Robust Deep Learning-based Indoor mmWave Channel Prediction Under Concept Drift

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***Abstract*—The mmWave WiGig frequency band can support high throughput and low latency emerging applications. In this context, accurate prediction of channel gain enables seamless connectivity with user mobility via proactive handover and beamforming. Machine learning techniques have been widely adopted in literature for mmWave channel prediction. However, the existing techniques assume that the indoor mmWave channel follows a stationary stochastic process. This paper demonstrates that indoor WiGig mmWave channels are non-stationary where the channel's cumulative distribution function (CDF) changes with the user's spatio-temporal mobility. Specifically, we show significant differences in the empirical CDF of the channel gain based on the user's mobility stage, namely, room entering, wandering, and exiting. Thus, the dynamic WiGig mmWave indoor channel suffers from concept drift that impedes the generalization ability of deep learning-based channel prediction models. Our results demonstrate that a state-of-the-art deep learning channel prediction model based on a hybrid convolutional neural network (CNN) long-short-term memory (LSTM) recurrent neural network suffers from a deterioration in the prediction accuracy by $11-68\%$ depending on the user's mobility stage and the model's training. To mitigate the negative effect of concept drift and improve the generalization ability of the channel prediction model, we develop a robust deep learning model based on an ensemble strategy. Our results show that the weight average ensemble-based model maintains a stable prediction that keeps the performance deterioration below 4%.**

***Index Terms*—Channel prediction, WiGig, mmWave, concept drift, deep learning, generalization, domain adaptation.**

I. Introduction

The Wireless Gigabit Alliance (WiGig) operates in the 60 GHz millimeter wave (mmWave) frequency band [1]. This band enables high-speed data transfer rates of up to 7 Gbps and low latency of less than 10 milliseconds [2]. These attractive features are due to the large available bandwidth in the relatively uncongested WiGig band, which allows for the transmission of large amounts of data in a short period. As a result, this band can support emerging applications such as virtual and augmented reality, high-quality video conferences, 4K multimedia streaming, real-time online gaming, etc [3]. Several advanced technologies have been integrated into the WiGig band to further enhance the perceived quality of service such as directional beamforming [4], device-to-device communications [5], and simultaneous multiple device connections [6].

One major challenge in the WiGig band is to enable seamless connectivity with user mobility. Specifically, channel blockages occur with user mobility resulting in signal attenuation and channel outages. To address this issue, beamforming and proactive handover strategies have been proposed in the literature. First, beamforming is employed to direct the wireless signal toward the receiver, hence, avoiding obstacles and enhancing the signal strength. For instance, autoencoders have been adopted in [7] to determine the optimal beam direction for unconstrained and hybrid beamforming in mmWave communication systems, which demonstrated significant performance gains. Furthermore, stochastic geometry and support vector machine have been used in [8] for analog beam selection in millimeter-wave heterogeneous networks. Second, proactive handovers have been proposed in the literature to maintain a stable signal strength with user mobility while avoiding unnecessary handovers. In specific, a convolutional neural network (CNN) is used in [9] to predict the future channel quality and trigger user handovers in advance to avoid signal deterioration.

In both solutions, beamforming and proactive handover, channel gain prediction is required. As such, several works have examined data-driven channel prediction techniques in the mmWave band. These data-driven approaches are motivated as recent research demonstrated that general channel models in high-frequency bands are inaccurate [10]. Hence, machine learning-based channel prediction in the mmWave frequency band has been investigated in [11]–[14]. However, one common limitation with the existing channel prediction models is the underlying assumption that the mmWave follows a stationary stochastic process, and hence, the developed models cannot generalize well under different scenarios.

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In this paper, we focus on an indoor setup as 80% of mobile data are generated indoors [15]. The contributions of our paper can be summarized as follows:

- We demonstrate that the indoor WiGig mmWave channel data follows a non-stationary stochastic process that depends on the user mobility stage, namely, room entering, wandering, and existing. Hence, we show that the indoor WiGig mmWave channels suffer from concept drift as the channel distribution changes with the user mobility stage.
- We study the impact of the WiGig channel concept drift on a state-of-the-art deep learning-based channel prediction model, which indicates the inability of the prediction model to maintain a stable accurate prediction performance across the user's trajectory. Specifically, we show that the accuracy of the channel prediction model deteriorates by $11-68\%$ depending on the user's mobility stage and the model's training.
- We improve the generalization ability of the channel prediction model using an ensemble strategy that utilizes only the wireless channel data without requiring any additional information on the user's location or mobility stage. Our results show that the ensemble-based model maintains a stable prediction that keeps the performance deterioration below 4% regardless of the user's mobility stage.

The rest of this paper is organized as follows. Section II discusses the system model. Section III presents the statistics of the dynamic indoor WiGig channel gain, which indicates a non-stationary behavior. Section IV discusses a state-of-the-art deep learning channel prediction model and presents its performance under concept drift. Also, this section discusses the improvement of the channel prediction model following a voting ensemble strategy that offers a stable prediction performance under concept drift.

II. SYSTEM MODEL

This section presents the indoor layout, the user mobility model, and the generation of the dynamic WiGig channel data.

A. Indoor Setup

In this paper, we consider an indoor layout that has been used in the literature [16]–[18]. However, it should be highlighted that the conclusions of this paper are not limited by this specific layout, as indoor human mobility that influences the WiGig channel data exhibits scale-free statistics [19].

Consider a 5m×5m×3m office room with nine desks. The dimension of the desks and their distribution in the room are shown in Fig. 1. The room is covered by four WiGig base stations (BSs) that are evenly distributed across the ceiling as shown in Fig. 1. Mobile users are represented by cuboids with dimension 1.8m×0.2m×0.45m, mass of 70 kg, a maximum speed of 2.1 m/s, and a maximum acceleration of 1 m/s.

B. Mobility Model and Channel Data Generation

To mimic indoor human mobility, the realistic mobility model of [10] is adopted, which has been validated in [10]

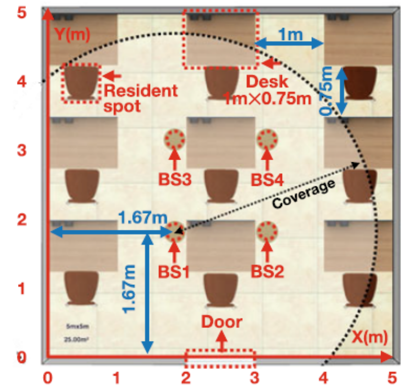

Fig. 1. Illustration of the indoor layout.

against real measurements. This model simulates human behavior on two timescales, namely, macro and micro scales. The macro-scale determines when and where a person moves to the next destination point using a semi-Markov renewal process incorporating regular return patterns and bounded Levy-walk behavior. The micro-scale captures the details of mobility, namely, the shortest path, steering behavior, and user equipment (UE) orientation. The details of the adopted mobility model are summarized in the top half of Fig. 2.

Once the mobility traces are generated, the location and orientation of the UE and the location of the BSs are used to decide channel blockage and calculate the channel gain. Define the mmWave line-of-sight (LoS) channel gain from the transmitter (BS) to the receiver (UE) as [20]

$$\mathbf{G} = \mathbf{G}_{\mathrm{LoS}} + \mathbf{G}_{\mathrm{NLoS}}, \tag{1}$$

where

$$\mathbf{G}_{\mathrm{LoS}} = \sqrt{G_e\left(\theta_{\mathrm{LoS}}\right) L_{\mathrm{LoS}}} e^{j\varrho} \mathbf{a}\left(\phi_{\mathrm{LoS}}, \theta_{\mathrm{LoS}}\right), \tag{2}$$

$$\mathbf{G}_{\mathrm{NLoS}} = \gamma \sum_{c=1}^{C} \sum_{s=1}^{S_c} \beta_{c,s} \sqrt{G_e\left(\theta_{c,s}\right) L_{c,s}} \mathbf{a}\left(\phi_{c,s}, \theta_{c,s}\right), \tag{3}$$

$$L_{\mathrm{LoS}/c,s} = -20\log_{10}\left(\frac{4\pi}{\lambda}\right) - 17.3\log_{10}\left(d_{\mathrm{LoS}/c,s}\right) - X_\sigma, \tag{4}$$

$$G_{\mathrm{e}}\left(\theta_{\mathrm{LoS}/c,s}\right) = 2(2q+1)\cos^{2q}\left(\theta_{\mathrm{LoS}/c,s}\right), \tag{5}$$

$$\pi/2 < \theta_{\mathrm{LoS}/c,s} < \pi/2, \tag{6}$$

where it is assumed that the beams are grouped under C clusters and each cluster contains S_c sub-rays, and γ stands for a normalization gain factor among sub-rays defined by $\gamma = \sqrt{\frac{1}{\sum_{c=1}^{C} S_c}}$, $\beta_{c,s} \sim \mathcal{CN}(0,1)$ is the complex path gain, $\mathbf{a}(\cdot)$ is the receiver's response vector, ϕ and θ represents the azimuth and elevation arrival angles with respect to the receiver's broadside, λ denotes the wavelength, d is the transmission distance, $X_\sigma \sim N(0,\sigma^2)$ is the fading term in logarithmic units, and $\varrho \sim \mathcal{U}[0,2\pi]$. Once an LoS is judged as blocked by any object (desks, another user, or the user's own body) using the method in [10], the term $\mathbf{G}_{\mathrm{LoS}} = 0$, and the reception is mainly due to $\mathbf{G}_{\mathrm{NLoS}}$.

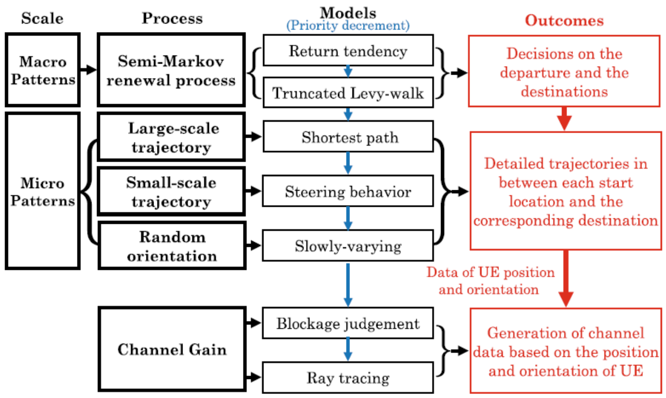

Fig. 2. Framework to generate dynamic channel impulse response.

III. Dynamic WiGig Channels Statistics

This section studies the statistics of the dynamic WiGig channel in terms of the average channel gain and the empirical cumulative distribution function (ECDF) of the channel gain considering indoor user mobility.

Using the framework presented in Fig. 2, we simulated the WiGig channel gain over 800 mobility traces that cover a user entering the room, wandering across the room, and exiting the room given the layout in Fig. 1. The average channel gain over all mobility traces is shown in Fig. 3. It is evident that the average channel gain varies over time with three distinct mobility stages, namely, entering, wandering, and exiting. These three distinct stages can be defined as follows:

- Entering stage: It indicates the user's mobility near the room entrance moving inwards the room.
- Wandering stage: It indicates the user's mobility away from the room entrance moving across the room.
- Exiting stage: It indicates the user's mobility near the room entrance moving outwards the room.

The spatio-temporal variations in the average channel gain suggest a non-stationary stochastic process. The average channel gain is lower in the entering and exiting mobility stages than in the wandering mobility stage. This is because, in the wandering mobility stage, the user walks in close proximity to the BSs, while in the entering and the exiting mobility stages the user walks toward or away from the BSs. To elaborate

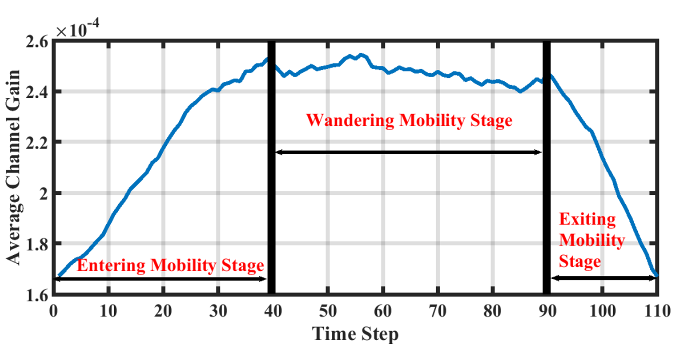

Fig. 3. Average channel gain over 800 mobility traces.

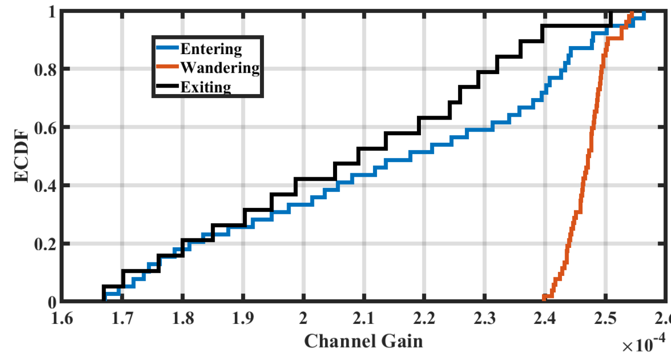

Fig. 4. ECDF of the WiGig channel gain for different mobility stages.

more, we show the ECDF of the WiGig channel gain for each mobility stage in Fig. 4. As shown, the statistics of the WiGig channel gain vary according to the mobility stage. Since the user trajectory changes over space and time, the channel gain could belong to any of these three different statistics. In the next section, we will investigate the impact of this non-stationarity on the performance of the WiGig channel prediction.

IV. Deep Learning-based Channel Prediction

As demonstrated in the previous section, the dynamic WiGig channel gain follows a non-stationary stochastic process. This suggests that deep learning-based channel prediction models will suffer from concept drift, i.e., deterioration in the prediction model performance depending on the user's spatio-temporal mobility stage. So, in this section, we will discuss data preparation, prediction model architecture, training, and testing. Then, we present the performance of the channel prediction models under concept drift and countermeasures.

A. Data Preparation

To prepare the time-series channel gain data for the prediction task, we carried out a min-max normalization step and converted the data into a labeled format. Min-max normalization is used to scale the input features to a specific range between 0 and 1, which allows fast convergence during the model training. In addition to normalization, the time-series channel data is converted to a labeled format to allow for supervised learning to carry out the prediction task. This involves creating input-output pairs, where the model's input consists of historical channel gain, and the model's output represents the next time step of the channel gain value to be predicted.

B. Prediction Model Architecture

We propose a deep learning channel prediction model based on a hybrid convolutional neural network (CNN)-long-short-term-memory (LSTM) recurrent neural network (RNN). The reason for selecting this model for channel prediction is that the channel gain represents time-series data, which is better predicted using an LSTM-RNN model that efficiently captures the temporal correlation within the data. However, to further enhance the convergence of the model training and enhance the prediction accuracy, the model is better trained using relevant features rather than using raw channel data. Hence, the first stage of the model consists of CNN layers used to extract relevant features and pass them to the next stage consisting of LSTM layers to further process the features and make predictions in the output layer. Specifically, CNNs are well-suited for capturing channel patterns/features related to the user's movement across different locations. On the other hand, LSTM layers are designed to capture sequential dependencies and temporal patterns in the channel data. Hence, the first layer is a 1D Convolutional (Conv1D) layer with an input shape that is based on the number of time steps in the input data, and it has one feature. The next layer is a 1D Max Pooling layer with a pool size of 2. This layer helps reduce the spatial dimensions of the output from the previous Conv1D layer, effectively down-sampling the feature map. The pooling layer is followed by LSTM layers that adopt dropout to prevent overfitting during training. The LSTM layers are followed by a Flatten layer that transforms the output into a 1D array, which is then fed into the dense output layer. The output layer of the regression task is a dense layer with 1 neuron that predicts a single continuous value that represents the next time step of the channel gain.

C. Model Training and Hyper-parameter Optimization

The channel data is split into training and testing data with a split ratio of $3:1$. Model training is carried out on the training data using backpropagation. Also, hyper-parameter optimization is done using a random grid search on the validation set created by cross-validation. The considered hyper-parameters are the number of LSTM layers (an integer between 1 and 10), the number of LSTM units per layer (an integer between 32 and 300), the activation function used in the LSTM layers and the Conv1D layer (ReLu or Tanh), and the dropout rate applied to the LSTM layers (a float between 0 and 0.5). Our hyper-parameter optimization led to the following parameters: using ReLu activation function with two LSTM layers with each layer having 200 neurons and a dropout of 0.3.

D. Performance Metrics

We evaluated the performance of the channel prediction models on the testing data using the root mean squared error (RMSE) metric, which measures the model's accuracy based on the square root of the average of the squared differences between predicted and actual channel gain values. Specifically, the RMSE can be described as

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2},$$

where N denotes the total number of samples in the test dataset, y_i represents the actual channel gain value for the i-th sample, and $\hat{y}_i$ represents the predicted value for the i-th sample.

E. Performance Evaluation and Countermeasure

This subsection presents the performance of the channel prediction models under concept drift and countermeasure. First, we establish benchmark performance for channel prediction. Since the channel gain data follows three distinct statistics depending on the mobility stage, the best channel prediction performance is expected when prediction models are trained and tested using channel data from the same mobility stage. We refer to those as *stage-specific* channel prediction models. Then, we show that these stage-specific models do not generalize well when tested using data from different mobility stages by quantifying the deterioration percentage in RMSE. Next, we study the performance of a prediction model that is trained using channel data from all mobility stages, referred to as *all stages* channel prediction model. Again, we show performance deterioration in RMSE. Finally, we present a countermeasure based on an ensemble model that combines predictions from stage-specific models and we demonstrate a stable RMSE performance regardless of the mobility stage.

1) Stage-Specific Channel Prediction Models: Herein, we develop three channel prediction models, each is trained using channel data from a specific mobility stage. Hence, we have (a) an entering model that is trained using channel data collected from the user's entering stage, (b) a wandering model that is trained using channel data collected from the user's wandering stage, and (c) an exiting model that is trained using channel data collected from the user's exiting stage. Table I shows the RMSE performance of the three models when tested on the channel data collected from the same mobility stage. It is expected that this is the best performance that can be attained since the training and testing channel data used in each model follows the same distribution. To study the generalization ability of the three models, we test each model on channel data collected from the other two mobility stages. Table II shows the performance results in terms of RMSE deterioration with respect to the benchmark performance shown in Table I. In Table II, the RMSE deterioration equals 0% when the model is trained and tested using channel data collected from the same mobility stage. However, the prediction accuracy in terms of RMSE deteriorates by $11-54\%$ when the models are trained and tested on channel data collected from two different mobility stages. This is because the channel data in each mobility stage presents a distinct distribution, as shown in Fig. 4.

2) All Stages Channel Prediction Model: Herein, we train a prediction model using channel data collected from all mobility stages. To test the model's generalization ability, we report in Table II the deterioration in the prediction's RMSE, compared with the benchmark performance in Table I, when the all stages model is tested against channel data collected from specific mobility stages. As shown in Table II, the deterioration in prediction accuracy ranges from 15% to 68%. This performance reduction compared with stage-specific models is expected as the channel data used in the model's training comes from different distributions, which confuses the model during testing.

The results for the stage-specific and all stages models indicate poor generalization ability, with performance degradation ranging from 11% to 68%. This performance is attributed to concept drift in dynamic WiGig channels. Next, we present a countermeasure and study its performance.

TABLE I. Benchmark performance of WiGig channel prediction.

Model	**Entering Model**	**Wandering Model**	**Exiting Model**
RMSE	1×10^{-4}	1.3×10^{-4}	1.3×10^{-4}

3) Ensemble Channel Prediction Models: Ensemble modeling combines the predictions of multiple individual models to create a more accurate and robust final prediction. Herein, we study two ensemble techniques, namely, simple averaging and weight averaging [21]. The simple averaging technique involves combining the predictions from multiple individual models by calculating their average. Each model provides its prediction of the channel gain, and the final ensemble prediction is obtained by taking the average of these individual model predictions. On the other hand, the weights average ensemble technique introduces individual weights for each model's prediction. Instead of giving equal importance to all models, we assign specific weights that reflect the relative importance of each model in the ensemble. In this work, we considered the weights of different models as hyper-parameters that are optimized via random search using cross-validation data. The optimal weights are found to be 70%, 15%, and 15% for the entering model, wandering model, and exiting model, respectively. As shown in Table I, the simple average ensemble maintains performance deterioration of $\leq 9\%$. The most stable performance is attained using the weight averaging ensemble strategy, which results in a deterioration performance of $\leq 4\%$.

TABLE II. Deterioration in performance of channel prediction models relevant to the benchmark models.

Channel Prediction Model	**Data**		
	Entering	**Wandering**	**Exiting**
Entering Model	0%	54%	48%
Wandering Model	31%	0%	11%
Exiting Model	19%	17%	0%
All Stages Model	15%	68%	48%
Simple Averaging Ensemble	9%	1%	1%
Weight Averaging Ensemble	3%	4%	0.3%

V. Conclusion

In this paper, we demonstrated that dynamic indoor WiGig channels suffer from concept drift as the probability distribution of the channel gain varies according to the user's spatio-temporal mobility with 3 distinct stages, namely, entering, wandering, and exiting. This concept drift causes deep learning-based channel prediction models to suffer from performance degradation ranging between $11-68\%$. To improve the model's generalization ability while relying only on channel gain data, two ensemble techniques have been adopted, namely, simple averaging and weight averaging, which improved the robustness of the prediction accuracy, with the best performance achieved by the weight averaging ensemble that maintains performance degradation $\leq 4\%$.

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