The Frontiers of Society, Science and Technology
ISSN 2616-7433 Vol. 1, Issue 10: 123-129, DOI: 10.25236/FSST.2019.011015

Analysis of Multiphase Flow Imaging Algorithms Based on Improved Range Factor

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ABSTRACT. *The phase distribution of oil, gas and water multiphase flow in horizontal wellbore can be visually reflected by the image formed by the logging data of capacitance array instrument. To overcome the shortcomings of existing algorithms, a dynamic subdivision method considering instrument rotation is proposed, and a new weighting function based on distance factor is proposed. An improved grid imaging algorithm with correction coefficient is presented. The processing results of the experimental data show that the image effect of the algorithm is in good agreement with the corresponding photographs.*

KEYWORDS*: Production logging; Capacitance array instrument; Flow imaging; Distance factor; Correction coefficient*

1. Introduction

In highly deviated wells and horizontal wells, when the downhole fluid is multiphase flow, natural stratification is produced due to gravity differentiation, which results in great errors in the traditional production logging tool with centralized pattern. To this end, Halliburton and Sondex jointly launched Capacitance Array Tool (CAT). CAT has 12 miniature capacitive probes, which are located in the same cross-section of the wellbore and are distributed along the radial direction. Each probe can accurately detect the consistency of the surrounding fluid, i.e. the attribute value (its detection distance is about 0.3mm). CAT can carry out continuous measurement and point measurement, visualize the data measured by 12 probes, and visually display the fluid distribution in the wellbore. However, the existing foreign literatures do not involve the visualization technology, and the Chinese literatures only see a paper published by Dai Jiacai, “Research on Flow Imaging Algorithms of Capacitance Array Logging Data”. The research on CAT imaging algorithm is not complete, so it is necessary to further study the flow imaging algorithm of capacitance array logging data.

Because the probe's detection distance is very small relative to the wellbore radius, for a certain cross section of the wellbore, it can be considered that the

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response value of 12 probes reflects the attribute value of 12 points on the cross section. Imaging is to estimate the attribute value of other points on the cross section according to these 12 local attribute values, which is essentially an interpolation problem. Without additional information, it is difficult to obtain the interpolation results with obvious practical significance only according to the attribute values at 12 probes. If we consider that the correlation between points decreases continuously with the increase of distance and assume that the fluid in the wellbore is in a laminar flow state, we can conclude that the velocity of the correlation in horizontal direction decreases continuously with the increase of distance is lower than that in vertical direction; that is to say, the influence range of the attribute value of a probe point in horizontal direction is larger than that in vertical direction. Therefore, the weight of the interpolation algorithm needs to consider the direction of the node to be interpolated relative to the probe. In this paper, a new weight function with influence distance factor is introduced, and the interpolation weight is improved by using the concept of correction coefficient. The effectiveness and stability of the proposed algorithm are verified by the processing results of the measured data.

2. Rotation of CAT and the Section of Wellbore Cross Section

In practical measurement, the instrument usually rotates. The CAT instrument has a special device to record the rotation angle of the instrument itself relative to the upper part of the wellbore in order to determine the exact position of the CAT in the wellbore. For the section of the wellbore, firstly, the dissection method shown in the literature is analyzed: firstly, without considering the rotation of the instrument, the section of the wellbore is directly divided by Delaunay triangular mesh, and then the probe is allocated to the dissection node. The disadvantage of this method is that, without considering the rotation of the instrument, the position of the node obtained by the dissection coincides with the actual position of the probe very little; forcibly allocating the probe to the dissection node will result in the position of the probe not in line with the actual situation. Therefore, it is unreasonable to divide the cross section of the wellbore without considering the rotation of the instrument. In order to overcome the shortcomings of literature methods, the author dynamically divides the cross section of wellbore under the premise of considering the rotation of the instrument. The specific methods are as follows:

Since the cross-section of the wellbore is a circular surface, the radius is taken in the direction of the rotating probe No. 1. Along the direction of the radius, the cross-section area is divided into N rings. The intersection point of the radius of each ring and probe No. 1 is the starting point, and the radius is divided into 12 equal parts, 24 equal parts, according to the counterclockwise direction. Divide into 12 N, that is, each ring has 12, 24,... The central ring is divided into 12 triangular elements, from inside to outside, with 24 triangular elements added to each layer. Thus, there are 6N * (N+1)+1 node and 24N2 triangular elements in the section area. On the one hand, the number of nodes on each layer of the ring is 12 times and symmetrically distributed; on the other hand, the intersection of the radius of probe No. 1 and each layer of the ring is node No. 1 of the layer, and because of the symmetry of the probe

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distribution itself, it can be seen that the probe can be perfectly matched to the splitting node[1].

2. Modified inverse distance weight interpolation algorithm

The interpolation algorithm of CT imaging is to estimate the measured values at other nodes on the cross-section when the positions of 12 probes are known. The modified distance inverse weight interpolation algorithm proposed by the author is as follows:

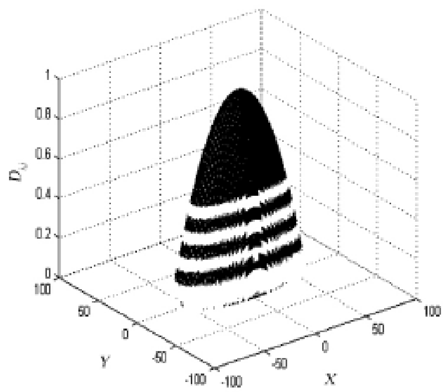
$$w_i = \sum_{j=1}^{12} k_j \times D_{ij} \times T_j \qquad (1)$$

In the formula, wi is the predicted response value at the first node; Tj is the measured response value of the j probe of CAT; Di, J is the contribution weight value of the j probe to the I node; kJ is the correction coefficient of the J probe.

The determination rules of weight Di, J and correction coefficient kJ are given below.

$$D_{i,j} = \begin{cases} 1-\left[\frac{(x_i-x_j)^2}{m^2}+\frac{(y_i-y_j)^2}{n^2}\right] & \frac{(x_i-x_j)^2}{m^2}+\frac{(y_i-y_j)^2}{n^2} \leqslant 1 \\ 0 & \frac{(x_i-x_j)^2}{m^2}+\frac{(y_i-y_j)^2}{n^2} > 1 \end{cases} \qquad (2)$$

Fig.1 rmula, m is the decreasing control coefficient in the horizontal direction; n is the decreasing control coefficient in the vertical direction; (xi, yi) is the coordinate of the first node; (xj, yj) is the coordinate of the first J probe, J = 1, 2,... 12. When (x j, yj) = (0, 0), Figure 1 shows that Di and j depend on (x, y) images, and compares the effects of different values of M and N on images. The results show that the larger m, the slower the attenuation of Di and j in the horizontal direction (X axis) and the larger the influence range in this direction; the larger n, the slower the attenuation of Di and j in the vertical direction (Y axis), the larger the influence range in this direction. Therefore, the change rule of Di and J can be controlled by M and n[2].



(a) m=64, n=25

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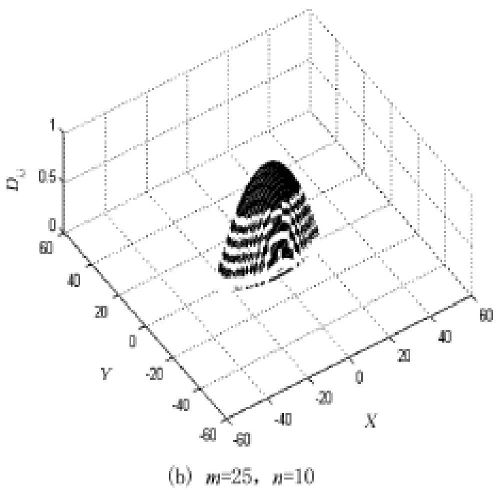

Figure.1 Di, J

Fig.2 tion of M and N depends on the radius of cross section of wellbore and the distribution of probe. Figure 2 shows the distribution of the probe in the wellbore, and the instrument will rotate when measured. According to the distribution characteristics of the probe, the radius of m_wellbore cross-section and n_wellbore cross-section/3 are selected. In this study, M = 25 and N = 9 were selected.

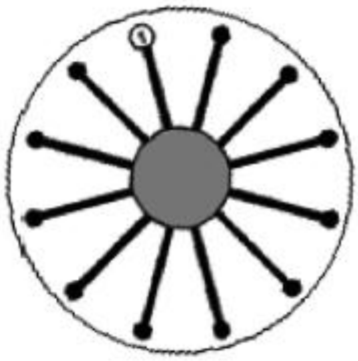

Figure.2 Distribution of CT probe (no rotation)

The rationality principle of imaging algorithm is that the estimated and measured values of the probe position should be the same or similar. Di and j determined only by formula (2) can not meet this requirement. Therefore, the correction coefficient kJ is introduced to correct the weight of the probe through kJ to ensure that the calculated and measured values at the probe are equal or have only minimal difference. Accordingly, in order to determine the correction coefficients k1, k2,...

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K12. Establish the following objective functions:

$$\min\sum_{j=1}^{12}(C_j-T_j)^2 \quad (3)$$

In formula (1), Cj is the calculated value at the j probe and Tj is the measured value of J probe. Only by using optimization methods, such as adaptive chaotic particle swarm optimization, when the objective function reaches the minimum, the corresponding correction coefficients can be obtained.

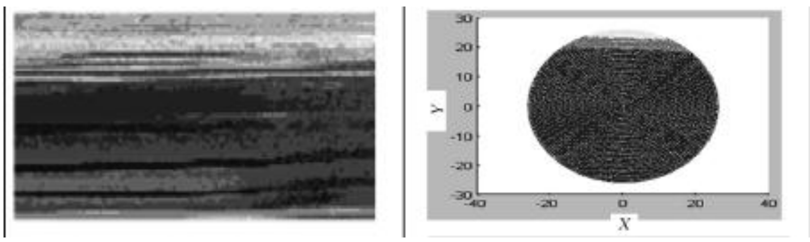
3. Conversion from Node Attribute Value to Color Display Attribute Value

In order to visualize the cross section of wellbore, it is necessary to transform the node response value (part of the calculated value) to the color display attribute value. The theoretical response value of CT probe in water phase is 1, in oil phase is 0.2, and in gas phase is 0. When the response value is processed, a neighborhood of the theoretical response value can be specified. As long as the response value falls into the corresponding neighborhood, it is considered as the corresponding phase state. In the image, light grey white is used to represent the gas phase, gray is used to represent the oil phase, and black is used to represent the water phase[3].

4. Application example

Fig.3 were collected from the three-phase test of oil, gas and water in the multi-phase flow simulator of CAT. The test temperature is 12-13 C, the pressure is 0.2 MPa, the medium is tap water, diesel oil and air, the well deviation is 90 degrees, the gas flow rate is 100 m3/d, the total flow rate of oil and water is 150 m3/d, and the water cut rate is 80%. According to the improved interpolation algorithm mentioned above, the correction coefficients are obtained by using adaptive chaotic particle swarm optimization algorithm with m=25 and n=9. For different measurement modes: point measurement (abbreviation: 0), upper measurement 4m/min (abbreviation: 4U), upper measurement 12m/min (abbreviation: 12U), upper measurement 20m/min (abbreviation: 20U), imaging was carried out. The imaging results and the corresponding flow tube side photos are shown in Figure 3[4].

0



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4U

12U

20U

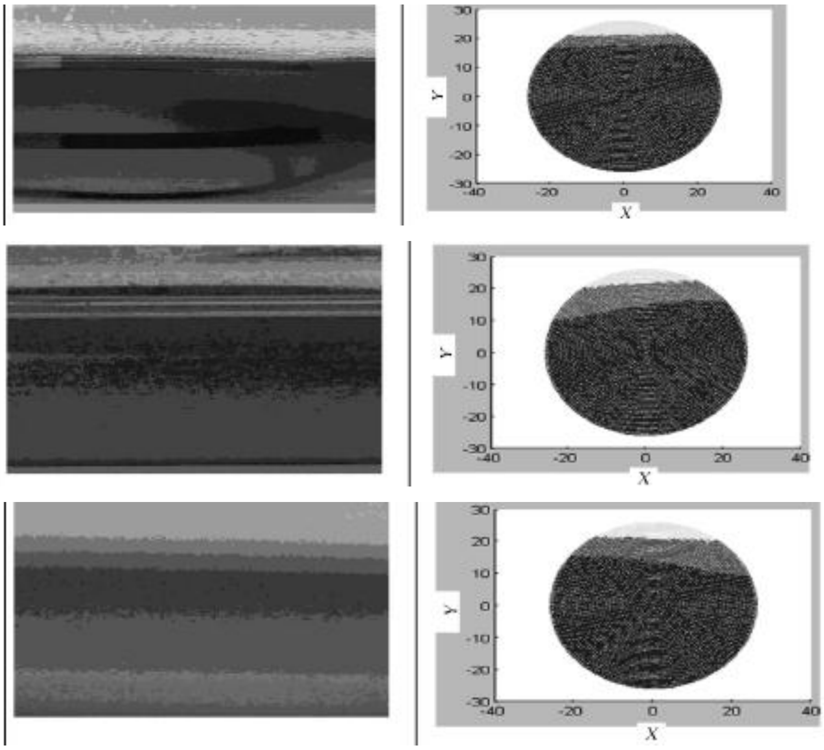

Figure.3 Comparison of image processing results of CAT test data with corresponding photographs under different measurement modes

Fig.3 e-phase laminar flow in the horizontal pipe is measured, and the image generated by the algorithm also reflects the layered characteristics. Therefore, the improved algorithm proposed by the author is feasible. Comparing the measured velocity with the corresponding imaging results, it is found that the measured velocity has some influence on the stratified state of wellbore fluid, but it does not change the general distribution state of fluid. The purpose of this study is to study the distribution of fluid in wellbore by imaging. The phase holdup can also be obtained from the image. In Figure 3, the ratio of the area occupied by the corresponding phase color to the cross-sectional area of the wellbore can be used to estimate the phase holdup, but it needs to be calibrated[5-8].

Twelve probes of CAT measure the local phase holdup in different directions in the cross section of wellbore, and the phase distribution on the cross section can be visually displayed by the image of the measured data. For highly deviated wells and horizontal wells, the flow pattern in the wellbore is complex and changeable. The interpolation algorithm proposed by the author can comprehensively consider the effects of deviation and rotation, adapt to deviation with different correction coefficients, and match the efficiency of the algorithm with the measured data through optimization. The comparison between the imaging results of the

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experimental data and the corresponding photographs shows the effectiveness and stability of the algorithm.

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