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An Improved Method of Support Vector Machine Algorithm with Choosing Segmentation in Electrical Capacitance Tomography

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Abstract: According to Support Vector Machine (SVM) has low training speed and precision to deal with large-scale data in Electrical Capacitance Tomography (ECT) system, an improved algorithm that combined SVM with Choosing Segmentation is presented. In the algorithm, the large-scale samples are divided into selective blocks for one imaging unit, training and predicting them by SVM algorithm, respectively. Then all imaging units are combined into one image. Compared to sole SVM algorithm,the numerical experiments show that the mixed algorithm has higher precision and shorten the time of reconstruction images in ECT system at the same time.

Key words: Support vector machine, choosing segmentation, electrical capacitance tomography, data preprocessing, image reconstruction

INTRODUCTION

Electrical Capacitance Tomography (ECT) has been developed very rapidly since the late 1980s (Marashdeh and Teixeira, 2004). It has the advantages of non-invasive, simple structure, low cost, fast response, good safety performance etc and with a wide range of applications in the petroleum, chemical, steel and other industrial fields (Yang, 2010). However, because of the restriction of less independent capacitance measurements, "soft market" characteristics, the non-linear of the problem to be solved and so on, image reconstruction is becoming a difficult process in ECT (Soleimani and Lionheart, 2005). And it is distant from the requirements of industrial application (Yang and Peng, 2003). So researching a good image reconstruction algorithm is important and urgent (Dahl *et al*., 2010). As a hot field of machine learning, Support Vector Machine (SVM) has been widely used to provide an effective method for ECT due to its reliability (Scholkopf *et al*., 2000), good generalization ability and having been proven superior performance in the multi-layered feed forward neural network areas (Jonsson *et al*., 2002). At present, SVM applications still have some problems, such as the difficult choice of kernel function parameters (Angulo *et al*., 2003), the low classification accuracy in complex problems and the long training time for large-scale classification, etc., (Sundararaghavan and Zabaras, 2005).

In this study, SVM algorithm with choosing segmentation is applied to electrical capacitance tomography to solve the mentioned problems. The SVM classifier is directly used when sample sizes is smaller than a certain threshold of data matrix? Otherwise Support Vector Machine with Choosing Segmentation (CSSVM) algorithm which obtains the best model from training by choosing the best-suited combinational small samples from the large samples for one block is applied. The algorithm can reduce the difficulty of the problem, cut down the training time and raise the precision by dividing the large samples into smaller ones. The experimental results show that CSSVM algorithm has higher accuracy and shorter imaging time than the SVM algorithm alone in image reconstruction.

IMAGE RECONSTRUCTION AND SVM ALGORITHM

Sensor mathematical model and the solving capacitance of the ECT system: The structure of the capacitive sensors is that 12 capacitor plates are arrayed equably around the pipe form a sensor array. The capacitance values between the different plates of capacitive sensor can be altered by the changing of the fluid flow state in the pipeline (Olmos *et al*., 2008). With the imaging algorithm, fluid flow distribution in the pipeline interface can be obtained by measuring the capacitance values between the plates (Watzenig and Fox, 2009):

$$C_{ij} = \int\int \varepsilon(x, y) S_{ij}[x, y, \varepsilon(x, y)]\, d_x d_y \tag{1}$$

where, C_{ij} is the value between electrodes i and j, $\varepsilon(x, y)$ is the distribution function for the dielectric constant and $S_{ij}[x, y, \varepsilon(x, y)$ is the distribution function of sensitive area measurement.

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Support vector machine: The columns of the sample set matrix of ECT system that to be solved are composed of 66 capacitance values and 66 sensitivity values. So it is a non-linear training set (Warsito *et al*., 2007). The sample space is mapped into a high dimensional feature space through a nonlinear mapping (Jandel, 2011). In the feature space, linear support vector machine is used by constructing an optimal separating hyper-plane (Widodo and Yang, 2007).

A known training sample set is $\{(x_i, y_i)\}_{i=1}^N$, i = 1, 2, ..., N, $x_i \in R^d$. $y_i \in \{-1, +1\}$. N is the number of training set samples. Nonlinear original problem is expressed as following:

$$\min_{w,b,\xi} \frac{1}{2}\omega^T\omega + c\sum_{i=1}^{l}\xi_i \quad \text{s.t } y_i(\omega^T\phi(x_i)+b) \geq 1-\xi_i \quad \xi_i \geq 0, i=1,...,l \tag{2}$$

where, $\phi(x_i)$ is that sample x_i is mapped from input space to high dimensional feature one; ω and b are optimal hyper-plane parameters to be determined and representing weight vector and bias, respectively. The penalty parameter for the classification of samples is c>0 and ξ_i is an introduced slack variable to solve nonlinear inseparable. The primal problem Eq. 2 is transformed into the following dual problem by applying the Lagrange multipliers (Zhang and Wang, 2009):

$$\begin{aligned} &\min_a \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} a_i a_j y_i y_j K(x_i, x_j) - \sum_{i=1}^{l} a_i \\ &\text{s.t } \sum_{i=1}^{l} a_i y_i = 0, 0 \leq a_i \leq c, i = 1,...l \end{aligned} \tag{3}$$

where, $K(x_i, x_j)$ is the kernel function. In this paper, the RBF kernel function is used:

$$K(x_i, x_j) = \exp(-\gamma\|x_i, x_j\|)^2, \gamma>0$$

The equation is converted into:

$$K(x_i, x_j) = \exp(-(\int_0^{+\infty} x^{g-1}e^{-x}d_x)\|x_i - x_j\|^2) \tag{4}$$

where, g (g > 0) is the gamma kernel function parameter. By substitution of RBF kernel function into Eq. 3, then the optimal separating hyper-plane parameter ω, the bias vector b_0 and the Lagrange multiplier a* are calculated.

At last, the discriminant function of SVM is shown in Eq. 5:

$$t\_label = \text{sgn}[\sum_{i=1}^{N} a_i^* y_i k(x_i, x) + b_0] \tag{5}$$

where, t_label is the decision making results of the imaging unit; x_i is training set data (componented of ECT capacitance values and sensitivity values, which is normalized before being trained. Lagrange multiplier a* and bias vector b_0 are obtained by Eq. 3 and $y\in(-1, +1)$ is the training sample label. RBF kernel function $k(x_i, x)$ is obtained by Eq. (4).

IMPLEMENTATION OF THE CSSVM ALGORITHM

Data preprocess: The index of the sample data in this experiment is ranged in [1.0E-13, 1.0E-4]. The data values are normalized in order to improve the experimental training and prediction accuracy (Sun and Li, 2008).

$\{x^1, x^2, \ldots x^l\}^T$ is suppose data matrix. The number of attribute is q, then $x^i = (x^i_1, x^i_2, \ldots x^i_q)$. Mapping relation f is established as following:

$$x_k^i \rightarrow f(x_k^i) = \frac{(x_k^i - \min(x^i))}{(\max(x^i) - \min(x^i))} \tag{6}$$

Each feature component of each mode standardized into $x^i_k \in [0, 1]$ after the normalization.

CSSVM algorithm realization: The CSSVM algorithm formulates that the maximum matrix is 200×132 for SVM algorithm processing, namely the matrix rows threshold is 200.

C^2_{12} = 66 capacitance values and corresponding to 66 sensitivity values constituted for 132 attribute columns are calculated in 12-electrodes ECT system. Suppose one imaging unit is water in pipeline, the label setted as 1; for oil, the label is regulated-1. CSSVM algorithm steps are as follows:

Step 1: According to fluid flow pattern in the pipeline, representative samples are produced:

- If the pipe cross-section is divided into 4 fan units numbered of 1, 2, 3, 4, then it has 16 kinds by the water and oil distribution combinations. If unit 1 is water, the combinations are 1, 12, 13, 14, 123, 124, 134, 1234, removing repeated samples of 14, 134, 124 which could get by unit rotation; If unit 1 is oil, the combination are 2, 3, 4, 23, 24, 34, 234, all oil, removing repeated samples of 3,4,34 which could get by unit rotation. In the experiment, the minimum number of samples should be 10, but 16 samples are chosen actually
- If the pipe cross-section is subdivided into r fan units, where r is 8 or 16 and numbered each unit. Water and oil distribution combination of r units is 2^r, namely it could have 2^r samples. After removing repeated samples which could get by unit rotation, the training sample number for the experiment is selected as Eq. 7:

$$(\left\lceil \frac{C_r^1}{r} \right\rceil + \left\lceil \frac{C_r^2}{r} \right\rceil + \ldots + \left\lceil \frac{C_r^r}{r} \right\rceil) \times 2 \tag{7}$$

- If the pipeline cross-section is equally divided into 32 units. First the pipe cross-section is divided into 8 fan units, whose combinations are 34×2 and getting rid of the repeated samples. Then each fan unit is subdivided into 4 portions and having 16 kinds of combinations. So the training sample number of experiment is selected as:

$$(\left\lceil \frac{C_8^1}{8} \right\rceil + \left\lceil \frac{C_8^2}{8} \right\rceil + \ldots + \left\lceil \frac{C_8^8}{8} \right\rceil) \times 2 \times 2^4 = 1088$$

The samples is structured matrix of L×132, where L is the sample number

Step 2: If L <= 200, go to step 4

Step 3: If L is larger than 200, the model is partitioned and labeled. The initial imaging unit number is set as r = 1, the largest imaging unit as P. Each imaging unit r is mapped to the smallest unit of rotating repeated and m combinations of samples labeled 1 of unit r_{min} are extracted from the original matrix of L×132 and extracting m samples which label is 0 of unit r_{min} from the rest, then combined into P training data matrixes of 2m x 132. Then Go to step 4

Step 4: Judging whether all the imaging units are disposed or not. If r> P, the training has ended and transfers to the prediction step 6; Otherwise the SVM algorithm is used, selecting the penalty parameter c and the kernel function g. The sample space is mapped into high dimensional feature space through Eq. 4 and substitutes into Eq. 3. The original problem optimal solutions a* and b_0 are calculated. The best training model is got in the end

Step 5: r = r +1, go to step 4

Step 6: The results of all cells are predicted by substitution of P units' training models into Eq. 5 and one-dimensional vector composed of p values is obtained, Then the image is reconstructed. The prediction error of the unit is calculated by substitution of predicted results into Eq. 8

$$A_r = \frac{\sum_{i=1}^{N}(y_i - Z_i)}{N} \tag{8}$$

where, r = 1, 2..., P. $Y_i \epsilon \{-1, +1\}$ is the actual value of the sample i. $Z_i \epsilon \{-1, +1\}$ is the predicted value of the sample i.

EXPERIMENTAL RESULTS AND ANALYSIS

A 12-electrode sensor model shown in Fig. 1 is established in the experiment with ANSYS10.0 software. According to Eq. 1, capacitance values are calculated with ANSYS CMATRIX macro and the ADPL language programming. When the pipe cross-section is equally divided into 4 portions, the sample combination is only 16 groups, so retains the repeated samples. When the pipe cross-section is equally divided into 16, the minimum number of non-repeated representative samples for experiment should be 4099 on the basis of the Eq. 7, but 1120 samples are extracted and solved in the experiment. When the pipe cross-section is equally divided into 32 portions, 1088 samples are solved.

We have three groups of experiments, The first group is that the pipe cross-section is equally divided into 4 parts, thus the image is reconstructed with SVM algorithm. The second group is that the pipe cross-section is equally divided into 16 parts, the SVM algorithm and the CSSVM algorithm are both used in reconstructing image. The last group is that the pipe cross-section is equally divided into 32 parts and the CSSVM algorithm is applied for reconstructing image.

When the pipe cross-section is equally divided into 4 parts, the training data matrix of 16×132 belongs to small training sample sets. The parameter values are adjusted until the prediction accuracy reaches to 100%. Then the predicted average time is 0.0508 sec.

When the pipe cross-section is equally divided into 16 parts, the predicted results of the training data matrix of 1120×132 with SVM algorithm are shown in Table 1.

When the pipe cross-section is equally divided into 16 portions, the accuracy of reconstructed image with SVM algorithm is low and time consuming is great. The

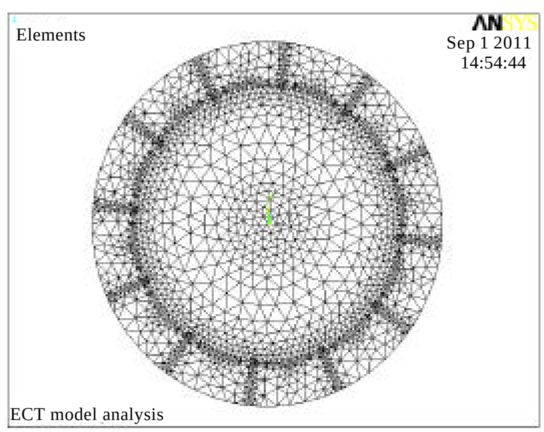


Fig. 1: Subdivision graph of ECT

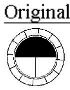
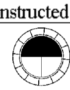
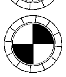
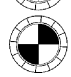
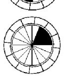
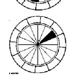
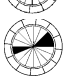
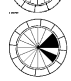
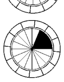
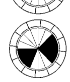
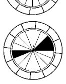
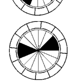
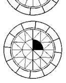
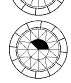
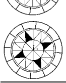
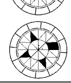
Table 1: SVM algorithm error and time of 16 portions of pipe

Units for water	Average error	Prediction time (sec)
1	0.0758	5.62
1,2,3	0.0747	5.82
1,2,9	0.0752	5.92

Table 2: Predicted results of unit for 16 portions of pipeline

Unit number	Optimal parameters	Predicted error	Prediction time (sec)
Unit 1	c 10, g 0.01	0.0556	0.4848
Unit 2	c 15, g 0.02	0.0541	0.3824
Unit 3	c 15, g 0.02	0.0503	0.4248
Unit 4	c 15, g 0.02	0.0524	0.3904
Unit 5	c 10, g 0.02	0.0552	0.4077
Unit 6	c 10, g 0.02	0.0522	0.4038

Table 3: Reconstructed images

Original image	Algorithm used	Prediction time (sec)	Reconstructed image
	SVM	0.05	
	SVM	0.06	
	SVM	92.81	
	SVM	93.74	
	CSSVM	0.58	
	CSSVM	0.52	
	CSSVM	2.00	
	CSSVM	2.08	

more the pipeline is subdivided, the lager the experimental data matrix is and the more the memory is occupied.

With CSSVM algorithm, the selected data matrix is 138×132, the single penalty parameter c and nuclear parameter g are adjusted until the error is the minimum. The experimental results are shown in Table 2. The sample group is selected for each imaging unit.

Table 2 shows that the optimal parameter of each unit is different. The value of average error is 0.0530.

The pipe cross-section is equally divided into 32 portions and labeled. The training data matrix of 164×132 is selected for each unit with the CSSVM algorithm and then preprocessed with Eq. 6. The best model is obtained with training the data matrix, adjusting the penalty parameter c and the kernel parameter g until the prediction is highest. The reconstructed image result is shown in Table 3.

The result show that when the pipe cross-section is divided into 4 portions, which is a small-scale sample data matrix, the image is reconstructed fast and high precision directly with SVM classifiers. If the pipe cross-section is divided into 16 or 32 units, CSSVM algorithm for reconstructed images has higher precision and faster speed. The more subdivision of pipe cross-sections, such as 64 units or 192 units, the better results the CSSVM algorithm for reconstructed images could be obtained.

DISCUSSION

Owing to SVM algorithm has low accuracy and longer training time while ECT system has a grate-scale sample set, the CSSVM image reconstruction algorithm is used widely. The difficulty of the problem is reduced by choosing extraction-blocks from large-scale data matrixes and the optimal kernel parameter is selected to make the training accuracy reach to the highest. The CSSVM algorithm has not only higher precision than SVM algorithm in reconstructed image, but also shorter prediction time in large-scale issues. In future work, the hardware FPGA will be introduced in order to achieve higher precision and shorter time in image reconstruction.

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