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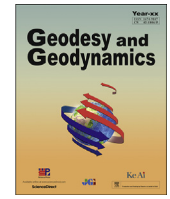

An image segmentation based algorithm for imaging of slow slip earthquakes☆

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A B S T R A C T

Laboratory experiments next to a variety of observations, especially in subduction zones, have explored the existence of a premonitory stable slow slip growth phase preceding large earthquakes. These phenomena play an important role in the earthquake cycle and thus precise imaging and monitoring of these events are of great significance. In the literature, ENIF (extended network inversion filter) has been proposed as a rigorous algorithm capable of isolating signal from different types of noise and thereby provides us with deep insight into spatio-temporal evolution of slow slip events. Despite its considerable advantages, ENIF still suffers from some limitations. ENIF applies Tikhonov method of regularization with a quadratic form of cost function. While anomalous slip regions have clear contrast with the background slip in reality, Tikhonov regularization tends to over smooth (globally smooth) the slipping portion on the estimated images. In order to avoid over smoothing phenomenon, we have incorporated into ENIF an image segmentation step which tries to preserve edges of slow-slip event. As a second limitation, due to the nonlinearity imposed by such constraint as non-negativity of slip rate, uncertainty propagation through model is not simple. As the core of ENIF, EKF (extended Kalman filter), performs uncertainty propagation by linearization of nonlinear model using Jacobian and Hessian matrices. As an alternative for EKF, we have also investigated the application of UKF (unscented Kalman filter) which uses UT (unscented transform) for uncertainty propagation. Finally, we tested our proposed algorithm using a low signal to noise ratio synthetic data set. The results show a significant improvement in the performance of ENIF when the segmentation step is incorporated into the algorithm.

1. Introduction

Laboratory experiments next to a variety of observations, especially in subduction zones, have explored the existence of a premonitory stable slow slip growth phase preceding large earthquakes [1–3]. These phenomena play an important role in the earthquake cycle such as great impact on the moment budget of the fault, stress transfer and redistribution in the crust, impact on nucleation and triggering processes, and triggering earthquake swarms [4–6]. They are also considered as a potential earthquake precursor especially in subduction zones. For example, in the 2011 Mw9.0 Tohoku-Oki megathrust earthquake, a slow slip event was detected before the main shock [3]. As a result, precise imaging and monitoring of these events using crustal deformation data sets are of great significance in tectonic and seismotectonic studies.

Besides developing highly dense, continuous and large scale geodetic arrays such as GEONET (GPS Earth Observatory Network) and the PANGA (Pacific Northwest Geodetic Array), the need for an efficient processing technique for slow slip studies is crucial. In this regard, we are facing with some challenges. First, because our signal of interest, which is related to the slip on the fault, has been

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contaminated with different types of noise sources like local benchmark motion, measuring device errors, etc., the imaging problem is not straightforward and is thus challenging [7]. Furthermore, we don't have knowledge about functional form of spatio-temporal evolution of these events which means that we are facing with a non-parametric modeling problem [8].

In the literature, McGuire and Segall [9] have developed ENIF (extended network inversion filter) which is a rigorous algorithm capable of isolating signal from different types of noise. This technique provides us with a powerful tool for studying spatio-temporal evolution of slow slip events. To date, considerable advantages have been enumerated for applying this filter. Since EKF (extended Kalman filter) forms the core of ENIF and EKF is in turn a framework for data fusion, it is possible to combine different types of surface deformation data sets (e.g. GPS, GNSS InSAR, UpSAR) via ENIF [10]. Furthermore, as a variant of Sequential Bayesian Filter, EKF is also an effective tool for stochastic estimation of slip, slip rate and more importantly their associated uncertainties [11]. Finally, being a time domain filter, ENIF yields an automatic method for detecting and monitoring of slow slip events.

Despite its considerable advantages, ENIF still suffers from some limitations. ENIF applies Tikhonov method of regularization with Laplacian operator in the form of quadratic cost function. While anomalous slip regions have clear contrast with the background slip in reality, Tikhonov regularization tends to over smooth (globally smooth) the slipping portion on the estimated images. This situation results in images with blurred edges of anomalous regions. Over smoothing is a common challenge among a variety of imaging problems, particularly in the field of medical imaging of dSPECT (dynamic single-photon emission computed tomography). In this study, we are going to reapply some effective measures taken by dSPECT imaging experts to our case of slow slip imaging problem [12,13]. In this regard, we have incorporated into ENIF an image segmentation step in combination with some mathematical morphology operations aiming to detect slipping portion on the fault. In the next step, by some changes in the ENIF formulation, we enforce this filter to focus smoothing just onto the slipping portion of the fault.

As the second limitation, with regard to the nonlinearity imposed by non-negativity constraint of slip rate, uncertainty propagation through nonlinear model is not simple. The EKF performs uncertainty propagation by linearization of nonlinear models in the form of Jacobian and Hessian matrices. Nevertheless, linearization is reliable only under specific circumstances. For example, EKF yields reliable results only when linearization approximates error propagation. Furthermore, Jacobian and Hessian matrices do not exist in all problems or in the cases of existence, their calculation are difficult and apt to human errors [14,15]. Accordingly, as an alternative for EKF, we have also investigated the application of UKF (unscented Kalman filter) which uses UT (unscented transform) for uncertainty propagation.

In the following sections, we will first describe the standard ENIF formulation along with a detailed description of changes in the ENIF. Then a brief description of UT is presented. Finally, using a low signal to noise ratio synthetic data set, the performance of our proposed algorithm will be compared with the standard ENIF.

2. Methods

McGuire and Segall [9] developed ENIF which is a recursive filter for estimation of spatio-temporal changes in slip and slip rate on the faults and subduction zones. In this context, surface displacements recorded by GPS stations as a function of time t, are modeled as the following expression

$$X(t) = \sum_k H\left(t - t_{\mathrm{eq}(k)}\right) X^{\cos(k)} + \int_A s_p(\xi, t - t_0) G^r_{pq}(x, \xi) n_q(\xi) \mathrm{d}A(\xi) + Ff(t) + L(x, t - t_0) + \epsilon \tag{1}$$

where the first term in the right hand side indicates coseismic offsets $X^{\cos(k)}$ resulting from earthquakes at different times t_{eq}, and $H(t)$ is the Heavyside function. Since we are going to address a pure aseismic slip in this study, this term has been excluded from our calculations. The second term represents deformation due to slow slip events with an initiation time of t_0. In this term, $G^r_{pq}(x, \xi)$ is the Green's function relating site displacements to the slip on the fault. The Green's functions applied in this study is derived from analytical expression for uniform half-spaces, although there are also some sophisticated Green's function for heterogeneous and layered medium. $n_q(\xi)$ is the unit normal to the faults surface $A(\xi)$ and the summation is performed on repeated indexes ($p,q,r = 1,2,3$). Finally, the last three terms indicates reference frame errors $Ff(t)$, random benchmark motions $L(x, t - t_0)$, and measurement errors ϵ, respectively. In this study, for the sake of simplicity we have also omitted the reference frame term from calculations.

EKF, which forms the core of ENIF, uses state space modeling to estimate state vector containing all required quantities for imaging problem. The state vector contains two sets of states; the first is concerned with slip and slip rate on each subfault, $(S^i_k, \dot{S}^i_k, \lambda^i_k)$ and the second set models random benchmark motion in each GPS station (β^j_k). The quantities S and $\dot{S}$ indicate slip and slip rate, and λ is a dummy variable to guarantee the non-negativity of slip rate. The superscripts i and j respectively represent the indices of subfault and GPS stations and the subscript k indicates the time step. To estimate state vector in each time step k, EKF uses two models, measurement and process models. The measurement model relates the state vector to the observed data and the process model relates the state vector in the previous time step *k-1*, to the current time step k. The algorithm begins with an initial estimate for state vector as well as its associated covariance matrix at the first time step. Then, the state vector at the next time step is predicted using process model and again this predicted state vector is updated (corrected) using measurement model and corresponding observed data. This procedure continues iteratively until all the observed data in the time series are processed [16]. Fig. 1 illustrates a complete picture on how EKF performs as the core of ENIF.

The data vector at each time step k, contains three different types of values $\boldsymbol{z}_k = [z^{\mathrm{GPS}}_k, z^{\nabla}_k, z^{+}_k]$. These data types includes GPS observations z^{GPS}_k, pseudo-data regarding spatial smoothing z^{∇}_k, and pseudo-data responsible for non-negativity of slip rates z^{+}_k . The measurement model is stated as the following expressions

$$z^{\mathrm{GPS}}_k = G_{ij} S^j_k + \beta^i_k + \epsilon^i_k, \qquad \epsilon_k \sim N\left(0, \sigma^2 \Sigma^{\mathrm{GPS}}_k\right) \tag{2}$$

$$z^{\nabla}_k = 0 = \nabla^2 \dot{S}_k + \epsilon_k, \qquad \epsilon_k \sim N\left(0, \gamma^2 I\right) \tag{3}$$

$$z^{+}_k = 0 = \dot{S}^i_k - \lambda^{i2}_k + \epsilon_k, \qquad \epsilon_k \sim N\left(0, \rho^2 I\right) \tag{4}$$

In addition, the covariance matrix associated with data vector is represented as

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