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5G throughput prediction using LiDAR information

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***Abstract*—In order to support the increased traffic demands resulting from the rise of 5G networks, the use of higher frequencies in the super-high-frequency band is being investigated. One of the challenges that comes with high-frequency communication is the increased propensity to be affected by path-loss and shadowing, which both cause link quality degradation. We investigate the use of a neural-network model to estimate 5G throughput, using noninvasive LiDAR data collected from a testbed modelling pedestrian shadowing and path-loss using humanoid robots. We show that our model is able to generally match throughput trends as far as 1 s into the future.**

***Index Terms*—5G, throughput prediction, physical space information**

I. Introduction

The rapid rise in wireless traffic poses interesting challenges for any next-generation system or architecture, namely increased demand for both higher capacity and higher numbers of connected devices [1]. A promising approach to dealing with increased congestion is to use higher frequencies, especially the millimeter wave (mmWave) bands.

One issue with mmWave is that at higher frequencies, the effects of path loss and shadowing, even by human bodies is more pronounced [2]. Both of these factors have a strong influence on the throughput of the wireless link, and therefore the overall quality of experience (QoE).

Given the importance of developing robust systems in such conditions, the prediction of radio propagation and link quality has been of interest to the research community. Research has confirmed the possibility of predicting link quality in standard commercial Wi-Fi systems with a moving user equipment (UE) terminal [3], using its exact self-reported position, focusing on the modelling the effects of path loss.

As the exact position of user terminals is often unavailable or highly invasive to obtain in many real world scenarios, using external sensors like cameras is also of interest, and was explored in [4], again with commercial Wi-Fi systems. While cameras have been confirmed to be useful in predicting mmWave link quality [5] received power, they are privacy invasive in practical usage.

Using LiDAR or camera data has another key advantage over abstracted single dimensional data: it contains very rich information about the environment, including multipath characteristics and line of sight obstructions which also have a big impact on the user's QoE in radio environments.

Of particular importance to real-life applications of 5G are multi-UE pedestrian environments, in which a terminal can be significantly shadowed by human bodies – of both the UE holder and other pedestrians blocking the line of sight (LOS) to a base station. These pedestrian scenarios were explored in [5], where a model was trained on data gathered from computational simulation.

Although LiDAR point cloud information has been used to predict received power [6], which is also affected by path loss and shadowing, directly predicting link quality via server-side throughput in commercial setups has yet to be explored. Furthermore, we're interested in extending the application of LiDAR to this problem in cases where the both the obstructions and the terminal itself are in random motion – which greatly increases the complexity of the machine learning task.

This paper presents a combination and extension of several of the ideas explored in the prior literature. In particular, we develop a physical testbed with mobile humanoid robots are autonomously operated along fixed routes with random stopping points. One of the robots carries a commercial 5G terminal which communicates to a server via a base station. We collect a large dataset of server-side throughput and LiDAR point clouds that capture both the environment and moving pedestrians, for the purpose of training a neural network.

II. Experimental setup

A. Testbed

Fig. 1. Testbed environment. Two mobile robots are pictured, one with a wireless terminal inside its backpack.

The cornerstone of this paper is the experimental testbed, pictured in Fig. 1. Two robots are pictured, but one is carrying a black backpack which contains the commercial 5G terminal supporting mmWave which communicates to the base station. The base station is directly above the camera, mounted inside the ceiling. Other points of interest are the white metallic partition-walls, and the concrete pillar.

Fig. 2. Robot close-up

Each robot, shown in Fig. 2 consists of a mobile base that can be controlled via the Robot Operating System, and a humanoid mannequin. The mannequin is intended to model a pedestrian, and thus has similar dielectric properties to the human body. The entire mannequin-robot combination is approximately 170cm tall.

B. Scenario

For the scenario described in this paper, both robots move in straight lines at the back of the testbed, furthest away from the base station. The robot that is not carrying the 5G terminal is closer to the base station, creating a shadowing event every time the two robots cross each other. This route is shown in Fig. 3.

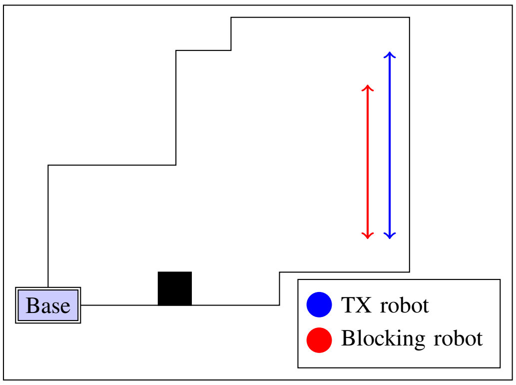

Fig. 3. Robot course on map

The robot that carries the terminal stops twice between endpoints at random points along its route. The obstruction robot stops once at a random point along its route. This is done to give the data extra randomness to add to the challenge for machine learning models and vary the training data by creating shadowing events in different locations.

C. Data collection

All data was measured at 0.1 s intervals.

Throughput was measured and collected server side.

LiDAR data was collected using one Velodyne VLP-32C sensor mounted on a short tripod. The sensor has a 360° horizontal field of view, 32 channels, and spins at 600 rpm. The raw data is a point cloud, as shown in Fig. 4.

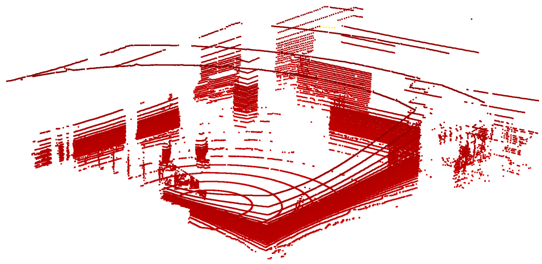

Fig. 4. LiDAR point cloud. Two robots visible in the left.

Fig. 5. Processed 2D LiDAR image

LiDAR data was then filtered and projected onto a 100 by 100 pixel top-down-view image. These images, one of which is shown in Fig. 5, are used in the machine learning model.

III. Prediction

The machine learning task is to use the LiDAR image data to output throughput values, $\hat{t}$.

A. Input data

We use two frames of LiDAR images per data point, spaced 1 s apart, in order to allow the model to infer velocity. Each pixel is a binary state: either 0 or 1.

Due to the presence of outliers of high throughput, and given the problem's focus on throughput degradation rather than improvement, the throughput data was clipped at $2{\times}10^8$ bits/s.

We used 388,308 data points, approximately 10 hours of data collected over 3 days. 10% of this data was used for testing, leaving 349,477 points for training.

TABLE I
MAE ERRORS

Offset type	Mean absolute error
offset: 0.0 s	22.75 Mb/s
offset: 0.1 s	23.8 Mb/s
offset: 0.2 s	22.85 Mb/s
offset: 0.5 s	24.57 Mb/s
offset: 1.0 s	24.42 Mb/s

B. Model

We opted for a convolutional neural network given the visual nature of the input data.

The structure of the model is shown in Fig. 6. It has two convolutional LSTM layers followed by a fully connected layer.

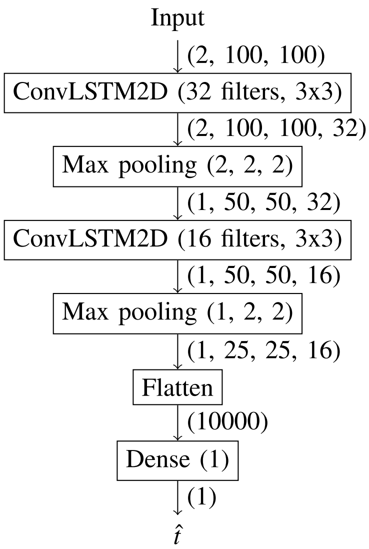

Fig. 6. Neural network architecture

In total, the model has 75,857 parameters, 10000 of which are the in last fully-connected layer alone. The model is trained with the Adam optimization algorithm using a learning rate of 0.001.

We train and evaluate the model on several prediction problems. First, we're interested in simply predicting the throughput at the instant the last LiDAR point cloud was taken. However, for adaptive applications, we're also interested in the possibility of predicting throughput ahead of time. Therefore, we train the model to predict the throughput Δt = 0 s, 0.1 s, 0.5 s, 1 s ahead.

IV. Results

The mean absolute errors of each training run is shown in Table. IV We observe that the error generally gets larger as the model attempts to predict the throughput further into the future.

A plot of the distribution of prediction errors is shown in Fig. 7.

Despite a reasonably high average error, this model is visibly able to predict throughput drops. A section of the testing dataset (previously unseen by the model) is shown alongside

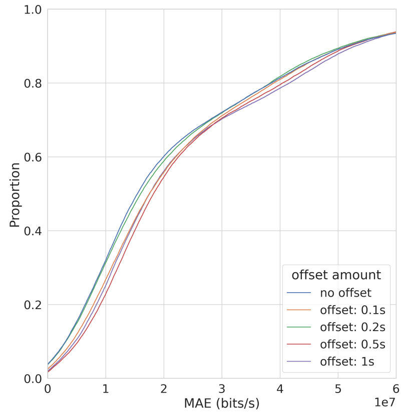

Fig. 7. Error cdf plots

TABLE II
CONFUSION MATRIX TREATING REGRESSION OUTPUT AS BINARY CLASSIFICATION

	Actual high	Actual low
Predicted high	19267	8968
Predicted low	2260	8336

predictions in Fig. 8. The strong similarity of the no-offset and 1 second offset predictions indicate that the model learns mostly the same pattern with both training sets.

There are in essence, three main factors dynamically affecting propagation in our scenario. The first is simple line-of-sight path loss. We hypothesize that as the terminal moves further away from the base station, the lower the throughput will be. The second is self-shadowing by the robot carrying the user terminal, as well as the rapid acceleration of the terminal as it makes a 180° turn at each endpoint of its route. Finally, the pedestrian crossing events in which the line of sight to the terminal is blocked by *another* pedestrian robot.

We observe that throughput degradation is dominated by the endpoint cases, where the terminal-carrying robot makes a 180 degree turn. In Fig. 9

Our neural network fails to consistently predict the extent of these drops, as shown by the 180 degree turn event at around 40 seconds in Fig. 8. Second, both models tend to predict the throughput to drop several seconds before the correct timing. One possible explanation for this behavior is that it has learned to model the endpoint-case in two steps, where the robot first decelerates to a stop, pauses briefly, and then quickly rotates.

As for the pedestrian crossing cases, labeled on Fig. 8, we can clearly observe the model predicting reduced throughput. The ground-truth data is inconsistent, as the pedestrian crossings sometimes result in little to no degradation at all.

It is also of interest to treat the regression outputs as classification, since identifying degradations is particularly useful. As a simple method, we treat throughput values below the mean as "low' values, and above the mean as "high' values. Using the no offset model results in the confusion matrix in Table. IV We observe a 68% accuracy in predicting "high' values correctly, and a 79% accuracy in predicting "low' values correctly.

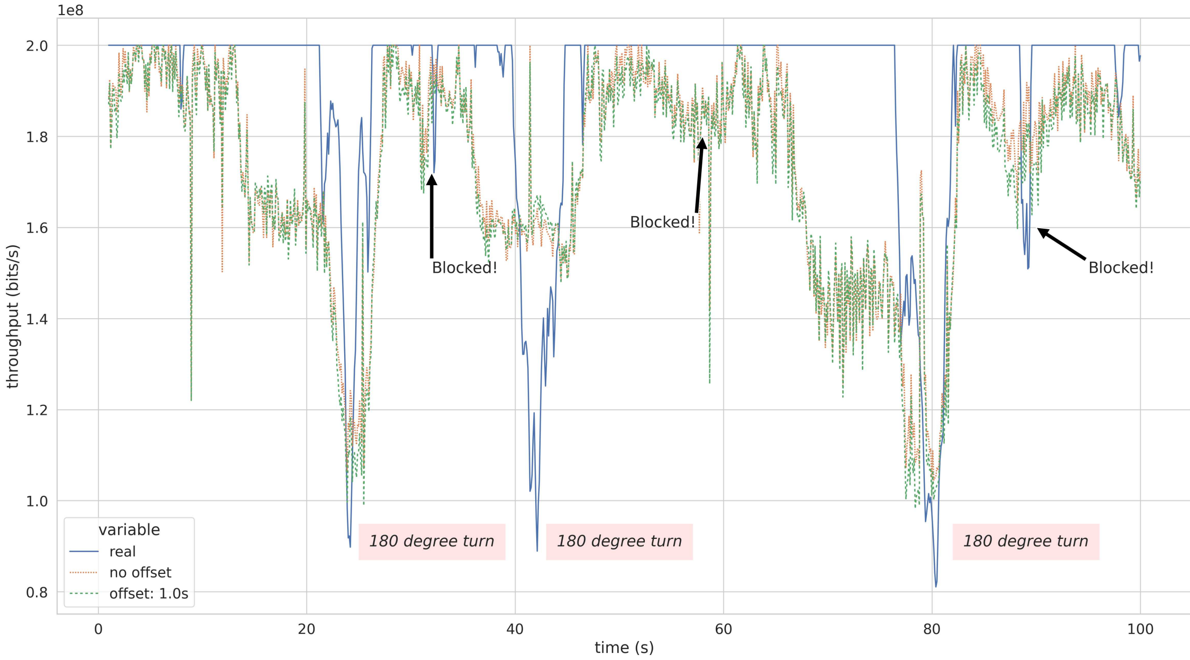

Fig. 8. Sample predictions

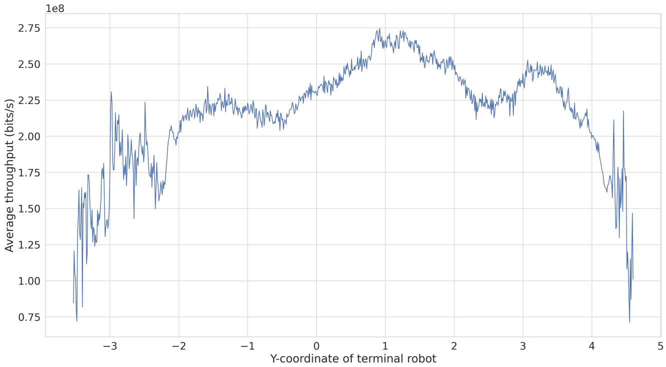

Fig. 9. Average throughput by y-coordinate of terminal. Positive values are closer to the top of the map.

V. Conclusion

We demonstrated the training and evaluation of a neural network that predicts 5G throughput *only* from LiDAR sensor data, thereby requiring no coupling to the wireless infrastructure during usage. Our scenario is novel in its complexity: we use visual data to predict 5G throughput from a randomly moving terminal that is additionally obscured by a model pedestrian with random timing.

Despite this, our neural network model is able to learn the patterns of throughput degradation. It should be noted that the absolute regression accuracy is likely insufficient for practical use, but treating the regression's outputs as simple binary classification yields reasonable results.

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