Initialisation of deep brain stimulation parameters with multi-objective optimisation using imaging data

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Abstract. Following the Deep Brain Stimulation (DBS) surgery, the stimulation parameters are manually tuned to reduce symptoms while minimising side effects. This procedure can be time-consuming, especially with newer multiple electrode contacts (e.g. directional leads). We propose an automated methodology to initialise contact configurations using imaging techniques. The goal is to maximise the electric field on the target while reducing the spillover, and minimising the electric field on regions of avoidance. By superposing pre-computed electric fields, we solve the optimisation problem in less than a minute, much more efficient compared to finite element methods. Our method offers a robust and rapid solution, and it is expected to considerably reduce the time required for manual parameter tuning following DBS implantation.

1 Introduction

Deep Brain Stimulation (DBS) is a surgical treatment for a number of neurological disorders, including Essential Tremor (ET) and Parkinson's disease (PD). It reduces the symptoms of the disease by stimulating specific region of the brain via implanted electrodes. The region of stimulation varies according to the disease, for instance, Ventral intermediate nucleus (VIM) in ET and Subthalamic nucleus (STN) in PD are established target regions [1].

After the electrode implantation, a parameter tuning session is performed. The goal is to cover the target region as much as possible with the effective electric field, while reducing it outside of the target [2]. The effective electric field, or the volume of tissue activated (VTA), encompass neural volumes with additional action potentials due to the DBS-induced electrical stimulation [3]. Another goal of the parameter tuning session is to avoid stimulating the regions associated with side effects, like the Ventral posterolateral nucleus of thalamus (VPL), adjacent to VIM, known to cause paresthesias in ET patients [4]. Normally, the tuning procedure is performed manually, until an improvement in symptoms is observed. Numerous possible combinations for contact configuration often cause

the tuning procedure to be long and demanding for both patients and physicians. Moreover, it might not conclude with the maximal clinical benefits [5].

Several algorithms have been proposed to find the optimal parameters, including, the simple scoring method [6], weighted metric method [4], fuzzy and probabilistic optimization [7,8], and constraint optimization [2,5].

We propose a novel method suggesting an initial contact configuration for the DBS parameter tuning session using the weighted sum method for the first time. The algorithm has three objectives: maximizing the electric field on the target, minimising the electric field outside of the target, and minimising the electric field on the region of avoidance (ROA). We formulate our multi-objective problem by optimising over a weighted-sum cost function, which also includes priorities for each objective region to be defined by the user. We chose the weighted sum method, as it enables prioritization of the objective according to the subject's case. With two case studies, we demonstrate the importance of the user-defined weights enabling personalised medicine. Benefiting from FastField [9], an algorithm for electric field simulation, the optimisation algorithm solves in only 20-40 seconds. Thanks to its rapidity, the optimisation can also be solved for different amplitude values. Performing a trade-off between the evaluation metrics of the three objectives for different amplitude values, the optimal amplitude and contact configuration can be chosen. The solution of this algorithm is robust and comprehensive and can be used for both cylindrical and directional leads.

2 Method

In order to maximise the effect of the DBS on a patient, a computational model of DBS-induced electric field in the patient's brain is necessary. We reconstruct the patient's brain structures and the electrode location using MRI and CT scan. Once the DBS case is reconstructed, our multi-objective approach is solved for the initial contact configuration.

2.1 Target and Electrode reconstruction

We reconstruct the target and the region of avoidance similarly to the DBSAR pipeline using patient's MRI [10]. The MRI is registered to the Montreal Neurological Institute (MNI) space using Advanced Normalization Tool (ANTs, http://stnava.github.io/ANTs/). The location of the target is extracted using an atlas registered into the MNI space. For this study we use Distal and Thomas atlas. For the electrode reconstruction, the CT scan is used. Patient's CT is registered to the MRI using FMRIB's Linear Image Registration Tool (FLIRT, https://fsl.fmrib.ox.ac.uk/fsl/fslwiki/FLIRT) . We use the PaCER algorithm to extract the location of the electrode in the brain [11], and the DioDe algorithm to detect the rotation of the electrode [12].

2.2 Initialisation of DBS parameters

The procedure of finding the initial setting is divided into two parts. First, it identifies the contacts that are close to the target, in particular, the segmented contacts facing towards the target. Second, it solves the optimal contact configuration problem for the selected contacts, while fixing amplitude, pulse width and frequency to keep the energy consumed constant. The electric field $E(g)$ around the electrode is simulated using FastField [9] over a 3D grid $\mathcal{G}$ with constantly spaced points $\{g\}$. The points where the electric field value is higher than the threshold (200 V/mm) are considered as the VTA volume [13].

Ranking the contacts. In this step, we measure the Euclidean distance between the center gravity of each contact with the center gravity of the target of interest. Contacts are ranked based on their proximity to the target (Fig. 1, left). Next, for the segmented contacts, we measure the angle between the center of the contact and the center of the target. Contacts facing towards the target are ranked higher (Fig. 1, right). Once all the contacts are ranked, the optimisation can be solved on the top 3-4 highly ranked contacts. This ranking step is optional and the optimisation can also be solved on all the contacts.

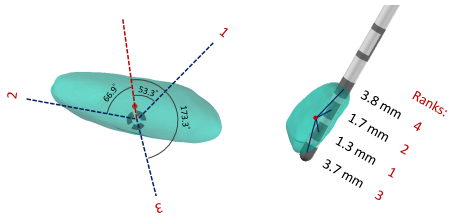

Fig. 1. A Boston Scientific Versice directional lead is shown for the ranking. The 4 rings are ranked based on their distance to the target. The segmented contacts are ranked based on their angle to the target.

Optimisation problem. In this step, we solve a multi-objective optimisation for the weight of contacts (w_n). The objectives include maximizing the electric field on target, minimising the electric field outside of target and minimising the electric field on the region of avoidance (ROA). The latter is optional. We formulate this multi-objective problem with the weighted sum method as in Eq. 1. Partition the simulation grid $\mathcal{G}$ [9] into the three areas of interest: $\mathcal{K}$ (target), $\mathcal{O}$ (off-target), $\mathcal{R}$ (ROA), such that $\mathcal{G} = \{\mathcal{K}, \mathcal{O}, \mathcal{R}\}$. Solve:

$$\begin{aligned} &\min_{w_n} \left[\alpha \sum_{g \in \mathcal{G}} E(g, w_n) - \beta \sum_{g \in \mathcal{K}} E(g, w_n) + \gamma \sum_{g \in \mathcal{R}} E(g, w_n) \right] \\ &\text{subject to } \sum_{n}^{N} w_n = 1, \text{ with } \forall_n \in N : w_n > 0 \,, \end{aligned} \tag{1}$$

where

$$E(g, w_n) = \sum_{n}^{N} E_n^0(g) \cdot \frac{w_n \cdot A}{A_0} \cdot \frac{\kappa_0}{\kappa} \tag{2}$$

is the electric field produced by each contact $n = [1 \dots N]$ and computed at each point g of the 3D grid $\mathcal{G}$. α, β, γ are user-defined priority terms that can be used to prioritize one objective over another; their default values are 1, 2, and 1. $\alpha = 1$ and $\beta = 1$, and $\gamma = 0$ corresponds to minimising the electric field outside of the target. $\beta = 1$, $\alpha = 0$, and $\gamma = 0$ corresponds to maximizing the electric field on the target. $\gamma = 1$, $\alpha = 0$, and $\beta = 0$ corresponds to minimising the electric field on ROA. N is the number of contacts of the electrode, w_n is the weight associated to each contact. E_n^0 is the pre-computed e-field for each contact. A is the amplitude and κ the brain conductivity value. A_0 and κ_0 are amplitude and conductivity values used to generate the pre-computed e-fields. Refer to the Fastfield paper for detailed information about the pre-computed electric fields [9]. The brain conductivity value is 0.1 S/mm for all the calculations in this study but can be easily adjusted when necessary and does not affect the methodology. The optimisation problem is solved using MATLABs `fmincon` function with the interior point method. We keep the total energy consumed by fixing the amplitude value.

2.3 Performance evaluation

To evaluate the performance, we measure the percentage of the target and the ROA covered by the VTA (Target coverage, and ROA coverage), and the percentage of the VTA outside of the target (VTA spillover).

2.4 Amplitude evaluation

The optimisation algorithm is solved for different amplitude values for each patient, ranging from 1 to 8 mA. A simple trade-off between the objectives is performed to initialise the amplitude value. The VTA spillover and the ROA coverage are deducted from the target coverage. The amplitude with the highest trade-off (TROFF) value is chosen as the initial stimulation amplitude. Amplitudes higher than 6 mA are shown for comparison purposes and are not suggested as initial settings for clinical usage.

3 Results

We use the imaging data from two de-identified patients to evaluate our optimisation approach.

3.1 Case study 1

Case 1 is an Essential tremor patient, with VIM as the target and VPL as the ROA. The implanted electrode is a Boston Scientific Vercise directional lead. The optimisation is solved for the contact configuration using different amplitude values, 1 to 8 mA. The target coverage, ROA coverage , and the VTA spillover for different amplitude values are shown in figure 2. The amplitude with the highest TROFF value, and its corresponding contact configurations are chosen as the final setting, in this case, 5 mA with TROFF value of 16. The optimal Contact configuration for this case is shown in figure 2. The Target coverage, ROA coverage, and the VTA spillover 62% , 2%, and 44%.

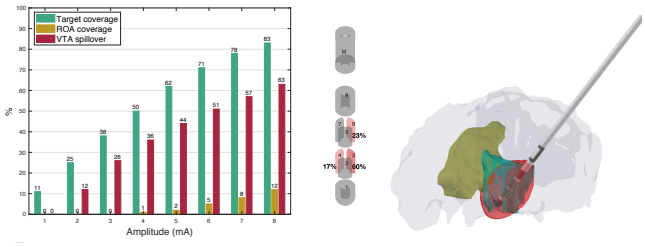

Fig. 2. Case study 1. The evaluation metrics when solving the optimisation with different amplitude values are plotted on the left. For this optimisation, the electrode is precisely inside the target; hence, we assign same priorities for the three objectives, $\alpha = 1$, $\beta = 2$, and $\gamma = 1$. On the right, the chosen contact configuration corresponding to amplitude 5 mA is plotted. VTA is plotted in red, VIM in green, VPL in yellow, and the whole Thalamus in gray.

3.2 Case study 2

Case 2 is a Parkinson patient, with STN as the target structure and no ROA. The implanted electrode is a Boston Scientific Vercise directional lead. The optimisation is solved for the contact configuration using different amplitude values, 1 to 8 mA. The target coverage, and the VTA spillover for different amplitude values are shown in figure 3. In this case, there is no ROA considered. The amplitude with the highest TROFF value, and its corresponding contact configurations are chosen as the final setting, in this case, 2 mA with TROFF value of 23. The optimal Contact configuration for this case is shown in figure 3. The Target coverage and the VTA spillover are 48% and 24%.

3.3 Evaluation of ranking and time efficiency

In order to evaluate the performance of the ranking method, the optimisation algorithm was run for both case 1 and 2 once on all contacts and once on the chosen contacts with the selected amplitudes values of 5 and 2 mA. The algorithm resulted in similar contact configuration in both cases.

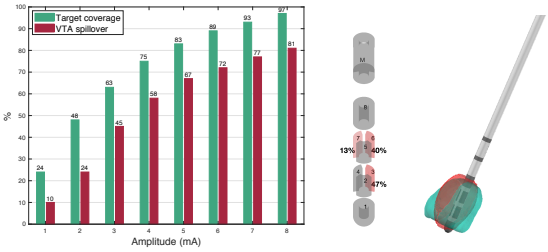

Fig. 3. Case study 2. The evaluation metrics when solving the optimisation with different amplitude values are plotted on the left. For this optimisation, the electrode is in the lateral part of the target, therefore, we assign a higher weight (β) to prioritize the maximisation of the electric field on the target. α, β, and γ values thus equal to 1, 4, and 0 were chosen. On the right, the chosen contact configuration corresponding to amplitude 2 mA is plotted. VTA is plotted in red, and STN in green.

Once extracting the location of the target, the average time needed to run the optimisation algorithm was 41.7, and 20.0 seconds for case 1 and 2 respectively. We used the same laptop for both (MacBook Pro, 2.3 GHz Intel Cori5, 16 GB memory).

4 Discussion

In this paper, we propose an efficient method for optimising the contact configuration for DBS programming session. We start with an initial ranking to define the closest contacts to the target. The ranking outputs a reasonable result (Sec. 3.3). This shows that our simple ranking can already define the final active contacts.

For the optimization step, our objective function is defined to satisfy three objectives while considering their corresponding weights, in contrast to other existing method that optimise the DBS settings on one of the objectives and maintain other objectives lower than a threshold. We leave the priority terms α, β, and γ as free parameters, to be chosen by practitioners depending on their needs. The method is evaluated on two case studies, one with a ROA (Case 1), and one without (Case 2), with associated priority values (Figs. 2 and 3).

Like for other optimisation algorithms, the result depends on the correct image registrations, target segmentation, and electrode localization. Any uncertainty in the previous steps impacts the result of the optimisation. This work is evaluated on patients imaging data, but it has not been tested on patients. Future steps will involve testing the suggested contact configuration on patients and evaluate the symptoms response. We recall that this algorithm suggests plausible settings to initiate the tuning session, and not the final optimal setting. Thus, fine tuning from the practitioners' side might be necessary.

Overall, this study shows that the weighted sum method can be used to form the DBS multi-objective optimisation problem, to maximise the electric field on the target while reducing the electric field outside of the target and on the region

of avoidance. The method is robust, efficient, and it is expected to considerably reduce the time needed for the DBS programming session. Furthermore, the method will be publicly available upon acceptance.

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