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Interactive MWA Planning via Probabilistic Inverse Inference

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Abstract. Microwave ablation (MWA) is a well-established curative treatment for unresectable tumors. However, current clinical planning strategies rely predominantly on geometric heuristics that neglect patient-specific physiology, often resulting in incomplete tumor ablation or unintended damage to healthy tissues. While physics-based bioheat finite element simulations can model the underlying electromagnetic and thermal interactions, their computational cost renders them impractical for interactive clinical planning. We propose a novel, human-in-the-loop computational framework for interactive, patient-specific preoperative MWA planning. At its core there is a deep learning inverse model that directly infers clinically actionable ablation parameters (generator power, ablation duration, and axial depth) given a target tumor mask. The model assesses with sub-second latency the feasibility of insertion paths proposed by the clinician. When viable, it predicts optimal settings to maximize tumor coverage while minimizing collateral damage. Our framework also supports multi-antenna strategies via a sequential optimization scheme. It has been validated against *in vivo* porcine experiments and tested on patient data. Our solution achieved an overall Technical Success Rate of 97% across 116 clinical cases and generated viable multi-antenna treatment plans with sub-second latency (~ 300 ms per antenna). This interactive framework bridges the gap between high-fidelity bioheat modeling and interactive clinical decision-making, enabling safe, efficient, and personalized MWA strategies.

Keywords: Thermal ablation · Planning · Deep Learning

1 Introduction

For cancer patients ineligible for surgical resection, minimally invasive thermal ablation represents the preferred curative alternative. While Radiofrequency Ablation (RFA) has historically been the clinical standard, Microwave Ablation (MWA) is now a preferred option as it permits obtaining larger and more uniform ablation zones in shorter times [12, 1, 13]. Performing MWA procedures, however, is challenging, and planning is key to achieving optimal results. Currently, this planning relies essentially on manufacturer charts linking power and duration

to expected lesion sizes. Such geometric heuristics neglect patient-specific physiology, particularly the heat-sink effect caused by perfused tissue and adjacent vasculature, leading to systematic errors in tumor coverage or unnecessary damage to healthy parenchyma [4, 2].

Unlike RFA, where treatment control is primarily temporal, MWA is governed by a sophisticated interplay between tissue dielectric properties, electromagnetic propagation, and heat diffusion. Optimizing MWA, therefore, requires the simultaneous coordination of multiple coupled parameters - generator power, exposure time, and antenna pose - under anatomical and physiological constraints. Due to this complexity, no existing work provides a simulation-based framework for MWA planning. The few efforts toward automated ablation planning primarily target RFA. Some rely entirely on geometric heuristics, assuming predefined ablation shapes while neglecting the underlying physics [8]. Conversely, recent learning-based studies for RFA focus on accelerating forward simulations [15, 9, 10]. While some of these frameworks demonstrate planning as a downstream application, they rely on iterative optimization loops to exhaustively search for a solution, such as incrementally adjusting ablation diameters, rather than performing direct parameter inference [10]. While such iterative approaches are feasible for RFA, where the parameter space is relatively small, they do not scale to MWA planning. Introducing generator power as an additional coupled parameter expands the search space. Consequently, achieving interactive MWA planning requires a shift toward a direct inverse-parameter inference approach.

To develop an interactive planning solution for MWA, a computational framework capable of simulating outcomes in real time is essential. Solving the coupled electromagnetic-thermal equations (Maxwell and Pennes equations) remains numerically challenging and computationally prohibitive [14, 4, 3]. Keshavamurthy *et al.* proposed a deep learning solution requiring a large database of CT ablation images for training and limited to low-perfusion tissues [7], making it unsuitable for capturing complex heat-sink effects.

We introduce a novel inverse model that directly infers optimal treatment parameters, specifically, generator power, ablation duration, and axial depth adjustment along a user-defined trajectory from a target tumor mask, a patient-specific perfusion map, and a clinician-proposed initial trajectory. The system instantly evaluates the safety of the proposed trajectory, identifying the plan as infeasible if it intersects critical anatomical structures or if a complete ablation is impossible with realistic parameters. For viable initializations, it instantly fine-tunes depth and energy delivery to balance tumor coverage with healthy tissue preservation. To enable both the training and instantaneous evaluation of this inverse planner, we simultaneously introduce a forward surrogate model. Trained on high-fidelity synthetic FEM-generated data, this surrogate takes as input a 3D map of the patient’s blood perfusion together with the antenna position, power, and duration, to predict ablation outcomes in real time. Integrated into an interactive interface, these components enable the immediate, safety-aware exploration of multi-antenna strategies. We validate lesion prediction on *in vivo*

porcine liver ablations and evaluate preoperative planning on a clinical dataset of hepatic tumors.

2 Methods

2.1 FEM simulation framework

Heat transfer during MWA was modeled using coupled electromagnetic and thermal equations (Maxwell and Pennes equations). The resulting multiphysics problem was discretized and solved using the finite element method framework described in [5].

Tissue temperature evolution follows the classical Pennes bioheat equation [11], with microwave power deposition derived from a frequency-domain electromagnetic solve at 2.45 GHz under standard boundary conditions, and the resulting thermal damage was quantified using an Arrhenius model. As demonstrated in [5], these biophysical simulations are exceptionally sensitive to the blood perfusion parameter, which dictates the magnitude of the local heat-sink effect. Therefore, rather than assuming constant tissue properties, blood perfusion was explicitly modeled as a spatially heterogeneous field $\omega_b(\mathbf{x})$ distinguishing between liver parenchyma, macroscopic blood vessels, and tumor tissue.

2.2 Forward surrogate model

To enable rapid plan evaluation and provide differentiable supervision for the inverse planner, we developed a forward surrogate model. This model predicts the 3D ablation zone from a patient-specific perfusion map and three procedural parameters: generator power P , ablation duration t , and the axial insertion depth d along the planned trajectory. To reduce the spatial variance the network must learn, inputs are mapped into an antenna-centric space. Specifically, the perfusion volume is resampled so that the clinician-defined insertion trajectory aligns precisely with the longitudinal Z -axis, ensuring the position of the microwave antenna is fully defined by the axial depth d .

The surrogate architecture is based on a conditioned 3D U-Net. To inject strong spatial priors, the scalar depth d is converted into a 3D Gaussian distance heatmap H along the canonical Z -axis, explicitly modeling the active antenna tip. This heatmap H is concatenated with the perfusion volume, forming a two-channel, 5D tensor $[B, C, X, Y, Z]$ that is passed to the model alongside a spatial coordinate vector, where B is the batch size. The global conditions P and t are concatenated, linearly projected to match the bottleneck channel dimension, and fused with the encoded features at the deepest U-Net level. The decoder then reconstructs these features to output a voxel-wise probability map $\hat{M}$, supervised end-to-end by the FEM-derived necrosis mask M . To ensure smooth gradients and handle spatial class imbalance, we minimize a Soft Dice loss over all N voxels i :

$$\mathcal{L}_{\text{fwd}} = 1 - \left(2 \sum_{i=1}^N M_i \hat{M}_i + \epsilon \right) / \left(\sum_{i=1}^N M_i + \sum_{i=1}^N \hat{M}_i + \epsilon \right), \quad (1)$$

where ϵ ensures numerical stability. Once trained, this fully differentiable surrogate cuts plan evaluation time from several minutes to a fraction of a second. The architecture is detailed in Fig. 1b.

2.3 Probabilistic inverse planning model

The core of our framework is a deep learning inverse model that directly predicts the optimal ablation strategy from a clinician-proposed trajectory. The input volume is rotated to align the trajectory with the canonical Z -axis. The model processes a two-channel 3D tensor comprising the perfusion map $\mathbf{V}_{\text{perf}}$ and the target tumor mask $\mathbf{T}$.

A 3D CNN encoder extracts latent spatial features, which are fed into a Probabilistic Mixture Density Network (MDN) regression head. Because inverse thermodynamic problems are ill-posed (multiple parameter combinations can yield similar ablations), the MDN predicts the parameters of a Gaussian mixture model ($K = 5$). This approach provides multiple plausible treatment strategies, each with associated confidence scores, thereby intrinsically supporting our safety-aware framework. The network outputs three clinically actionable parameters: axial depth adjustment $\hat{d}$, generator power $\hat{P}$, and ablation duration $\hat{t}$.

Directly supervising this model via parameter-space distances (*e.g.* Mean Squared Error) is suboptimal, as it ignores the non-linear thermodynamic consequences of parameter deviations. Instead, we optimize the inverse model end-to-end via a forward-in-the-loop strategy (Fig. 1a). The predicted parameter set $\hat{\phi} = (\hat{d}, \hat{P}, \hat{t})$ and $\mathbf{V}_{\text{perf}}$ are passed through the pre-trained, frozen forward surrogate to generate the predicted ablation zone $\hat{\mathbf{M}}$. The inverse model is then penalized based directly on the clinical quality of $\hat{\mathbf{M}}$ relative to $\mathbf{T}$. The objective

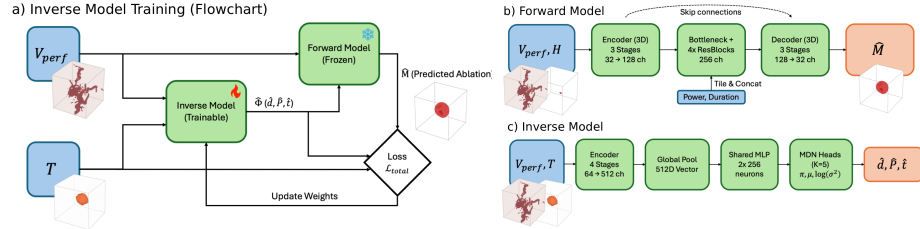


Fig. 1. (a) Training flowchart: the inverse model predicts parameters $\hat{\phi} = (\hat{d}, \hat{P}, \hat{t})$, which are passed to the frozen forward surrogate to optimize the network directly on the expected clinical outcome. (b) Forward model: a 3D U-Net mapping a tensor $[B, C, X, Y, Z]$ (perfusion V_{perf} ; antenna tip Gaussian heatmap H) and a coordinate vector to a predicted necrosis mask $\hat{M}$. (c) Inverse model: a 3D CNN with a Mixture Density Network (MDN) head ($K=5$) inferring multiple plausible treatment strategies.

function mirrors clinical priorities: ensuring complete tumor destruction before

minimizing collateral damage. The total loss is defined as:

$$\mathcal{L}_{\text{total}} = \alpha \mathcal{L}_c + \Gamma(C) (\lambda_s(1 - \text{AE}) + \lambda_e \mathcal{L}_{\text{energy}}) + \lambda_b \mathcal{L}_{\text{bounds}}. \quad (2)$$

The components evaluate specific clinical metrics: **Coverage** ($\mathcal{L}_c = 1 - C$) ensures total tumor ablation, where $C = (\sum \mathbf{T}\hat{\mathbf{M}} + \epsilon) / (\sum \mathbf{T} + \epsilon)$. **Tissue Sparing** ($1 - \text{AE}$) penalizes ablation in healthy parenchyma, where Ablation Efficiency (AE) is computed as $(\sum \mathbf{T}\hat{\mathbf{M}} + \epsilon) / (\sum \hat{\mathbf{M}} + \epsilon)$. **Energy Regularization** ($\mathcal{L}_{\text{energy}} = \frac{1}{2}(\hat{P}^2 + \hat{t}^2)$) prevents excessive heating. Note that $\hat{P}$ and $\hat{t}$ are min-max normalized to $[0, 1]$. **Parameter Bounds** ($\mathcal{L}_{\text{bounds}}$) penalizes predictions that fall outside the physical operating limits of the MWA generator (*i.e.* power outside 30–130 W or duration outside 180–500 s). The sparing and energy penalties are modulated by a dynamic coverage gate $\Gamma(C) = \sigma(k(C - 1.0))$. This smooth step-function ensures the network focuses entirely on destroying the tumor until complete ablation ($C_{\text{target}} = 1.0$) is achieved, safely refining parameters only after satisfying this primary clinical endpoint. The weighting coefficients ($\alpha, \lambda_s, \lambda_e, \lambda_b$) were empirically fine-tuned to balance coverage maximization and tissue preservation objectives. Figure 1a depicts a flowchart of the inverse model training, while Figure 1c details its architecture.

2.4 Synthetic dataset generation

To train the proposed forward and inverse models, while ensuring they learn generalized electromagnetic and bioheat physics rather than memorizing static patient anatomies, we generated a fully synthetic dataset of 2400 procedurally perfused parenchymal volumes using the aforementioned FEM pipeline. Each training sample contains the exact inputs and targets required by our framework: (i) a heterogeneous perfusion map $\mathbf{V}_{\text{perf}}$; (ii) the procedural parameters (axial insertion depth d , generator power P , and ablation duration t); and (iii) the resultant necrosis mask M obtained from FEM simulation.

For each synthetic case, we initialize a label map as background tissue and procedurally generate vascular trees. A tumor, modeled as an irregular ellipsoidal mask with random morphological perturbations, is then inserted and spatially carved against the vessels to ensure anatomical realism. For every accepted anatomy-tumor configuration, treatment parameters are uniformly sampled, with generator power ranging from 30 to 130 W, and ablation duration from 180 to 500 s. Finally, heterogeneous perfusion values are assigned: background perfusion is randomly sampled from 4 discrete levels within $[0.015, 0.075] \text{ s}^{-1}$; vessel perfusion is scaled according to the vessel radius [5]; and tumor perfusion is fixed at 1.5 times the surrounding parenchymal rate [18].

2.5 Multi-antenna sequential planning

Complete ablation of large or irregular tumors typically requires multiple ablations, performed either simultaneously or, more commonly, sequentially [6]. For the first antenna, the clinician specifies an insertion trajectory. The system

immediately verifies its safety by tracing the shaft within the global volume, and any intersection with critical anatomy (*e.g.* major vessels, ribs) triggers an instant collision warning, prompting path correction. Once a viable trajectory is confirmed, the inverse model processes the antenna-centered perfusion volume to infer the optimal parameters $\hat{\phi}_1 = (\hat{d}_1, \hat{P}_1, \hat{t}_1)$. The forward surrogate then evaluates these parameters to predict the initial ablation zone. For each subsequent antenna k , the target is dynamically updated by subtracting the cumulative ablation mask $\mathbf{U}_{k-1}$, yielding a residual tumor mask $\mathbf{M}_{\text{res},k} = \mathbf{T} \setminus \mathbf{U}_{k-1}$. If $\mathbf{M}_{\text{res},k} = \emptyset$, full coverage is achieved; Otherwise, the clinician proposes a new trajectory targeting the remaining tumoral tissue and the inverse model infers $\hat{\phi}_k$ for the updated spatial crop. This loop enables clinicians to rapidly and safely iterate complex multi-antenna strategies within seconds.

2.6 Experimental setup and evaluation metrics

The model was trained and evaluated across three data domains. The synthetic dataset ($n = 2400$) was divided into 2100 training and 300 validation cases to optimize the core networks. Physical accuracy of the forward surrogate was validated on an *in vivo* porcine liver dataset ($n = 6$ procedures, ethics committee approved). Finally, the clinical viability of the inverse planner was evaluated on the public 3D-IRCADb-01 dataset (20 patients, 116 hepatic tumors) [16]. 12 tumors were excluded from the evaluation: 5 were located outside the liver parenchyma (patients 7, 12, 14), and 7 exceeded the maximum treatable volume for MWA, as attempting complete coverage for targets of this size is generally contraindicated and would require a clinically impractical number of antennas. Forward predictions were compared with ground-truth macroscopic necrosis using the Dice Similarity Coefficient (DSC) and the 95th percentile Hausdorff Distance (HD95). Inverse model clinical efficacy was measured via the Technical Success Rate (TSR), defined as the percentage of plans achieving a Tumor Coverage (C) = 100%. Healthy parenchyma preservation was quantified using Ablation Efficiency (AE), defined as the ratio of the ablated target volume to the total ablation volume, using a clinically suggested 5 mm margin-expanded target, rather than the raw tumor. This isolates true algorithmic over-treatment from necessary oncological safety margins [17]. Computational performance was assessed by recording the inference time for sequential multi-antenna planning against traditional iterative FEM solvers. Both the forward and inverse models were trained using an Adam optimizer (learning rate 10^{-4} , batch size 4) over 250 epochs.

3 Results

3.1 *In Vivo* validation of the forward surrogate

To ensure optimization against a physically accurate baseline, we evaluated the forward surrogate on the *in vivo* porcine dataset. The surrogate achieved a mean

Table 1. Clinical evaluation on the 3D-IRCADb-01 dataset ($n = 116$).

Metric	Single-Antenna	Multi-Antenna	Overall
TSR ($C = 100\%$)	100%	89%	97%
Tumor Coverage (C)	$100\% \pm 0\%$	$99.3\% \pm 1.2\%$	$99.8\% \pm 0.8\%$
Ablation Efficiency (AE)	0.44 ± 0.21	0.71 ± 0.12	0.52 ± 0.23

DSC of 0.82 ± 0.04 and an HD95 of 2.0 ± 0.4 mm against ground-truth necrosis, outperforming the manufacturer’s standard charts (DSC: 0.59 ± 0.12). Furthermore, the surrogate demonstrated high fidelity to the FEM solver, achieving a DSC of 0.90 ± 0.00 for *in vivo* ablations and 0.94 ± 0.01 across 300 synthetic samples. Figure 2a displays a CT scan from ablation session 5, where the model prediction (red) is overlaid with the ground-truth necrosis segmentation (blue). The FEM solver required ~ 3 minutes per antenna, whereas our surrogate model needed only 4 ms on an NVIDIA GeForce RTX 5070 GPU.

3.2 Clinical efficacy of the inverse planner

On the clinical IRCAD dataset, trajectories were initialized by an expert clinician. The framework achieved an overall TSR of 97% over the $n = 116$ tumors (Table 1). For the 38 tumors out of 116 requiring multi-antenna configurations, defined by a maximum diameter > 3 cm, the sequential strategy maintained a mean coverage of 99.3% with an Ablation Efficiency of 0.71. Our overall AE of 0.52 compares favorably to the work of Meister et al. [10], which used an identical 5 mm margin expansion and reported an AE between 24% and 50%. This comparison highlights our network’s success in balancing the tissue-sparing penalty ($1 - \text{AE}$) against the geometric requirements for total margin-inclusive tumor destruction. Lower AE values were primarily observed in single-antenna treatments for sub-centimeter tumors ($n = 23$; maximum diameter < 10 mm), reflecting the fact that even the lowest MWA settings generate a minimum lesion of approximately 20 mm in diameter, rather than an optimization failure. The complete inverse planning loop, including spatial crop extraction, parameter inference ($\hat{\phi}$), and safety-aware forward verification, averaged 0.3 seconds per antenna. This sub-second latency enables a truly interactive, clinician-in-the-loop workflow. Figure 2b illustrates the graphical user interface (GUI) used for interactive treatment planning.

4 Discussion and conclusion

We presented a clinician-in-the-loop framework for interactive, patient-specific MWA planning. Unlike prior RFA and MWA methods that rely on accelerated forward simulations [15, 9, 10] or geometric heuristics [8], our approach learns the inverse mapping from target outcomes to procedural parameters, enabling instant inference without iterative search. By adopting a probabilistic MDN-based

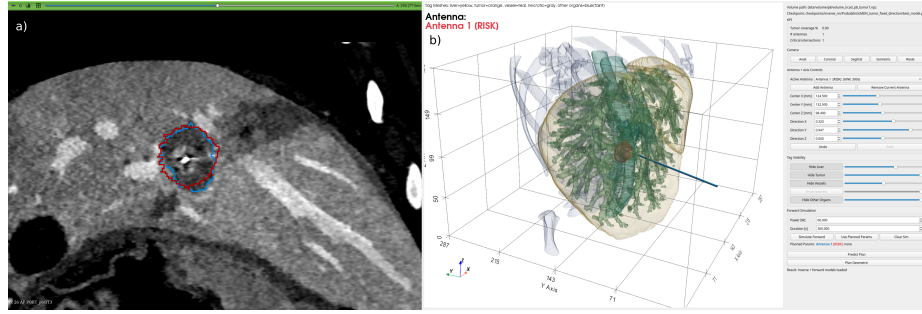


Fig. 2. *In Vivo* validation and Planning interface. (a) Comparison between predicted ablation zone (red) and *in vivo* macroscopic necrosis (blue) in porcine liver. (b) Interactive GUI showcasing the features of the implemented framework.

formulation, the model captures multiple feasible strategies consistent with biophysical constraints. We demonstrated a DSC of 0.82 during *in vivo* porcine studies, providing a rare evaluation against macroscopic necrosis that successfully accounts for active heat-sink effects, unlike previous studies that used *ex vivo* ablations. Despite challenges like tissue contraction and dynamic perfusion, this spatial overlap confirms the forward surrogate provides realistic physical constraints for the inverse planner. On the 3D-IRCAdb-01 dataset, the model successfully generalized from synthetic training to complex human anatomies. A 97% TSR across single- and multi-antenna treatments demonstrates that the loss function prioritizes tumor destruction, while Ablation Efficiency indicates that the MDN effectively refined power and duration to spare healthy tissue. A key advantage is seamless clinical integration: radiologists retain trajectory autonomy while the planner replaces static vendor charts with physiology-aware thermodynamic parameters. Reducing computation time from minutes to milliseconds enables interactive planning with automated safety checks. Because training relies on procedurally generated anatomies, the surrogate learns the underlying physics rather than memorizing cases, ensuring robustness.

Despite this potential, limitations exist. First, "optimality" is difficult to validate *in vivo* as ablations cannot be repeated on the same tumor. Consequently, validation is restricted to comparing the forward surrogate against observed necrosis, while clinical efficacy is demonstrated retrospectively. Second, the framework assumes unchanged anatomy during antenna insertion, neglecting possible deformation and target displacement. Third, our sequential multi-antenna strategy is greedy and keeps pre-treatment tissue properties after each virtual ablation, which may limit global optimality. Future work will focus on the *in vivo* validation of the inverse planner's generated treatment plans on porcine models to assess actual clinical efficacy. Furthermore, we plan to investigate joint multi-antenna optimization architectures to improve global thermodynamic outcomes compared to the current sequential strategy.

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