

## Tissue Mobility Imaging Based on Differential Eigenvalue Analysis

### 微分型固有値解析による組織動きイメージング

Hironari Masui<sup>†</sup> and Takashi Azuma  
(Hitachi CRL)

増井裕也<sup>†</sup>, 東隆 (日立 中研)

#### 1. Introduction

Defining the boundary between a tumor region and surrounding normal tissue is essential for non- and minimally invasive therapies. Estimating the volume of the tumor based on this is also essential to optimize medication. Many tumors consist of a central necrotic core and peripheral intact tumor tissue. The former can normally be detected as a hypo-echoic region in a B-mode image. However, the boundary between the latter and the normal tissue surrounding it cannot be detected in conventional B-mode images because the difference between their echogenicity is too small. The extent and the aspect of adhesion at the boundary depend on the type of tumor. Some possibilities are that metastatic tumors tend to have a loose boundary and move along this relatively smoothly by respiratory motion. Such a boundary may not be detected in a single B-mode frame, but can be recognized as mobility in a B-mode movie [1].

Tissue strain imaging is effective for tissue characterization [2], and it is possible to transform it to a color map, but this involves computational complexity. Tissue boundaries on color maps are not always clearly defined because nonlinearity exists in the transformation [3]. Various studies using a correlation-based method have recently been conducted to measure the elastic properties [4]. Several groups have studied the vector maps of tissue motion to investigate tissue elasticity [5].

We propose tissue mobility imaging based on detecting the spatial discontinuity in the tissue motion vector [6,7], which is estimated by using the SAD (sum of absolute differences) of images between sequential frames [8]. We used the eigenvalue decomposition technique to transform a vector map to a scalar one [9].

To estimate a grade of invasion correctly, a scalar mapping must keep linearity. In this paper, we introduce vector differential operation as preprocessing. This method was studied by cyst phantom experiment.

#### 2. Differential Eigenvalue Analysis

**Figure 1** shows the outline flowchart for the tissue mobility imaging. A motion vector was detected from two image frames based on block matching. A window array, which was the search area, was set in each frame to measure motion. We set the region of interest (ROI) at the size of a speckle caused by ultrasonic measurement. After the motion vector was mapped, image processing was used to detect any spatial discontinuity. For the motion vector map, vector differential operations were applied by using the gradient calculation

$$\left( V_x', V_y' \right) = \left( \frac{\partial V_x}{\partial x}, \frac{\partial V_y}{\partial y} \right), \quad (1)$$

where  $V_x$  and  $V_y$  are the x- and y-components of the motion vector and  $V_x'$  and  $V_y'$  are the x- and y-components of the differential motion vector. For the differential vector map, eigenvalue decomposition analysis was applied. The eigenvalue decomposition method used the maximum absolute value of eigenvalues.

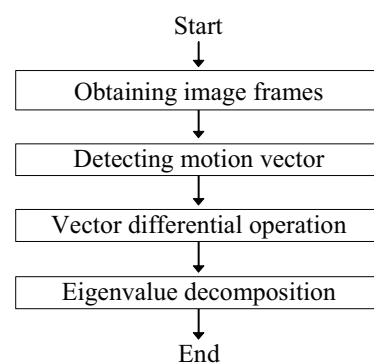


Fig. 1 Outline flowchart

**Figure 2** shows typical models of invasion mobility. In this figure, shear stress is shown on the upper sides. In the case of a low degree of invasion, the displacement of the lower part was small (Fig. 2 (a)). While with a high degree of invasion, it was large (Fig. 2 (b) and (c)). The difference of displacements along with the depth direction can be represented as displacement gradient parameter  $D$ .

Then we can introduce an index of invasion  $H$  as below:

$$S = H \cdot D, \quad (2)$$

where  $S$  is the shear stress. A constant  $H$  gives linearity between  $S$  and  $D$ . In general, this linearity is not ensured. Figure 2(a) shows the case of  $H = 0$ , (b)  $H = 0.5$ , and (c)  $H = 0.9$ .

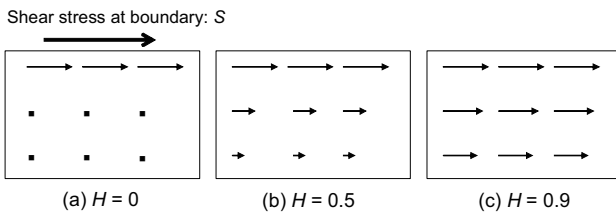


Fig. 2 Mobility imaging of invasion

To verify linearity between  $H$  and the imaging scalar value in the micro area, the differential eigenvalue method was compared to the eigenvalue method for the models of invasion mobility. The matrix size of  $3 \times 3$  was selected according to Fig. 2. Figure 3 shows the relation between the imaging scalar value and index of invasion. The index of invasion was surveyed from 0 to 1.0. The eigenvalue method has nonlinearity (Fig. 3(a)), while the proposed one had linearity (Fig. 3(b)). Accordingly, differential preprocessing was effective for a linear response.

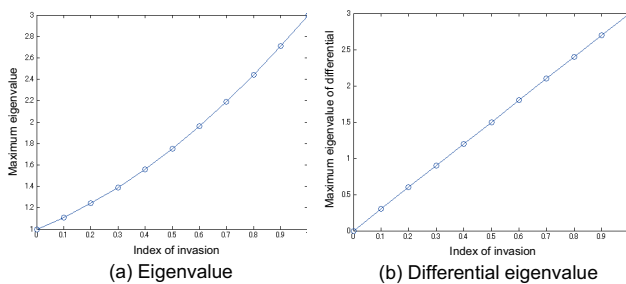


Fig. 3 Mobility imaging of invasion

### 3. Experimental Results

In vitro experiment, the imaging methods [9] were compared by using a spherical cyst-phantom. **Figure 4** shows a B-mode image and calculated images. The rotation and eigenvalue methods were sensitive for the region itself. The differential eigenvalue method clearly described the boundaries of the regions.

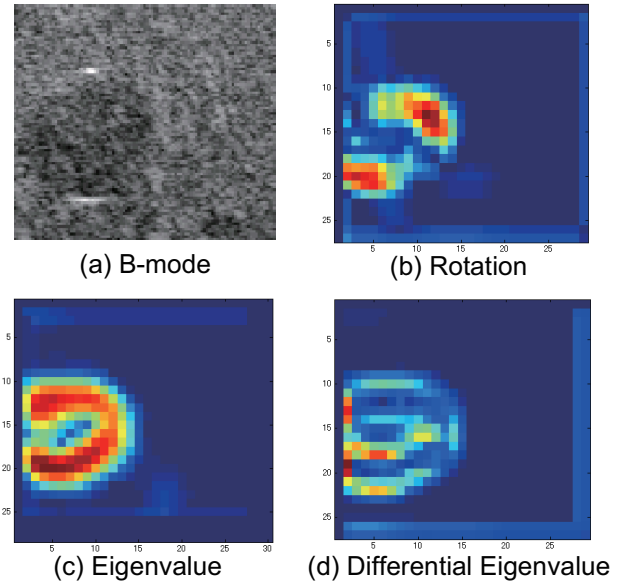


Fig. 4 Cyst phantom experiment

### 4. Conclusion

We proposed the tissue mobility imaging method that ensures linearity for tissue invasion and conducted the phantom experiment to compare the characteristics of several imaging methods.

The mobility imaging is expected to improve the accuracy of tissue characterization in combination with elastic analysis.

### References

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