the limited channel coherence time, assigning an orthogonal pilot to every IoT device is not feasible. Despite its great potential, grant-free random access is vulnerable to pilot contamination degrading the channel estimation and activity detection.

In this paper, we propose a deep learning-based user activity detection scheme by utilizing the characteristics of channel virtual representation (CVR). The virtual representation describes the channel with respect to fixed spatial basis functions defined by fixed virtual angles [2]. Due to the high directivity of mmWave, the multipath characteristics are sensitive to the transmitter's location, and the CVR can emphasize the characteristics of a mmWave channel. If there are multiple active devices in the channel, significant changes can be detected in the CVR. Based on these observations, we propose eliminating the CVR's dissimilarities due to the non-orthogonal pilot transmission and improving activity detection.

†Corresponding author.

This work was supported by the "Technological Innovation R&D Program" (S3154388) funded by the Ministry of SMEs and Startups (MSS, Korea).

## II. mmWave Grant-free IoT Networks

We consider a typical uplink IoT network where a base station (BS) equipped with $M$ antennas serves a large number of single-antenna devices. All IoT devices are fixed, and uplink transmissions are supported with mmWave communications.

### A. Channel Model

The channel between the BS and $k$-th device $\mathbf{H}_k \in \mathbb{C}^{M\times 1}$ can be modeled as

$$\mathbf{H}_k = \sqrt{\frac{M}{\rho}} \sum_{l=1}^{L} \alpha_l \mathbf{a}_r(\theta_l), \tag{1}$$

where $\rho$ and $\alpha_l$ denote the path loss and $l$-th path's complex gain, respectively. The path amplitudes are assumed to be Rayleigh distributed. In addition, $\theta_l \in [-\pi/2, \pi/2]$ is the $l$-th path's physical angle of arrival (AoA), and the steering vector $\mathbf{a}_r(\theta_l)$ is defined for receiving a signal in the normalized direction $\vartheta$. In our work, we consider the critically spaced antenna arrays. Moreover, based on the user activity $\tau_k$ in the coherent time slot, the effective channel becomes $\tau_k \mathbf{H}_k$.

### B. Channel Virtual Representation

If an antenna array consists of an $N$-dimensional uniform linear array (ULA), the virtual representation corresponds to system representation with respect to uniformly spaced spatial angles $\vartheta_i = i/N$, $i = 0, \cdots, N-1$ [2]. In particular, based on a unitary discrete Fourier transform (DFT) matrix $\mathbf{U}$, the virtual representation is given as

$$\mathbf{H}_k^v = \mathbf{U}^* \mathbf{H}_k. \tag{2}$$

If the number of antennas is significantly larger than the number of paths, the virtual channel tends to be sparse [3]. Therefore, most of the energy will concentrate on a few elements associated with the indices corresponding to the physical AoA. Moreover, due to high carrier frequency, devices must be separated in millimeters to achieve similar CVRs in a mmWave system. Therefore, in the case of channel estimation and activity detection, significant differences can be detected when multiple devices are in the channel.

## III. The proposed User Activity Detection Scheme

Even though physical AoA depends on the location of the device and scatterers, the corresponding path's gain is random due to the channel fading. Therefore, obtaining all the training samples is challenging. As a solution, we utilize variational autoencoders (VAEs), one of the generative models in deep learning and neural network.

In architecture, variational autoencoders resemble autoencoders and consist of the generative model (decoder) and variational approximation (encoder) [4]. The significant difference is the latent space vector generated from VAEs is continuous. Therefore, VAEs are good at generating new data from the latent space and can reconstruct data similar to that they are trained on but also generate many variations.

The proposed scheme represents the noisy channel observations as virtual based on the DFT matrix. Then, the dimension of CVR samples is reduced via encoding layers. We can obtain the mean and covariance matrices after the encoder's latent space encoding. The reparameterization trick makes the gradient descent possible despite the random sampling occurring halfway through the architecture. After reparameterization, the decoder goes in reverse order as that of the encoder. Consequently, the decoder returns the reconstruction with the same dimension as the CVR samples.

For activity detection, we train the VAE model with the target CVR samples so that the model only learns the features of the target CVR. Then, the trained VAE model can reconstruct the CVR similar to the target, even if the CVR samples are contaminated by the non-orthogonal pilot transmission.

## IV. Simulation Result

Three scatterers contributing to one main path for each are considered. The BS has 128 antennas, and the devices are with a single antenna. Moreover, the distances between the BS and each device are assumed to be the same. To train the VAE model, we generated 1,000 CVR samples, $70\%$ for training and the remaining for the validation. For the non-orthogonal pilot transmission, target devices are randomly active with the probability of 0.5, while interfering devices are always awake. The signal-to-noise ratio is set to 20 dB.

We constructed a VAE with six linear layers. The first three are for the encoder layers, and the other three are for the decoder layers. The number of input features of the first encoder is 128, identical to the number of receiving antennas. Each encoder returns half of the input features. After achieving the parameters for sampling from the encoder's latent space encoding, the decoder layers go in reverse order as that of the encoder layers. The path's gain is not constrained in the interval $(0, 1)$, and the mean squared error (MSE) loss is considered as the reconstruction loss. The final reconstruction is activated with the leaky ReLU, and the ReLU function is used at other decoders and encoder layers. The Kullback-Leibler divergence loss is obtained with a Gaussian latent space. We use the Adam optimizer for training and define epochs, batch size, and learning rate as $500$, $64$, and $0.0001$, respectively.

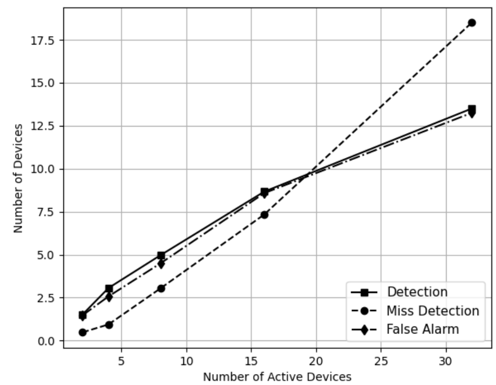

Fig. 1. Detection accuracy.

The training was untractable due to the randomness of the path's gain and activity and observed noisy channels, however, the reconstruction from the contaminated samples was thoroughly verified. As illustrated in Fig. 1, the detection was evaluated under multiple active device scenarios considering various performance measures. For preliminary evaluation, the activity detection was attained by comparing the energy in the reconstructed CVRs with the noise variance. As the number of devices increases, the reduced channel sparsity resulted in inefficient training performance. Accordingly, the detection accuracy degrades with an increasing number of active devices, and many more active devices have remained miss detected.

## V. Conclusion

Grant-free random access can support massive machine connections in the IoT networks, and channel estimation and activity detection are crucial to enable data transmission without grants. To detect the activities in mmWave grant-free IoT networks, we exploited the characteristics of CVR concerning the mmWave channel. Then, we designed and trained the VAE model to reconstruct the CVRs, and the detection performance was evaluated with the trained model. Reduced channel sparsity resulted in inefficient training and inaccurate detection. To tackle the problem, we will focus on the advanced VAE model to improve the reconstruction performance.

## References

[1] M. B. Shahab, R. Abbas, M. Shirvanimoghadda, and S. J. Johnson, "Grant-free non-orthogonal multiple access for IoT: A survey," *IEEE Commun. Surveys & Tut.*, vol. 22, no. 3, pp. 1805-1838, 3rd Quarter 2020.

[2] A. M. Sayeed, "Deconstructing multiantenna fading channels," *IEEE Trans. Signal Process.*, vol. 50, no. 10, pp. 2563-2579, Oct. 2002.

[3] P. Schniter and A. Sayeed, "Channel estimation and precoder design for millimeter-wave communications: The sparse way," *Proc. 48th Asilomar Conf. Signals, Systems and Computers (Asilomar 2014)*, pp. 273-277, Pacific Grove, CA, USA, Nov. 2014.

[4] D. P. Kingma and M. Welling, "Auto-encoding variational Bayes," *arXiv:1312.6114*, pp. 1-14, May 2014.