DEVELOPMENT OF A MODEL OF THE ELECTRIC FIELD DISTRIBUTION INSIDE THE HUMAN BRAIN

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The study optimizes FEM-based brain electric field simulations by enhancing computational efficiency. It employs advanced solvers, parallel computing, and memory-efficient algorithms to accelerate convergence and reduce resource usage. Key strategies include optimized matrix assembly, preconditioning, and load balancing. Algebraic multigrid solvers and parallelized computations in Julia further improve performance in large-scale simulations.

INTRODUCTION

Simulating electric fields in the brain is computationally demanding due to its complex and heterogeneous structure. Finite Element Methods (FEM) are well-suited for such tasks, but traditional direct solvers struggle with the scale and resolution needed for realistic 3D brain models. Our research focuses on scalable, efficient solutions using iterative solvers — especially algebraic multigrid methods — to handle large FEM problems. By using cubic elements, we avoid complex tetrahedral meshing, enabling direct use of voxel-based medical data. We further optimize performance through memory-efficient matrix assembly and parallel computing in Julia.

ALGORITHMS FOR EFFICIENT COMPUTATION

Existing research has focused on improving FEM-based brain electric field simulations through advanced solvers and parallel computing. Algebraic multigrid (AMG) methods, including Ruge-Stuben [1] and Smoothed Aggregation AMG [3], have been effective in solving large, sparse systems, with parallel implementations enhancing scalability [2]. FEM has been widely applied in brain stimulation modeling, with optimizations in segmentation and solver efficiency improving accuracy [4]. State-of-the-art approaches integrate memory-efficient algorithms and high-performance computing techniques to accelerate convergence while reducing computational overhead [5].

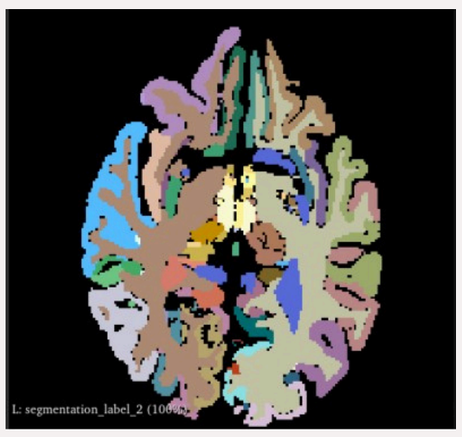

Figure 1. NRRD label map visualization.

PREPROCESING

A 3D brain model from the Open Anatomy Project [6] was processed in 3D Slicer, segmented into labeled tissue regions, and converted into an NRRD label map (Figure 1). This map was transformed into a 3D matrix, preserving tissue details for FEM simulations. Tissue types were grouped into four categories with permittivity values (Table 1) from the IT'IS Database [7], enabling a representative electrical model. The finalized matrix (Figure 2) served as input for FEM-based electric field calculations, providing a detailed field distribution across brain regions.

Tisuue	Cerebellum	Cerebrospinal fluid	Gray matter	White matter
Permitivity	89,8	88,9	80,1	56,8

Table 1. Permitivity values

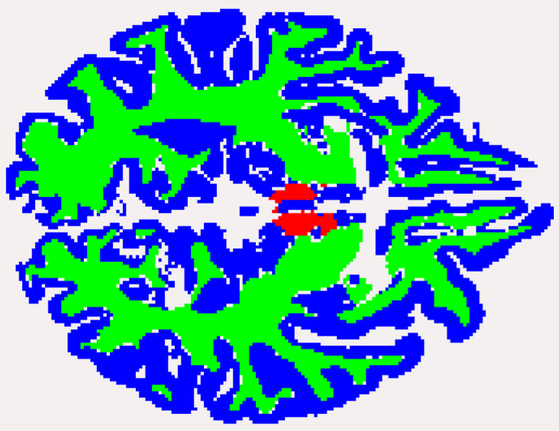

Figure 2. Final matrix visualization.

IMPLEMENTATION

The FEM-based numerical solution of Poisson's equation was implemented using algebraic multigrid (AMG) preconditioning. The computational domain was discretized with hexahedral elements, incorporating spatially varying permittivity values for different brain tissues. While a direct solver provided accurate results for smaller models, it proved infeasible for high-resolution simulations due to excessive memory requirements. Instead, AMG methods were employed, with Smoothed Aggregation AMG significantly outperforming Ruge-Stuben AMG in both convergence speed and efficiency. For the full-resolution model, only Smoothed Aggregation AMG successfully solved the system, highlighting its robustness in handling heterogeneous brain tissue properties.

ANALYSIS

This study developed a computational framework for simulating electric field distribution in the human brain using the finite element method (FEM). The results demonstrate significant variations in field intensity based on tissue properties, with cerebrospinal fluid exhibiting stronger field concentrations and white matter showing weaker intensities. This highlights the critical role of tissue permittivity in shaping the electric field distribution (Figure 3).

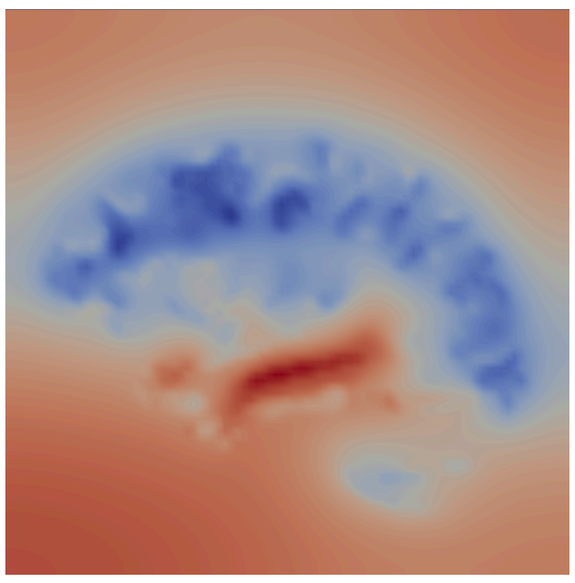

Figure 3. Computed electric field visualization

A key focus was computational efficiency in solving large-scale FEM models. Direct solvers, while accurate, proved impractical for high-resolution models due to excessive memory demands. Algebraic multigrid (AMG) methods, particularly Smoothed Aggregation AMG (SA-AMG), outperformed other approaches in both time (Figure 4) and memory usage (Figure 5).

For high-resolution models, SA-AMG was the only solver capable of converging, demonstrating superior efficiency in handling complex, heterogeneous brain structures. These findings validate the use of advanced numerical solvers for large-scale bioelectric modeling, improving computational feasibility for neuroscience and medical applications.

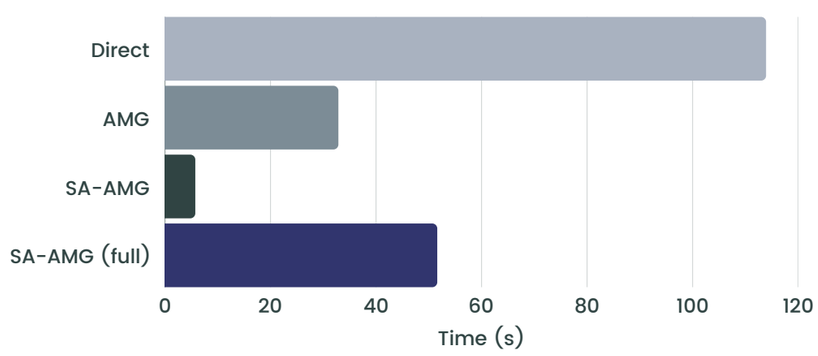

Figure 4. Mean execution times.

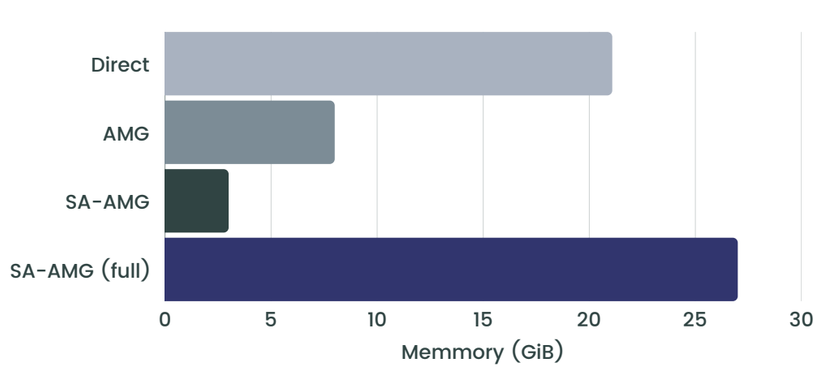

Figure 5. Mean memmory allocations.

CONCLUSION

This research not only highlights the importance of computational efficiency in brain modeling but also opens pathways for future work in the field. The successful integration of advanced solvers like Smoothed Aggregation AMG indicates that high-resolution simulations of complex biological systems, such as the human brain, are becoming computationally feasible.

A key limitation of the current model is its reliance on a fixed frequency of 100 MHz for permittivity values. Since the dielectric properties of tissues vary with frequency, incorporating dynamic frequency selection would enhance the flexibility and accuracy of the model. Integrating a database like the IT'IS tissue property database, which provides dielectric parameters for a wide range of frequencies, could allow the model to adjust permittivity values dynamically.

In conclusion, the work presented here successfully addresses the challenges of simulating electric fields in complex biological structures like the human brain. Through the use of advanced computational techniques and optimized solvers, the study not only provides detailed insights into brain field distributions but also contributes to the ongoing advancements in computational neuroscience and medical engineering.

RELATED LITERATURE

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