NUS-DSO Graduate Programme

Research topics

1. Machine-learning-based vegetation RF link prediction from photos

RF communication by a terrestrial user often requires relay via a satellite or airborne node to overcome line of sight issues. When the user is in a vegetated environment, the RF link will be affected by the vegetation. There has been various works in open literature on the prediction of RF link generated via EM or empirical modelling. In such modelling, one usually has to parameterize the vegetation parameters to input into the model. Examples of such parameters include height of trees, some measure of density of canopy, density of tree stands etc. Real world vegetation may not fit precisely into the parameterization employed by such traditional approach

The objective of this proposed research is to develop a neural network that can predict the RF link performance from aerial photo of vegetation, ground user location, and elevation angle from the ground user to the airborne/satellite node. The first phase of research will include measurement of through-vegetation RF link quality values (such as attenuation) to use as labels for subsequent supervised training of the neural network. The neural network will be trained to associate RF link quality with the visual appearance of vegetation, location of ground user relative to vegetation, and elevation of ground user to the air/satellite node.

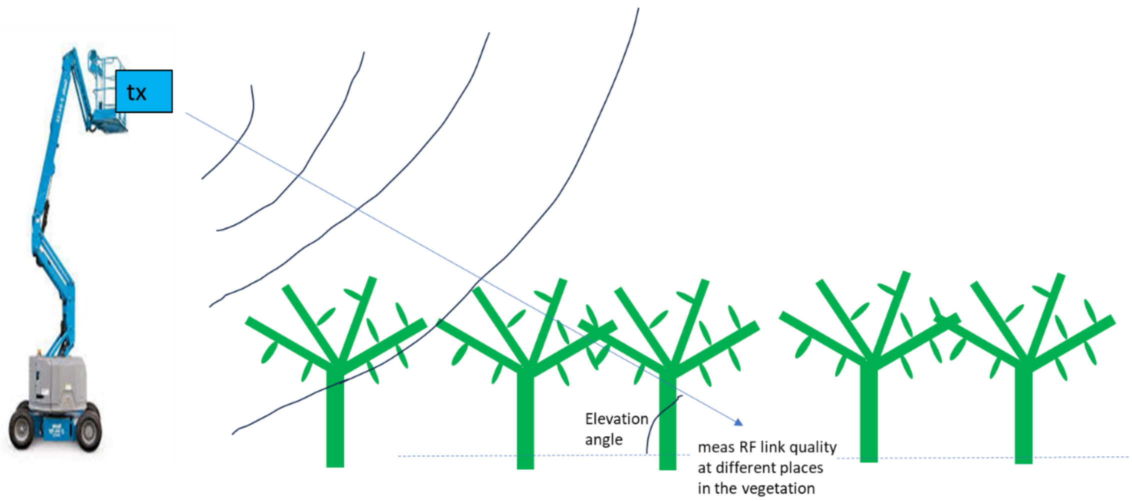

Figure 1. Data collection for supervised learning labels

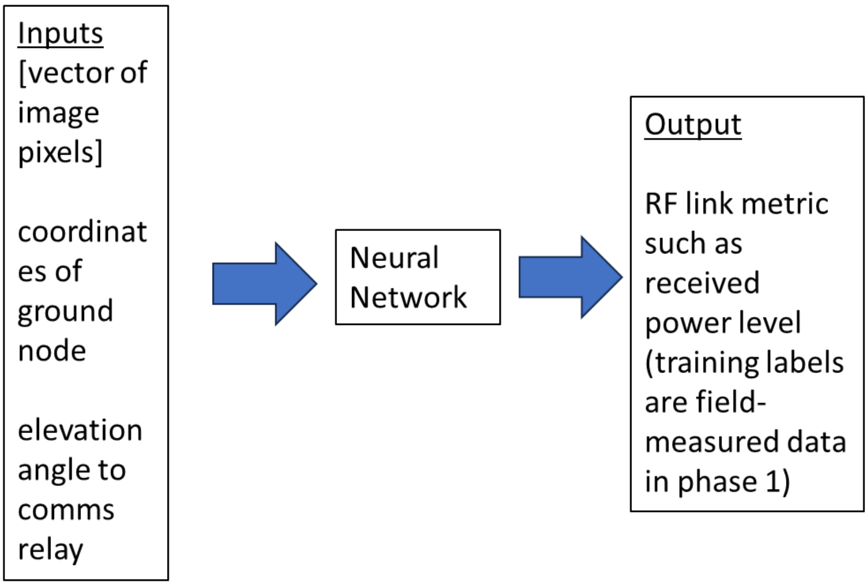

Figure 2. Supervised learning framework

Figure 3. Inference of RF link at with specified locations (eg the stars) relative to vegetation, and specified elevation angle

Possible variations/extensions of the research include:

- The preferred frequency band is UHF which has a higher likelihood of penetrating through the vegetation. However, higher frequency bands such as S band or Ku band (which are used in satellite comms) can also be considered.
- Variation of elevation angles. The vegetation occlusion mechanism is expected to be dominated by canopy at steep elevations and by tree trunks at shallower elevation.
- Exploration of other quality metrics such as dispersion to infer the extent of multipath
- Explain the AI in EM terms and derive analytical formulas for predicting RF link.
- Generalize the neural network by training on different types of vegetation.
- Use of additional input image data to provide more physics-correct information of the vegetation to the neural network. For example, stereo photos can be used to provide 3D height/structure information of the canopy; synthetic aperture data to provide more information of the unilluminated areas that cannot be observed by photos etc.

2. Radio Frequency Interference (RFI) mitigation in Synthetic Aperture Radar (SAR) using machine learning

RFI degrades the performance of radar and communication systems by raising the noise floor. In SAR, a traditional approach of mitigating RFI is to notch out the frequency bins of the interferers. However, from classical transform domain duality theory, introduction of notches in the frequency domain raises spatial domain sidelobe levels, which degrades the quality of the SAR image, especially when the interferers are many and/or wideband. This research aims to investigate machine learning based methods for mitigating the effect of RFI. One possible approach is to use machine learning based superresolution techniques. In open literature, ML based superresolution has been used to improve the resolution of optical and SAR images. In the signal processing sense, improving spatial resolution is equivalent to using AI to increase the spectral support in the frequency domain. A way of thinking about this research problem is to use AI to fill in the notched spectral regions instead of extending the spectral regions.
There are likely other ML methods for mitigating RFI which the candidate is encouraged to explore. Given the data-abundant and stochastic nature of RFI, ML is a promising approach for the problem.
The envisaged research approach includes literature survey, development of SAR image formation tools, and algo development on actual SAR data. Potential data sources for the research include DSO data and open source/commercial source SAR data. While some existing data contains RFI, different levels of RFIs can also be investigated by synthetically adding RFI to the datasets.

3. Neural Networks for computational electromagnetics

Maxwell’s equations may be solved with finite-difference time-domain (FTDT) method, also known as Yee's method or full-wave computation. It is a fully explicit computation that does not require matrix inversion, is accurate (with well-characterized errors, e.g. due to discretization), and robust. However, it requires that the entire computational domain be gridded, the grid spatial discretization to be sufficiently fine to resolve both the smallest electromagnetic wavelength and the smallest geometrical feature. Thus, for large computational domains, it results in very long solution times. In addition, the space-time steps must satisfy the CFL condition for a stable solution of electric (E) and magnetic (H) fields. Furthermore, when applied to inverse problems, Maxwell's equations do not give unique values for material permittivity and permeability.

We propose the use of neural networks for computational electromagnetics. In the forward solving of Maxwell’s equation, we can initialize the neural network with a meta-learned prior distribution of E and H fields. When applied to inverse problems, we can fit the neural network to measured E and H fields while regularized to fit Maxwell’s equations and a prior distribution of material permittivity and permeability. For more challenging experiments with only magnitude measurements, the neural network may be trained to retrieve phase information. Neural networks are continuous and can represent the fields and materials at all points in space and time, no gridding required. To reduce computation, we can explore the trade-off between a uniform distribution of training points in space and time and flexibility training only on areas and times of interest. In addition, neural networks are differentiable, thus no approximation is needed to compute the difference in Maxwell’s equations. As part of the PhD, we can also explore if different formulations of Maxwell’s equations are more amiable to training with neural networks. E.g. solving for a deep generalized Green’s function (response to step input) instead of Green’s function (response to Dirac delta input), followed by post-processing to recover Green’s function or use integration-by-parts to change the mathematical framework to use generalized Green’s function instead. Neural networks may also be trained to get a surrogate model of Maxwell’s equations. Neural networks can also be flexibly conditioned and constrained to include additional sources of information. E.g. in ionosphere modelling, we may include solar power, soundings, GPSRO and WSPRnet.

Using neural networks to solve PDEs is an active line of research, including quantum physics, seismic modelling, and medical imaging. Key techniques include physics informed neural networks (PINNs) and diffusion models. Using neural networks for inverse problems is also an active line of research. Key technique includes neural radiance field (NeRF) to learn a latent 3D representation for novel view generation in both electro-optical and synthetic aperture radar (SAR) images, where the neural network takes in spatial coordinates and outputs opacity in EO images, and radar cross-section in SAR images.