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State Estimation of Hemodynamic Model for fMRI Under Confounds: SSM Method

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Abstract—**Through hemodynamic models, the change of neuronal state can be estimated from functional magnetic resonance imaging (fMRI) signals. Usually, there are confounds in the fMRI signal, which will degrade the performance of the estimation for the neuronal state change. For the reason, this paper introduces a state space model (SSM) with confounds, from a conventional hemodynamic model. In this model, a successive state estimation method requires a state value vector, an error covariance, an innovation covariance and a cross covariance to be re-derived. Thus, a confounds square-root cubature Kalman smoothing (CSCKS) algorithm is proposed in this paper. We use a Balloon-Windkessel model to generate simulation data and add confounds signals to evaluate the performance of the proposed algorithm. The experiment results show that when the signal-to-interference ratio (SIR) is less than 21 dB, the CSCKS proposed in this paper reduced estimation error to 16%, whereas the traditional algorithm reduced it to only 73%.**

Index Terms—**fMRI, confounds, hemodynamic model.**

I. Introduction

BECAUSE functional magnetic resonance imaging (fMRI) technology has the advantage of non-invasive, non-radiative, repeatable and accurate positioning, and has high temporal and spatial resolution, it has become an important imaging technology applied to brain function and clinical research. In brain cognitive activity, neuronal changes are a dynamic process that produces a series of hemodynamic responses in the region of the neuronal population or source. The responses are manifested by changes in cerebral blood flow and blood oxygen concentration as neurons change. The fMRI technique measures the responses and uses hemodynamics to study the neuronal activation of the brain regions [1]-[2], so hemodynamic studies are critical for the application of fMRI to studies of brain function.

The relationship between neuronal state changes in functional brain regions and blood flow, blood oxygen concentration and other measured values is a complex electrophysiological process [3], which can be described by state space models. For instance, differential equations could be used to establish a hemodynamic model [2], where the neuronal activation is associated with a series of parameters, which mainly consists of two parts. The first is a coupling process that describes how neuronal activity induces blood changes. The second is a hemodynamic process that describes the changes of cerebral blood flow, cerebral blood volume, and total deoxyhemoglobin content. Through the inversion of the state space model, we can use brain blood observations to estimate changes in the hidden neuronal state and make inferences about neuronal coupling (see below).

The hemodynamic model described by the differential equations is not only dynamic but also highly nonlinear [6]-[7]. For this nonlinear problem, many researchers have proposed various algorithms to estimate the hidden neuron state or related parameters of the model [8]-[23], [26], [31], where Friston et al. conducted a more in-depth study of the problem. First, they used a Volterra series kernel to estimate the hemodynamic model parameters [8], and then proposed to use Bayesian estimation theory to invert the hemodynamic model [10]. Next, they extended the algorithm to coupled neuronal sources, where the connection parameters of distinct brain regions were estimated [11]. These brain-regions coupling models are called dynamic causal models (DCM). In recent years, DCM has been widely used in analysis of effective connectivity and electrophysiological studies in functional brain architectures. In order to consider the effects of physiological and stochastic noise [14]-[15], Riera et al. considered a stochastic model [16], which uses a local linearization filter (LLF) [18] and parameterized radial basis functions (RBFs) [16] to estimate hidden neuron states and model parameters. In addition, a successive state estimation method was shown to solve the nonlinear problem of hemodynamic model inversion. Johnston et al. [19] used a particle filter algorithm to estimate hidden neural states, and it was found its performance was better than LLF. Murray et al. [20] proposed a two-direction particle filter algorithm based on this method, and others have used the unscented Kalman filter (UKF) [22], which both show better performance in state estimation under nonlinear conditions.

However, sometimes we need to know both the hidden

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