EEG/MEG Kalman-like Source Estimation

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Abstract

The estimation of the instant location and strength of sources takes a considerable importance for many areas of sensor space-array processing, e.g., brain activity in non-invasive electro-medicine.
State-space models are a well suited framework for solving that dynamic estimation problem and they are in the core of our studies. Related to brain electrical activity, the state estimation problem can be solved by analyzing spatio-temporal data provided by EEG/MEG measures.
Nonlinear Kalman-like filter is proposed for estimating locustemporal data related to electrical activity in the brain. The experimental framework is described.

Objective: Locustemporal Data Estimation

Electrical activity in the brain can be seen as locustemporal data. Location refers to points over the brain where significant activity is present at a time. EEG/MEG array sensors bring spatiotemporal data. In this context, space refers to sensor array positions where data is observed at discrete time samples or snapshots. Spatiotemporal data is understood as the aggregate of the noise degraded outcomes of a nonlinear direct relation. That relation is evaluated for each sensor over a countable set of locustemporal points where electrical dipoles are active.

Ideally, the activity of a source is concentrated on a point and then well represented by a single dipole per snapshot. In practice, there is set of activated points per snapshot[1]. This situation would be better represented by more than one dipole attending to the replication of the spatiotemporal data. The coordinates of the active dipole/dipoles evolving over time are the primary estimation goal. The secondary estimation goal is the strength of the activity of those dipoles, i.e., the data values themselves.

[1]The activity eventually spreads along a travelling instant direction [2].

Therefore, non evident locustemporal data is estimated using suitable estimators over EEG/MEG spatiotemporal measures. See [15] for a discution of optimability in this context. A frequently used estimation tool is the MUSIC localizer. MUSIC uses the availble spatiotemporal data, block by block along time, for estimating one or a few dipole locations per snapshot [1], [2]. Note that MUSIC is able to estimate more than one dipole location at a time, but it is not clear if the resolution is fine or coarse [8].

We propose the use of a nonlinear Kalman-like filter for estimating locustemporal data. The recursive filter uses the spatiotemporal data, point by point along time, for estimating a single point on state space per snapshot. Points on state space correspond to locustemporal data points.

For any snapshot, the active dipoles may be grouped into sets. By using the filter, the members of each set are fused into a representative dipole. That single dipole stands for a source of activity at that instant around its location. In the case of multiple sources, i.e., two or more sets of activated points per snapshot, our problem becomes a multiple target tracking task or level 1 data fusion process [14].

Method: Kalman-like Filtering

Let us have a preliminary response to the following question: Which are the advantages of using Kalman-like filtering instead of, e.g., MUSIC? The a priori advantages of Kalman-like filtering over MUSIC localizer are:

1. Kalman-like filters integrate a priori information about state dynamics.
2. Kalman-like filtering estimates not only state but also error.
3. Recursive processing is usually faster than sliding window block processing.

The estimation framework is established as state-space model II (see [2] for details),

$$\text{model II} \qquad \begin{array}{rcl} \boldsymbol{x}_{t+1} & = & \mathcal{F}_t\, \boldsymbol{x}_t + \boldsymbol{w}_t \\ \boldsymbol{z}_t & = & m(\boldsymbol{x}_t) + \boldsymbol{\imath}_t \end{array}$$

The *model for propagation is linear*: $\boldsymbol{x}_t$ is the unknown vector parameter of the source at time t, $\mathcal{F}_t$ is a known matrix describing the dynamics of the propagation, and $\boldsymbol{w}_t$ is characterized by a known symmetric covariance matrix $\Sigma_{\boldsymbol{w}_t}$.

The *model for observation is nonlinear*: $m(\cdot)$ is the nonlinear relation between $\boldsymbol{x}_t$ and the array observations $\boldsymbol{z}_t$, and $\boldsymbol{\imath}_t$ represent the observation and modelling noise which is assumed Gaussian, non-correlated and zero-mean.

Direct nonlinear relation $m(\cdot)$ is a model for the transformation of locustemporal data into spatiotemporal data minus noise, and can take several forms. In a quite realistic form, $m(\cdot)$ models a three layers 3D irregular head with both EEG and MEG sensor arrays [9]. In a simpler view, $m(\cdot)$ models a one layer 2D circular head model with only MEG sensors.

Rigorously speaking Kalman filter refers to linear state-space model, both in propagation and observation equations. Widely, we call Kalman-like filter other recursive Bayesian estimation tools suitable for solving nonlinear problems as those appearing in [4], [5], [6], [7], [12].

When it comes to state estimation for nonlinear systems there is not a single solution available that clearly outperforms all other strategies. Up to now the extended Kalman fillter (EKF) has unquestionably been the dominating state estimation technique [3]. The EKF is based on first-order Taylor approximations of state transition and observation equations about the estimated state trajectory. Several estimation techniques are available that are more sophisticated than the EKF, e.g., re-iteration, higher order filters, and statistical linearization. The more advanced techniques generally improve estimation accuracy, but it happens at the expense of a further complication in implementation and an increased computational burden.

Recently there has been interesting developments in derivative-free state estimation techniques. Consequently, we use a new set of estimators, which are based on polynomial approximations of the nonlinear transformations obtained with particular multidimensional extension of Stirling's interpolation formula [10]. Based on the formula two new fillters have been proposed. The divided difference 1st order filter (DD1) is based on first-order approximations and the DD2 filter is based on second-order approximations.

Based on Gaussian assumptions, the accuracy of the DD1 filter is comparable to the EKF in terms of expected error. The accuracy of the DD2 filter is comparable to the modified Gaussian second-order filter. As the employed polynomial approximations utilize knowledge about the covariance of the state estimates, we expect that the new filters will be superior to conventional (Taylor approximation based) filters for highly nonlinear systems, and systems with high noise levels.

Experimental Framework: Models and Routines

An experimental framework has been defined for verifying the use and characteristics of Kalman-like filtering in EEE/MEG brain source estimation. The component taxonomy of the framework is the following.

Activity Model: Many situations arise when modelling activity. The components are the following,

- Dipoles are sequences of active points following fixed-location paths over the locustemporal hyperplane, i.e., their activities are curves over time. Different dipoles follow similar moment dynamics or templates for their activation curves [13].
- Sources are composed by active points laying over connected locustemporal regions. Those active points come from dipole activation curves[2]. Location dynamics may be embedded in source locustemporal shapes. Consequently, a source can classified as *still* or *travelling* according to the modelled location dynamics.
- Actions are simply aggregates of sources.

Using the above components we can build the following experimental actions (in the next s- means single and m- means multiple):

1. s-dipole s-source
2. m-dipole s-source
3. s-dipole m-source
4. m-dipole m-source

Action 1 models a non travelling or still activity. From an estimation point of view is better to use a time block point-estimator for action 1. That is the approach when using MUSIC in EEG/MEG estimation [8].

Action 2 is usefull to model travelling activities. Estimation over action 2 can be seen as a *single tracking task*. For action 2 is needed a surface-estimator or eventually a curve/point-estimator applied on a snapshot by snapshot basis.

Action 3 is better estimated using a time block multipoint-estimator. Estimation over action 4 can be regarded as a *multiple tracking task*.

MEG Model: In a first approach a 2D circular one layer head has been modelled. The simulated MEG device has 32-channel radial seensors regularly distributed arround a 10 cm radius circle.

Estimation Tools: DD1 and DD2 filters from Magnus Norgaard [11]; sliding window MUSIC algorithm; testing environment and miscellanea. All the routines are implemented in Matlab®.

[2]Graphically, a source is a connected component composed like a raster image where the lines are dipole activition curves.

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