Rain Estimation Over a Region Using CycleGan

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Motivation

Commercial microwave links (CMLs) offer a unique opportunity for signal processing, providing valuable insights into wave propagation in the atmosphere. Machine learning (ML) models have shown state of the art results for rain estimation, however those models require paired datasets limiting its applicability. In this work, we propose a new training method for rain estimation using unpaired cyclic consistency, which enables the translation of attenuation measurements to rain rate observations and vise versa without explicit pairing stations.

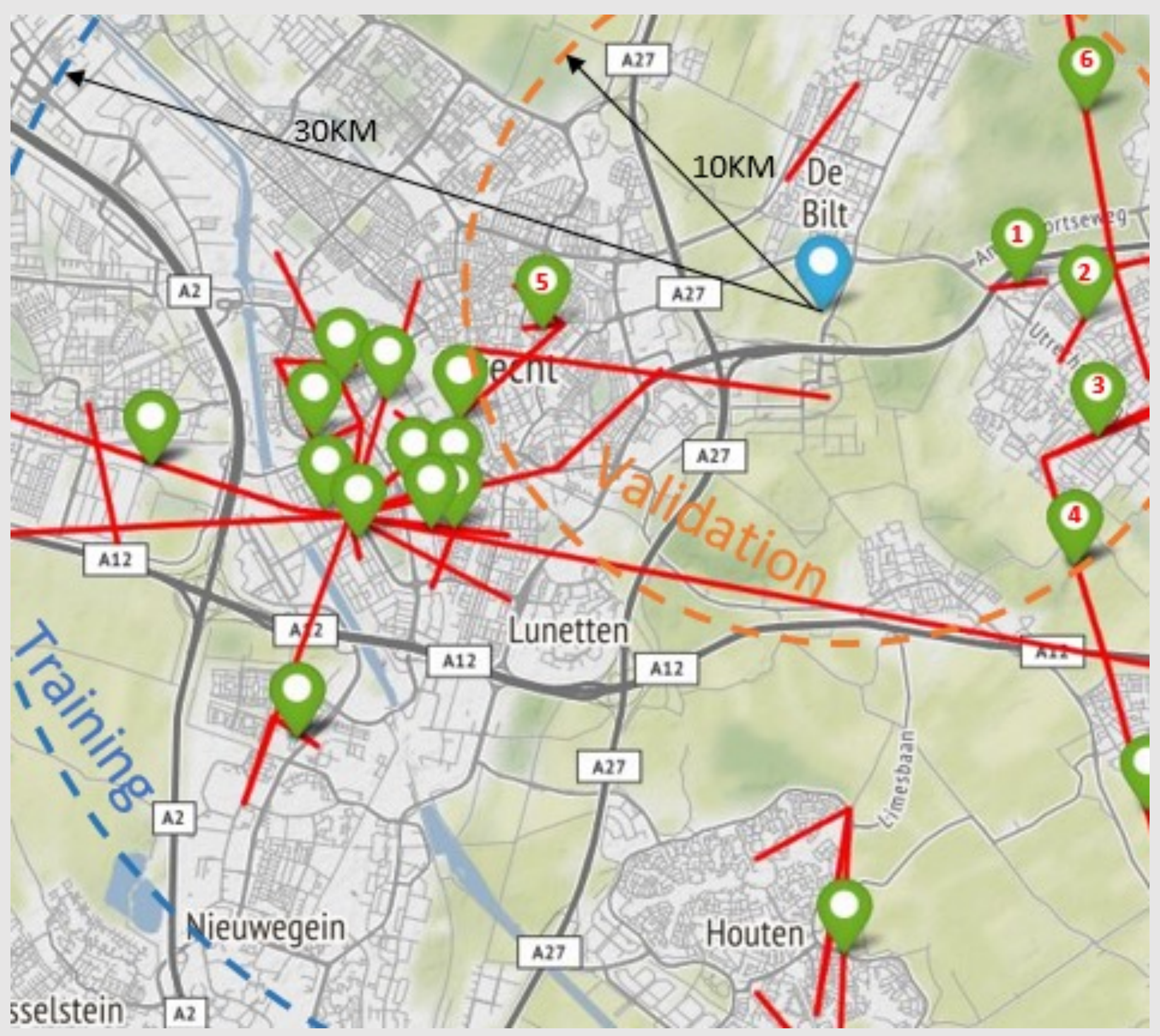

Fig. 1: Location of real CMLs [red], real rain gauges [blue], and inferring rain gauges [green] in the Netherlands during the training phase. We visualize inferring rain gauges only on the validation set. Notice that rain gauges 1-6 are in the radius of 1 km from a real rain gauge, which will serve as ground truth for the validation phase.

Methodology

In this work, we use a dataset that contains 29 CMLs which operate at the frequency range of 30 GHz - 45 GHz and three rain gauges. All CMLs are in the same region as the rain gauges of the Netherlands. Rain rate and attenuation sequences were pre-processed in a method inspired by the dynamic baseline evaluation [1], and rain rate sequences account for dataset imbalance [2] which was also reflected in the loss function. We define a model which consists of two generators and two discriminators.

Attenuation ($\mathcal{A}$) to Rain Rate ($\mathcal{R}$)

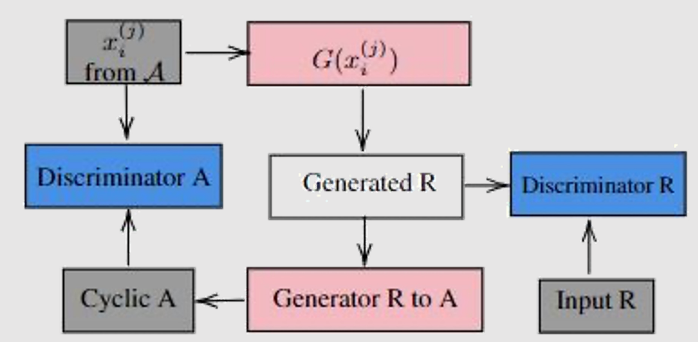

Fig. 2: The model selects a sample from the source domain and converts it into the destination domain using a generator. This generated sample is then passed to another generator to convert it back into a cyclic sample. To maintain consistency with the original input, we enforce similarity between the generated cyclic sample and the original sample. The discriminator evaluates the similarity between the generated and real samples, identifying samples generated by the adversary.

Multiple rain events were considered, and the performance of the inferring rain rate using the root-mean-squared-selective-error (RMSSE) metric [3].

$$RMMSE_j = \sqrt{\frac{1}{N}\sum_{\substack{i\in I_j \\ p}}\left(G\left(x_i^{(j)}\right)_p - y_{i,p}^{(k(j))}\right)^2}$$

Where k(j) is the index of the closest rain gauge to the j^{th} CML. And the set I_j is used to calculate high-intensity rain event with actual rain rates greater than 1 mm/h and predicted rain rates higher than 0.5 mm/h.

Low RMSSE values show close agreement between the generated attenuation measurements from the CML sequence and the true rain rate observations for all validation set stations.

Results

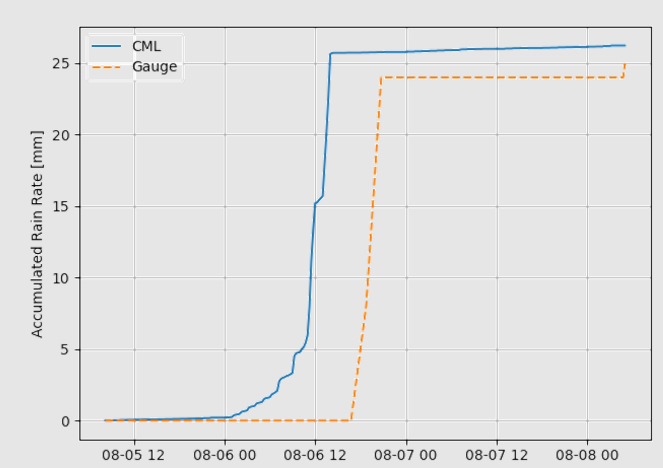

Fig. 3: Predicted accumulated rain rate [blue] vs ground truth accumulated rain rate [orange] for CML #6.

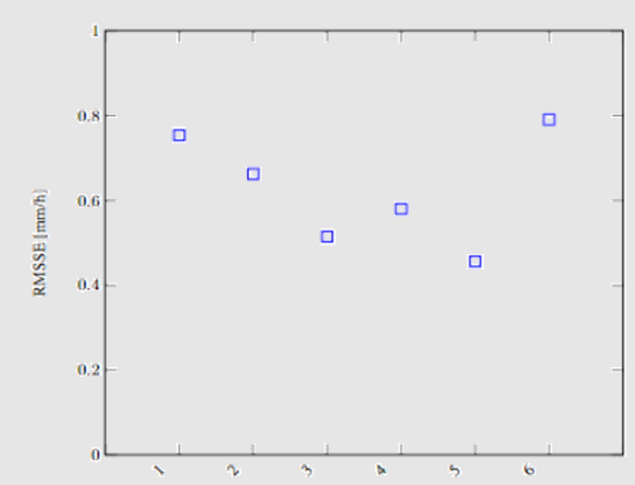

Fig. 4: RMSSE values of six inferring CMLs in within a 10 km radius of a nearby rain gauge for the validation iteration.

Conclusion

We use an unpaired dataset of CML attenuation and rain gauge observations to train a rain estimation model via cycle consistency. Our modified method accounts for rain rate imbalance and yields promising results from the Netherlands. However, further research is needed to determine the required amount of data and training region size.

References
[1] J. Ostrometzky and H. Messer, “Dynamic determination of the baseline level in microwave links for rain monitoring from minimum attenuation values”
[2] D. Salisu, S. Supiah, A. Azmi, et al., “Modeling the distribution of rainfall intensity using hourly data”
[3] Weiss, T. Routtenberg, and H. Messer, “Total performance evaluation of intensity estimation after detection”

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