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A Bayesian particle filtering method for brain source localisation

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ABSTRACT

In this paper, we explore the multiple source localisation problem in the cerebral cortex using magnetoencephalography (MEG) data. We model neural currents as point-wise dipolar sources which dynamically evolve over time, then model dipole dynamics using a probabilistic state space model in which dipole locations are strictly constrained to lie within the cortex. Based on the proposed models, we develop a Bayesian particle filtering algorithm for localisation of both known and unknown numbers of dipoles. The algorithm consists of a region of interest (ROI) estimation step for initial dipole number estimation, a Gibbs multiple particle filter (GMPF) step for individual dipole state estimation, and a selection criterion step for selecting the final estimates. The estimated results from the ROI estimation are used to adaptively adjust particle filter's sample size to reduce the overall computational cost. The proposed models and the algorithm are tested in numerical experiments. Results are compared with existing particle filtering methods. The numerical results show that the proposed methods can achieve improved performance metrics in terms of dipole number estimation and dipole localisation.

1. Introduction

In recent years, the development of non-invasive brain signal measuring techniques such as MEG and electroencephalography (EEG) have seen rapid progress. These techniques are helpful in diagnosis of mental diseases such as epilepsy, Alzheimer's and Parkinson's disease [1,2]. In non-invasive brain signal processing, we are particularly interested in the signal generated from the cerebral cortex which is the outer layer of the cerebrum [3,4]. Cortical activity in different cortical regions (such as somatosensory, visual, motor or auditory cortex) can be elicited by suitable stimuli (such as an image or a piece of song). A single active neuron is too weak to be measured directly, so tens of thousands of synchronously active neurons are needed to produce a measurable brain signal. For modelling purposes, many spatially neighbouring active neurons can be summarised and modelled as a dipolar current source, which can be simply named as a "dipole". The electromagnetic field generated by such a dipolar source is measurable using MEG/EEG devices.

Brain source localisation is fundamentally an ill-posed inverse problem [2,4]. The main barrier is that there may exist many possible solutions for the same set of data, and hence no unique solution can be obtained in the general case. In this paper, we aim to accurately localise the spatio-temporal brain sources using the electromagnetic signals collected outside the surface of the head, employing physiological constraints and soft prior information to regularise the undetermined problem.

1.1. Related work

Brain source localisation is an active research field where a significant amount of work has been done in the past two decades (see, e.g., [3–15] and the references therein).

There are two main types of methods: distributed source approaches, and point-wise dipole approaches [3]. Distributed source methods identify the potential active brain sources that are distributed on a dense grid of fixed locations throughout the whole cerebral cortex (or the whole brain volume if under a looser constraint). Since the number of unknown sources is larger than the number of the M/EEG sensors, mathematical assumptions or constraints are required for a unique solution. Some existing methods include the least squares minimum norm estimation (MNE) [3], dynamic statistical parametric mapping (dSPM) [16], standardised low-resolution electromagnetic tomography (sLORETA) [5], and Kalman filter related approaches [8,6].

On the other hand, point-wise dipole approaches treat the brain currents as point dipole sources, and estimate the states (this may include dipole location, moment, and orientation) of the point source dipoles. In this type of modelling, the state of each dipole source is treated as a random unknown target.

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A number of works have been published under this type of modelling; these include multiple signal classification (MUSIC) related approaches [17], Markov chain Monte Carlo related approaches [18,7], and sequential Monte Carlo (or particle filtering) related approaches [9,12,13,15,14].

Among the various methods proposed, Bayesian particle filtering seems one of the most promising methods for tackling the source localisation problem. In this paper, we develop a point-wise dipolar source localisation approach using Bayesian particle filtering.

1.2. Bayesian particle filtering methods for dipole localisation problem

Particle filtering methods have been developed for this application over the last decade. Somersalo et al. [9] applied a sequential importance resampling (SIR) particle filter for the dipole localisation problem using artificial planar/3D geometry. Results of a two-dipole localisation example was shown using an ideal spherical head model. Campi et al. [12] proposed a Rao–Blackwellised particle filter (RBPF) for dipole tracking with single dipole and two dipole examples. It was shown in that work that the RBPF provided better localisation results with lower computational cost than those from a standard particle filter. Sorrentino et al. [13] integrated a random finite set scheme into the particle filter. The method was able to track a time-varying number of dipoles with the maximum dipole number specified in advance.

Recently, Sorrentino et al. [15] suggested to model the problem using a static dipole setup. The work employed a resample-move particle filter to recursively estimate the dipole moment. Chen et al. [19,20] integrated an MNE step into a multiple particle filter method to localise an unknown number of dipoles. The estimation of the dipole number relied on both the MNE step and the previous localisation history. Miao et al. [14] also adopted a multiple particle filter method to localise multiple dipoles, using a probability hypothesis density (PHD) filter to perform the estimation of the unknown/time-varying dipole number. The algorithm was implemented and assessed in a real-time field-programmable gate array (FPGA) board. However, it modelled the brain under the ideal spherical head model, which cannot provide a realistic description of the true human brain.

1.3. Our work

In this paper, we propose a Gibbs multiple particle filtering (GMPF) algorithm for the multiple dipole source localisation problem. The work is developed based on our previous work [19,20]. The contribution of this work is described as follows.

Firstly, a continuous head model which forces the state dynamics to strictly remain on the cerebral cortex is developed. To fit with real world applications, we adopt a 1-layer realistic head model, the Nolte model [21]. Although this head model is quite realistic, the off-the-shelf software implementations of it can only be used to evaluate the model at a discrete set of points (the mesh nodes). For distributed source implementations this is all that is needed. However, in our case we need a smooth manifold which defines the cortex surface and hence the discrete set of points is not enough. For this purpose, we adopt a nearest-neighbour (NN) interpolation method to form an approximate continuous cortical manifold. This allows us to formulate the particle filter state directly in terms of the location on the continuous cortex surface.

Secondly, we develop a particle filtering algorithm by integrating a Gibbs sampling iteration step into a multiple particle filtering (MPF) [19] algorithm. Instead of running each component of the MPF only once at each time step, the GMPF iteratively runs the individual components, conditional on the state of the remaining sources, until the state samples converge. This enables the MPF to iterate to obtain a stable state estimate prior to entering the next time step.

Thirdly, we develop a dipole number dynamic model along with the GMPF method [22,23] for localisation with an unknown dynamic number of dipoles. The model generates three potential dipole number predictions based on the estimate from the previous time step. All three predictions are examined and their corresponding state estimates are calculated. A selection criterion is then applied to obtain the optimal prediction results in each time step. Although approximate in a Bayesian sense, this approach improves the accuracy in estimating the number of dipoles, and thereby improves the overall localisation performance of GMPF.

Finally, we apply a computationally adaptive scheme to adjust the number of particles and the state transition range at each step of the algorithm run. In order to generate candidate numbers of sources at each time step, we integrate a standard noise normalised MNE method [3] and a spatial clustering method [24] to gain some knowledge on the potential dipolar sources. These prior information are used to evaluate the localisation accuracy. We could then adjust the particle size and the state dynamic space in the next algorithm run.

The remainder of the paper is organised as follows. Section 2 introduces the data modelling procedure. A discrete/continuous head model, a dipole state transition model, and a dipole number dynamic model are described in this section. The localisation algorithm is proposed in Section 3. Both the models and the algorithms are evaluated in Section 4. Section 5 concludes the article.

2. Data model

We consider a clinical application using an MEG system with $M = 204$ magnetometers – the proposed method can be applied to other M/EEG settings with slight modifications. Here we use the 204-sensor MEG application as an example. All the sensors are placed outside the brain surface to obtain non-invasive measurements. We are interested to infer the neural activities within the brain cortical region. The state space is constrained to lie within the cerebral cortex and is denoted as Ω.

For MEG data, a 1-layer realistic head model is introduced to generate the lead-field matrix (the forward matrix), based on a total of G fixed vertices on the cortex. An NN (nearest neighbour) interpolation method is used to interpolate the locations between these vertices.

As described above, the head model comprises G vertices, $\{\mathbf{g}_1 \cdots \mathbf{g}_v \cdots \mathbf{g}_G\}$; and F triangular faces on the surface of the cortex, created assuming a 1-shell Nolte model for MEG. The width of the head model is 136 mm, and the distance between two adjacent vertices varies between 2.3 mm to 8.4 mm. The lead-field matrix $\mathbf{L}$ was generated using the statistical parametric mapping (SPM) software [25]. Although $\mathbf{L}$ provides a relatively accurate approximation for the source distribution in the cortical space, it is discretised artificially to a limited number of fixed-location points. We first introduce the traditional discrete real head model using $\mathbf{L}$. The neural current density is, by contrast, in reality a continuous spatial flow. For this reason, we then propose an interpolated realistic head model for continuous point-wise dipole localisation.

Fig. 1 shows the triangulation of the cortex. The blue dots are the pre-defined vertices on the cerebral cortex, and the 5 coloured small areas are example sub-planes that represent the individual triangular faces on the cortex. In order to better fit real world applications, we strictly enforce that the trajectory of a point-wise dipolar source lies within the modelled cerebral cortex. Each individual dipolar source may only move within a single triangular cortical region defined by the fixed vertices and the triangular faces. Thus we model each dipole as semi-static within a small spatial volume for the whole observation interval.