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Physics Regulated Deep Learning for Traffic Density Estimation with Small Noisy Data

Traffic density plays an important role on efficient traffic control and operation for intelligent transportation systems. In recent years, data-driven deep learning approaches have been widely adopted for traffic density estimation. However, the limited observation data and the presence of noise in the available data result in low-quality estimation. Through computer simulations, this study investigates the feasibility of physics regulated deep learning approach in the improvement of the estimation accuracy and physics consistency when only small amount of noisy data is available. The physics regulated deep learning approach trains the deep learning model by using the violation of the estimated data to the analytical traffic model as an additional regularization term in the loss function. The first study is on generated synthetic dataset by using the Greenshields' model. Only 0.6% of the data was used in deep learning training. The Lighthill-Whitham-Richards (LWR) and Greenshields models were used to regulate the loss function. After that, the trained model was used to estimate the complete dataset. Finally, the performance of the physics regulated deep learning approach was compared with the data-driven only deep learning approach in terms of the Frobenius norm based normalized error measurement. Simulation results show that the physics regulated deep learning approach improved the estimation accuracy and demonstrated better physics consistency with the analytical traffic models. Comparing with the data-driven only deep learning approach, when only 0.6% data corrupted with 50% Gaussian noise were used in model training, the physics regulated deep learning approach improved 1.5% estimation accuracy. When only 0.6% data corrupted with quadrupled binary noise were used in model training, the physics regulated deep learning approach improved 3.83% estimation accuracy.