Surgical Data Analysis for Decision Making Support and Knowledge Discovery in Deep Brain Stimulation

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1 Introduction

High frequency and continuous electrical stimulation of deep brain structures (DBS) has been demonstrated as an efficient minimally invasive surgical treatment for motor related diseases and recently for severe neuropsychological diseases [1]. The quality of the clinical improvement, as well as the occurrence of motor, neuropsychological or psychiatric side effects strongly depend on the location of the electrodes [2]. However, even though DBS provides excellent clinical results, there is no consensus in the neurosurgical community about the optimal location of the area to be stimulated as well as corresponding electrical parameters. It is also expected that this is different among patients. The choice of the best target is usually based on a combination of patient specific and generic anatomical, functional and clinical information and knowledge. Patient specific data and information are based on multimodal medical images, clinical and electrophysiological data, whereas most of the generic information and knowledge are implicit. To make it explicit, some groups suggested digital atlases [3]; some atlases were computed from population analysis [4,5].

In this paper, we present the global approach we implemented in the context of Deep Brain Stimulation aiming both at assisting surgical planning, performance and post operative programming and evaluation, as well as better understanding neurological phenomenon for knowledge discovery. Our approach is based on numeric and symbolic surgical data analysis. The clinical motivation is to improve targeting and post operative evaluation for better outcome and reduced side effects.

2 Methods

The main characteristics of our approach include: 1) computation of pre, intra and post-operative patient-specific models from multimodal medical images, clinical and electrophysiological data, 2) analysis of patient population for outlining common patterns and outcome, 3) computation of generic models from population analysis to help pre, intra and post operative decisions and actions.

2.1 Patient specific models: The PyDBS platform

The first step of surgical data science stands in data collection, from which modeling approaches allow the transformation of such data into patient specific models, from data to information.

We have developed a software environment (called pyDBS) allowing fully automatic computation of a pre-operative patient specific model from his/her multimodal medical images and from anatomical atlases (allowing segmentation of anatomical targets non-visible on medical images) [8]. This software also includes visualization and interaction modules with few interactions. Such patient specific models provide neurosurgeons with more precise anatomical information for preoperative planning. pyDBS segments patient's brain structures by registering ParkMedAtlis anatomical atlas to patient's magnetic resonance (MR) images. After surgery, pyDBS segments, from a postoperative CT scan image, the implanted electrodes. By registering this CT image to the preoperative MR image, and combined with the inversed atlas to patient MR image transformation, we can calculate the coordinates of electrode contacts in the ParkMedAtlis atlas space.

In addition, we have developed a database that includes data from more than 240 patients. In addition to images, it includes clinical data from more than 80 different clinical scores acquired before and at different time-points after surgery. It covers various aspects including motor, neuropsychological, psychiatric, and quality of life related scores. Intra operative electrophysiological data, acquired with awake patients during surgery, are also stored into the database.

2.2 Generic models

One key element of surgical data science is the computation of generic models that gather knowledge about the covered domain. Such models allow explicit modeling of surgical knowledge to be used for assisting the whole surgical workflow. Different types of knowledge may be concerned, covering all aspects of surgical expertize from technical and non technical skills. Models may be numeric and symbolic. They may be computed from different knowledge acquisition strategies from expert interviews to data analysis. In this section, we briefly illustrate this concept with three examples in the context of DBS.

ParkMedAtlis: a dedicated anatomical atlas for Parkinson disease: The target for DBS in Parkinson's disease has been moved from the thalamus to the globus pallidus and the subthalamic nucleus (STN). The STN, in addition to its role in motor control, has been shown to be involved in the development of non-motor diseases such as obsessive compulsive disorders. In these pathologies, it is believed that a non motor portion of the STN may receive associative and limbic information from the associative and limbic portions of the external globus pallidus. It is thus increasingly important to be able to localize with a high degree of precision not only the STN and the other nuclei of the basal ganglia, but also the topography of their functional subdivisions. Mainly due to contrast and spatial resolution limitations, the usual targets are not easily visible in the MR images available to the surgeon, even though MRI offers the best contrast compared to other medical imaging modalities. Also, many deep

brain structures do not exhibit detectable contrast and thus remain poorly visible or invisible at anatomical MRI. Consequently, the surgeon needs additional information and knowledge for indirect identification of such small targeted structures.

For helping anatomical identification of targets all along the surgical workflow, we have developed an anatomical atlas called ParkMedAtlis [6]. In order to take into account specific anatomy of PD patients, the atlas was computed from averaging T1-weighted and T2-weighted MR images of 57 patients with Parkinson's disease. Twenty-four deep brain structures were manually segmented on the atlas. In order to adapt such knowledge to each patient, we have implemented atlas based segmentation approaches allowing to accurately identifying the anatomical knowledge within patient images [6].

Anatomo-clinical atlases as predictive maps: In order to improve pre operative decision making, we introduced the concept of anatomo-clinical atlases, which consists of analyzing retrospective data of previously implanted DBS patients [7]. In opposition to classical works using anatomical and electro-physiological data [4,5], we studied the correlation between stimulated areas and clinical scores. By non-linear registration of the patient specific models and the anatomical atlas, we are able to compensate anatomical differences between individuals and to express stimulated areas of a population of patients into a same anatomical coordinate system. Then, within a homogenous population, we are able to correlate the clinical scores, expressing the clinical outcome, with the anatomical location of the stimulated areas. The corresponding computed 3D atlases highlight areas with best clinical results according to different clinical scores. We introduced the concept of such atlas for outcome prediction. The cross validation of the atlas computed for 26 STN implanted patients with UPDRS Part 3 score (UPDRS3) covering assessment of motor disorder shown predictive performance around 70%.

Neural network models for predicting stimulation side effects: Since DBS uses electric current to stimulate brain tissue, some side effects could be triggered if inadequate stimulation configurations are applied. Among all known side effects, the pyramidal tract side effect (PTSE) is a contraction time-locked to the stimulation when the current spreading reaches the motor fibers of the pyramidal tract within the internal capsule close to the implantation target. We used machine learning based methods and Artificial Neural Networks to model the PTSE [9]. The model was learned from a prospective study on twenty patients implanted in the STN and globus pallidus. Appearance of PTSE was tested by gradually increasing the stimulation current. The model to predict the occurrence of PTSE accounted for the current of the stimulation, the 3D electrode coordinates and the angle of the trajectory. Cross validation showed that the kappa index between the data predicted by the model and the labeled data was .78.

3 Conclusion

In this paper, we show how analysis of surgical data could help the surgical decision making process. Anatomical atlas helps identification of anatomical targets hard-

ly visible in MR images during surgical planning. Anatomo-functional atlases may give access to prediction maps identifying expected outcome when stimulating in corresponding anatomical areas, allowing optimization of target selection during planning. ANN models may predict appearance of clinical side effects as regards to location of the electrode and electrical parameters. This could help optimizing electrical parameters intra and post operatively. Additionally, being able to have access to such knowledge directly impacts understanding of neurological phenomenon [10,11]. However, quantitative demonstration of clinical added value is still required. It is expected to improve clinical outcome, reduce operative time and infections, and simplify surgical workflow. Predictive performance of such models still needs to be improved. Improvement may come from both identification of additional parameters influencing outcome, having more homogeneous populations and increasing number of patients for higher statistical power.

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