Application of Improved Non-local Mean Filtering Algorithm in Detection of Oil and Gas Wells

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Abstract. As the oil and gas exploration in most parts of China has entered into the middle and late stages, the aging and wear problems of mining equipment have become increasingly prominent. In the process of visual image acquisition of oil and gas well casing damage, due to the influence of the complex environment of light and dust, the image data source noise is serious, and the image recognition model has low accuracy. This paper improves the neighbourhood filtering algorithm block search process with the ant colony pheromone correlation theory, optimizes the block matching process with the Pearson algorithm, and eventually applies the optimized non-local mean filtering algorithm to the oil and gas well casing damage visual detection process. The experimental results show that the improved non-local mean filtering algorithm has a significant impact on the adaptability and effectiveness of the noise reduction effect.

1. Introduction
As China's oil and gas exploration enters the middle and late stages, the repair of oil and gas well casing wear has become an important task for the sustainable exploitation of oil and gas [1]. At present, the method based on visualized oil and gas well casing damage detection is a more effective and intuitive detection method in complex environments. However, due to the complexity of the visual inspection environment and the complex noise generated during data transmission, pre-processing operations such as noise reduction and enhancement are required before the data processing process. Research on image pre-processing has always been one of the more important research branches in the field of machine vision. With the development of the industrial revolution in recent years, the technology and theory in the field of machine vision have also achieved great results [2]. At present, the most common noise reduction algorithms are BM3D [3], median filtering algorithm [4], NL-means algorithm [5-6], wavelet filtering algorithm [7]. Both the BM3D algorithm and the NL-means algorithm are non-local filtering ideas and look for similar block principles. Since the block search process of the two algorithms adopts the global search or local range search method, the block matching process often uses a single Euclidean distance algorithm to calculate the similarity coefficients of the two algorithms. Therefore, the intelligence and similarity judgment conditions of the algorithm are relatively simple. Due to its poor real-time performance, its scope of application is limited. In view of the above problems, this paper uses ant colony pheromone theory [8] and Pearson algorithm [9-10] to improve block search and block matching respectively, and the improved results are applied to the image detection process of oil and gas well casing damage.
2. Improved non-local mean filtering algorithm

2.1. Non-local mean filtering principle

The traditional non-local mean filtering algorithm is divided into three steps [11]: block search, block matching, and calculation of the final value. The following are the detailed steps of the non-local mean filtering algorithm:

Let the acquisition image is \( f(x, y) \), the noise is \( g(x, y) \), the real image is \( w(x, y) \), \( x \) and \( y \) are pixel index values, and the relationship between the variables is as shown in equation (1). For the convenience of processing, the multiplicative noise of the image is approximated as additive noise and subsequent processing.

\[
f(x, y) = g(x, y) + w(x, y)
\]

Block search process: the non-local mean filter block search process is divided into two types, one is global search, and the other is local range search. Both search principles are based on the noise reduction point, and the radius is obtained by using \( a=2 \) pixel points as the radius. \( S \) collection of surrounding pixels, here labelled as a basic pixel point set \( B \); traversing the remaining pixels in the global range or local range, taking the same \( a \) pixels as a radius, and obtaining the surrounding area pixel set of the remaining pixels, denoted as \( S_i, i = 1,2,3,\ldots,n \).

Block Matching Process: calculates the similarity between \( S \) and \( S_i \) obtained by the block search process. As shown in formula (2).

\[
\omega(S, S_i) = \frac{1}{\varphi(x)} \exp\left(-\frac{\|S - S_i\|_2^2}{b^2}\right)
\]

\( \omega(S, S_i) \) is the similarity coefficient between \( S \) and \( S_i \), and \( \varphi(x) \) is the normalization coefficient. The calculation method is the sum of the similarity calculation values between the corresponding pixels of \( S \) and \( S_i \), \( b > 0 \) is the filter coefficient, and \( c > 0 \) is the \( S \) and \( S_i \) in the Euclidean distance process.

Calculation of the final pixel point: in the non-local mean filtering algorithm, the calculation is performed using equation (3). In the BM3D algorithm, the similarity values obtained are usually sorted, and the partial data sets with the largest similarity are selected to form a 3-dimensional array, and further operations such as 3-D transformation and cooperative Wiener filtering are performed.

\[
g(x, y) = \sum_{i=1}^{n} \omega(S, S_i) f(x, y)
\]

Where \( g(x, y) \) represents the image after noise reduction.

2.2. Improved non-local mean filtering algorithm

Based on the above principle of non-local mean filtering algorithm, this paper performs simulation tracking for algorithm block search process and block matching process. In the experiment, it is found that the block search process usually uses horizontal and vertical traversal to search, and does not consider the local features of the image. The search process cannot optimize the route based on the relevant parameters calculated by the previous noise reduction point, resulting in more invalid block search processes. Therefore, the ant colony pheromone parameter is used to mark similar block regions, and the pheromone area corresponding to the noise reduction point is reached. When the parameters are calibrated by the system, the key search is performed in the area marked by the pheromone, and in order to prevent the loop into the local search, the relevant threshold is set, and when the similar block matching result is poor, the pheromone marked area is jumped out. The following are the detailed steps of the block search process.
The pixel block $S$ is initialized by traversing, and the pheromone mark content is $S_{signal}[x, y]$, $x \in [1, S_x]$, $y \in [1, S_y]$. The principle of the algorithm is that $S_{signal}$ moves in the same direction as the $S$ block moves, and the block search is focused on the marked area.

Step 1: set the original image to $s_a \times s_b$ size, and traverse the $S$ block to perform local block search and block matching in the global or large range within the $s_a \times s_b$ range size.

Step 2: set the $S_{signal}$ marker block to mark the $S_i$ concentration area generated by the block matching process.

Step 3: perform the block search process of step 1 in the area marked by $S_{signal}$, that is, perform block matching preferentially in the $S_{signal}$ range. When the similarity of the similar blocks matched in $S_{signal}$ is small, jump out of the marked $S_{signal}$ area, perform a global search or a wide range of local search, and step 4 is performed.

Step 4: after step 3 jumps out of the marked $S_{signal}$ area, re-mark $S_{signal}$ according to the matched area, repeat step 3, and finally complete the improved block search process, reducing step 3 unnecessary global search or local search.

In the above steps, when the marked $S_{signal}$ traversal exceeds the index, the $S_{signal}$ block search is uniformly jumped out, and step 4 is executed, and finally the non-local mean filtering algorithm is completed with the improved block matching.

For the single problem of the block matching algorithm, we tested the common Euclidean distance and the characteristics of the Pearson algorithm. In order to facilitate the comparison, we change the similarity range of the Euclidean distance, and 0 to 1 represent the range that is not related to the
correlation. Six sets of 5×5 sized pixel blocks are traversed from Fig. 1, and the data in the pixel block is dimensionally arranged. As shown in Fig. 2, some similar point sets exist in the same picture, corresponding to the two shown in Table 1. The similarity comparison is calculated by an algorithm. Therefore, for the similar data set with partial linearity in Fig. 2, we intend to use the linear transformation method to transform the similar group, recalculate and assign higher similarity coefficient, and then participate in the calculation.

As shown in Figure 2, these data have the same trend, and there is a certain linear relationship between the corresponding points. If a single Euclidean distance algorithm is used, as shown in Table 1, these points will give lower similarity weights. For the single problem of the Euclidean distance calculation method in block matching, we improve the following algorithm.

Table 1. Algorithm similarity coefficient comparison table.

| Number | Euclidean distance algorithm similarity | Pearson algorithm similarity |
|--------|----------------------------------------|-----------------------------|
| 1      | 0.3715                                 | 0.8617                      |
| 2      | 0.3765                                 | 0.8231                      |
| 3      | 0.3644                                 | 0.8003                      |
| 4      | 0.3639                                 | 0.8352                      |
| 5      | 0.3521                                 | 0.8097                      |
| 6      | 0.3413                                 | 0.8728                      |

Compared with the traditional non-local mean filtering algorithm, this paper modifies the kernel function of the block matching process and determines the Pearson correlation coefficient $\rho(S, S_i)$ between $S$ and $S_i$ as shown in equation (4). If the condition $((0 \leq \rho_{emp1} < \rho(S, S_i) \leq 1 \& \& -1 \leq \rho(S, S_i) < \rho_{emp2} \leq 0) \& \& 0 \leq \omega(S, S_i) < \omega_{emp} \leq 1) \Rightarrow 1$ is met, $\rho_{emp1}$, $\rho_{emp2}$, $\omega_{emp}$ represent custom thresholds. You need to set the size according to the similarity of the actual image, $0 < \rho_{emp1} = 0.80$, $\rho_{emp2} = -0.80 < 0$, $0 < \omega_{emp} = 0.40$, $\rho(S, S_i)$ are pearson correlation coefficients, $\mu_S$ and $\mu_{S_i}$ are the average values of $S$ and $S_i$, $E$ is the variance, $\sigma_S$ and $\sigma_{S_i}$ are the standard deviations of $S$ and $S_i$. The correlation coefficient $\rho\omega(S, S_i)$ between $S$ and $S_i$ is calculated by using equations (5) and (6), otherwise, calculate the noise reduction graph $g(x, y)$ using equations (2) and (3).

$$\rho(S, S_i) = \frac{E[(S - \mu_S)(S_i - \mu_{S_i})]}{\sigma_S \sigma_{S_i}}$$  \hspace{1cm} (4)

$$S_i = S_i + \text{sign}(\text{dis}(S, S_i))\omega(S, S_i) = S + \text{sign}(\text{sum}(S, S_i)) \frac{1}{\phi(x)} \exp \left( \frac{||S-S_i||_2^2}{b^2} \right)$$  \hspace{1cm} (5)

Where $\text{dis}(S, S_i)$ represents the difference between the $S$ and $S_i$ blocks, and the function $\text{sign}()$ represents the positive and negative values of the variables in the parentheses.

$$\rho\omega(S, S_i) = \frac{1}{\phi(x)} \exp \left( \frac{||S-S_i||_2^2}{b^2} \right)$$  \hspace{1cm} (6)

Calculate the noise-reduced image $g(x, y)$ using equation (7).

$$g(x, y) = \sum_{i=1}^{N} \rho\omega(S, S_i)S_i$$  \hspace{1cm} (7)
3. Simulation experiment results

3.1. Block search experiment analysis
In this paper, based on the simulation experiment of oil and gas pipeline casing damage diagram, through the simulation experiment, for the block search process, we get the path diagram shown in Figure 3: Figure 3.a shows the search path before improvement; Figure 3.b shows the improved partial search path, wherein the pixel in the ② area is the similar block of the search corresponding to the ① area, the ③ area represents the pixel to be optimized, and the ④ area represents the optimized similar block priority search range corresponding to the ③ area. Compared with the improved search path, the improved search path fully considers the global features of the image, so that the search path not only avoids the local global search, but also avoids the problem of time-consuming and resource-consuming global search. Therefore, it is shown in the simulation experiment that the theory has an effective test effect.

Figure 3 Search path alignment chart.

3.2. Formatting the title
As shown in Table 2, we select 10 sets of random pixel points in the gray map corresponding to Figure 1, and simulate and calculate by the traditional block matching algorithm, set to global search, and obtain the similarity corresponding to 10 sets of random pixel points. The number of similar blocks greater than 0.9, the same parameters are set, and the improved block is matched to the similar block number. It can be seen from Table 6 data 6-10 that the improved block matching algorithm has a good experimental effect.

| Number | Pixel coordinates | Improve the number of previous block matches | Number of block matches added after improvement |
|--------|-------------------|--------------------------------------------|-----------------------------------------------|
| 1      | (3,5)             | 109                                        | 9                                             |
| 2      | (5,9)             | 48315                                      | 27                                            |
| 3      | (8,377)           | 13326                                      | 82                                            |
| 4      | (7,345)           | 29235                                      | 98                                            |
| 5      | (8,340)           | 18499                                      | 87                                            |
| 6      | (5,380)           | 3                                          | 32                                            |
| 7      | (7,370)           | 1317                                       | 13                                            |
| 8      | (4,379)           | 10                                         | 54                                            |
| 9      | (5,169)           | 2                                          | 225                                           |
| 10     | (4,172)           | 13                                         | 221                                           |

Finally, the algorithm is applied to the detection of casing damage in oil and gas wells. The noise reduction visual effect obtained by this algorithm is better. As shown in Fig. 4, Fig. 4.a is a noise map, and 4.b is a processed diagram.
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Figure 4 Noise reduction effect diagram.

4. Conclusion
As the problem of oil and gas well casing damage continues to rise, accurate detection of casing damage has become the focus of research in the field of oil and gas production casing maintenance. In this paper, the improved non-local mean filtering algorithm is used for image enhancement for the problem of poor image quality of oil and gas wells. And in order to solve the problem that the algorithm takes a long time, the ant colony pheromone theory and the statistical Pearson similarity algorithm are used to improve the non-local mean filtering algorithm. Simulation experiments show that the proposed algorithm has a good effect on the number of effective similar blocks, accuracy, adaptability and noise reduction.

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