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A Review of Forward Numerical Methods for Electroencephalography (EEG) Data

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ABSTRACT

Despite its temporal resolution and relatively low cost, electroencephalography (EEG) is one of the most popular methods for investigating brain dynamics because it is noninvasive. Nonetheless, the interpretation of EEG signals essentially relies on the solution of the forward problem, accounting weakly for the electrical activity produced in the brain and how it diffuses, thus arousing scalp potentials. Over the past few years, the development of computational neuroscience and numerical modeling has resulted in increasingly complex forward models using realistic head geometries, anisotropic tissue conductivities, and fine numerical solvers. This review provides an in-depth discussion of the latest forward numerical techniques applied in the analysis of EEG data, including Boundary Element Methods (BEM), Finite Element Methods (FEM), Finite Difference Methods (FDM), and hybrid-computational methods. Other strategies for head modeling, recent computer advances, and the importance of software structures for EEG modeling are also discussed in this review. In addition, it highlights existing issues, such as ambiguity with respect to conductivity, intersubject variability, and computational cost. Finally, new advances in physics-inspired and data-driven modeling techniques are addressed, and the evolution towards more realistic and explainable EEG forward answers is discussed. The review finds that although there have been tremendous advances, the discipline still requires better integration of anatomical realism, numerical stability, and computational efficiency. This review comprises recent advances in AI-supported forward modeling, physics-guided computational methods, and subject-specific conductivity estimation techniques published between 2020 and 2026, none of which have been summarized in any of the prior reviews on EEG forward modeling, which have mostly focused on numerical solutions only. Moreover, it compares classical and emerging numerical methods and presents their advantages and disadvantages, particularly in terms of their applicability to current neuroimaging and brain-computer interface systems.

Keywords: *EEG Forward Problem, Numerical Modeling, FEM, BEM, Head Modeling, Source Localization, Computational Neuroscience*

1. Introduction

EEG is one of the most commonly used non-invasive neuroimaging methods because it has excellent temporal resolution, is portable, and is relatively easy to perform, making it a valuable tool for investigating brain activity. EEG measures the electric potentials produced by the coordinated activity of neuronal populations, mainly pyramidal cells of the cerebral cortex [1]. EEG does not measure the neural activity of individual neurons but rather the cumulative activity of populations of neurons, which provides information on cognitive, sensory, and motor processing [2].

The conductive properties of tissues, such as the brain, cerebrospinal fluid (CSF), skull, and scalp, allow the measured electrical signals at the electrodes on the outside of the head to be affected by the characteristics of these tissues. These have specific electrical conductivities and together create a complex volume conductor that alters the spatial distribution of neural signals before reaching the scalp surface [3, 4]. Therefore, a thorough comprehension of the biophysical mechanisms of signal propagation in the head is necessary for accurately interpreting EEG recordings.

The EEG inverse problem involves determining the location of the neural sources of a given measurability in the brain, based on scalp electric potentials. The EEG forward problem is a mathematical prediction of the electric potentials recorded on the scalp from the neural current source inside the brain. This is because it forms a basic part of EEG analysis, as it is used to solve the inverse problem of inferring the location and strength of the underlying generators of brain activation from measurements of EEG signals [5, 6]. The source localization accuracy and neurophysiological interpretation of the same rely heavily on the quality of the forward model used in this study.

With the advent of a new era of computing related to neuroscience and medical imaging, forward modeling of EEG has significantly improved in recent years. Modern numerical methods allow the inclusion of complex tissue geometries and heterogeneous conductivity distributions [7], and high-resolution magnetic resonance imaging (MRI) allows the construction of anatomically realistic head models. Additionally, high-fidelity simulation models have been developed to more accurately simulate physiological conditions with higher computational power [8].

This review provides a thorough description of the latest numerical solutions to the EEG forward problem, such as the Boundary Element Method (BEM), Finite Element Method (FEM), Finite Difference Method (FDM), and hybrid modeling. Head modeling strategies, recent computational advances, and new trends influencing the future of EEG forward modeling and source localization research are also discussed.

2. EEG Forward Problem Fundamentals

The EEG forward problem defines the connection between the sources of neural currents within the brain and the electrical scalp-recorded potentials. It is based on the

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quasi-static approximation of Maxwell's equations, which is appropriate for examining low-frequency brain activity [9].

The neural activity model is that of primary currents that produce electric fields in the brain. These areas extend to the scalp electrodes through various head tissues. The conductivity of various tissue layers by electricity controls its propagation process; hence, the head is a complex volume conductor [10].

The EEG forward problem is commonly expressed as

$$\nabla \cdot (\sigma \nabla \phi) = \nabla \cdot J^p$$

Where: σ denotes the electrical conductivity tensor of the head tissues, ϕ represents the electric potential distribution, J^p denotes the primary current density generated by neuronal activity, where ∇ is a vector differential operator. This equation explains the behavior of internal brain sources in generating measurable electrical potential on the scalp.

Several components must be defined to solve this equation. First, the geometry of the head should be modeled by incorporating the brain, skull, cerebrospinal fluid, and structures of the scalp [11]. Second, the conductivity values of each tissue type must be assigned, considering that there can be anisotropies in some areas, such as the white matter. Third, the makeup of the neural sources should be provided, usually by equivalent current dipoles or distributed-source models. Finally, the placement of electrodes and reference schemes should be provided to obtain the scalp potentials.

The forward problem is mathematically well-posed; that is, there is only one solution, given a set of inputs. However, it is highly sensitive to the modeling parameters used. Minor anomalies in the conductivity values, especially in the skull, or errors in the head geometry may have a serious influence on the scalp potentials obtained [12]. Sensitivity necessitates proper forward modeling to obtain reliable EEG source localization and interpretation.

3. Head Modeling Approaches

EEG forward modeling is heavily dependent on the quality of the representation of the human head as a volume conductor. Head modeling is an essential process for ascertaining the accuracy of a forward solution because scalp potentials are calculated based on the electrical properties and geometry of internal tissues [13]. Modeling techniques have been developed over the years to address these issues. Initially, models were based on very simplistic geometry, but they are now represented in detail, with the anatomy based on MRI data to represent the realistic structure of the brain and the conductivity distribution.

3.1 Spherical Head Models

Strongly influenced by the earlier modeling of both radio frequency and microwave artifacts, their earliest models of EEG forward modeling utilized the principle of a spherical head, where the brain, skull, and scalp were modeled as concentric spheres [14]. These models presuppose homogeneous conductivity in each layer and ideal symmetry of the head's geometry. Their main strength is their mathematical simplicity, which enables analytical or semi-analytical solutions of the forward problem at a low cost. Therefore, the early history of EEG theory and source localization techniques extensively applied spherical models [15].

Nevertheless, there are serious constraints to using spherical models. A human head is not geometrically spherical; its geometric shape differs significantly among individuals and is anatomically different. Complex aspects of brain structures, such as cortical folding, skull thickness variation, and asymmetry, cannot be addressed using such simplified models [16]. In addition, localized variations in conductivity or complicated interactions between tissues at the edges cannot be correctly represented in spherical models. Such models tend to generate faults in the location of sources and do not realistically depict the spatial distributions of scalp potentials [17].

3.2 Realistic MRI-Based Models

To solve the shortcomings of the solution of EEG by a set of spherical approximations, recent EEG forward modeling has increasingly been based on MRI head models. These models are built based on high-resolution structural MRI scans, thus providing the ability to segment individual tissues within the head [18]. The head comprises several compartments, including the gray matter, white matter, cerebrospinal fluid (CSF), skull, and scalp. Every compartment is specified with particular conductivity values, and in certain instances, anisotropic conductivity is also added, especially in the case of white matter regions [19].

The realism of forward simulations in MRI models is significantly enhanced. They consider individual brain variations in the form of brain structure, skull thickness, and tissue boundaries, which result in a more effective estimation of scalp potentials [20]. This is especially relevant when localizing sources is of interest, as a small error in the forward modeling may cause large errors in the estimated positions of the neural sources.

Although MRI-based models have multiple benefits, they require complicated preprocessing, such as image segmentation, mesh creation, and conductivity value determination. These are computationally expensive processes with the potential for error when there is incorrect segmentation [21]. Moreover, it is not always possible to build subject-specific models using large datasets or clinical settings. However, MRI-based modeling can be regarded as the gold standard for high-precision EEG forward modeling because of its anatomical validity.

3.3 Tissue Conductivity Modeling

One critical issue in head modeling is the assignment of electrical conductivity values to different tissues. Conductivity is the ease with which electrical currents can flow within each part of the head, and it directly affects the distribution of scalp potentials. The skull has one of the most important functions in all tissues because it has low conductivity compared with brain tissue and cerebrospinal fluid [22]. This forms a resistive barrier that contributes significantly to the spatial smoothing of the EEG signals.

Recent studies have indicated that skull conductivity varies tremendously among individuals, creating uncertainty in forward models. This variability may have a significant impact on the accuracy of EEG source localization unless it is well considered [23]. Despite the assumption of isotropic conductivity, more recent studies have accounted for anisotropic conductivity, notably in the white matter, where the direction of the current can be affected by the fiber orientation. Anisotropy can be incorporated to enhance physiological realism, although at the cost of computation.

4. Numerical Forward Methods

4.1 Boundary Element Method (BEM)

One of the most commonly used numerical methods in EEG forward modeling is the Boundary Element Method, which is computationally efficient. The BEM does not discretize the total volume of the head but considers only the boundaries between various tissue compartments [24]. This drastically minimizes the number of elements required for a calculation, making it relatively faster and less resource-demanding than volumetric techniques.

The BEM is effective in layered models of the head with isotropic conductivity when the interfaces between the tissues are well-defined. It has been widely applied to EEG toolboxes and is widely used in source-localization pipelines. However, its performance is reduced in the case of complex geometries or anisotropic conductivity distributions [25]. BEM cannot accurately model the directionality of electrical flow in some tissues, such as white matter, because of the assumption of homogeneous conductivity within compartments. Consequently, it might not be very accurate when it comes to very realistic modeling.

4.2 Finite Element Method (FEM)

The Finite Element Method is now considered one of the most precise methods for solving EEG forward problems. The FEM divides the entire volume of the head into many small parts, thus enabling an intricate description of the geometry and conductivity distribution [26]. This renders it the most appropriate modeling tool for intricate anatomical structures and the incorporation of the anisotropic properties of tissues.

Recent studies have pointed out that in situations with non-regular geometry and non-uniform conductivity, FEM offers better performance. This enables an accurate simulation of cortical folding, skull thickness, and tissue anisotropy, resulting in a more lifelike simulation of scalp potentials [27].

However, this greater precision comes at the cost of significantly higher computational requirements. Mesh generation also needs to be performed carefully and can be technically and time-consuming in the FEM.

4.3 Finite Difference Method (FDM)

The Finite Difference Method uses differential equations by approximating them using a grid of the head volume. It is less frequently used in current EEG research; however, it is still applicable in reduced simulations because of its easy implementation [28]. FDM is numerically efficient for regular grid systems and offers consistent numerical results under controlled conditions. However, FDM is less flexible in depicting complex anatomical geometries. It is difficult to model irregular tissue compartment boundaries realistically; hence, it is less realistic for modeling the head than the other methods. When used on actual EEG data, its accuracy is generally lower than that of the FEM and BEM [29].

4.4 Hybrid Methods

Hybrid computational techniques are a more recent development that strikes a compromise between computational speed and anatomy. They are based on a combination of FEM and BEM or analytical and numerical methods to enhance performance. The aim is to maintain the precision of volumetric procedures while decreasing the computational cost [30].

Recent developments have been made in high-resolution EEG source localization systems, in which hybrid models are expected to be used with respect to their efficiency and realism [31].

These techniques are especially promising for large-scale or real-time EEG applications, where the conventional FEM is computationally prohibitive.

One approach is known as domain decomposition, in which each part of the head's representation is derived from a separate numerical approach. For instance, when the skin structure is characterized by homogeneous outer layers, BEM can be employed. In contrast, complex tissues, such as inner tissues, can be characterized as skin tissues with heterogeneous and/or anisotropic conductivity, which is paralleled by the application of the FEM. This reduces the risk of wasting time and causes inaccurate results.

Interface matching methods are also used to cure electric potential and current density discontinuities at common interfaces between the numerical domains. These must be performed to reduce the numerical errors and ensure physical realism. A recent study suggests that the hybrid model can achieve similar accuracy as the full-FEM model of smaller computational costs, especially for high-resolution source localization and real-time neurofeedback and brain–computer interface (BCI) applications.

4.5 EEG Forward Modeling Software Platforms

Because of the increasing complexity of EEG forward modeling, different software packages have been developed to allow realistic head modeling and numerical simulations. The tools vary according to their numerical and application bases, computational features, and the types of problems they address. Open MEEG is a popular open-source package that implements the Boundary Element Method (BEM) [32].

It offers forward solutions for multilayer head models efficiently and is often incorporated into EEG/MEG analysis pipelines. It has a significant advantage in terms of computational efficiency, but is less applicable for simulating the behavior of anisotropic conductivity.

The main method used in SimBio is the Finite Element Method (FEM), which can model complex anatomical structures and different tissue conductivities in detail [33]. This increases the consumption of computational resources and adds complexity to meshing; however, it increases the modeling accuracy.

Brainstorm is a popular neuroimaging software with a user-friendly GUI and the possibility of integrating solvers for the field created by the BEM or FEM [34]. 2023). It is easy to use and can be incorporated into clinical and research work; however, it may require additional software for advanced modeling options.

FieldTrip is a MATLAB toolbox for multiple forward modeling approaches, such as spherical models, BEM, and FEM [35]. It is flexible and allows researchers to compare various modeling techniques in one place. The setup is quite complex, but the intricacies would make it difficult for amateur users.

MNE-Python is an all-encompassing open-source research platform featuring tools for forward modeling, source localization, visualization, and incorporation into MRI [36]. Although some advanced FEM packages are required, it is highly flexible and is used extensively in computational neuroscience. These platforms have greatly enhanced the accessibility and replicability of EEG forward modeling and continue to contribute to the progress of neuroimaging studies.

5. Comparative Analysis of Methods

EEG forward modeling methods vary significantly in terms of their accuracy, computational efficiency, and anatomical realism. These variations define their appropriateness for diverse applications, both in clinical EEG interpretation and state-of-the-art research in computational neuroscience [37]. Some of the most widespread methods include the Boundary Element Method (BEM), Finite Element Method (FEM), Finite Difference Method (FDM), and hybrid methods that use a combination of more than two different methods. Table 1 summarizes the major characteristics of the EEG forward numerical methods discussed in this study.

The BEM is well known to be computationally efficient and comparatively easy to implement. It also works well in stratified head models, in which the tissues are considered homogeneous and isotropic. However, it is not very accurate for complex geometries or anisotropic conductivity distributions [38]. FEM offers the most anatomical realism because it considers the full volume of the head and allows for a detailed representation of the heterogeneity of the tissues.

Table 1: Comparative Characteristics of EEG Forward Numerical Methods

Method	Accuracy	Computational Cost	Anatomical Realism	Use Case
FEM	High	High	High	Research-grade modeling
Hybrid	High	Medium	High	Advanced EEG studies
BEM	Medium	Low	Moderate	Clinical EEG
FDM	Low–Medium	Low	Low	Simplified models

This renders FEM more applicable to precise research applications, but it is significantly more expensive than the other methods. FDM is easy to use and requires minimal computation time; however, it is not flexible enough to describe realistic anatomical structures, which is why it is not applicable to more complex EEG applications. In hybrid approaches, trade-offs are balanced by integrating the advantages of various methods to provide better accuracy and moderate computational costs.

6. Applications in EEG and BCI

A large variety of applications involving the use of EEG depend on forward modeling because of the need to determine the correlation between neural and electrical sources measured at the scalp. EEG data cannot be accurately interpreted without correct forward models, which are subject to misleading findings. Another significant application is source localization, which involves solving inverse problems using forward models [39]. By more faithfully simulating the propagation of electrical activity through the tissues of the head, life scientists will be in a better position to make more accurate estimates of the location and intensity of brain sources. This is especially essential in neuroscience studies and clinical diagnoses, where the localization of neural activity must be precise.

Forward modeling in brain-computer interface (BCI) systems aids in the better interpretation of signals by enhancing spatial filtering and feature extraction. Proper evaluation of the scalp potentials will be used to differentiate between relevant neural signals, noise, and artifacts, thus enhancing decoding performance [40]. This is particularly significant in real-time systems, such as neuroprosthetics, communication systems used by paralyzed patients, and adaptive control systems.

Examples of the clinical uses of forward modeling include the localization of epilepsy, where the localization of a seizure-onset zone is important for planning treatment. It is also applicable for assessing brain injury, where variations in electrical activity may indicate functional impairment [41].

In addition, neurological conditions such as Alzheimer's disease and those related to stroke are influenced by better EEG readings, which are made possible by precise forward models.

In cognitive and affective neuroscience, forward modeling is used to analyze the distributed brain activity involved in mental processes, including attention, memory, decision-making, and emotion regulation. Given that these processes are mediated by complex, spatially distributed neural networks, proper modeling of the effects of signals transmitted to the scalp is critical for a meaningful interpretation [42]. Comprehensively, forward modeling improves the validity and use of EEG in scientific and clinical settings.

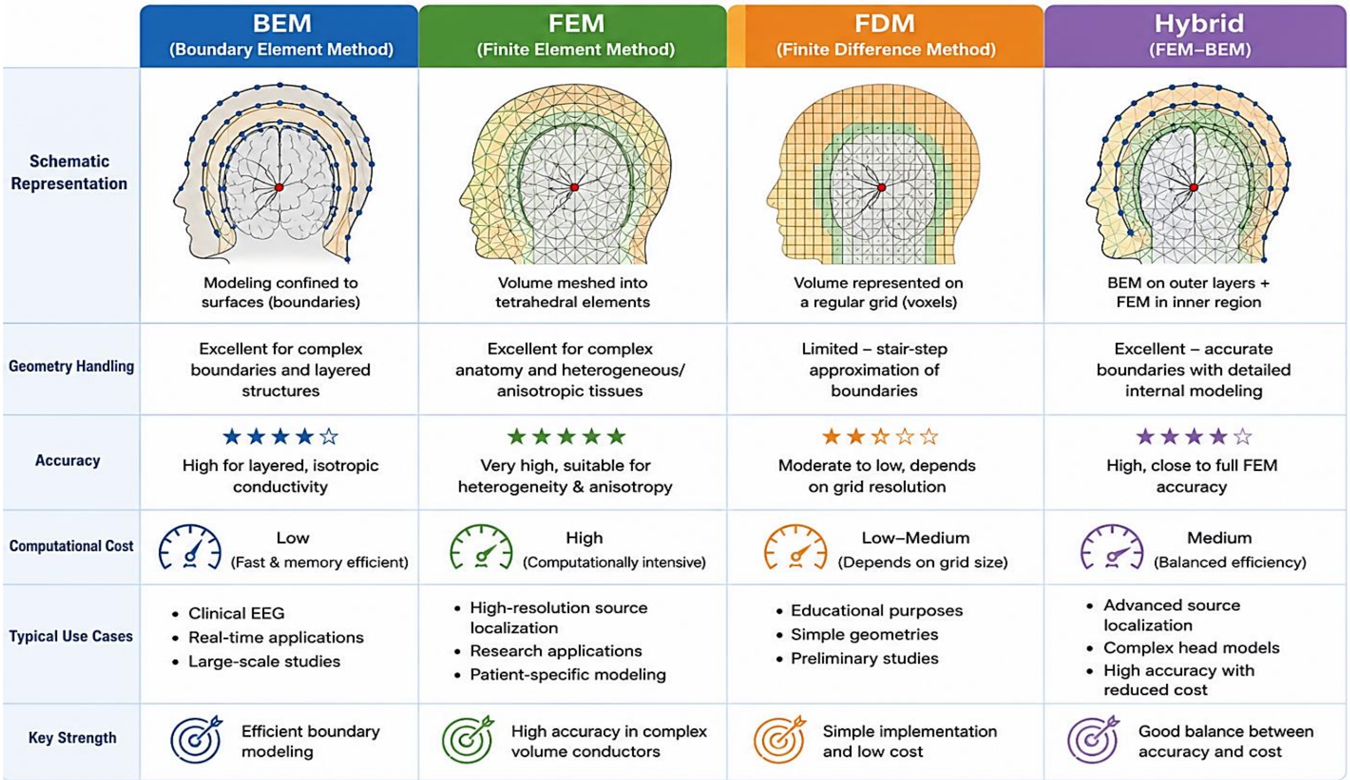

Fig. 1: Comparison of EEG Forward Numerical Methods

7. Current Challenges

Although EEG forward modeling has made great strides, several obstacles constrain the accuracy and generality of the current models. Conductivity uncertainty is one of the most critical factors, particularly in skull tissue [43]. The conductivity of the skull can vary widely over time in different individuals, and even minor differences in the assumed values can produce significant errors in the estimated scalp potentials. This makes conductivity estimation one of the most significant sources of uncertainty in forward modeling.

Another significant obstacle is the anatomical differences between people. Variations in brain structure, skull thickness, and tissue composition imply that what works well in one subject might not be an accurate generalization to another [44]. Although subject-specific MRI-based models have the potential to reduce this issue, such models cannot be used in large-scale investigations or clinical practice because of cost and accessibility issues.

Another significant problem is the misplacement of the electrodes. A minor mistake in electrode placement can create serious deviations in the outcome of source localization. This is particularly topical in the case of clinical and wearable EEG systems, where there may be a problem with the consistent implementation of an accurate electrode placement [45].

Computational costs are also a significant constraint, particularly for high-resolution FEM models. Such models require a large amount of processing power and memory and are difficult to use in real-time applications or with large datasets [46]. This has raised concerns regarding more efficient hybrid practices, although trade-offs between speed and precision remain. Finally, model validation is an essential challenge in this field. Given that the real locations of neural sources are immeasurable in human subjects, it is difficult to determine the absolute ground truth of the forward models. Most validation methods are based on simulations or indirect comparisons, which prevents a complete evaluation of model accuracy. The limitations of this study highlight the importance of further studies on stronger, more effective, and more physiologically realistic forward model mechanisms.

8. Recent Developments (2020-2026)

The last several years have also seen rapid development in EEG forward modeling owing to advancements in computing capacity, numerical models, and data-based models. Among the biggest changes, the development of physics-informed forward models is one of the most important advancements [47]. They combine the laws of physical propagation of electromagnetism with numerical solvers to ensure that the solutions are consistent with the underlying biophysics and are more computationally efficient. This combination enables the interpretation of models and reduces the drawbacks of older computational-optimization methods.

AI-aided mesh aided by AI is another important development. In legacy finite element models, mesh construction is performed manually or semi-autonomously, thus consuming time and having the possibility of errors. Mesh refinement is currently being automated using machine learning techniques, resulting in better precision and speed in the construction of models [48]. This is especially helpful for high-resolution head models based on MRI data, where anatomical complexity requires adaptive meshing strategies.

Deep learning has also been applied to conductivity estimation (specifically to estimate skull conductivity), which is one of the most challenging parameters to estimate in EEG forward modeling. Data-driven methods can be used to learn to map observed EEG patterns to known conductivity distributions to produce better parameter estimates for the subject [49]. Although these methods are still being developed, they have promising capabilities for alleviating one of the most significant contributors to forward model errors.

Another valuable innovation is the real-time forward-solver. Owing to the progress in computing GPUs and mathematical algorithms, it is now possible to compute forward solutions faster than before. This is especially true for brain-computer interface (BCI) systems, where real-time processing is required to achieve good performance within the system [50]. Finally, subject-specific conductivity calibration has received increasing interest. Instead of using literature values of conductivity, current methods seek to approximate the values of conductivity directly using personal data. This increases the personalization of head models and improves their research and clinical applications. In general, recent research (2022-2025) points to the combination of machine learning and traditional numerical solvers as the main method for enhancing efficiency and interpretation.

9. Discussion

The history of the development of EEG forward modeling shows an evident shift from simplified analytic representations to extremely detailed numerical modeling that includes realistic anatomy and complicated conductivity architecture [51]. Approaches founded on approximations based on sphericities offer background knowledge but cannot accurately identify sources owing to the absence of the anatomical details needed in such approximations. In contrast, modern head models based on FEM and MRI-based head reconstructions have greatly enhanced the realism of forward solutions.

The Finite Element Method is the most precise numerical method because it can account for complex geometries and heterogeneous tissue characteristics. Nevertheless, it is still computationally expensive and can only be applied in a few cases in real time or on a large scale [52]. The reason is that the Boundary Element Method remains a highly efficient method, but is not as effective in the anisotropic conductivity of materials, as well as with highly irregular geometries. This accuracy/efficiency trade-off remains the primary focus of EEG forward modeling.

A recent shift towards hybrid and data-driven methods, which combine physics-based modeling with machine learning techniques, has been observed. The goals of these methods are to maintain classical numeric model interpretability and enhance computational performance and flexibility [53]. The trend is a general shift in computational neuroscience towards a combination of mechanistic models and statistical learning.

One major lesson from the recent literature is that the problem of improving forward models is not a numerical problem. Rather, it relies on various interacting factors, such as anatomical accuracy, conductivity estimation, electrode placement, and preprocessing quality. Even the most developed numerical solvers might yield false results in the case of some incorrect anatomical or physiological assumptions. Thus, forward modeling must be considered a holistic issue that incorporates physics, biology, and computation.

EEG and magnetoencephalography (MEG) both seek to describe the behavior of the brain by measuring electromagnetic fields, but they have different requirements in terms of forward modeling. EEG is sensitive to differences in the conductivity of tissues, especially the skull, because electrical potentials are transmitted through conductive tissues to the electrodes on the scalp. In contrast, MEG measures magnetic fields that are comparatively less influenced by the conductivity heterogeneity. This implies that EEG forward models are more strongly constrained by the detailed characterization of conductivity, whereas MEG forward models are more sensitive to the correct source geometries. The complementary nature of EEG and MEG has encouraged the development of multimodal approaches that combine the high temporal resolution of both types of sensors with improved spatial localization accuracy.

10. Conclusion

Forward numerical modeling is a vital element of EEG analysis because it allows the transformation of neural electrical activity into scalp potentials. No interpretation of the EEG signals and credible source localization would have been feasible without the correct forward model. In the last ten years, there have been considerable advancements in the accuracy, realism, and computational efficiency of such models.

More recent developments, especially those using the Finite Element Method (FEM) and MRI-based head geometries, have significantly improved the physiological reality of forward simulations. Such advancements have allowed for a more precise depiction of brain tissue heterogeneity, skull conductivity variations, and individual anatomical variations. Simultaneously, the increase in computing power has enabled the use of increasingly complex models in real-world applications. However, several challenges remain to be addressed in this regard. The uncertainty of conductivity, particularly in skull tissue, remains a significant drawback. Moreover, intersubject anatomical variations challenge the transfer of models between populations. High-resolution FEM-based approaches are also limited by their computational cost, particularly in real-time applications. Moreover, it is not possible to complete the validation of forward models because of the absence of direct ground-truth information about neural sources.

Researchers are likely to follow such directions in the future, attempting to overcome the disadvantages of hybrid modeling frameworks and AI-aided numerical simulations. These approaches exploit the advantages of physics-based modeling and machine learning to achieve high accuracy and efficiency. Adaptive conductivity estimation and subject-specific modeling are also bound to gain greater significance in improving model performance.

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