Dynamic imaging of metallic contamination plume based on self-potential data

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Abstract: A dynamic imaging method for monitoring self-potential data was proposed. Based on the Darcy's law and Archie's formulas, a dynamic model was built as a state model to simulate the transportation of metallic ions in porous medium, and the Nernst equation was used to calculate the redox potential of metallic ions for observation modeling. Then, the state model and observation model form an extended Kalman filter cycle to perform dynamic imaging. The noise added synthetic data imaging test shows that the extended Kalman filter can effectively fuse the model evolution and observed self-potential data. The further sandbox monitoring experiment also demonstrates that the self-potential can be used to monitor the activities of metallic ions and exactly retrieve the dynamic process of metallic contamination.

Key words: dynamic imaging; self-potential; metallic contamination; extended Kalman filter

1 Introduction

The environmental problems during metallic mining and smelting attract increased attention. Particularly, the solid and liquid metallic wastes always threaten the surrounding soil and groundwater safety [1,2]. Duly detecting and monitoring the contamination sources is an active way to reduce the risk of metallic contamination. Because of the conductivity of metallic ions and the electrochemical characteristics of the redox reaction, there are obvious resistivity and self-potential anomalies in metallic contaminated zone. Thus, the electrical resistivity method, self-potential method, or other geophysical methods are widely used to monitor and evaluate metallic contamination [3,4]. Besides, the convenience of passive source, the self-potential method is very sensitive to redox potential. Many researchers have measured distinctive self-potential anomalies on the ground which is contaminated by metallic ions [5−8]. Thereby, the self-potential method plays an important role in the environmental geophysics and is very suitable for performing soil and groundwater monitoring for the

prevention and treatment of metallic pollution [9,10].

The routine contamination plume tomography based on monitoring data depends on independently inverting all the data of each observation [11]. This kind of independent inversion is based on static models. The correlation information among model evolution is ignored. Thus, the performance of data interpretation is always suffered from observation error and the inaccuracy of inversion algorithms [12,13]. Some researchers tried to use the inversion result of previous data as the initial and reference model for the inversion of subsequent datasets and received a better inversion result [14,15]. In order to take full advantages of the correlation information among monitoring data, the Kalman filter technique is used to estimate the model parameters of dynamic system by fusing the observation data and model evolution [16−18]. LEHIKOINEN et al [19,20] and NENNA et al [21] introduced the Kalman filter into the inversion for monitoring electrical resistivity data and imaging the movements of groundwater. The metallic wastes contaminate environment through the diffusion of metallic ions to surrounding soil and underground water during its

transportation in the underground porous medium. In order to effectively monitor metallic contamination plume, we adopt the self-potential method to measure redox potential induced by metallic ions and use the extended Kalman filter to process observed self-potential data. Through metallic ions diffusion model construction and self-potential observation, we build an extended Kalman filter cycle to perform dynamic imaging of metallic contamination plume.

2 Description of method

2.1 Dynamic geoelectric modeling

In the process of metallic contaminant diffusion in underground porous medium, the movement of fluid in saturated porous media is governed by [21]

$$v = -\frac{K}{\phi\mu}(\nabla P + \rho g\nabla z) \tag{1}$$

where v is the Darcy velocity; K is the permeability; ϕ is the porosity; μ is the dynamic viscosity of the pore fluid; P is the differential pressure; ρ is the fluid density; g is the acceleration of the gravity; and z is the height difference.

Let some abstract particles unify specific metallic ions, and then the activities of metallic contamination can be treated as a macroscopic embodiment of all particles' movement. At time k, the location of particle i can be denoted as

$$X_i^k = X_i^{k-1} + (v + r_c)dt \tag{2}$$

where X_i^{k-1} is the location at time $k-1$; dt is the time interval or time step; and r_c is a random velocity used to simulate the anisotropy and the motion noise of particles.

After all particles' locations are certain, the relative particle concentration (S) can be expressed as

$$S = n/n_{all} \tag{3}$$

where n is the number of particles in a grid, and n_{all} is the number of particles in the whole space.

According to the Archie's law, the electrical conductivity of porous media is mainly governed by the pore fluid.

$$\sigma = (1/a)\sigma_w\varphi^m B_w^\xi \tag{4}$$

where σ is the electrical conductivity of the solution saturated porous media, a is the tortuosity factor, σ_w represents the electrical conductivity of the solution, ϕ denotes the porosity, B_w is the solution saturation, m is the cementation exponent of the porous media, and ξ is the saturation exponent. In a metallic contaminant diffusion case, all the parameters can be regarded as constants except the solution saturation. And the solution saturation varies proportionally with the metallic ion

concentration.

Thereby, a linear relationship between the electrical conductivity distributions of the porous media and the metallic ion concentration can be built by using a linear coupling coefficient k_c.

$$\sigma(S) = k_c S \tag{5}$$

Considering the movements of metallic ions in porous medium as a dynamic system with electrical conductivity distribution variation, the model state at present time k can be evolved from the model state at previous time $k-1$ of the dynamic system.

$$\sigma(S)_k = H_k\sigma(S)_{k-1} + w_k \tag{6}$$

where H_k is a nonlinear state evolving operator determined by the diffusion model based on the Darcy's law. For simplicity, rewrite Eq. (6) as

$$M_k = HM_{k-1} + w_k \tag{7}$$

where H is the state evolving operator; M_k is the model state expressed by the relative particle concentration S; and w_k is the process noise which is assumed to be drawn from a zero mean multivariate normal distribution with covariance Q.

$$w_k \sim N(0, Q) \tag{8}$$

2.2 Self-potential observation

While a solution of metallic ions flows through a porous medium, there will be complex redox reactions accompanied. The redox potential can be calculated by Nernst formula [22]:

$$E_H = 2.3(k_B t/e)p_\varepsilon \tag{9}$$

where k_B is the Boltzmann constant; t is the absolute temperature; e is the elementary charge of the electron; and p_ε is the relative electron activity.

In this case, the redox potential induces self-potential anomalies when it is monitored on the ground. The self-potential and redox potential obeys the Poisson's equation.

$$\nabla\cdot(\sigma\nabla\varphi) = -\nabla\cdot(\sigma\nabla E_H) \tag{10}$$

where σ is the electrical conductivity of the underground medium; and φ is the self-potential.

Define Z_k to be the self-potential data measured from model M$_k$ at time k, and then,

$$Z_k = FM_k + v_k \tag{11}$$

where F is the nonlinear forward calculating operator denoting the solving process of Eq. (10) by using the finite element method or other numerical simulation methods; and v_k is the observation noise which is assumed to be drawn from a zero mean multivariate normal distribution with covariance R.

$$v_k \sim N(0, R) \tag{12}$$