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Energy-driven Microwave Medical Sensing for Post-acute Brain Stroke Monitoring

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Abstract—This paper presents a simple microwave-sensing framework for monitoring post-acute stroke evolution, featuring three key innovations: a low-complexity helmet-like device employing only sixteen antennas in a cross-sectional multi-view architecture, an ad-hoc anthropomorphic multi-tissue head phantom, and an energy-based algorithm designed to detect and track temporal pathological changes. The method interprets the Frobenius norm of the differential scattering matrices as a global energy indicator of dielectric variations, enabling the detection of volumetric stroke evolution. Experimental validation on the multi-tissue phantom demonstrates consistent performance across different progression scenarios, showing that the proposed indicator correlates with clinically relevant centimetric volume changes. These results support the method's suitability for bedside use and highlight the potential of low-complexity microwave sensing as a practical tool for non-invasive, real-time follow-up of stroke evolution in clinical workflows.

Index Terms—Acute ischemic stroke, brain, electromagnetic propagation, electromagnetic scattering, intracerebral hemorrhage, microwave medical sensing, noninvasive monitoring.

I. INTRODUCTION

STROKE is a highly prevalent and severe neurological event that disrupts the normal oxygen-rich, well-nourished blood perfusion to the brain. It stands as the second leading cause of death and the third leading cause of death and disability combined, reaching about twelve million cases worldwide annually, and with a projected incidence increase due to population aging [1], [2]. Stroke is a post-onset, rapidly patient-specific progressive pathology, especially during the first hours, that leads to rapid neuronal death at a rate of millions per minute, resulting in neuronal deficits. There are two main categories of stroke: the Intracerebral Hemorrhage (ICH), accounting for about 20% of stroke cases, though the most deadly, and the Acute Ischemic Stroke (AIS), accounting for most of the remaining cases [3]. ICH occurs when a

vessel rupture provokes sudden bleeding into the brain tissues (parenchyma). Its spontaneous occurrence is often associated with high blood pressure and other vascular conditions [4], [5]. AIS occurs when a persistent vessel or artery occlusion, embolism (blockage), or reduced blood flow due to stenosis (vessel narrowing) leads to an infarction (brain tissue damage) [6]. AIS causes brain tissue necrosis and softening due to ischemia and hypoxia, and is characterized by an internal core, severely hypoperfused, and a penumbra, covered by idling cells.

Acute stroke management requires a prompt three-phase intervention, ideally within a few hours of onset, consisting of stabilization and diagnosis, treatment administration, and follow-up. The goal is to improve the prognosis and reduce the risk of post-event recurrence, disability, and fatality [7]. After stabilization, the diagnosis includes medical examinations, symptom evaluation (standardized clinical scales/questionnaires) [8], and medical imaging to determine the localization, severity, and nature and extent of the affection, and guide subsequent treatment, which is closely related to the latter. The gold standard imaging modalities are X-ray-based computed tomography (CT) and magnetic resonance imaging (MRI). These tools are used depending on availability and hospital-specific emergency protocols, and are limited by their intrinsic low portability, time-consuming operation, high cost, and ionizing radiation in the case of CT [9], [10], [11], [12].

Follow-up is aimed at assessing the patient's condition and their response to the treatment. It is as important as the baseline diagnosis. In this stage, the condition can take different courses and time signatures depending on the specific patient and treatment, and is difficult to predict.

However, due to limitations in current gold-standard techniques, physicians lack instruments that provide real-time feedback and detect changes in the patient's evolution, crucial information during the first 24 hours after onset [13], [14].

From an electromagnetic (EM) perspective, the stroke shows a dielectric contrast relative to healthy surrounding brain tissue, e.g., white and gray matter. For instance, in ICH, the blood accumulation exhibits higher permittivity and dielectric losses than the surrounding brain tissue. Conversely, AIS results from a deficit in blood supply, which leads to a decrease in permittivity. This circumstance enables the use of medical microwave imaging (MMI) and medical microwave sensing (MMS) for stroke diagnosis and monitoring. Accordingly, MMI and MMS devices have recently been investigated as complementary diagnostic alternatives to MR and CT, trading

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their limitations for reduced spatial resolution [15], [16], [17], [18], [19], [20], [21]. For monitoring, stroke follow-up using differential MMI was experimentally demonstrated in [22] with a low-complexity 22-antenna array capable of generating normalized dielectric contrast maps to image the progression of ICH and AIS lesions. In parallel, MMS for stroke classification was proposed in [23], employing a space-division-based classification method to detect and localize both ICH and AIS.

In this paper, we present a low-complexity MMS device designed to monitor the evolution of brain stroke in the post-acute stage. The novelty of this work lies in three key aspects: (i) a cross-sectional multiview sensing architecture implemented with a 16-antenna helmet-like system, selected through an experimental reduced-array sensitivity analysis as a trade-off between sensing robustness and hardware complexity; (ii) an anthropomorphic multi-tissue head phantom enabling controlled stroke-volume variations; and (iii) an energy-based algorithm capable of detecting temporal pathological changes from differential multistatic scattering responses. Unlike microwave imaging approaches that reconstruct dielectric maps, the proposed method uses the Frobenius norm of the differential scattering matrix as a global energy indicator for pathological evolution. This energy indicator aggregates dielectric variations embedded into a compact electromagnetic signature that can be tracked over time without requiring supervised training or image reconstruction.

The use of the proposed system is patient-specific and based on repeated short bedside monitoring sessions. In this workflow, acquisitions performed at clinically meaningful time points would be compared to assess whether the pathological condition is evolving, stabilizing, or regressing. For ICH, this may support the follow-up of hematoma progression or stabilization after treatment [24], whereas for AIS, it may help monitor secondary changes after reperfusion therapy, including hemorrhagic transformation [13], [14], [25], [26].

II. MEDICAL MICROWAVE SENSING TESTING SYSTEM

For MMS system, different antenna configurations have been investigated, ranging from monostatic circular scanning systems using a single movable antenna [27] to helmet-like

multistatic arrays with 16–24 antennas distributed around the head [28]. The MMS system developed for this study builds on our previous work [28] and consists of a simplified, sagittal-symmetric, helmet-like, low-complexity, multi-frequency, cross-sectional, multiview architecture. The system, whose schematic is shown in Fig. 1, consists of 16 antennas conformally distributed around the head, forming two ring-like arrays positioned at different heights to increase angular/spatial diversity and cover the whole brain. To promote through-head propagation, enable fast scanning, reduce hardware complexity, and limit information redundancy, the antennas are divided into two groups of eight elements. Each group is connected to an independent solid-state single-pole-eight-throw (SP8T) switch [29], denoted as Sw_A and Sw_B in Fig. 1. This configuration focuses on inter-group transmission responses between opposite or quasi-opposite antennas, which are expected to be more sensitive to dielectric perturbations inside the head. The 16-antenna cross-sectional multiview (CSMV) architecture is adopted as a practical trade-off between sensing performance and system complexity. Its experimental sensitivity with respect to reduced antenna configurations is discussed in Sect. VI. The proposed setup creates switched channels and allows the acquisition of a partially filled scattering matrix with 8^2 independent combinations, corresponding to a subset of the full 16×16 matrix. Due to the reciprocal nature of the problem, the information content in the upper-right quadrant of the 16×16 scattering matrix is equivalent to that in the lower-left quadrant. To acquire the scattering responses, a laptop, an HP EliteBook 830 G5 with 8 GB RAM, controls each channel and sequentially synchronizes a two-port compact P5003B vector network analyzer (VNA) [30] with the corresponding antenna pair. Overall, this architecture reduces the complexity of both the hardware implementation and the data acquisition procedure.

The antennas are held by a 3D-printed support and secured with elastic bands to maintain stability (see Fig.2 (a-b)). Here, it is worth noting that this setup leaves room for integrating other multimodal sensors, such as ultrasound or Electrocardiogram (ECG) sensors. Moreover, the helmet is wrapped with an electromagnetic absorber layer to limit the propagation of external fields, mitigate multipath reflections, and reduce coupling between nearby antennas (see Fig. 2(c-d)). A carbon-loaded three-layer foam optimized to operate in the microwave band Eccosorb AN77 is used for this purpose [31]. The antennas are a slightly modified version of those presented in [15]. Each radiating element is a structure that pairs a printed monopole (Ant) and a discrete matching medium (MM). For this study, each Ant-MM pair is optimized to work in contact with the external surface of a multi-tissue human head. The Ant-MM is a custom-made material consisting of a mixture of 20% graphite powder and 80% urethane rubber, having a relative permittivity, ϵ_r , of about 10 and a conductivity, σ , of about 0.04 S/m in the operating frequency range of 0.9–1.8 GHz, consistent with previous work [32]. The measured transmission scattering parameters of the antenna 1 are shown in Fig. 3, along with the dimensions of the designed Ant-MM. The dimensions of the radiator are found in [15].

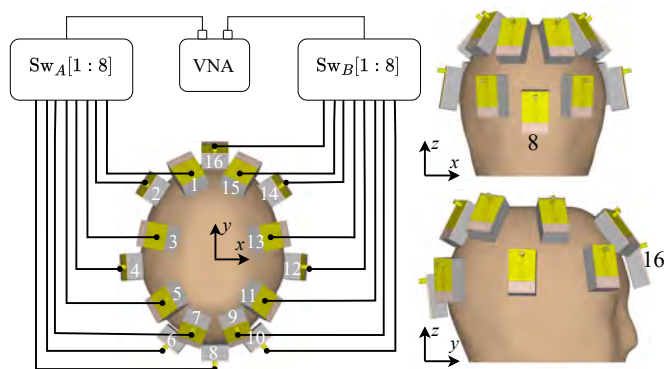


Fig. 1. Scheme of the system set-up: on the left, the top view showing the antennas, the phantom, and switches Sw_A and Sw_B ; on the right, the sagittal and frontal views.

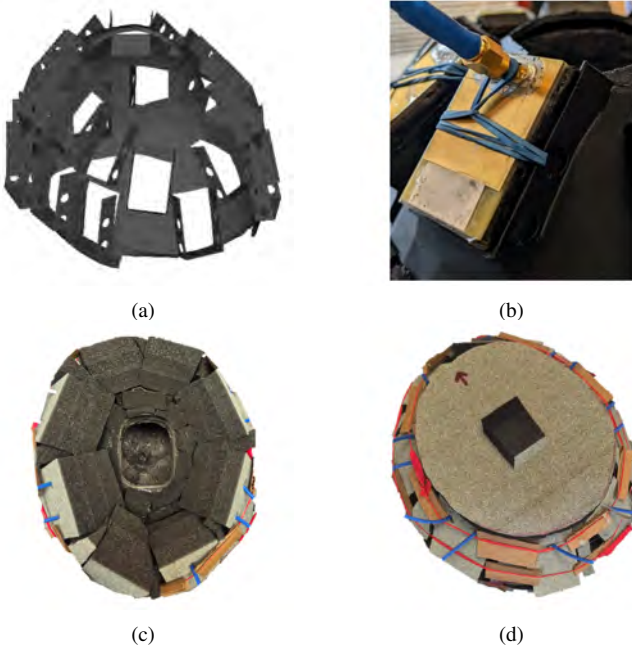


Fig. 2. Helmet development: (a) helmet; (b) antenna placement inside the helmet; (c) top view showing all the absorbers; and (d) phantom including the cup made of absorber material. The arrow indicates the nose direction.

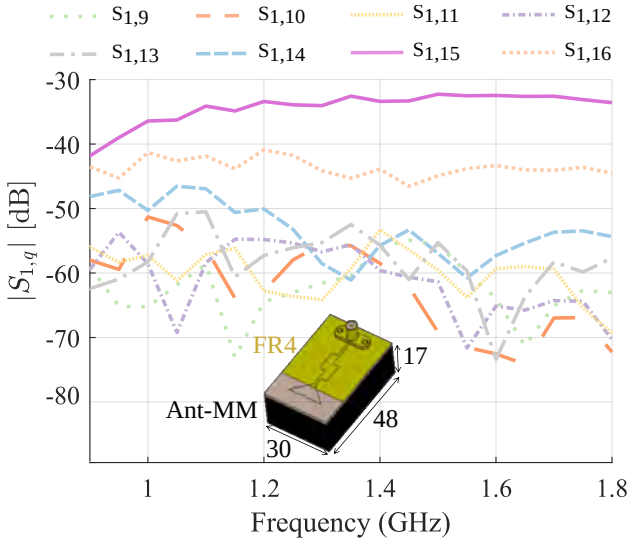


Fig. 3. Measured S-parameters: transmissions with $q = 9, \dots, 16$ and antenna scheme. The dimensions are expressed in (mm).

The overall system setup, including an ad hoc shielding chamber that reduces external electromagnetic interference, is shown in Fig. 4. The ad-hoc shielded chamber is a wooden box lined internally with a thin metal sheet and two 2 cm-thick layers of electromagnetic absorber foam [33]. The pumping system for controlling stroke volume and the active components, such as the laptop and VNA, are placed outside the shielding enclosure, as shown in Fig.4.

III. MULTI-TISSUE PHANTOM REALIZATION

The phantom is a fundamental element for the experimental MMI systems. Liquid-based head phantoms, often realized

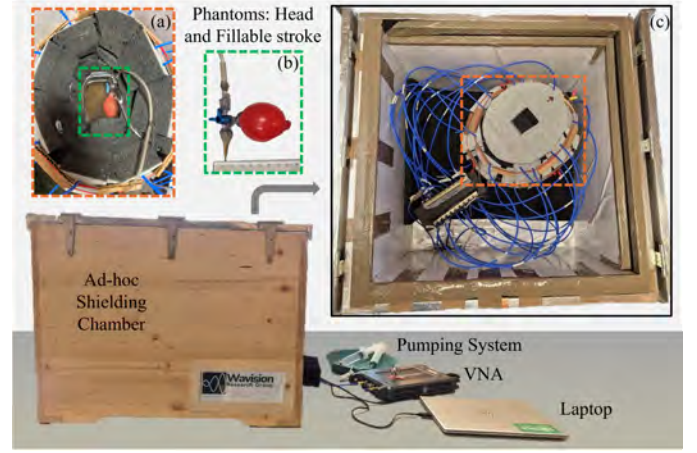


Fig. 4. System set-up. From left to right: the custom shielding chamber, the syringe used to emulate the stroke, the VNA, and the laptop. (a) A view of the phantom shows the stroke placed in the middle-right position, (b) the stroke phantom, and (c) the inside of the chamber, including the multi-tissue phantom and switches Sw_A and Sw_B .

by combining 3-D printed structures with tissue-equivalent liquid mixtures, have been used to emulate the dielectric properties of biological tissues over broad frequency ranges [34]. Semi-solid or gel-like phantoms provide an alternative for more realistic three-dimensional head models [35]. In addition, in [36], it is proposed a generic wideband phantom-design methodology based on water-oil mixtures to reproduce target dielectric properties for microwave medical applications. Other works have focused on stable solid or polymer-based phantoms to improve mechanical robustness and long-term dielectric stability for repeated electromagnetic testing [37]. For this study, a new biomimetic model of the human head that faithfully reproduces both the anatomical shape and the dielectric properties (DPs) of human tissues [38] has been developed. Compared to previous models used in our experiments [28] and to our preliminary multi-tissue phantom in [39], the new phantom represents a significant evolution. The phantom structure comprises two main parts: a solid component that simulates skin, fat, bone, and cerebrospinal fluid (CSF), and a liquid component that represents the brain, allowing easy dimensional variation of the stroke placed inside.

Three different materials are chosen for the phantom's construction: a solid material made of carbon-loaded plastic filament [40] with dielectric properties similar to human fat tissue; a semi-solid mixture of rubber (ReoFlex 40 [41]) and graphite with varying proportions to simulate the DPs of skin, bone, and CSF; and a liquid made of water, alcohol, and salt used to model the average brain and the ICH and IS strokes. The use of graphite-rubber composites is consistent with approaches adopted by other research groups in the construction of phantoms, as e.g. in [37], [42], [43]. The phantom is equipped with a hole at the top, allowing easy liquid filling, stroke placement, and visual monitoring of stroke expansion. DPs of the materials mimic the nominal values reported in [38], and they are measured using the method described in [44]. All the recipes, along with the measured DPs (relative permittivity ϵ_r and conductivity σ at 1.3 GHz), are reported

in Table I. Figure 5 shows the frequency-dependent dielectric properties of all considered tissues. The solid lines represent the measured dielectric properties, whereas the dashed lines correspond to the nominal values reported in [38].

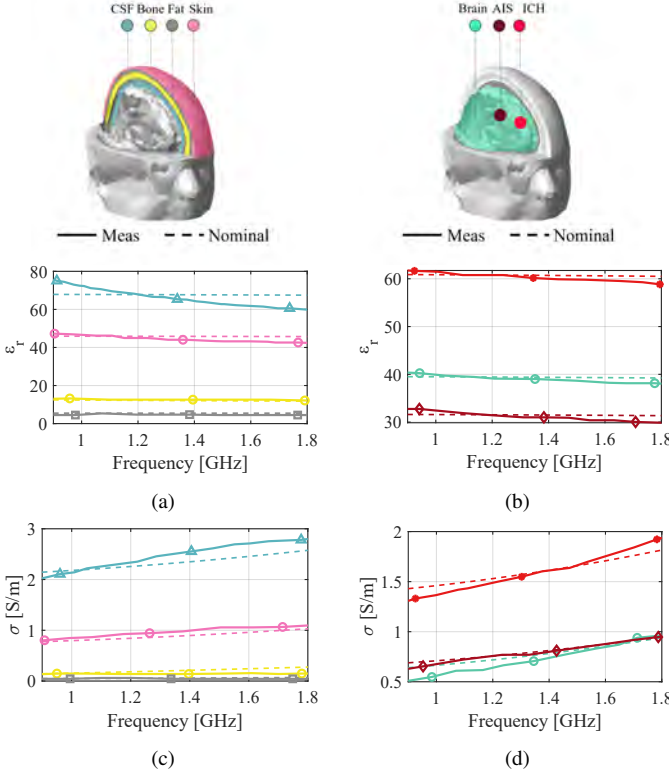


Fig. 5. Dielectric properties of all the tissues of the phantom. The nominal values are taken from [38]. Dashed lines correspond to the target values, and continuous lines correspond to the measured values.

The fat layer, shown in Fig. 6(a-b), provides structural stability. Because of the complexity, for manufacturing, the fat layer is split along the sagittal plane and designed with an interlocking system: a hole on the left side and matching interlocking pillars on the right ensure a stable assembly. This component serves a dual purpose: it encloses the bone layer and acts as a mold for the adjacent layers (skin and CSF).

The CSF is represented as a thin layer, approximately 5 mm thick, applied between the inner surface of the fat layer and the outer surface of the brain [see Fig. 6(a)]. After application, the two halves are glued together, and residual gaps are filled through the upper opening. The bone mixture, with a relatively low graphite content (23%), is a low-viscosity liquid that

fills the bone cavity inside the fat layer before curing [see Fig. 6(b)]. The skin layer is created as a thin coating applied over the fat layer outer surface. To mold this layer, the original CAD skin model is scaled up by 5% and 3D printed in standard PLA. The mixture of urethane rubber, graphite, and acetone is evenly spread on the phantom surface with spatulas to ensure a smooth and uniform coating, as illustrated in Fig. 6(c).

The brain is simulated as a transparent liquid mixture that reproduces the average DPs of white and grey matter. The phantom is filled with approximately 1.3 kg of this mixture occupying the entire brain volume. The remaining anatomical structures are omitted because their influence is negligible within the scope of the application. The stroke is simulated using a balloon connected to a valve: one side of the balloon is fixed to the phantom using a wooden stick that allows positioning in specific locations; the other side connects via tubing to an external syringe that inflates or deflates the balloon to replicate volumetric variations. Figure 4 depicts the liquid inside the phantom and the structure of the stroke.

IV. STROKE-EVOLUTION SENSING ALGORITHM

A. Problem Statement

The progression of the stroke over time, e.g., an increase/decrease in its volume and/or a switch between ICH and AIS, is encoded by the permittivity of the corresponding brain region. Accordingly, assuming the only detectable changes in the brain tissue occur due to changes in the stroke, these can be expressed by the differential permittivity:

$$\Delta\epsilon(\mathbf{r}) = \epsilon(t_n, \mathbf{r}) - \epsilon(t_{n-1}, \mathbf{r}), \quad (1)$$

where $\epsilon(t_n, \mathbf{r})$ represents the complex permittivity distribution at time t_n in $\mathbf{r}$. The corresponding differential scattering parameters between the p -th and q -th antennas are expressed as in [46]:

$$\Delta S_{p,q}(t_n, t_{n-1}) = -\frac{j\omega\epsilon_0}{2a_p a_q} \int_D \Delta\epsilon(\mathbf{r}) E_p^{\text{state}_{n-1}}(\mathbf{r}) \cdot E_q^{\text{state}_n}(\mathbf{r}) d\mathbf{r}, \quad (2)$$

where D is the domain of interest, j is the imaginary unit, $\omega = 2\pi f$ is the angular frequency, and a_p and a_q are the root-power waves at the p -th and q -th antenna ports, respectively. The “ $\cdot$ ” indicates the dot product. $E_p^{\text{state}_{n-1}}$ and $E_q^{\text{state}_n}$ denote the fields from port p and q in the states state_{n-1} and state_n , respectively at t_{n-1} and t_n .

According to the above, stroke progression can be monitored exploiting an energy-based strategy that processes the differential scattering parameters acquired at different time instants to appraise relative variations.

It is important to notice that, as long as that, the changes in complex permittivity within the monitoring interval are small (in terms of the electrical size of the volume and permittivity amplitude), the energy of the differential signal will be linearly related to the differential permittivity amplitude. Whereas, in presence of an abrupt evolution of the clinical conditions, this linear relationship will be lost. Nevertheless, this will produce

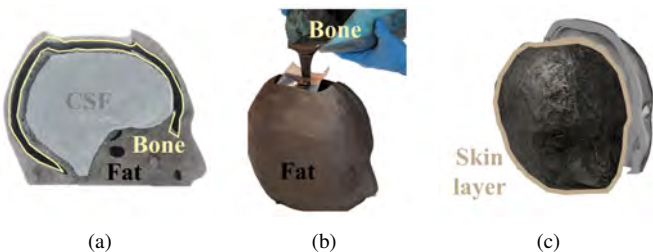


Fig. 6. Phantom development: (a) printed fat and CSF; (b) bone and (c) skin layer.

TABLE I
RECIPES AND DIELECTRIC PROPERTIES AT 1.3 GHz OF THE TISSUES OF THE PHANTOM.

Tissue	Rubber	Graphite	Acetone	Alcohol 96%	Deionized Water	NaCl	ϵ_r	σ [S/m]
CSF*	44	44	12	-	-	-	65 (68)	2.54 (2.61)
Bone*	77	23	-	-	-	-	11 (12)	0.15 (0.19)
Skin*	51	37	12	-	-	-	42 (40)	0.85 (1.01)
Fat*	-	-	-	-	-	-	4.9 (5.4)	0.05 (0.06)
Average Brain [†]	-	-	-	58	41.7	0.3	40 (42)	0.66 (0.71)
AIS Stroke [°]	-	-	-	29.5	69.9	0.6	31 (34)	0.71 (0.81)
ICH Stroke*	-	-	-	73.6	25	1.4	61 (60)	1.56 (1.73)

The values of the different components are expressed as weight percentages.

* DPs values shown in brackets correspond to nominal values reported in [38].

[†] The average brain mixture is formulated from 75% white and 25% gray matter according to their nominal DPs [38].

[°] DPs values in brackets refer to nominal values reported in [45].

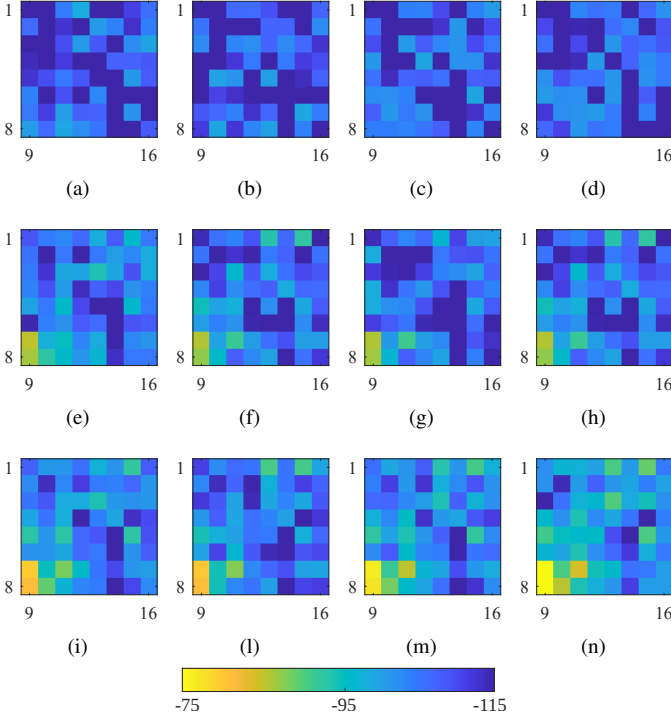


Fig. 7. Differential scattering matrices at 1.3 GHz: the first row (a–d) corresponds to $\Delta Volume = 0 \text{ cm}^3$, the second row (e–h) to $\Delta Volume = 10 \text{ cm}^3$, and the third row (i–l) to $\Delta Volume = 20 \text{ cm}^3$, and (m–n) to $\Delta Volume = 30 \text{ cm}^3$ and $\Delta Volume = 40 \text{ cm}^3$, respectively. The colorbar is expressed in (dB). The index represents the number of antennas.

a change in the signal energy with respect to the previous state, enabling the clinical intervention to be prompted.

Figure 7 shows the independent upper-right quadrant of the semi-filled differential scattering matrices acquired at 1.3 GHz. The first row, (a–d), illustrates $\Delta Volume = 0 \text{ cm}^3$ (i.e., no volume change), the (e–h) 10 cm^3 , (i–l) 20 cm^3 , (m) 30 cm^3 , and (n) 40 cm^3 . It can be seen that, when there is no volume change, the values are close to -100 dB (instrumental noise floor [30]). In contrast, with increasing volume variation, the matrices show progressively higher values, as expected due to the increased dielectric contrast generated by the stroke. From hereafter, we do not use the reflection parameters since these are more sensitive to non-through-head propagation.

B. Data pre-processing

We propose a technique to mitigate the impact of inaccuracies in the measured responses, ensuring that changes detected in the scattered responses reflect brain tissue alterations rather than measurement artifacts. Hence, an element-wise median-based method is adopted, where consecutive measurements are grouped in sets, each composed of N_{scan} independent measurements of the same phantom condition, and every single measurement is organized into a complex three-dimensional array $\mathbf{S}^{(i)}$, where i is the measurement index. In this experiment, measurements under identical conditions, i.e., the same state, are expected to be nearly identical; however, in practice, minor biases can be present in the data.

As described in Sec. II, the measurements are acquired consecutively, and N_{scan} consecutive measurements form a group, here defined as $\mathcal{S}^{(k)} = \{\mathbf{S}^{(i)}, \mathbf{S}^{(i+1)}, \dots, \mathbf{S}^{(i+N_{\text{scan}}-1)}\}$, where k is the index of the groups. Each element (p, q, f) of $\mathbf{S}^{(i)}$, with $p, q \in \{1, \dots, N_a\}$, N_a number of antennas, and $f \in \{1, \dots, N_f\}$, N_f number of frequency points, is subsequently analyzed to correct potential outliers introduced during data acquisition. For each group $\mathcal{S}^{(k)}$, and for every (p, q, f) entry, the median value across the N_{scan} measurements is computed element-wise to form the group median matrix $\mathbf{M}^{(k)}$. This matrix is then used to compute the element-wise deviation $\Delta \mathbf{D}^{(i,k)}$ for each element of the group $\mathcal{S}^{(k)}$ as:

$$\Delta \mathbf{D}_{p,q,f}^{(i,k)} = \mathbf{S}_{p,q,f}^{(i)} - \mathbf{M}_{p,q,f}^{(k)}. \quad (3)$$

If the magnitude of the deviation for a given (p, q, f) element exceeds a threshold τ , the corresponding value is replaced by the associated element of the group median matrix in order to reduce the impact of any outlier in the data. Thus, the filtered measurements $\hat{\mathbf{S}}_{p,q,f}^{(i)}$ are constructed following the expression:

$$\hat{\mathbf{S}}_{p,q,f}^{(i)} = \begin{cases} \mathbf{M}_{p,q,f}^{(k)}, & \text{if } |\Delta \mathbf{D}_{p,q,f}^{(i,k)}| \geq \tau \\ \mathbf{S}_{p,q,f}^{(i)}, & \text{otherwise,} \end{cases} \quad (4)$$

this data pre-processing is done for all i collected measurements, and the threshold τ is set to 1×10^{-5} (-100 dB), based on the noise floor of the VNA setup [30].

C. Energy-based Sensing

To capture the temporal structural variation of brain tissues, which generates specific electromagnetic signature, we use, as metric, the Frobenius norm [47], [48]:

$$\|\cdot\|_F = \sqrt{\sum_{n=1} \sum_{m=1} |a_{n,m}|^2}, \quad (5)$$

where n and m are the indices of each a matrix element. At a given frequency f , the Frobenius norm quantifies the energy of the differential scattering response, $\Delta\hat{\mathbf{S}}$, providing a scalar value that summarizes the cumulative variation of the pairwise antenna responses at that frequency. This frequency-specific energy metric is expressed as:

$$\phi_f^{(\Delta state)} = \|\Delta\hat{\mathbf{S}}_f^{(\Delta state)}\|_F, \quad (6)$$

where $\Delta state$ indicates the difference between two temporally distant states of the monitored scenario. Then, to expand and cover the frequency-depended information, we integrate across all the available frequency band to represent the structural variation of brain tissues in a single frequency-aggregated energy metric:

$$\Phi^{(\Delta state)} = \sum_{f=1}^{N_f} \phi_f^{(\Delta state)} \Delta f \approx \int_f \phi_f^{(\Delta state)} df, \quad (7)$$

where Δf is the sampling frequency. It provides a more robust frequency energy metric where high values in $\Phi^{(\Delta state)}$ signal changes in the multistatic scattered responses, produced by dielectric-contrast changes in the head tissues, and thereby associated with a progression or stabilization of an injury, and lower values correspond to stable conditions with no significant variations. It is worth noting that the proposed energy-based indicator is not a supervised classifier and does not require a training stage; instead, it provides a patient-specific differential metric to track temporal changes between monitored states.

D. Hierarchical Clustering

To interpret the information on the permittivity changes encoded in the norm, we adopt a hierarchical clustering (HC) approach. HC is an unsupervised, data-driven learning technique that groups data into homogeneous sets based on similarity. Unlike other classification techniques, it does not require a training phase or prior knowledge of the classes to be identified. This makes it ideal for scenarios where the data structure is not known a priori and must emerge directly from observations [49], [50]. The most common representation of HC is the dendrogram, a tree that shows how clusters gradually merge as a function of the distance between elements [51]. In this study, the dendrogram groups the different *state* of ICH and AIS, allowing for tracking the evolution within the scattering parameters in an entirely data-driven manner.

The HC is described in Algorithm 1. It receives as input the measured scattering parameters and then performs a three-step process consisting of: (1) multi-frequency aggregation, (2) pairwise distance computation, and (3) hierarchical clustering.

Algorithm 1 Hierarchical Clustering

- 1: **Input:** $\hat{\mathbf{S}}_f^{(i)}$
- (1) **Multi-frequency aggregation**
- 2: **for** $i = 1 \rightarrow N_m$ with $N_m = \text{number of measurements}$ **do**
- 3: Compute accumulated energy matrix:

$$\mathbf{A}^{(i)} = \sum_{f=1}^{N_f} \left| \hat{\mathbf{S}}_f^{(i)} \right|^2$$

- 4: Obtain RMS multi-frequency:

$$\mathbf{M}^{(i)} = \sqrt{\frac{1}{N_f} \mathbf{A}^{(i)}}$$

- 5: **end for**

- (2) **Pairwise distance computation** ($\mathbf{D} \in \mathbb{R}^{N_m \times N_m}$)

- 6: **for** $l_1 = 1 \rightarrow N_m$ **do**
- 7: **for** $l_2 = l_1 + 1 \rightarrow N_m$ **do**
- 8: Frobenius dissimilarity:

$$\mathbf{D}^{(l_1, l_2)} = \left\| \mathbf{M}^{(l_1)} - \mathbf{M}^{(l_2)} \right\|_F$$

- 9: **end for**

- 10: **end for**

- (3) **Hierarchical clustering**

- 11: Perform agglomerative clustering with average linkage:

$$\mathbf{Z} = \text{linkage}(\mathbf{D}, \text{"average"})$$

- 12: **Return:** Dendrogram, $\mathbf{Z}$
-

In (1), the algorithm aggregates the energy of the multi-frequency response across the whole band by computing the root mean square (RMS) of the accumulated mean energy, as shown in lines 3:4. The obtained matrix $\mathbf{M}^{(i)}$, has dimensions of $N_a \times N_a$. In (2), we calculate the pairwise distance defined as the Frobenius norm of the $\mathbf{M}^{(i)}$ of all the possible combinations of measurements, obtaining $(\mathbf{D}^{(l_1, l_2)})$. In (3), agglomerative hierarchical clustering (HC) with average linkage is used to construct the dendrogram. The procedure starts by treating each element as an individual cluster and iteratively merging the two clusters with the smallest energy distance. After each merge, the inter-cluster distance is updated to the average of all pairwise distances between the elements of the two clusters (average linkage). This hierarchical merging continues until all elements are combined into a single cluster, resulting in the dendrogram representation [51]. It provides a hierarchy of all possible partitions, allowing the identification of natural cutting points without pre-specifying the number of clusters.

V. MEASUREMENT PROCEDURE

The experimental protocol varies the stroke volume from an initial value of 10 cm^3 , representing the typical dimension of CMBs, up to 50 cm^3 . This range includes volumes below 30 cm^3 , which, for the ICH case, are generally associated with a more favorable prognosis (survival rates above 50%), as well as higher-risk volumes exceeding this threshold, for which

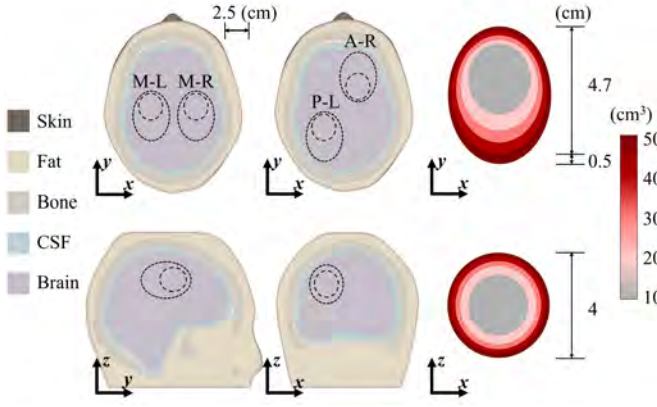


Fig. 8. Different positioning of the stroke: on the left, the first row shows the top view with the four positions (M-L, M-R, A-R, and P-L). The second row shows the sagittal and frontal views in the M-L position. On the right, the stroke dimensions are shown.

survival probability drops significantly (to approximately 10%) [52]. For AIS, volumes in the tens to hundreds of cm^3 (malignant MCA infarctions) are clinically relevant, with poor outcomes tied to infarcts above $70\text{--}100\text{ cm}^3$ [53], [54]. The stroke volumetric changes are made in steps of 10 cm^3 , corresponding to a maximum axial variation of about 0.5 cm , as illustrated in Fig. 8. Such fine volumetric and temporal control is clinically significant. Each adjustment mimics critical transitions in stroke evolution, such as the expansion of an ICH lesion or reduction following therapeutic reperfusion or edema resolution [55]. In the laboratory environment, temporal signatures are acquired every 6 minutes, but the method also supports flexible monitoring intervals for rapid intervention. The system is inherently capable of continuous or adaptive monitoring, providing essential temporal insights into the progression of both ICH and AIS stroke.

The experimental protocol involves inflating a balloon with a liquid mimicking the DPs of ICH and AIS, with volume changes externally controlled via a pumping system. Then, the multi-frequency scattering parameters, $\mathbf{S}^{(i)} \in \mathbb{C}^{N_a \times N_a \times N_f}$, where i denotes the measurement index, $N_a = 16$ is the number of antennas, and $N_f = 10$ is the number of acquired frequency points, are constructed sequentially by acquiring $2 \times 2 \times N_f$ scattering blocks. The system calibration is performed at the switching-matrix ports. Hence, a de-embedding step is applied to shift the reference plane from the switching-matrix ports to the antenna ports. Each acquisition takes about one minute. The VNA is configured with the following parameters: IF filter at 100 Hz , power 0 dBm , number of frequency points 10, and an operating frequency band of $0.9\text{--}1.8\text{ GHz}$, in accordance with previous work [32].

To mimic different conditions, we use four different positions distributed across the relevant brain region, as shown in Fig. 8, covering significant brain regions: the middle right and left (M-R, M-L), and the posterior left and anterior right (P-L, A-R). This configuration provides a preliminary assessment of the dependence of the proposed energy indicator on lesion position and of possible location-dependent sensitivity reductions within the investigated sensing domain. The similar frequency-

dependent behavior observed across these cases suggests the absence of pronounced blind spots in the considered phantom configurations. The experiment is repeated at each of the four positions for both stroke types (ICH and AIS), across the five different volume settings, from 10 cm^3 to 50 cm^3 in increments of 10 cm^3 . For each stroke *state*, a total of $N_{\text{scan}} = 6$ successive measurements are performed for testing, with a total measurement time of about 6 minutes. Since each scan is much shorter than the typical timescale of stroke volume changes, multiple consecutive measurements can be performed for each *state*.

VI. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, we experimentally assess the proposed microwave-sensing framework from two complementary perspectives. First, we analyze the effect of the antenna configuration on the energy-based indicator, supporting the selected 16-antenna cross-sectional multiview architecture as a practical trade-off between sensing robustness and system complexity. Then, we evaluate the proposed approach's capability to detect and track stroke evolution using temporal signatures, frequency-dependent and cumulative energy indicators, multi-position responses, and hierarchical clustering of measured stroke states.

A. Experimental Sensitivity Analysis of the Antenna Configuration

Before analyzing the stroke-evolution indicators, we assess the effect of the antenna configuration on the proposed energy-based metric. Since the system is intended for differential microwave sensing rather than dielectric-map reconstruction, the antenna arrangement is selected by balancing sensitivity to stroke-volume variations and hardware complexity. To evaluate this trade-off experimentally, the measured dataset acquired with the 16-antenna CSMV architecture is reprocessed by extracting reduced sub-array configurations. The 16-antenna case is used as the reference and compared with 12-, 8-, and 4-antenna configurations, while preserving the same cross-sectional acquisition strategy. For each configuration, the same differential energy-based processing described in Sect. IV is applied, allowing the effect of antenna reduction to be assessed under the same measurement conditions.

Figure 9 reports the frequency-dependent energy indicator $\phi_f^{(\Delta\text{state})}$ obtained for the different antenna configurations. Each curve corresponds to the Frobenius norm of the differential scattering matrix between two measured states. The curves are grouped according to the absolute stroke-volume variation between the two states, ΔVolume , rather than according to the absolute volume of a single state. For example, a 10 cm^3 variation may correspond to a transition from 10 to 20 cm^3 , from 20 to 30 cm^3 , and so on. When two measurements correspond to the same nominal condition, the expected differential response is minimal and mainly associated with the measurement noise floor, leading to the lowest values of the energy indicator. As expected, reducing the number of antennas decreases the overall magnitude of the indicator, since fewer transmitting-receiving pairs contribute to

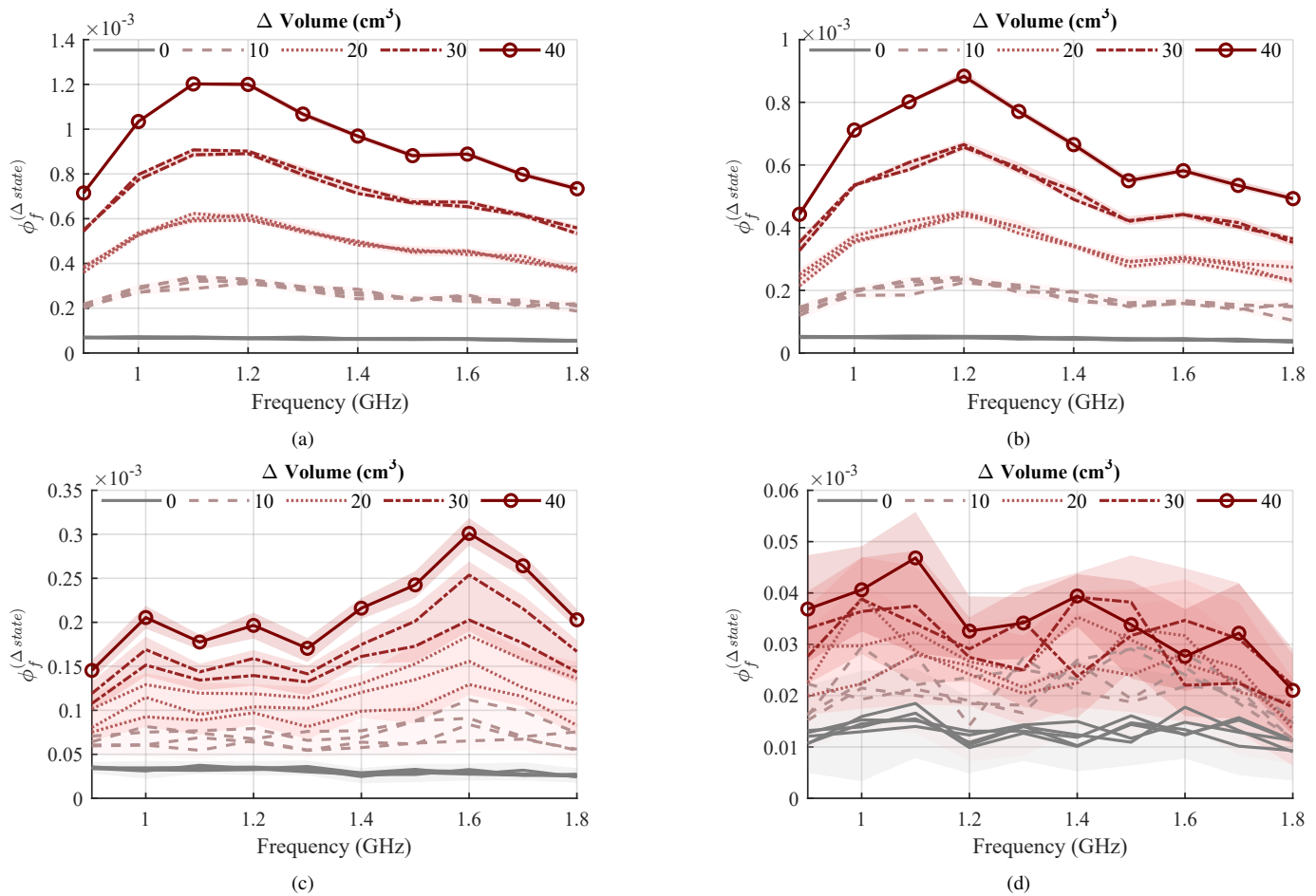


Fig. 9. Frequency-dependent energy indicators obtained from the measured dataset using reduced CSMV antenna configurations. The panels correspond to (a) 16-, (b) 12-, (c) 8-, and (d) 4-antenna configurations. The shaded colored bands represent the maximum and minimum values obtained for each ΔVolume case.

the Frobenius norm of the differential scattering matrix. More importantly, the discrimination capability deteriorates as the number of antennas is reduced. The 16-antenna configuration provides the clearest separation among the considered stroke-volume variations. The 12-antenna configuration still preserves partial separation, whereas the 8- and 4-antenna configurations exhibit a clear loss of sensitivity, making the distinction among the considered stroke-evolution states less reliable. Based on this experimental evidence, the 16-antenna architecture is retained as a conservative design choice. It provides full angular coverage of the head, improves robustness to lesion position and experimental variability, and remains compatible with a low-complexity implementation based on two SP8T switching matrices. Therefore, the selected architecture represents a practical trade-off between sensing performance and system complexity. In the present experimental validation, the smallest imposed stroke-volume variation is 10 cm^3 . Therefore, within the tested phantom scenarios, the proposed system demonstrates differential volumetric sensitivity to changes of at least 10 cm^3 . This value should not be interpreted as an intrinsic resolution limit of the system, but rather as the experimentally verified sensitivity under the considered phantom, antenna arrangement, calibration, and measurement conditions.

B. Stroke-Evolution Energy Indicators

Figure 10(a-b) shows the temporal signature that describes the pathological-specific progression rate by the envelope of $\Phi^{(\Delta \text{state})}$, for both an ICH in the M-R position and an AIS in the M-L one. If two successive states correspond to the same condition, the differential scattering response is dominated by the background noise of the system. Thus, $\Phi^{(\Delta \text{state})}$ has lower magnitude values in comparison with cases of dielectric contrast transitions. In the figure, the peaks indicate a *state* change, creating a pulse-like response. It verifies that the MMS system is able to detect focal changes in brain tissue by analyzing the energy of differential scattered responses over time. The dashed and continuous lines correspond to the $\Phi^{(\Delta \text{state})}$ calculated using raw measurements $\hat{\mathbf{S}}^{(\cdot)}$ without any pre-processing stage, and the filtered data $\hat{\mathbf{S}}^{(\cdot)}$, respectively. Notably, raw data results show much lower dynamic range, closer to the system's noise floor. Filtered data enhances the dynamic range of variations, potentially helping clinicians identify stroke changes. The background-color regions group all states belonging to the same condition, and the stroke volumes associated with each region are shown in the colorbar. Moreover, it is worth noticing that the x -axis, *state*-th, is actually a temporal axis, and that Fig. 10 depicts the signatures of the studied cases, which were controlled during

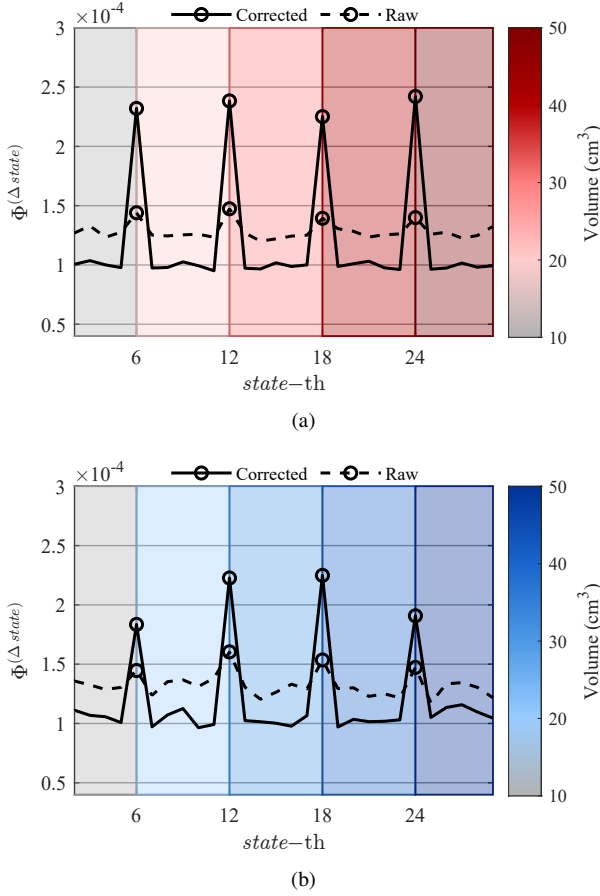


Fig. 10. Temporal signature. (a) ICH. (b) AIS. The colorbar indicates the volume at each $state-th$ instant in cm^3 .

the experiment. However, in a clinical scenario, the signature may indicate a pathological transformation or even the type of pathology [56], [57].

To analyze the sensitivity of the system to specific $\Delta Volume$, $\phi_f^{(\Delta state)}$ is evaluated at different states, with volume variations ranging from 10 to $50 cm^3$. The results are shown in Fig. 11, where the shaded colored bands represent the maximum and minimum values obtained for each $\Delta Volume$ case. When two states correspond to the same condition, the differential response $\Delta \hat{S}$ is expected to be minimal and ideally dominated by the system noise floor. Accordingly, this translates into lower energy values of $\phi_f^{(state)}$. When volume variations occur, the curves are grouped according to their absolute volume variation, regardless of the $state$, e.g., a $10 cm^3$ volume variation can correspond to stroke volume changing from 10 to $20 cm^3$, or from 20 to $30 cm^3$, and so on. This analysis is performed for both ICH at the M-R position, and AIS at M-L one, and the corresponding results are summarized in Figs. 11(a-b). AIS has larger variations with respect to the average, possibly due to lower dielectric contrast in injured tissues, which makes $\Delta \hat{S}$ more sensitive to the system noise floor. This behavior is consistent with the different dielectric contrasts of the two stroke models: ICH introduces a stronger lossy perturbation due to blood accumulation, whereas AIS is modeled as a lower-permittivity inclusion associated with reduced blood perfusion. Thus, AIS responses can be weaker

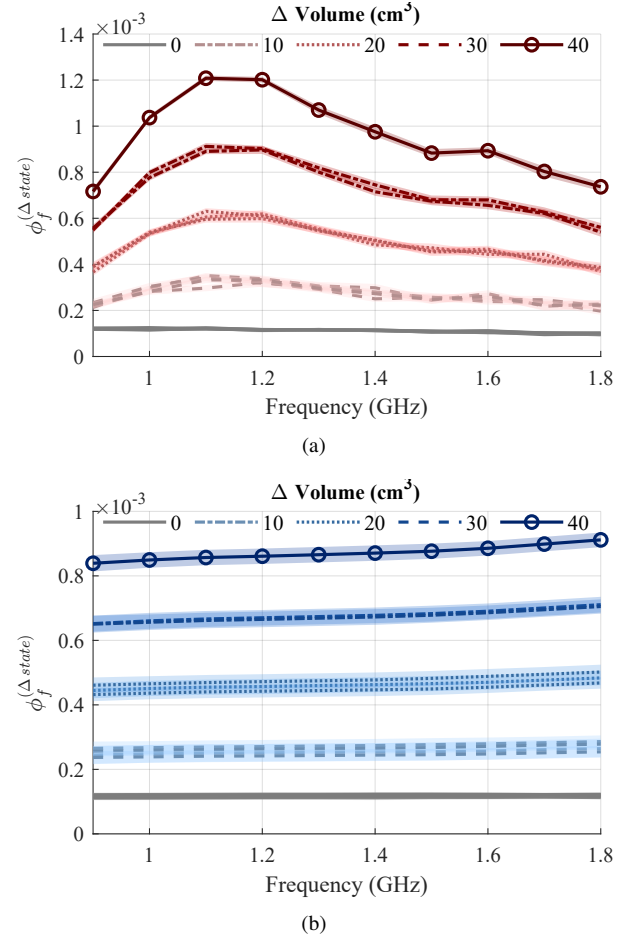


Fig. 11. Energy indicators. (a) ICH. (b) AIS. The shaded colored bands represent the maximum and minimum values obtained for each $\Delta Volume$ case.

and more sensitive to measurement uncertainty, although the final indicator also depends on volume, position, frequency, and antenna sensitivity. Nevertheless, in this experiment, for both stroke types, the curves corresponding to a specific volume variation are grouped into the same cluster, and each cluster is well distinguished from the other. The results show that the microwave system can detect structural changes in brain tissues associated with pathophysiological evolution and provide information on their extent.

To summarize the quantitative results presented in Fig. 11, where each curve represents a differential volumetric physiological change, the total energy $\Phi^{(\Delta state)}$ over the whole frequency band is reported in Fig. 12. The table in the upper-left part names the different $state$ conditions; meanwhile, the x -axis indicates the $state$ transition pairs, $\cdot, \cdot$. In agreement with the results reported in Fig. 11, all variations corresponding to the exact absolute stroke volume change have similar $\Phi^{(state)}$ levels, e.g., $10 cm^3$ variations corresponding to the transitions $a, b - b, c - c, d - d$ or d, e have comparable energy at around 1×10^{-3} . In both hemorrhagic and ischemic cases, the energy-based method demonstrates good sensitivity for detecting minor induced stroke volume variations.

To assess the sensitivity of the proposed approach to volume variations below those experimentally imposed, an additional

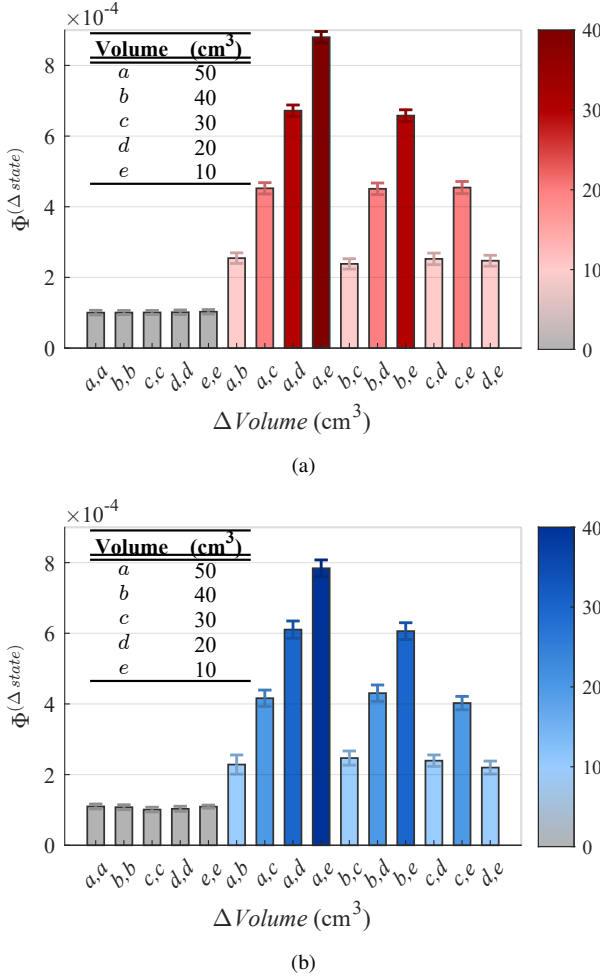


Fig. 12. Cumulative energy (bar diagrams). (a) ICH, (b) AIS. The colorbar indicates the $\Delta Volume (cm^3)$ between states.

full-wave numerical analysis is performed using the same 16-antenna CSMV architecture. Stroke-volume variations ranging from 1 to 5 cm^3 are simulated, and the corresponding scattering matrices are processed using the energy-based pipeline described in Sect. IV-C. The resulting cumulative indicators are compared with the upper level of the experimentally measured

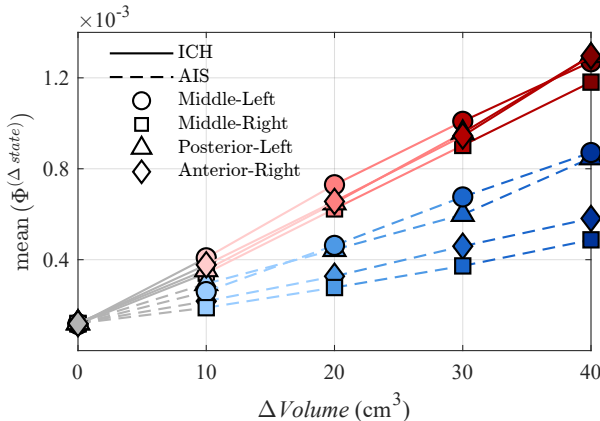


Fig. 13. Summary of all the cumulative energy indicators. The colors indicate the $\Delta Volume (cm^3)$ between states, as in Fig. 12.

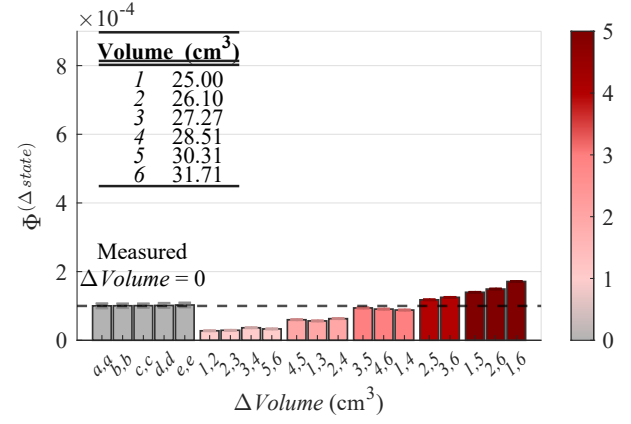


Fig. 14. Experimental-numerical comparison of $\Phi(\Delta state)$. Gray bars show repeated experimental comparisons performed with no volume variation ($\Delta Volume = 0 cm^3$). Colored bars show simulated volume changes grouped into effective $\Delta Volume$ classes from 1 to 5 cm^3 .

no-change response, approximately $\Phi_{noise} = 1 \times 10^{-4}$. As shown in Fig. 14, the responses associated with 1, 2 and 3 cm^3 variations remain below Φ_{noise} . Meanwhile, 4 and 5 cm^3 variations produce responses above Φ_{noise} . Accordingly, the results suggest, under the considered conditions, a conservative minimum detectable variation of approximately 5 cm^3 .

The cumulative energy indicator hardware sensitivity required for detecting sub-10 cm^3 variations is further investigated by adding additive white Gaussian noise (AWGN) to the simulated scattering matrices, considering signal-to-noise ratio (SNR) values between 85 and 140 dB as shown in Fig. 15. The SNR is calculated as the ratio of the input signal power at the antenna port to the equivalent input noise power. At low SNR, the noise contribution dominates the differential scattering response, causing these to converge to the no-change baseline and preventing discrimination among the volume classes. Conversely, as the SNR increases, the noise contribution progressively decreases, and the responses become distinguishable. Consequently, comparable discrimination levels can be reached with an SNR of around 100 dB in the case of $\Delta Volume \approx 5 cm^3$ and around 120 dB in the case of $\Delta Volume \approx 1 cm^3$, confirming, as expected, the challenge of detecting small variations.

The sensing pipeline applied to all cases defined in Sects. III and V, and illustrated in Fig. 8, is summarized in Fig. 13. In this plot, each line and marker type represent the stroke position; the continuous-red and dotted-blue lines indicate ICH and AIS, respectively, and the color intensity represents the relative $\Delta Volume$. Then, each point indicates the mean value of all considered cases with the same $\Phi(\Delta state)$.

Finally, Fig. 16 presents the HC of ICH and AIS as a dendrogram. These allow us to distinguish naturally aggregated lesion volume variations of at least 10 cm^3 . At this stage, the dendrogram is used as an exploratory analysis to assess the feasibility of automated classification based on an energy-distance metric. The obtained grouping structure is meaningful and indicates that HC can correctly separate the available data. Nevertheless, these results should be interpreted as preliminary, since the robustness of the clustering—e.g.,

when introducing new measurements, additional phantoms, or broader experimental variability—remains to be validated.

From a practical perspective, the proposed approach should be interpreted as a patient-specific monitoring strategy based on short-term bedside sessions performed at clinically meaningful time points. In each session, the proposed energy indicator provides a compact measure of the magnitude of the variation in the scattering response associated with the monitored condition. Small variations in the proposed energy indicator would suggest a stable condition, whereas higher values could indicate a more pronounced change in the monitored region. In a clinical workflow, this information could support decision-making by helping clinicians identify cases that may require closer observation, an additional monitoring session, or confirmation with standard imaging. When repeated sessions are available, the temporal evolution of the indicator may further support follow-up assessment before and after treatment, where a sudden increase or persistent upward trend could alert clinicians to a possible evolution of the monitored condition. Although the current prototype assumes stable positioning during each acquisition, clinical translation will require optimized helmet stabilization, repeatable antenna-to-skin coupling, standardized acquisition protocols, and dedicated assessment of inter-session motion effects.

C. Threshold-Based Detection Performance

To quantitatively assess the capability of the proposed indicator to detect temporal stroke evolution, we performed a threshold-based binary detection analysis using the cumulative energy metric $\Phi(\Delta_{state})$. The purpose of this analysis is not to classify the exact stroke volume or the stroke type, but to determine whether a relevant temporal change has occurred between two monitored states. This is consistent with the intended use of the proposed approach as a patient-specific differential monitoring tool.

For each monitoring session, a patient-specific threshold, T , is defined from repeated no-change measurements acquired immediately after the system setup, when no relevant physiological variation is expected. In this work, T is set as the 99th

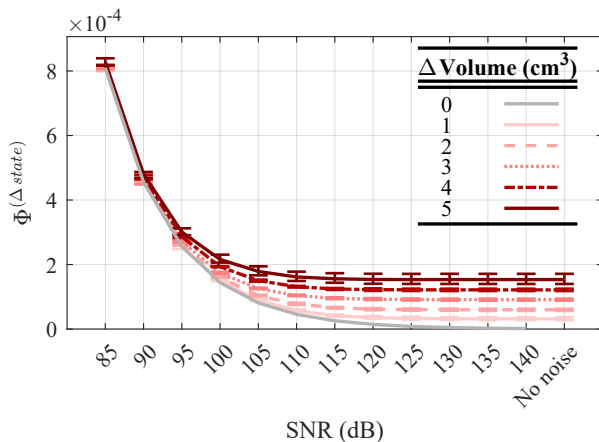


Fig. 15. Noise sensitivity analysis on $\Phi(\Delta_{state})$. Error bars denote the minimum-to-maximum range across the corresponding volume pairs.

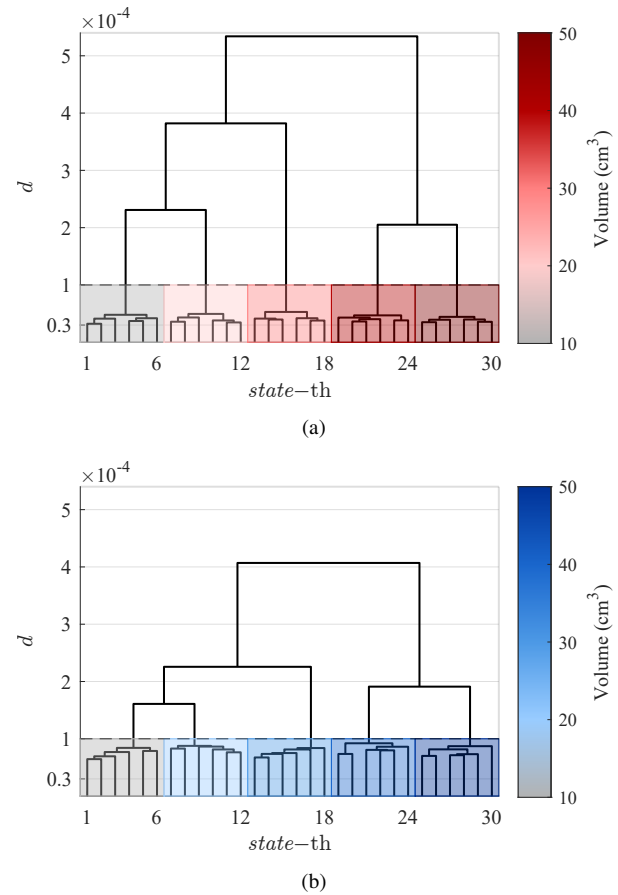


Fig. 16. Dendrogram analysis. (a) ICH, (b) AIS. The colorbar indicates the volume state in cm^3 .

percentile of the $\Phi(\Delta_{state})$ distribution obtained from these measurements. Values of $\Phi(\Delta_{state})$ lower than T are classified as stable states, whereas values higher than T are classified as evolving states.

The analysis is performed on eight experimental datasets acquired in different sessions, four corresponding to ICH and four to AIS. Each dataset consists of 54 consecutive measurements grouped into blocks of six acquisitions. Each block corresponds to a specific state of the stroke evolution, with repeated acquisitions. Between consecutive blocks, the stroke-volume state changes in steps of 10 cm^3 , following either a growth or a shrinkage evolution. The detection performance is quantified in terms of sensitivity, specificity, positive predicted value (PPV), and negative predictive value (NPV) [58].

As reported in Table II, the proposed indicator provides comparable detection performance for ICH and AIS. The high sensitivity indicates that most stroke-evolving events are

TABLE II
QUANTITATIVE DETECTION PERFORMANCE FOR ICH AND AIS MONITORING.

Metric	ICH	AIS
Sensitivity	1.0000	0.9844
Specificity	0.9889	0.9889
PPV	0.9412	0.9403
NPV	1.0000	0.9972

correctly detected, while the high specificity confirms that stable states are correctly identified and rarely identified as stroke-evolving states. In addition, the high PPV and NPV indicate a high predictive reliability, positive detections almost always correspond to true stroke-related changes, and negative detections are almost always associated with the absence of such changes. These results support the use of the cumulative energy indicator as a patient-specific decision-support metric for detecting relevant temporal changes during post-acute stroke follow-up.

VII. CONCLUSION AND PERSPECTIVES

In this work, we introduced a simple microwave-sensing approach for post-acute stroke monitoring, combining a low-complexity sixteen-antenna device, an anthropomorphic multi-tissue phantom, and an energy-based algorithm tailored to detect temporal pathological changes. The proposed method uses the Frobenius norm of differential scattering responses as a global indicator of stroke evolution, enabling the identification of volumetric variations and potential stroke-type transitions without the need for training or supervised classification. Experimental validation confirms that the approach is sensitive to clinically meaningful temporal dynamics and robust against noise and local artifacts, underscoring its potential as a practical tool for bedside monitoring. Future clinical translation will therefore require optimized helmet stabilization, repeatable antenna-to-skin coupling, and protocols for repeated patient-specific measurements at clinically meaningful time points after treatment. In addition, a hospital-oriented implementation should include a bedside-compatible shielding strategy, either through a dedicated local enclosure or helmet-integrated shielding, to preserve measurement stability in electromagnetically noisy environments.

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