

ROBUST KALMAN FILTER BASED INCREMENTAL ACTIVATION DETECTION FOR REAL-TIME fMRI

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Introduction

Real-time functional magnetic resonance imaging (rt-fMRI) is a technique that enables us to observe human brain activations in real time¹. However, the real-time activation analysis is affected by many unexpected sparse noises, such as acute swallowings, head movements and machine fluctuation. Hence, improving the robustness of fMRI data for the real-time activation analysis becomes a great challenge. We propose a new activation detection method for rt-fMRI data based on robust kalman filter. This method adds a variation to the update step in the extended kalman filter to fit the unexpected noise in the general linear model, and use the solved variation to modify the measurement step of the kalman filter. In clinical application, the method can be used in the functional localization run to obtain the brain regions associated with the tasks in real time, especially for the subjects who could not keep still during the experiments.

Theory

The extended kalman filter (EKF) based general linear model (GLM) estimation method was first proposed by Roche². The method can calculate activations in real time, but sparse noise may affect its estimation performance. To address this problem, an additional sparse measurement noise term is introduced in our method, where the sparse noise term z_i is added into the measurement update step and robust kalman filter is used to transform the solving of the noise term into a L1-norm minimization based convex optimization problem. The sparse noise term can effectively improve the model's robustness to sparse noise.

The modified GLM with an additional sparse noise term is $y_i = x_i\beta + \varepsilon_i + z_i$. $b = [\beta; a]$ is the state vector to be estimated, a is the estimated first-order autocorrelation coefficient of Gaussian noise ε , and β is the correlation coefficient of GLM. And then the likelihood function is linearized as $\rho(b, z_i) \approx q_i - u_i^T b - z_i$, where $q_i = y_i - a_{i-1}x_{i-1}^T\beta_{i-1}$, $u_i = [x_i - a_{i-1}x_{i-1}^T, y_{i-1} - x_{i-1}^T\beta_{i-1} - z_{i-1}]^T$, y_i is the measurement value at time point i . The L1-constraint optimization problem is as follows.

$$\min_{z_i} v_i^T V^{-1} v_i + (b - \hat{b}_{i-1})^T \Sigma^{-1} (b - \hat{b}_{i-1}) + \lambda \|z_i\|_1 \quad \text{subject to} \quad q_i = u_i^T b + v_i + z_i$$

Furthermore, the fast transform method proposed by Jacob Mattingley and Stephen Boyd³ is adopted to transform the original problem into an equivalent convex quadratic programming problem, so that to solve the problem more efficiently.

$$\min_{z_i} (e_i - z_i)^T Q_i (e_i - z_i) + \lambda \|z_i\|_1$$

In practice, z_i and e_i are not vectors but real numbers, hence this non-constraint optimization problem has an analytical solution, which means that no searching loop is needed to obtain the optimization solution, thus guarantee the solving speed of our method suitable for rt-fMRI application.

Material and method

We use healthy subject to perform a random block design left and right finger tapping task. The run consisted of 10 blocks, each block including one activation epoch(20s) and one control epoch (10s), containing 150 time points. MRI was performed on a GE Discovery MR750 3.0T scanner. fMRI was acquired using an T2* weighted echo-planar imaging sequence sensitive to the BOLD contrast. The data were preprocessed by the AFNI real-time 3D head motion correction. Then the data was arranged into the python interface to perform the algorithm.

Results and Discussion

Experimental results are shown in Fig.1. The blue curve in the first section of the figure is the original time series, from which we can see that there is an outlier at about the 45th TR. For the EKF based estimation method, this will result in a decline in the estimated T-test value, as is given by the red curve in the second section of the figure. Since our method can detect sparse noise and use it to modify the EKF model, the outlier does not affect the estimated T-test value of our method, as is presented by the blue curve in the second section of the figure. The third section of the figure shows the occurrence and value of the detected sparse noise.

A robust kalman filter based activation detection algorithm is developed in our paper. By introducing sparse noise term and utilizing convex optimization technique, the robustness of our method to sparse noise has been improved, and the estimation performance will not degrade rapidly when disturbances are involved. Applied to time series voxels, our method can obtain more stable T-test values in both active and inactive voxels. Our proposed method can improve the stability of functional location, and detect the occurrences and values of outliers in real time, hence may provide an additional means for data quality control, especially in real time applications.

References

1. Christopher deCharms R. Applications of real-time fMRI. *Nature Reviews Neuroscience*. 2008;9(9):720-729.
2. Roche A, Lahaye PJ, Poline JB. Incremental activation detection in fMRI series using kalman filtering. *Biomedical Imaging: Nano to Macro*, 2004 IEEE International Symposium on: IEEE; 2004.

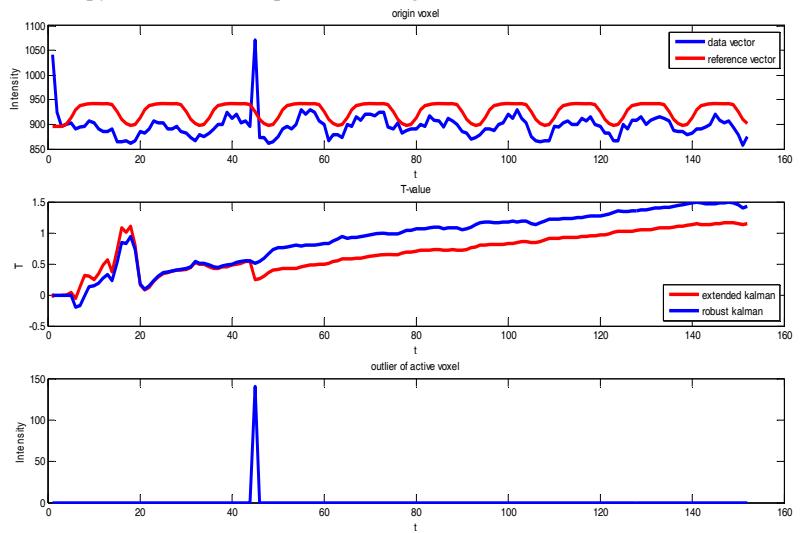


Fig.1 In the first section, the blue curve is the origin time series and the red curve is the reference vector, the middle section shows the comparison of the T-test value between the robust extended kalman filter and the extended kalman filter performing in an active voxel. In the third section, the blue curve is the value of detected outliers.