Wireless User Positioning via Synthetic Data Augmentation and Smart Ensembling

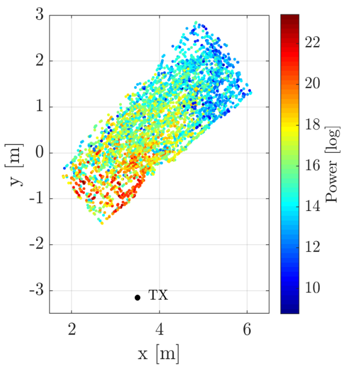
Umberto Michieli, Paolo Testolina, Mattia Lecci, Michele Zorzi

University of Padova – Padova, Italy – {umberto.michieli, paolo.testolina, mattia.lecci, zorzi}@dei.unipd.it

Dataset

- The given data are not normalized
  - Pathloss yields important distance information;
- Frequency and spatial correlations have to be taken into account;
- Models from the literature tend to have lots of parameters;
  - The low number of given samples might be problematic for deep-learning approaches;
  - For this reason we keep a large test set.

TOTAL	Train	Validation	Test
17486	11366	2623	3497

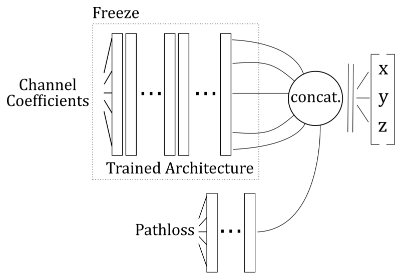


Ensembling

To exploit the correlation between the received signal power and the RX-TX distance, the following architecture is proposed:

- A deep network, chosen among the best-performing ones, extracts the information from the raw channel matrix;
- A shallower network conveys the power information to the output layers, giving it a higher relevance on determining the position.

The respective outputs are therefore concatenated and fed to a last, dense output layer.



To completely exploit the information contained in the received power and deliver it to the output layer, a simple multilayer perceptron was used.

Models

Several models from the literature were tested:

- U-Net [1];
- VGG [2];
- ResNet50 [3];
- DenseNet [custom];
- Others.

The architectures were adjusted to the different nature of our problem, enhancing their performance.

[1] Ronneberger O. et al., "U-Net: Convolutional Networks for Biomedical Image Segmentation", MICCAI 2015.
[2] Simonyan K., Zisserman A., "Very Deep Convolutional Networks for Large-Scale Image Recognition", ICLR 2015.
[3] He et al., "Deep Residual Learning for Image Recognition", CVPR 2016.

Results

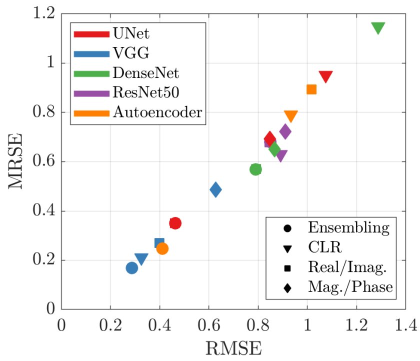


Fig.: Performance of some of the tested networks

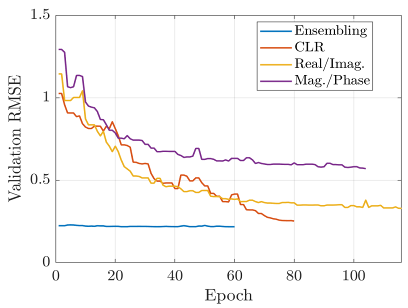
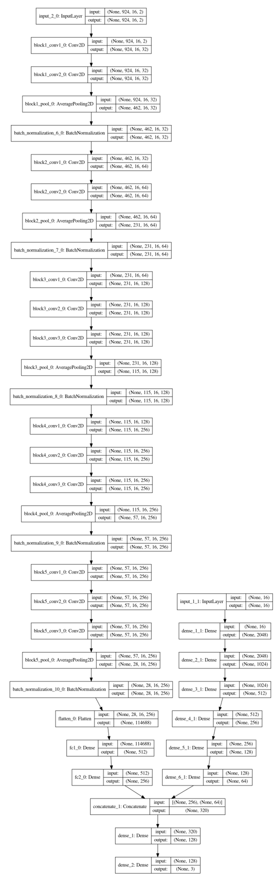
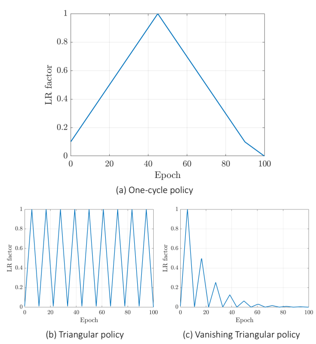


Fig.: Smoothed training curves for VGG-based networks



Cyclical Learning Rate (CLR)

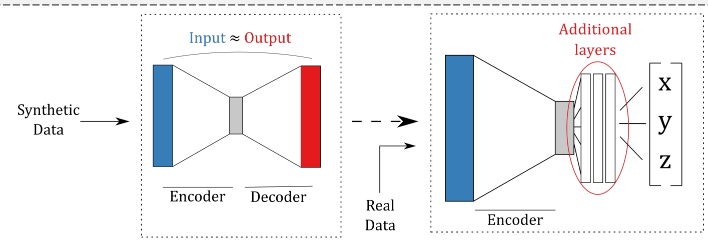
- Cyclical Learning Rate can train deep networks faster and better;
- CLR works especially well with Convolutional Layers;
- Regularization is necessary to avoid strong overfitting;
- CLR allows to find better minima;
- One-cycle policy performed best for us.



Autoencoder Pre-training

In the novel framework we proposed, first an autoencoder learns a compressed representation of the channel matrix using the synthetic data, in a completely **unsupervised** manner. Thus, positions (labels) are not needed during the first phase of the training.
After this phase, only the encoder part of the network is reused and the acquired knowledge is transferred to the real data domain.

We used an implementation of the 3GPP TR 38.901 indoor channel model to obtain a large number of synthetic, unlabeled channel matrices, making it possible for the autoencoder to understand the underlying correlations within a channel matrix.



Autoencoders: although the framework seems to be valid, further work is needed to achieve higher precision.

VGG: the most promising base architecture, future work should investigate the reasons why this specific convolutional model outperforms all the others.

Ensemble: the side information on the SNR can enrich the pretrained base network boosting the performance.

CLR: beside speeding up the training, CLR can help reaching better minima.

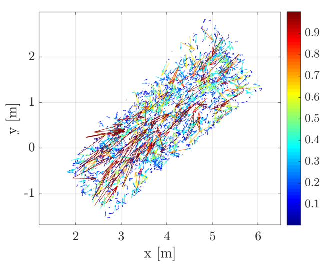


Fig.: Visualization of our best model's errors
Quivers are resized for aesthetic reasons.

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