Study of the Impact of Noise on Two Real-time Microwave Inversion Methods

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Over the past 45 years, microwave imaging has been studied extensively for use in medical diagnostics. Microwave imaging technology has clear benefits over current technologies including the non-ionizing nature of the radiation and the relatively low cost of the components. In spite of these advantages, the clinical use of microwave imagers is not yet a reality. This is due to challenges associated with the complex propagation medium that tissue presents. The two main methodologies, direct and iterative inversion, attempt to overcome these issues by improving the forward model of scattering. The iterative strategies update this model, and are thus capable of generating high-quality images. However, they require computationally expensive simulators, leading to reconstruction times lasting several hours or longer. On the other hand, direct methods are capable of generating images in seconds using linear models of scattering. Though image quality is reduced, these strategies can generate quantitative information, which demonstrates a potential to use them as modules within the iterative methods. This enables fast, accurate, and clinically viable image reconstruction schemes. Before integration in the iterative schemes, the fidelity of the direct algorithms must be evaluated, especially their robustness to noise.

Two direct quantitative inversion algorithms, quantitative microwave holography (QMH) [1] and scattered-power mapping (SPM) [2], are studied. Both methods are similar in that they depend on an experimentally acquired resolvent kernel, which can be described as the system point-spread function (PSF) that accounts for the field interaction with the specific environment of the acquisition setup. The resolvent kernel linearizes the scattering model thus enabling a fast inverse solution either in Fourier space (QMH) or in real space (SPM). Thus, the methods are based on the same scattering forward model but perform the inversion differently. QMH solves a small system of equations in Fourier space at each spectral position. The size of the system matrix is determined by the number of frequency samples in the data set and the number of range samples in the image. This leads to a fast reconstruction time within a fraction of a second, even with thousands of image voxels. This speed, however, comes with the cost of vulnerability to noise at the high spatial frequencies due to the overdetermined nature of system matrices. On the other hand, SPM initially generates a new set of qualitative images known as power maps, which are in essence projections of the imaged object onto the PSF space. Power maps are then put through a similar inversion process to QMH with the advantage that they are constructed with full-rank matrices, avoiding the inherent ill-posedness in QMH. The downside is a longer computational time. These differences are explored to determine which algorithm performs more optimally in a given scenario.

To analyze the noise performance of the QMH and SPM, a simulation example is presented. An object is imaged, and white noise is added to the data. The noise level is increased until the reconstruction fails to produce an image, giving an indication of which method can operate at a lower signal-to-noise ratio (SNR). To further explore the algorithms’ robustness to noise, colored noise is added to observe any variations from the white noise behavior. The impact of high noise levels is made evident in these experiments, showing the necessity of preprocessing techniques. Preprocessing strategies such as filtering and a novel denoising algorithm operating similar to empirical-mode decomposition [3] are discussed, and their effectiveness is demonstrated through an experimental tissue-imaging example. The resultant processing time and image quality provide an indication of which algorithm performs more optimally in noisy scenarios, sets baseline requirements for SNR, and establishes preprocessing strategies that are important for optimal functionality within an iterative scheme.

References

