Improving the Temporal Resolution of Magnetic Induction Tomography for Molten Metal Flow Visualization

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Abstract—**Magnetic induction tomography (MIT) is a nondestructive monitoring technique for imaging the electromagnetic properties of an object by mutual induction data of pairs of excitation and sensing coils. MIT has potential application in monitoring of molten metal flow in continuous casting. The main advantage of the MIT for this application is the contactless nature of the measurement process and its potential to generate images with high temporal resolution. Traditionally, the MIT image is formed using one frame of measured data that includes data from all excitation coils. In this paper, we study the improvement of the temporal resolution by reconstructing MIT images using data from one excitation at a time and using the Kalman-filtering approach. The images are presented using experimental data of the MIT system tested in a continuous casting unit. The MIT system used in this study can produce images 8 times faster than before by using new dynamical image reconstruction technique.**

Index Terms—**Conductivity mapping, dynamic imaging, electromagnetic induction tomography, inverse problem, Kalman filter (KF).**

I. Introduction

MAGNETIC induction tomography (MIT) is a new nondestructive monitoring technique with application in areas such as medical imaging, industrial monitoring, and geophysical surveys [1], [6]. The measurement data are the mutual inductances between pairs of coils. The contactless nature of this type of tomography makes the technique of interest for noninvasive and nonintrusive applications. The technique operates as follows: Passing an alternating current through the excitation coil(s) produces a primary magnetic field. When this magnetic field interacts with either a conductive and/or a magnetic object, a secondary magnetic field is created. The sensing coils can then detect this secondary field. As the secondary field depends on the materials present, the measured induced voltage is a nonlinear function of their electrical properties, e.g., conductivity [7] and permeability.

MIT has a potential to be used in many industrial applications [6]. This paper concentrates on imaging the molten steel flow, particularly the online flow visualization approach [5], [7]. Online flow visualization often requires very fast tomography data. Among noninvasive imaging techniques, MIT has a much higher temporal resolution than others, such as X-ray computed tomography. This makes MIT one of the best candidates that are capable of long-term monitoring of fast-varying dynamic flow. However, the spatial resolution of MIT is low due to facts such as the following: the measurement being effectively insensitive to deep internal conductivity changes and MIT reconstruction being severely ill conditioned. To solve the ill conditionness of MIT, *a priori* knowledge of true images is necessary for regularization techniques. *A priori* knowledge is interpreted as a regularized matrix, which represents the underlying image probability distribution in Bayesian theory.

To enhance the temporal resolution of dynamic imaging, different techniques have been proposed. Most previous work in similar applications is based on the utilization of Kalman filters (KFs) [2], [3], [8], [9] for situations where the conductivity distribution rapidly changes. This paper applies the KF approach, which provided encouraging results in imaging tests carried out in a laboratory in [5], in a real situation for data collected from a continuous casting unit.

II. Formulations of the Dynamic Modeling and Estimation Problem

In the time-varying estimation approach, we formulate the underlying inverse problem as a state estimation problem to estimate the dynamic conductivity distribution. Suppose that a measurement has been made at time t_k and that the information it provides is to be used in updating the estimate of the state of a system at time t_k. It is assumed that the problem has been discretized with respect to the time variable. In the state estimation problem, we need a time-varying model, which consists of the state equation for the temporal evolution of the conductivity distribution and the measurement equation, which is a relationship between the conductivity distribution and the measurements on the boundary.

In general, the temporal evolution of the discretized conductivity distribution σ_k in the domain Ω is assumed to be of linear form

$$\sigma_{k+1} = F_k \sigma_k + w_k \tag{1}$$

where F_k is the state transition matrix at time t_k. In particular, we take $F_k = I_N$ (identity matrix) for all t_k's to obtain the so-called random-walk model. It is assumed that w_k is

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white Gaussian noise with a known covariance matrix $P_k^w \equiv E\lfloor w_k w_k^T \rfloor$ that determines the rate of time evolution in the conductivity distribution.

For the observation model, let z_k be the measurement data induced by the kth excitation pattern. Then, the measurement equation can be described as the following linear mapping with measurement error:

$$z_k = H_k \sigma_k + v_k \tag{2}$$

where the measurement error $v_k \sim N(0, R_k)$ is assumed to be white Gaussian noise with covariance matrix R_k. Here, H is the Jacobian matrix that can be calculated by the sensitivity formula. A derivation of the Kalman-filtering iteration has been given in [8] and [9]; here, we only present the conductivity update formula used in each time step. The iteration of the Kalman-filtering method is given as follows:

$$\sigma_{k|k} = \sigma_{k|k-1} + \left(P_{k|k-1} H_k^T \left(H_k P_{k|k-1} H_k^T + R_k \right)^{-1} \right) \times (z_k - H_k \sigma_{k|k-1}). \tag{3}$$

We used a 132 067 tetrahedral element to solve the forward problem and the Jacobian matrix of the aforementioned MIT system [10]. Since a linear KF approach has been adapted here, the forward problem and the Jacobian matrix need to be calculated once, so it can be done before image reconstruction. The image reconstruction problem (only the area inside coil array) has been done in a $20 \times 20 \times 4$ grid. We used very few elements in the horizontal direction, because there is only one plane of coils. The inverse problem, as formulated by KF, includes a problem of 1600 image elements and 28 measurement data.

III. Experimental Results

A. MIT System

In this paper, an MIT sensor, as shown in Fig. 1, is used to generate data for image reconstruction [5]. The sensor array consists of eight coils for excitation and detection. The inner diameter of the coils is 4 cm, the outer diameter is 5 cm, and the length is 2 cm. The coils are arranged in a circular ring surrounding an object to be imaged. The distance between the centers of two opposite coils is 16 cm. The excitation frequency is 5 kHZ. Continuous monitoring of the flow pattern by means of MIT includes the following: MIT coils; a cooling system, which is required so that the measurement system can properly work; and a personal computer for online image reconstruction.

B. Continuous Casting

Continuous casting is a key process by which molten steel is formed into semifinished billets, blooms, and slabs. Liquid steel from basic oxygen steelmaking or electric arc furnace processes and subsequent secondary steelmaking is transferred from a ladle, via a refractory shroud, into the tundish. The tundish acts as a reservoir for both liquid steel delivery and

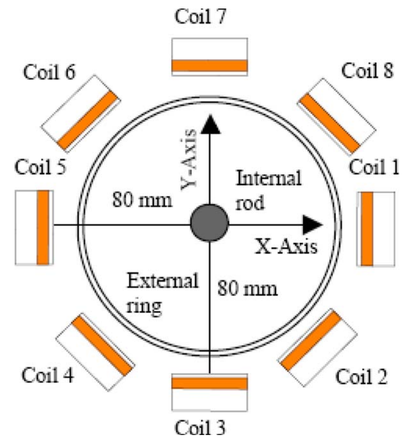

Fig. 1. Eight-coil sensor array with the object space.

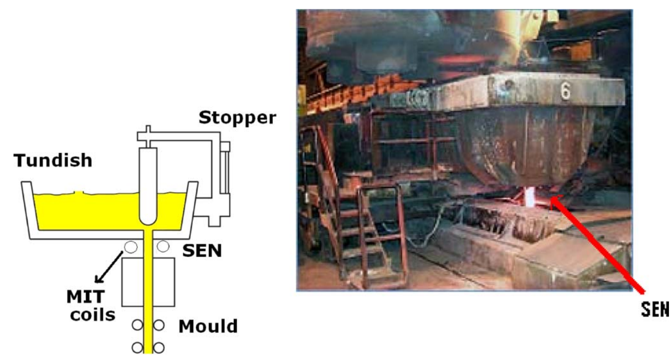

Fig. 2. MIT system is located in the SEN area under the tundish and above the mold. (Left) Schematic. (Right) Continuous casting unit with the SEN shown.

removal of oxide inclusions. A stopper rod or sliding gate liquid (not shown) is used to control the steel flow rate into the mold through a submerged entry nozzle (SEN) (see Fig. 2). The SEN distributes the steel within the mold, shrouds the liquid steel from the surrounding environment, and reduces air entrainment, thus preventing reoxidation and maintaining steel cleanliness. Primary solidification takes place in the water-cooled copper mold, and casting powder is used on the surface to protect against reoxidation and serve as a lubricant in the passage of the strand through the mold. Exiting the mold, the strand consists of a solid outer shell surrounding a liquid core.

Real-time information is required, concerning the flow pattern in SEN, so that the flow pattern can be detected.

C. Experimental Test

First, a dynamically changing scenario was created by changing the location of the representation test in the laboratory for hot metal flow. The static imaging technique failed to obtain a satisfactory temporal resolution for the reconstructed images when rapid changes in the conductivity distribution happen within the data acquisition time. However, the dynamic imaging technique can provide an estimate of the conductivity distribution, which shows the moving object. Hence, the temporal resolution can be enhanced with the aid of the linearized KF. Fig. 3 shows three examples of the results. In the first example, the copper bar moves toward the center in seven discrete steps.

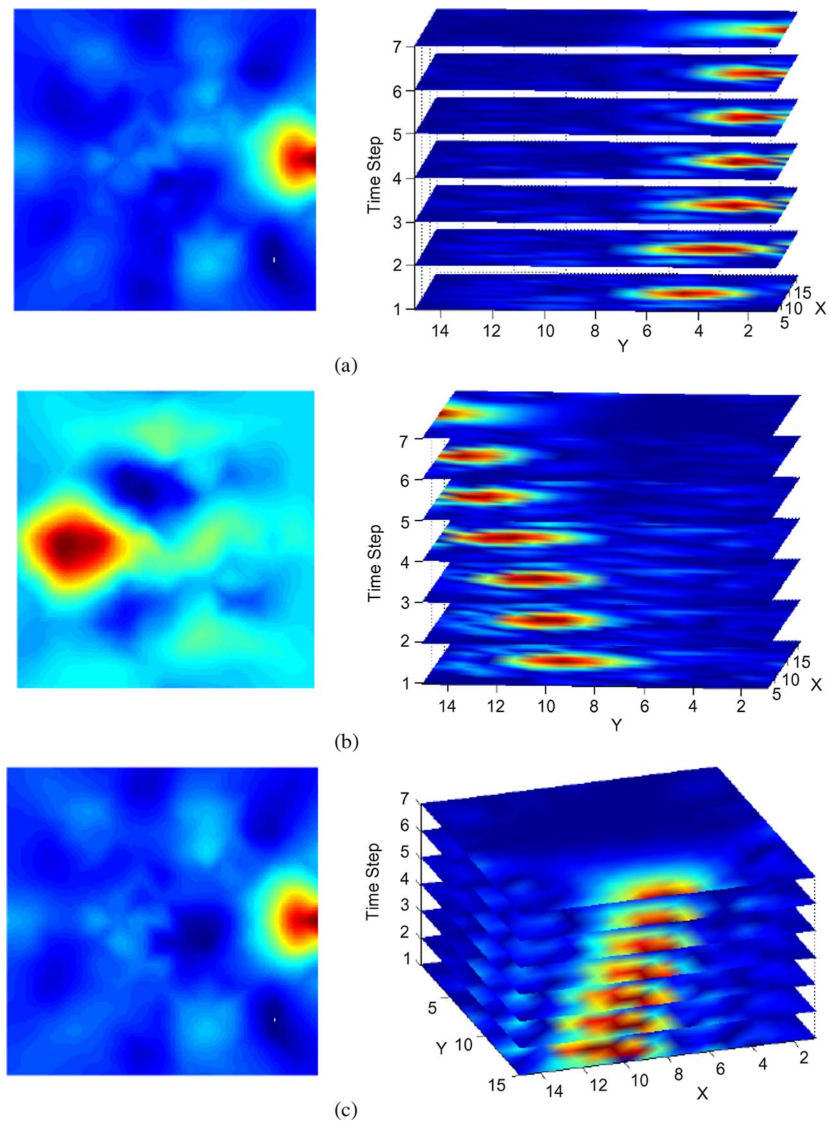

Fig. 3. Dynamical image reconstruction of a moving object under laboratory conditions. The dimensions are expressed in centimeters. In images (a)–(c), the right-hand side shows the reconstruction of a moving object using the proposed KF, and the left-hand side shows reconstruction using traditional static image reconstruction, which cannot reconstruct the movement of the object.

For each step, the bar is moved by half its radius. As can be seen, the position of the bar can clearly be reconstructed for each step, despite the change in excitation. In the second example, the copper bar is moved toward the center but, this time, in steps that are equal to the radius of the bar. Again, the position of the bar can be distinguished. Finally, in the third example, the copper bar is moved in a circle of constant radius; each step is half the radius of the bar. The object moves in sequence with each step of each excitation field, so data collected in static imaging mode will be one set of 28 measured data corrupted by the movement of the object. The proposed dynamic image reconstruction uses data within each excitation pattern and creates images by using not only spatial regularization but also temporal correlation between frames.

Here, we use MIT data from a continuous casting unit. Fig. 4 shows the movement of the actual flow and the movement of the metal flow. The data used here are six sets of full-frame data including 28 measurements. For frames 1, 2 and 3, the metal flow is in the bottom half of the cross section, and for frames 4, 5, and 6, the flow regime moves to the top half. For the dynamical image reconstruction, we excite one coil at a time, and the data include induced voltages in seven remaining coils.

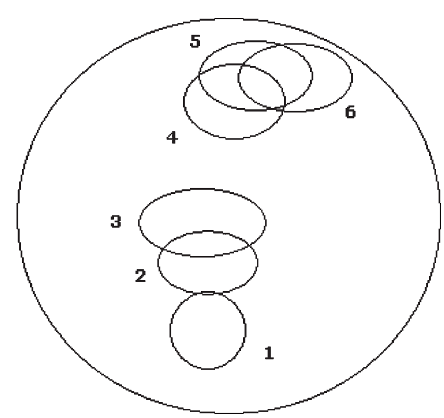

Fig. 4. Six locations of the actual flow in SEN, with each circle corresponding to a different position of the metal flow.

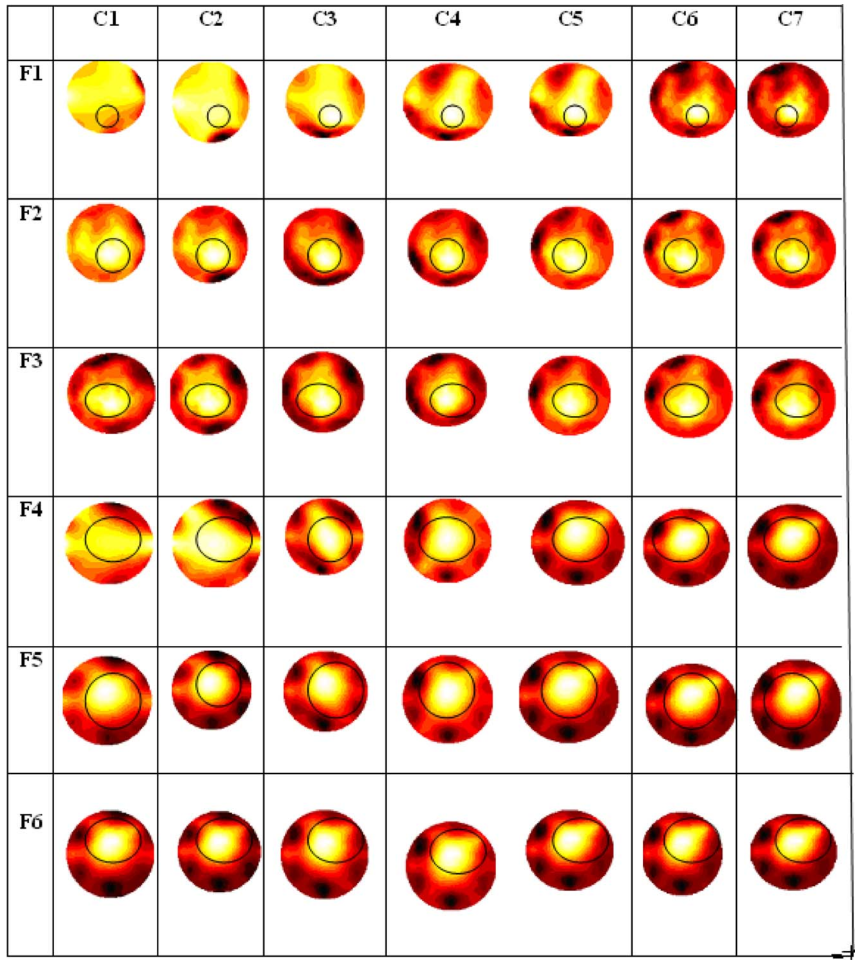

Fig. 5. Temporal image. Each row includes seven images for excitation coils 1–7. The six rows represent the six flow regimes shown in Fig. 4. In these images, the bright area represents the molten steel flow, whereas the dark area represents the surrounding air.

The initial value of electrical conductivity in each step of dynamical imaging is the value from the previous step. For the first step, we use free space (conductivity zero) as the initial guess. From Fig. 5, it can be seen that it requires a few time steps to recover the actual shape of the metal flow from this initial guess as it is different from the actual flow regime. The images show consistency with the actual flow regime [10] until the fourth row; here, the metal flow suddenly moved, and the initial guess of the previous time step is no longer close to the actual flow regime. It requires a few more time steps until we can see the consistency again.

The results demonstrate that the proposed linear Kalman-filtering approach using single excitation data in each frame can provide satisfactory estimation of the flow regime in the SEN. The response of the proposed technique to sudden movement of the flow regime is not very good, which makes a few frames of the time-varying images faulty.

As a result of our observation in this study, we propose to build an MIT system, in which the measurement of induced voltage due to each excitation can be measured in parallel, so that measurements of each excitation used for time-varying image reconstruction can be done very fast. Additional information is required to be fed to the linear Kalman-filtering algorithm, so that sudden changes in the flow regime can be taken into account.

IV. Conclusion

In MIT, an estimate of the cross-sectional conductivity distribution is obtained from the object by using induced voltage measurements made from excitation and sensing coils. The static image reconstruction methods use the full data set to reconstruct the conductivity distribution. In some applications, the conductivity changes may be so fast that information on the time evolution of the conductivity distribution is either lost or severely blurred. A Kalman-filter-based approach to MIT reconstruction is able to track fast changes in the conductivity distribution. The method has been tested using experimental data of MIT for continuous casting flow monitoring. The images are observed to have acceptable quality with improved temporal resolution. The time-varying MIT images can be used for direct process diagnosis such as monitoring of stopper purging and/or SEN filling ratio, improvement of product quality, and increase in productivity. The image quality can further be improved by taking into account the computational fluid dynamic (CFD) model of the metal flow. Combining the CFD with the

Kalman-filter image reconstruction of the MIT is part of our plan for future study.

The eight-coil experimental system used in this study is able to create images of 10 frame/s [5]; with the extension presented in this paper, the system can potentially create an image of 80 frame/s. The 80-frame/s image is achievable with the new temporal image reconstruction algorithm. Without additional CFD models to support nonsmooth temporal changes, some of the frames in this new algorithm will be intermediate frames to accommodate larger changes.

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