Study on Support Vector Machine for Image Reconstruction Algorithm of Electrical Capacitance Tomography

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Abstract-Support vector machine (SVM) is based on the special small samples theory with strong generalization ability, and is selected as an optimal theory for small samples classify problem. Electrical capacitance tomography (ECT) is a typical small samples and nonlinear mapping problem. In this paper the ECT image reconstruction algorithm based on SVM is proposed and a novel training method is proposed to improve the efficiency of SVM classifier by selecting active penalty parameters. Programming software based on Matlab6.5 and VC6.0, the simulation and experiment results indicates this algorithm has stronger space resolution and generalization ability, overall performance of the algorithm is better than some classic reconstruction algorithm such as LBP, etc. However, the algorithm requires the higher quality of training samples, otherwise less real-time, less of application value.

Keywords-support vector machine; electrical capacitance tomography; image reconstruction; space resolution; generalization ability

Identification of Multiphase Flow widely in petroleum, chemical industry, river training and other areas of national product, as the complexity of multiphase fluid, random much, it is difficult using traditional detection techniques to accurately measure. Electrical Capacitance Tomography (ECT) technology is the use of multiphase medium tending to have a different dielectric constant, through the array of electrode capacitance changes, reflecting the multiphase medium pipeline distribution to extract the phase of each phase medium concentration, relative size, flow patterns and other characteristic parameters. The technology can be used to detect two-phase / multiphase flow processes, real-time display phase distribution images of multiphase fluid in the pipeline to achieve phase concentration, flow patterns and other characteristic parameters, is a measurement of high speed, non-invasive, low cost, applicable to a wide range of a new generation non-destructive functional imaging techniques [1].

Electrical capacitance tomography system includes capacitance sensor, data acquisition and signal processing unit, image reconstruction and analysis display three functional modules. As the "soft field" feature of system sensitive field, less independent capacitance measurements and other factors, makes the image reconstruction algorithm for the overall performance of the system plays a decisive role. As the current practical image reconstruction method are mostly qualitative algorithms (such as linear back projection algorithm), at the expense of accuracy to improve the real-time imaging, making the reliability of the extracted characteristic parameters less, and some high precision real-time imaging algorithm more poor, and no practical value.

For less of independent capacitance value for the system, this paper design an image reconstruction algorithm for electrical capacitance tomography based on support vector machine (SVM) from statistical learning theory [2].

I. SVM ALGORITHM DESIGN

Support vector machine by Vapnik first proposed (Vapnik, 1995), is the structural risk minimization method to achieve approximate. It integrates the largest interval of hyper-plane, Mercer core; convex quadratic planning, sparse solutions and slack variable technologies can be used for pattern recognition and nonlinear regression, which has become a standard tool for machine learning [3]. The 12-electrode capacitance sensor, for example, the system has 66 independent capacitance values, then an output unit for the support vector machines architecture shown in Figure 1, the number \( m_0 \) of the input layer units are equal to 66, the number \( m_1 \) of hidden layer units are decided by support vector number in the system. The core of support vector machines makes the non-linear input space into linearly separable feature space through the inner core function \( K(x,x') \) [4].

Make \( \{\varphi(\tilde{x})\}_n \), express a collection of non-linear
transformation from the input space to feature space, in which $\bar{x}$ is the input space vector.

$$y_i = d_i = +1 \text{ Indicate existence of high dielectric constant material in the output unit.}$$

$$y_i = d_i = -1 \text{ Indicate existence of low dielectric constant material in the output unit.}$$

Where $y_i$ is output value of the output unit, $d_i$ is target value of the output unit.

So the inner product kernel function as

$$K(\bar{x}, \bar{x})_i = \langle \phi(\bar{x}_i) - \phi(\bar{x}) \rangle = \sum_{j=1}^{N} \phi(\bar{x}) \phi(\bar{x}_j)$$

Where $\bar{x}, \bar{x}_j$ of training samples.

Selecting the radial basis function for the inner product kernel function:

$$K(\bar{x}, \bar{x}) = \exp\left(-\frac{1}{\sigma^2} \| \bar{x} - \bar{x} \|^2 \right)$$

Supposing the $k$ output unit:

A given training sample $(\bar{x}_i, \bar{d}_i)_{i=1}^N$. Using convex quadratic planning algorithm for maximizing the objective function.

$$\max Q(\alpha) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j d_i d_j K(\bar{x}_i, \bar{x}_j)$$

$$\text{Constraints: } \sum_{i=1}^{N} \alpha_i d_i = 0$$

$$0 \leq \alpha_i \leq C \quad i = 1, 2, \cdots, N$$

And to meet the constraints of the Lagrange multiplier $\alpha_i$, then its corresponding training sample $\{\bar{x}_i\}$ is a support vector. So that does not meet the constraints of the Lagrange multiplier set $0$. $C$ in the constraints (2) for the penalty parameter[5].

Corresponding to the optimal weight vector is

$$\bar{w}_d = \sum_{i=1}^{N} \alpha_i d_i \phi(\bar{x}_i)$$

The output of the number $k$ unit is as follows:

$$y_k = \sum_{i=1}^{N} \alpha_i d_i \bar{K}(\bar{x}, \bar{x}) + b_k$$

Where $b_k$ takes the $b$ value arithmetic mean value of the support vector collection substitution equation (5).

II. IMAGE RECONSTRUCTION SIMULATION

By the two dimensional finite element method analyzing system sensitive field, adopts triangle meshing and linear interpolation to seeking sensitive field electric potential distribution and examination pole plate capacitance [6]. If the sensitive area, the pipeline wall and the pipeline outer wall to the shielding layer region's meshing layer respectively is 4 and 3 and 3. Programming software based on Matlab6.5 and VC6.0, meshing map shown in Figure 2.
Simulation Capacitance value using equation (6) for normalized [7].

\[
\tilde{C}_{ij} = \frac{C_{ij}^* - C_{ij}^{-*}}{C_{ij}^* - C_{ij}^{-*}}
\] (6)

If imaging medium is A, B and \( \varepsilon_A > \varepsilon_B \), among: \( C_{ij}^* \), \( C_{ij}^{-*} \) is respectively the capacitance value when the tube filled with A-phase and B-phase medium, \( C_{ij} \) is the capacitance value when the tube filled with A, B for the two-phase medium.

\[
C_c = \frac{L_1}{L_1 + L_2} C, \quad C_s = \frac{L_2}{L_1 + L_2} C
\] (7)

Where, \( L_1 \) and \( L_2 \) is the number of positive class and negative class point sets. \( C_c \) and \( C_s \) are penalty parameters of positive class and negative class point sets. Then the equation (3) change as:

\[
\alpha_i^+ + \alpha_i^- = 1, \quad i = 1, 2, \ldots, N
\]

III. EXPERIMENT AND ANALYSIS

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<td><img src="image5" alt="Simulation image" /></td>
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Fig.3 SVM image reconstruction comparison chart based on static and dynamic penalty parameter.

A-phase and B-phase medium, \( C_{ij}^* \) is the capacitance value when the tube filled with A, B for the two-phase medium.

Based on 700 groups of training samples, select the equation (3) constraints \( \sigma \) training network of the \( C = 8 \) to generate support vector set. Static \( C \) reconstructed image in figure 3 for the test samples (as distinct from the training sample) is the simulation images based on the support vector set through static threshold filtering. By the diagram shows, Space resolution, generalization ability of the algorithm is better than the linear back-projection, radial basis function neural network image reconstruction algorithm. But its space resolution error is still large, poor usability.

As great differences of the numbers between positive class and negative class point sets. But the penalty parameter \( C \) in the equation (3) is static, this means that the number of certain types is more, then the penalty will be heavier, but we hope the same degree of punishment to positive class and negative class point sets, so structure the different penalty parameters:

\[
\begin{align*}
\max Q(\alpha) = & \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j \rho_{ij} - \sum_{i=1}^{N} \alpha_i d_i & \\
\text{Constraints:} & \quad \sum_{i=1}^{N} \alpha_i = 1 & \\
& \quad 0 \leq \alpha_i \leq C, \quad d_i = 1 & \\
& \quad 0 \leq \alpha_i \leq C, \quad d_i = -1 & \\
& \quad i = 1, 2, \ldots, N
\end{align*}
\] (8)

Based on the same 700 groups training samples, select the equation (8) constraints \( \sigma \) training network of the \( C = 8 \) to generate support vector set based on the equation (7). Dynamic \( C \) reconstructed image in figure 3 for the test samples (as distinct from the training sample) is the comparison chart based on the support vector set through static threshold filtering. From the diagram shows, the space resolution error, generalization ability of the algorithm is better than image reconstruction algorithm based on static \( C \), strong usability [8][9].


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Algorithm performance testing mainly study imaging experiments of the different numbers, different sizes and different locations of static objects, a single object, two objects, multiple objects, imaging experiments were selected to a diameter of 10mm and 20mm and 30mm of the Plexiglas rods.

The following conclusions from the experimental results figure 4:

① The small diameter objects reconstructed images results rather vague, large diameter objects better reconstructed images;
② The closer to the center, the reconstruction image more blurred, the closer to the edge, the better the reconstructed image;
③ Images from SVM algorithm based on dynamic C than based on static C clearer, more precise.

IV. CONCLUSIONS

Image reconstruction problem of electrical capacitance tomography can be reduced to a class of linear inseparable problems, this paper based on dynamic penalty parameter, and convex quadratic planning in support vector machine, programming software based on Matlab6.5 and VC6.0, the image reconstruction of the simulation and experimental results show that the algorithm has stronger space resolution capacity, generalization ability, overall performance of the algorithm is better than LBP, etc. However, the algorithm requires the higher quality of training samples, otherwise less real-time, loss of application value.

REFERENCES