ERT Image Evaluation Based on Sparse Representation Algorithm

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Abstract. Most of the existing image quality evaluation is to extract image features, and then use support vector regression, sparse representation and other algorithms to evaluate the image quality. In this paper, an adaptive sub-dictionary image evaluation algorithm based on sparse representation is used. By extracting relevant image features such as gradient features and color features, a complete dictionary is first constructed using the features, and then a sparse representation method based on the sub-dictionary is used to obtain the sparse corresponding to the ERT image. Coefficient, the final image quality score is obtained by the corresponding formula.

Keywords: sparse representation, Sub-dictionary, OMP algorithm, image quality evaluation.

1. Introduction

Electrical resistance tomography (ERT) is a high-tech detection technology developed in recent years. It can visually measure objects in closed pipes [1], and can reconstruct images based on the measured data. The reconstructed image can be judging the position of foreign objects in the pipeline, etc., so the quality of ERT reconstruction image is particularly important.

For image quality evaluation methods, a large number of image quality evaluation methods have appeared in recent years, including support vector machines [2], sparse representation algorithms [3], and sparse representation has achieved good results in image quality evaluation. In this paper, an image evaluation method based on the sparse representation adaptive sub-dictionary [4] is used to evaluate the quality of ERT images. Two different algorithms are used to generate different quality ERT images. Good quality images are used as reference images, and the other is used as a standby. Measure the image and extract relevant image features such as image gradient features [5] and color features. The sparse representation adaptive sub-dictionary model is used to evaluate the quality of the ERT image, and finally the image quality evaluation score is obtained.

2. ERT reconstructed image and causes of distortion

The mathematical model of ERT can be divided into positive and negative problems [6]. The positive ERT problem: The conductivity distribution in the sensitive field is known, and the potential distribution in the sensitive field is solved by the boundary conditions. The inverse problem of ERT is: the known boundary measurement voltage, through the image reconstruction algorithm, to reconstruct the distribution of the conductivity in the field of the measured object. However, in the process of
solving the inverse problem of ERT, the measurement voltage will include some coupling noise and measurement error. Therefore, the current ERT image reconstruction algorithms cannot avoid the measurement error caused by the "soft field" [7] characteristic. In addition, the ERT image reconstruction algorithm will generate a certain loss of accuracy, which cannot achieve distortion-free image reconstruction. Therefore, the sparse representation-based sub-dictionary model used in this paper is used to evaluate the distortion-generated ERT image.

3. Sub-dictionary model based on sparse representation
Sparse representation is inputting a signal, which can be represented by some basis vectors on a trained and complete dictionary. The sparse representation sub-dictionary algorithm uses an over-complete dictionary to capture the similarity between the reference image and the distorted image. Given a reference image block, and use the OMP algorithm to complete its sparse representation in the complete dictionary D, and get the sparse coefficient $x'$ and the basis vector in D used, then use the base vectors to form a sub-dictionary $\Omega$, and then use the OMP algorithm to sparsely represent the distorted image blocks and obtain the sparse coefficients $d_x$. This ensures that the reference image block and the distorted image block are represented by the same base vector.

This paper uses two types of ERT images of different quality generated by two ERT imaging algorithms. Relatively high-quality ERT image blocks are sparsely represented in an over-complete dictionary using the OMP algorithm. After obtaining the sparse coefficients, the sub-dictionary $\Omega$ is composed of the used base vectors, and then the ERT image with relatively poor quality is used to perform sparse representation in the sub-dictionary $\Omega$ using the OMP algorithm. Figure 1 is an example. A better-quality ERT image is linearly represented by the base vector in the over-complete dictionary D. These base vectors form an incomplete sub-dictionary $\Omega$. A poor-quality ERT image is represented by the sub-dictionary $\Omega$.

4. ERT image quality evaluation method

4.1. Sparse feature
In this article, the image is a block-based sparse representation. A good-quality ERT image represents a reference image, and a poor-quality ERT image represents a distorted image. The image size is 370 × 370. The image is first divided into 37 × 37 non-overlapping image blocks. The reference image block can be represented by the dictionary D using the OMP algorithm, and find the sparse coefficient with sparseness $x_{i,j}$, where i and j represent the rows and columns of the image block in the image. Then use these L basis vectors to form a sub-dictionary $\Omega$, and the distorted image block is represented by the sub-dictionary $\Omega$ using the OMP algorithm. Find the sparse coefficients $d_{i,j}$. Both images are represented by the same combination of base vectors. This ensures that sparse
features can be accurately used in the comparison of similarity. Using the two sets of coefficients to sparsely generate two feature maps, then use the feature maps to calculate the similarity between the reference image and the distorted image. Calculated as follows

\[ FM'(i, j) = \sqrt{< x'_i, x'_j >} \]

\[ FM^d(i, j) = \sqrt{< x^d_i, x^d_j >} \]

where \( F' \) and \( F^d \) are the feature maps, which represent inner products. The sparse feature similarity can be obtained from the two feature maps, as shown in Equation 5.

\[ S_{FM}(i, j) = \frac{2FM'(i, j)FM^d(i, j) + c_1}{\left( FM'(i, j) \right)^2 + \left( FM^d(i, j) \right)^2 + c_1} \]

\( i, j \) represent the rows and columns of the image block in the image, and are constant.

4.2. Auxiliary features

In this paper, three auxiliary features are used to combine sparse features to obtain a more accurate image quality assessment. These three features are gradient, chroma, and brightness. Before extracting the gradient features, first transform the image from RGB space to YCbCr space [8] in order to better distinguish the luminance and chrominance components in the ERT image. Among them, the characteristics of the reference image are \( Y' \), \( Cb' \) and \( Cr' \) brightness and chromaticity. Distorted image features \( Y^d \) is brightness, \( Cb^d \) and \( Cr^d \) are chroma, at the same time, the second chrominance auxiliary feature can also be obtained from Cb and Cr. When finding the gradient features of the ERT image, the Sobel operator is used to calculate the gradient features \( G' \) and \( G^d \). The gradient similarity feature calculation formula is shown below. The gradient similarity feature calculation formula is shown below.

\[ S_G(i, j) = \frac{2G'(i, j)G^d(i, j) + c_2}{\left( G'(i, j) \right)^2 + \left( G^d(i, j) \right)^2 + c_2} \]

Similarly, the chromaticity similarity \( S_c(i, j) \) and the luminance feature \( Q_L(i, j) \) can be calculated.

4.3. Sparse feature weighting

In image evaluation, the features of different regions in the image generally have different contributions, that is, the texture features [9] have a greater contribution than the features of the smooth regions, so the obtained features must be weighted, that is,

\[ W(i, j) = \max( FM'(i, j), FM^d(i, j) ) \]

\( W \) is the weighting map used, which weights the gradient features, chrominance features, and brightness features, respectively. The weighted gradient similarity score \( Q_G \), chroma similarity score \( Q_C \), and brightness similarity score \( Q_L \) are obtained. Use Equation 8 to calculate the final image final score.

\[ Q = Q_{FM} \cdot (Q_C)^{\beta} \cdot (Q_G)^{\gamma} \cdot (Q_L)^{\alpha} \]

The parameters \( \alpha, \beta \) and \( \gamma \) range between 0 and 1. The overall flowchart is as follows.
5. Experimental results and analysis

5.1. Experimental setup
The simulation is used to build the image library, and the circle is divided into 1024 grids, that is, 1024 pixels. Kedida CT-3031 conductivity tester, measuring range: 0.00S / m-1.99S / m, measuring accuracy: 0.001S / m, is used to measure the conductivity of the water that comes with it is 0.02S / m. In the circulation and bubble flow, the air conductivity is set to 0S / m, and the water conductivity is set to 0.02S / m. Since there is too much air in the laminar flow, some electrode pads are insulated, so it is difficult to reconstruct the image. Therefore, the air conductivity is set to 0.00001S / m, and the water conductivity is set to 0.02S / m. Then use one-step Newton iteration method and Newton iterative algorithm [10] to generate reconstructed images, which are used as distorted images and reference images, of which 300 are laminar flow and 300 are bubble flow. A total of 600 images are used as the image library in this paper.

In order to verify the pros and cons of the evaluation model proposed in this paper, the relative error [11] of the image is selected as the evaluation index, and the relative error formula is as follows.

$$\varepsilon_{\text{image}} = \frac{\|\bar{g} - g\|}{\|g\|}$$

$$\bar{g}$$ is the conductivity distribution obtained by the reconstruction algorithm [1], and g is the set conductivity distribution value in the measured area. In the constructed model, the smaller the relative error of the ERT image, the higher the image quality. In the ERT image set, \(\beta = 0.02\), \(\alpha = 0.25\), and \(\gamma = 0.65\). In order to verify the performance of the algorithm in this paper, 20 images were randomly selected as test images from 600 images, and the remaining 580 images were used to construct a dictionary. Finally, the OMP algorithm was used to calculate the sparse coefficient to calculate the image quality score.
5.2. Analysis of results
The following figure is a fitting map of objective quality scores based on the sparse representation sub-dictionary for the test images in the experiment. It can be seen that the sparse representation algorithm has an ideal effect on the ERT image quality score.

![Figure 3. Objective mass score fitting.](image)

Finally, Pearson’s linear correlation coefficient (PLCC), Spearman’s rank ordered correlation coefficient (SROCC), and root mean square error (RMSE) [12] are used as objective indicators to measure the performance of the image quality model. The PLCC coefficient and RMSE are mainly used to evaluate the accuracy of the predicted value, and the SROCC coefficient is mainly used to evaluate the correlation between the predicted value and the subjective value. The values of PLCC and SROCC are between 0 and 1. The larger the value, the better the prediction result.

| Evaluation criterion     | PLCC | SROCC | RMSE |
|--------------------------|------|-------|------|
| Sparse representation    | 0.854| 0.842 | 0.067|

6. Concluding remarks
Sparse representation has been widely developed in image compression, image denoising and other related fields since it was proposed. In this paper, sparse representation has achieved better results in ERT image evaluation. In this paper, the method of sparse representation of the sub-dictionary is used to calculate the ERT image gradient features, and the image auxiliary features are extracted to evaluate the ERT image set. From the experimental results, it can be concluded that the evaluation effect is relatively satisfactory.

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