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Microwave Imaging Evaluation of Prior Structural Information on the Inversion-Kernel Building Apply to a Brain Stroke Monitoring Scenario

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***Abstract*—This work investigates the impact of prior structural information on the inversion kernel used to follow up on a brain stroke condition. To that end, we perform a numerical study that mimics an intracranial hemorrhage and aims to retrieve the morphological evolution of the stroke-affected area between different time instants via a direct inversion based on the Born Approximation and the truncated singular value decomposition. Then, we consider different operators, imaging kernels, adding tissue shape information, and evaluating the imaging retrieval performance via the structural similarity index, the dice similarity coefficient, the normalized Hausdorff distance, and a size-based metric, similarity metrics. The results confirm that more a-priori information improves overall performance; however, more importantly, they show that even with approximated kernels, less information, and a more realistic clinical scenario, the imaging might perform well enough as a medical indication.**

***Index Terms*—Brain stroke monitoring, electromagnetic biomedical imaging, inverse scattering, microwave imaging.**

I. Introduction

BRAIN stroke is a health concern that results from a rupture or blockage of a blood vessel, hemorrhage, or ischemia, respectively. This causes a morphological variation of the affected area and, thus, a dielectric contrast spot, which microwave imaging (MWI) techniques exploit to map the pathology by solving an inverse scattering problem via direct or iterative methods [1], [2]. However, whatever the inversion approach, the a-priori information about the scenario under test, either unavailable, distorted, or limited, would impact the retrieval performance, especially in complex scenarios—for instance, the acknowledgment of an initial scenario in a monitoring task.

To study the impact of a-priori information, we propose a realistic numerical experiment mimicking the monitoring of an intracranial hemorrhage using a low-complexity MWI system while modifying the amount of tissue structural information included in the building of the imaging kernel. This point is relevant since, in realistic clinical scenarios, the head patient-specific information is not always fully available.

II. Numerical Experiment

To mimic a realistic scenario, we setup realist 3-D EM full-wave simulations consisting of a five-tissue anthropomorphic head phantom, including the skin, fat, skull, cerebrospinal fluid, and the gray and white matter as a single tissue with average brain permittivity, a right-back-lobe capsule-shaped hemorrhage, a 22-antenna MWI system comformly placed around the upper head. This system works at 1 GHz and has been previously proposed and numerically and experimentally tested in [3], [4]. Then, to resemble a meaningful clinical situation, the stroke is mimicked like a homogeneous mass of blood that grows axially from 20 ml to 40 ml.

For the imaging, we adopt a differential approach that uses the scattering responses at two instances, the time frame under investigation, and a distorted linearized kernel that maps from the differential s-parameters to a dielectric map. This approach uses the Born approximation to linearize the problem, exploiting the weak scatterer nature of the scenario under test, and a truncated singular value decomposition (TSVD) to invert and regularize. To build the kernel, we employ the electric fields of a reference scenario, computed via a realistic full-wave simulation [3]. Then, we consider four kernels to assess the impact of the a-priori information, specifically, the head tissue morphology and the initial stroke. This is a reasonable assumption considering it is contained within the magnetic resonance or a computerized tomography performed during the patient's initial evaluation. The first kernel, dubbed herein MT and stated for multi-tissue, contemplates a "healthy" head including all five tissues. The second one, MT-stroke, adds to MT the initial 20-ml stroke. Instead, the third and fourth, Hom and Hom-stoke, respectively, approximate the head as a single tissue mimicking the average dielectric properties of the head. The latter, Hom-stroke, includes the initial 20-ml stroke. Finally, the differential scattering parameters used as input of all cases are computed from a multi-tissue head with the evolving stroke.

III. Results

The results of the imaging reconstruction are presented in Fig. 1, where the dashed red lines indicate the ground truth shape contour of the stroke at different instants, and each image is a transverse cut at the middle of the stroke-affected 3-D normalized contrast map. Overall, at a glance, the results indicate that all kernels can retrieve the contrast variation and perform well. To evaluate their differences, we use four different metrics that compare the retrieved images with the ground true: Structural Similarity Index (SSIM) [5], Dice Similarity Coefficient (DSC), and the normalized Haudsdorff Distance

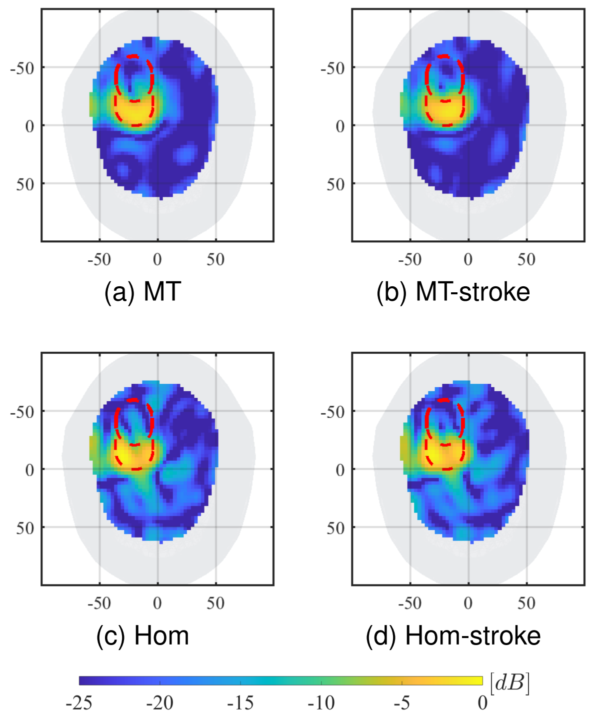

Fig. 1. Transverse plane of the normalized dielectric contrast for the stroke changing from 20 to 40 ml, retrieved by using different kernels.

TABLE I
IMAGING PERFORMANCE METRICS

Metric	MT	MT-stroke	Hom	Hom-stroke
DSC	0.482	0.496	0.379	0.465
S-BM	0.613	0.591	0.549	0.598
N-HD95	0.581	0.594	0.545	0.587
SSIM	0.914	0.917	0.904	0.910

95% percentile (N-HD95), the Size Based Metric (S-BM), the latter two proposed in [6], [7]. SSIM evaluates how well the reconstructed binary mask of the stroke evolution matches the expected distribution. DSC measures how much the stroke region of the reconstructed image and the ground truth overlap in the imaging domain. N-HD95 is a boundary-based metric that measures the mismatch distance between the boundary of the reconstructed stroke region and the ground truth stroke boundary. It specifically calculates the 95*th* percentile of the Hausdorff distance between the two boundaries. Finally, S-BM is a metric that normalizes the size difference of the stroke between the ground truth and the reconstructed image. All these metrics are bounded from 0 and 1, where 1 indicates the highest similarity to the ground truth. Moreover, to determine the binary mask, we consider the normalized reconstructed dielectric contrast values above -5 dB as 1, and the others 0.

Comparing the results in Table I, it is observed that both MT-stroke and MT, which consider the exact head model with and without the initial state of the stroke, respectively, achieve the highest performance across all metrics. As more tissues are simplified, a consistent degradation in image reconstruction is observed, as indicated by the lower scores of Hom and Hom-stroke.

IV. Conclusions and Perspectives

The presented work explored different inversion-kernel operators and their impact on image reconstruction for brain stroke monitoring. The results demonstrate that when no a-priori information about the structure of the imaging region is available, approximate modeling to build the operator is a good resource for monitoring the evolution of the lesion. This is remarkable, considering the limited patient-specific information in a possible clinical scenario. For future work, it is planned to extend the analysis to assess the impact of inaccuracies in modeling individual head tissues to build the inversion-kernel operator for the monitoring of hemorrhagic and ischemic strokes when prior information is available from complementary biomedical imaging techniques.

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