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Ensemble-transfer-learning-based channel parameter prediction in asymmetric massive MIMO systems

Key words: Asymmetric massive multiple-input multiple-output (MIMO) system; Channel model; Ensemble learning; Instance transfer; Parameter prediction

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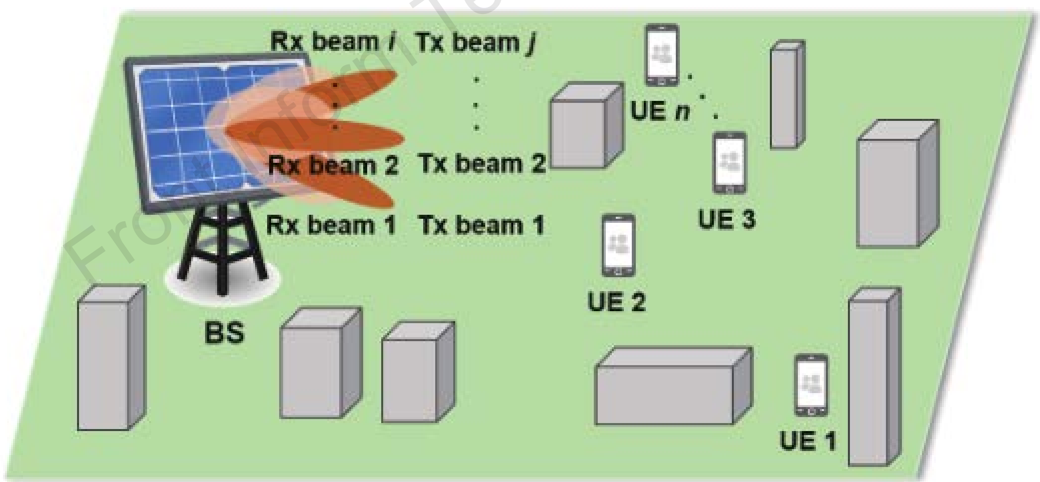
Motivation

➢In the asymmetric massive MIMO system, reciprocity between the uplink (UL) and downlink (DL) wireless channels is not valid. As a result, pilots are required to be sent by both the base station (BS) and user equipment (UE) to predict double-directional channels, which consumes more transmission and computational resources.



A typical application scenario of the asymmetric massive MIMO system

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Motivation

- Some research work has been carried out in investigating the impacts of the beamwidth on channel parameters and can be divided into two categories. The first category is based on empirical models. However, they could only provide statistical results and the accuracy was limited. The second category is to employ ray-tracing techniques. The ray-tracing-based methods can provide accurate results, but a large amount of computation and time consumption are required.

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Main idea

- A prediction method based on ensemble learning and instance transfer is proposed to predict downlink (DL) parameters in non-reciprocal DL channel parameters. The proposed method is able to predict multiple DL channel parameters including pathloss (PL), path number (PN), dalay spread (DS), and angular spread.
- We propose a two-step feature selection algorithm that can determine a feature importance ranking and an optimistic feature combination.
- The instance transfer method is introduced to assist the prediction model in new propagation conditions. By using this transfer-learning-based approach, it is possible to deploy our method in a new propagation condition where enough training data are difficult to collect within a short time.

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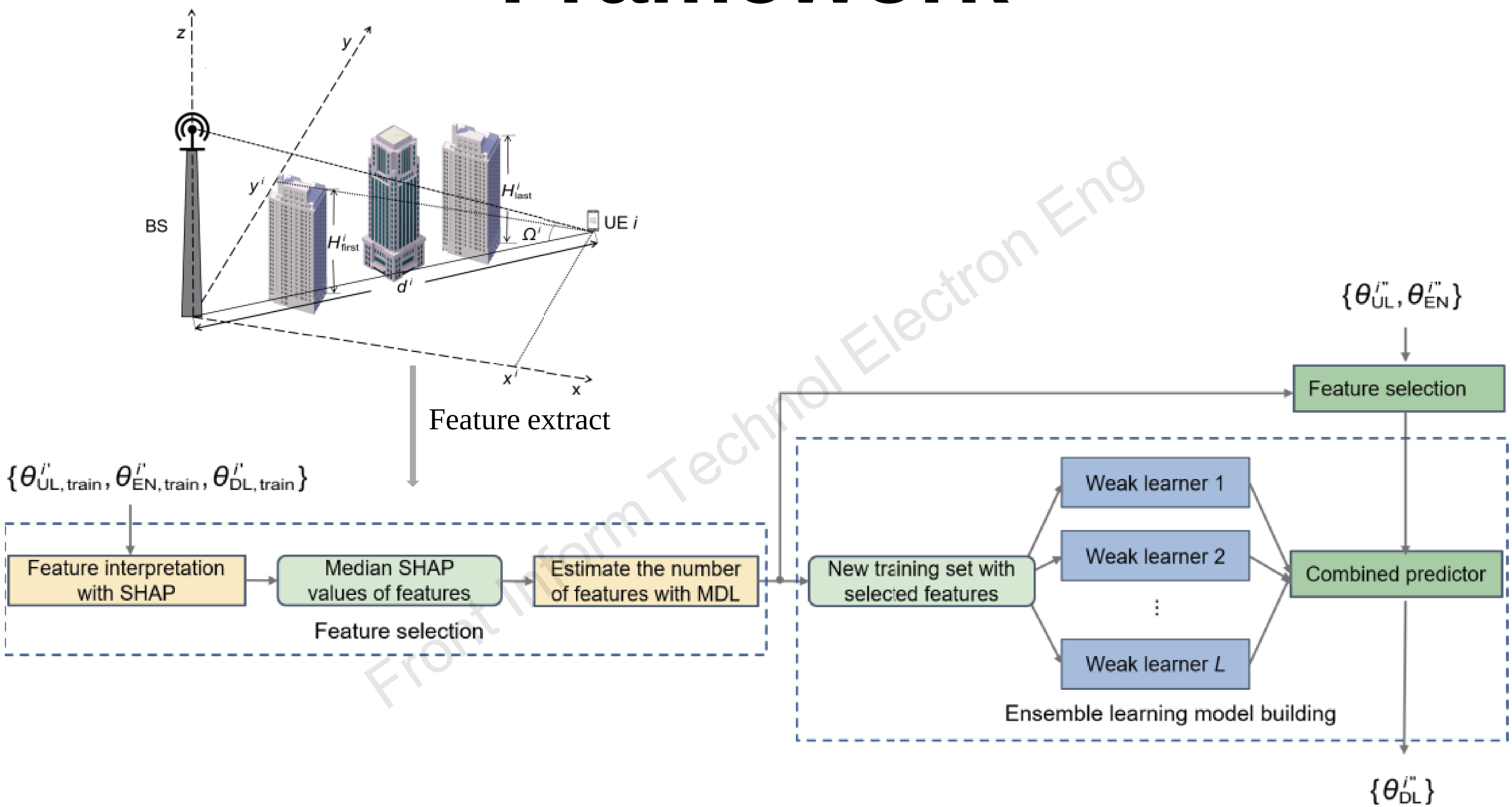
Framework



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Framework of the proposed downlink parameter prediction in the same condition (SHAP: SHapley Additive exPlanations; MDL: minimum description length)

Method

- We consider the prediction of DL parameters in the same propagation condition with the training set. To achieve balance between prediction accuracy and time consumption, the first step of the prediction model training process is to select the features from $\{\theta_i^{\mathrm{UL}}\}$ and $\{\theta_i^{\mathrm{EN}}\}$. The second step is to feed the selected features and DL parameters of the training samples into the weak learners of the ensemble learning model for training.

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Method

- It is difficult to obtain enough training samples under the new condition in a short time, which affects the prediction accuracy of the data-driven ensemble learning model. In this paper, we employ the two-stage TrAdaBoost.R2 algorithm for the prediction of DL channel parameters with a small number of samples under new propagation conditions. In the first stage, only the weights of source instances are adjusted to a certain point and the weights of target instances remain unchanged. In the second stage, the weights of all source instances are frozen and the weights of the target instances are updated.

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Simulation scene

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Fig. 4 Propagation environment and sector partition in an Ottawa urban area (BS: base station)

A typical urban propagation environment in Ottawa, Canada. It is an urban scene consisting of buildings and streets.

Major results

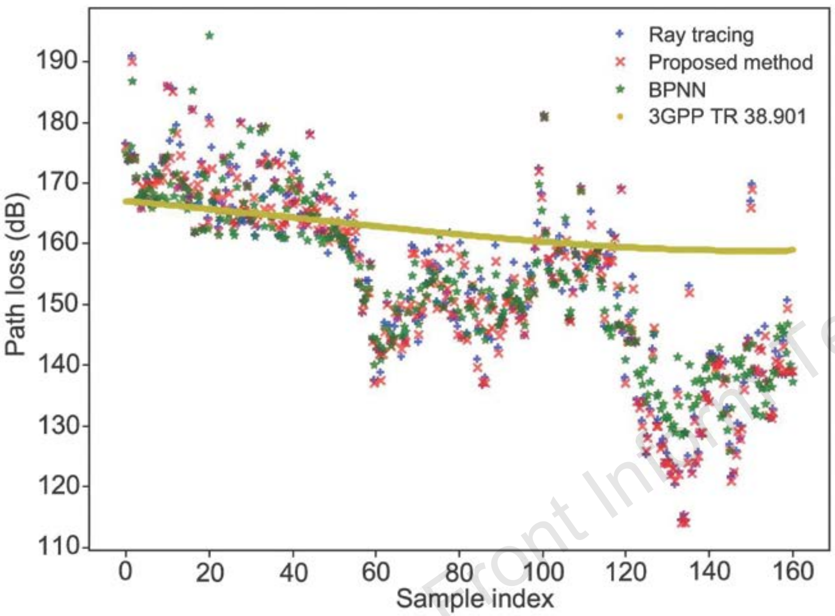

Fig. 5 Path loss prediction values of the proposed method with AdaBoost and other methods

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Table 5 Running time of different methods

Prediction method	Training time (s)	Prediction time (s)
Our method with		
AdaBoost	4.56	0.13
LightGBM	0.45	0.02
XGBoost	1.34	0.05
BPNN	105	32
Ray tracing	–	1703

Major results

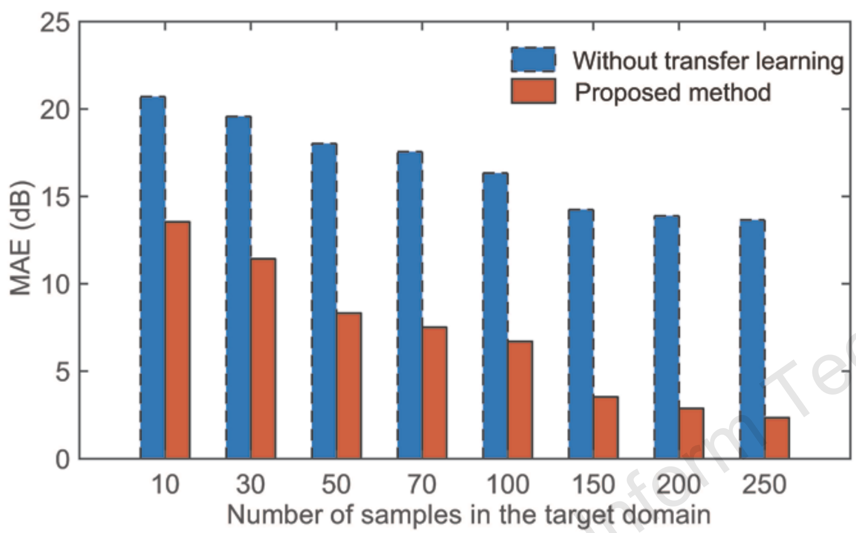

Fig. 6 Comparison of the path loss prediction accuracy of the proposed method and the method without transfer learning when the downlink beamwidth changes from 30° to 10° (MAE: mean absolute error)

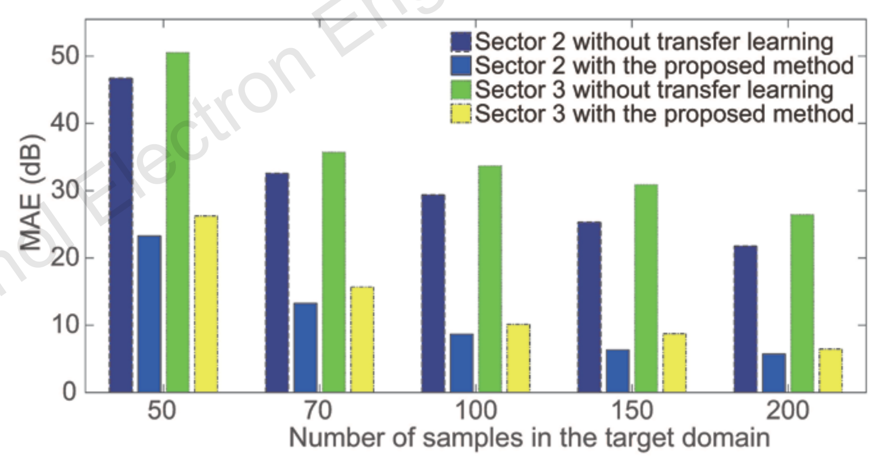

Fig. 7 Comparison of the path loss prediction accuracy of the proposed method and the method without transfer learning when the sector changes (MAE: mean absolute error)

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Conclusions

- The proposed method could be used to predict PL, PN, DS, and angular spread. Its performance was compared with those of the 3GPP TR 38.901 channel model and BPNN. Simulation results showed that the prediction accuracy of the proposed method was better than those of the compared methods.
- When the Tx beamwidth or the sector changed, the instance-transfer-based DL parameter prediction method provided higher prediction accuracy than the method without the transfer learning algorithm with a small number of new samples.

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