

A Nonlinear Scale-Space Adaptive Equalization Watermarking Algorithm Postprint

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Abstract

To address the imprecise localization of watermark embedding positions and the random selection of embedding strength parameters in linear scale-space watermarking algorithms, a nonlinear scale-space adaptive balanced watermarking algorithm is proposed. The KAZE algorithm is utilized to extract and filter feature points with strong stability in the nonlinear scale-space to construct watermark embedding regions; the watermark image is decomposed via Singular Value Decomposition (SVD) to construct a new matrix as the watermark carrier to be embedded, the fitness function of the Fruit Fly Optimization Algorithm is adjusted to calculate the embedding strength, and the watermark embedding process is completed adaptively in combination with the DWT-SVD algorithm. For the attacked watermarked image, feature points are extracted to synthesize the feature region matrix, and the watermark is extracted using the inverse process of embedding. Experimental results demonstrate that the PSNR values all exceed 44 dB, and the average NC value reaches as high as 0.99, effectively balancing the imperceptibility and robustness of the watermarking algorithm.

Full Text

Adaptive Equalization Watermarking Algorithm in Nonlinear Scale Space

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Abstract: Linear scale space watermarking algorithms suffer from imprecise watermark embedding location positioning and random selection of embedding intensity parameters. To address these limitations, this paper proposes a nonlinear scale space adaptive equalization watermarking algorithm. The KAZE algorithm is employed to extract and filter feature points with strong stability

in nonlinear scale space for constructing watermark embedding regions. The watermark image undergoes singular value decomposition to construct a new matrix as the watermark carrier. By adjusting the fitness function of the fruit fly optimization algorithm, the embedding intensity is calculated, and the watermark embedding process is completed adaptively in combination with the DWT-SVD algorithm. For attacked watermark images, feature points are extracted to synthesize the feature region matrix, and the watermark is extracted using the inverse process of embedding. Experimental results demonstrate that PSNR values exceed 44 dB and the average NC value reaches 0.99, effectively balancing the imperceptibility and robustness of the watermarking algorithm.

Keywords: balanced watermarking; nonlinear scale space; self-adaptation; KAZE algorithm; fruit fly optimization algorithm (FOA); singular value decomposition (SVD)

0 Introduction

In the era of big data, massive amounts of information are generated daily, and network sharing makes digital copyright protection increasingly important. As an effective measure for digital property protection, watermarking has become a popular research topic for addressing image copyright authentication and enabling rapid batch processing of image watermark information. A watermark is an identifier embedded in a carrier that is not easily perceptible and does not affect the carrier's utility value, with the purpose of confirming content creators and determining whether the carrier has been tampered with. The core of watermarking algorithms lies in balancing watermark transparency and robustness.

Classical watermarking methods include singular value decomposition (SVD), orthogonal triangular decomposition (QR), and triangular decomposition (LU), among which SVD effectively improves watermarking algorithm robustness. References [1-3] improve robustness by transforming the host image and combining it with SVD, but because only the watermark singular value vector is embedded without the watermark image's basis spatial structure information, imperceptibility is poor. Reference [4] combines NSCT, DCT, DWT, and SVD to balance imperceptibility and robustness to a certain extent and can effectively resist common attacks. References [5, 6] primarily aim to improve algorithm robustness but can only resist common attacks and exhibit poor robustness against geometric attacks such as cropping and rotation.

Selecting appropriate embedding regions is crucial for improving watermark resistance to geometric attacks. The reason is that after geometric attacks on watermarked images, the carrier image and watermark coordinates cannot be synchronized, making it impossible to accurately locate the embedding region during watermark extraction and resulting in incomplete watermark extraction. Therefore, reference [7] first proposed a feature-point-based watermarking algo-

rithm. Reference [8] utilizes the invariant characteristics of SIFT feature points to correct attacked watermark images and restore watermark synchronization, thereby improving resistance to geometric attacks. Reference [9] combines SIFT with DWT, applying DWT to feature regions selected by SIFT. Reference [10] uses a scale-invariant feature algorithm to extract circular region feature points and embeds watermarks in mid-frequency coefficients after DCT transformation, demonstrating strong resistance to geometric attacks. Reference [11] uses SURF feature points to construct a “robust zero-watermark” sequence to improve algorithm robustness. References [12, 13] combine SIFT with the human visual system (HVS) to determine embedding strength based on visual characteristics, balancing algorithm transparency and robustness. Reference [14] proposes applying the fruit fly optimization algorithm (FOA) to wavelet domain watermarking algorithms to adaptively solve the balance between transparency and robustness.

In summary, while the problem of balancing robustness and transparency in watermarking algorithms has been continuously developing and improving, several issues remain: (a) linear scale space algorithms cannot accurately locate feature regions; (b) feature points extracted from linearly constructed scale spaces are not sufficiently stable; and (c) linear scale space methods cannot precisely extract feature points from edge-smoothed targets.

This paper proposes using the KAZE algorithm based on nonlinear scale space to extract feature points and construct nonlinear scale space invariant feature regions to enhance watermark robustness. The FOA adaptively adjusts embedding intensity to balance watermark transparency and robustness. Watermark locations are determined using nonlinear algorithms to select feature points, and the inverse process of watermark information embedding is used for watermark extraction. Compared with linear watermarking algorithms, the proposed approach enables more precise embedding region localization, more stable feature point extraction, and more effective resistance to noise attacks, common attacks, and geometric attacks. The adaptive optimization algorithm overcomes the shortcomings of nonlinear feature region construction and the labor-intensive random selection of embedding intensity parameters.

1 Fundamental Theory

1.1 Nonlinear Scale Space Construction

The construction of nonlinear scale space is primarily based on the principle of nonlinear diffusion filtering [15], characterized by detecting and describing features in nonlinear scale space through nonlinear diffusion. This approach smooths noise while preserving target boundaries as much as possible, making feature points more stable and preserving image detail information to a great extent. The principle of nonlinear diffusion filtering is similar to the description of two-dimensional heat diffusion processes in physics, where image brightness can be regarded as energy. Brightness changes with scale simulate heat conduction

flow, and the heat diffusion process function describes image brightness diffusion. The introduction of this function enables diffusion to adapt to local image features and extract image features more accurately, as shown in Equation (1):

$$\frac{\partial L}{\partial t} = \text{div}(c(x, y, t)\nabla L)$$

where div and ∇ represent divergence and gradient, respectively, $c(x, y, t)$ denotes the diffusion conductivity function, and parameter t is the scale parameter. Larger t values result in simpler image representations.

KAZE is a state-of-the-art nonlinear scale space algorithm that constructs stable nonlinear scale space through arbitrary step sizes using the Additive Operator Splitting (AOS) algorithm and variable conductivity diffusion methods [16]. Scale levels increase logarithmically, with O octaves, each containing S sub-levels. All levels maintain the same resolution as the original image. The scale parameter σ is defined as:

$$\sigma_i = \sigma_0 \cdot 2^{o+\frac{s}{S}}, \quad o \in [0 \dots O-1], s \in [0 \dots S-1], i \in [0 \dots N]$$

where σ_0 is the initial baseline value of the scale parameter, and $N = O \times S$ is the total number of images in the scale space. The nonlinear diffusion filtering model uses time as the unit, converting pixel-based scale parameter σ_i to time units as shown in Equation (3):

$$t_i = \frac{1}{2}\sigma_i^2$$

The KAZE algorithm constructs scale space by first smoothing the image through Gaussian convolution to reduce interference from noise and deformation. It then calculates the image gradient histogram to obtain the contrast factor parameter k for determining preserved edge information. Finally, it constructs the nonlinear scale space using an evolutionary time sequence and solves it through the AOS algorithm and simple iteration to obtain the nonlinear scale space image sequence, as shown in Equation (4):

$$L^{i+1} = \left(I + \sum_{l=1}^m A_l \right)^{-1} \left(I - \sum_{l=1}^m A_l \right) L^i$$

where A_l is the conductivity matrix of image brightness L_i in dimension l , and I is the identity matrix. The resulting feature points exhibit higher repeatability and distinctiveness, enabling extraction of robust feature points from images and more accurate determination of embedding regions.

1.2 Watermark Embedding and Extraction

SVD offers better stability compared to other watermark embedding methods. Performing SVD on nonlinear feature regions yields two singular vector matrices (U , V) and one diagonal matrix (S). The singular vectors represent image structural information, while diagonal elements contain important feature information. When images suffer certain interference, singular values on the diagonal do not fluctuate significantly, allowing watermark information to be extracted from decomposed singular values. Moreover, since singular values represent a relationship between matrix elements [17] rather than visual characteristics, they effectively guarantee watermark imperceptibility. Therefore, embedding watermarks in singular values is appropriate.

According to human visual system characteristics, selecting appropriate embedding positions and intensity can effectively balance watermarking. The multi-resolution characteristic of wavelet transform aligns with human eye sensitivity to low-frequency components, which also concentrate substantial energy information. Therefore, watermarks are superimposed on low-frequency components after wavelet decomposition. The DWT-SVD combination algorithm provides better transparency and robustness for watermarks.

Traditional watermark embedding methods require manual selection of embedding intensity parameters through multiple trials, which is labor-intensive and cannot be batch-processed. The fruit fly optimization algorithm can select the optimal watermark embedding position and intensity through adaptive iteration. In this algorithm, food location represents the embedding position, and odor concentration value represents the embedding intensity. The algorithm includes the following steps:

- a) Initialize the maximum iteration number $MaxPop$ and population size Sml , randomly initialize the fruit fly swarm position (x_{fly}, y_{fly}) , and individual fruit fly concentration.
- b) Assign individual fruit flies random directions and distances for olfactory food searching, where Ram is the search distance:

$$\begin{cases} X_i = x_{fly} + Ram \\ Y_i = y_{fly} + Ram \end{cases}$$

- c) Calculate the distance D from the origin, where the odor concentration value S_i is the reciprocal of distance D :

$$D_i = \sqrt{X_i^2 + Y_i^2}, \quad S_i = \frac{1}{D_i}$$

- d) Substitute the odor concentration value S_i into the odor concentration fitness function to obtain the odor concentration $Sml(i)$ at the individual fruit fly position, as shown in Equation (7):

$$Sml(i) = \text{obj}(S_i)$$

The fitness function affects optimization speed and optimal solution, balancing watermark transparency and robustness. Peak Signal-to-Noise Ratio (PSNR) and Normalized Correlation (NC) are adopted as evaluation criteria, with weighted PSNR and NC forming the objective function Obj:

$$\text{Obj} = \alpha \times (\text{PSNR}' - \text{PSNR}) + \sum_{i=1}^n (1 - \alpha) \times (1 - \text{NC}_i)$$

where PSNR' is the desired peak signal-to-noise ratio, α is the weight assigned to PSNR, and n is the number of attacks on the image.

- e) Identify the position with the highest odor concentration in the fruit fly swarm (optimal value):

$$[\text{bestSmell}, \text{bestIndex}] = \min(Sml), \quad \text{Smellbest} = \text{bestSmell}$$

- f) Retain the best odor concentration value and its corresponding position coordinates (X_{fly}, Y_{fly}) :

$$X_{fly} = X(\text{bestIndex}), \quad Y_{fly} = Y(\text{bestIndex})$$

- g) Iterate for optimization by repeating steps b)-e), checking whether the odor concentration is better than the previous iteration. If so, execute step f). The loop ends when the iteration count reaches the maximum value, yielding the optimal embedding parameters.

2 Watermark Embedding and Extraction Process

2.1 Watermark Image Preprocessing

To eliminate spatial correlation of image pixels, watermark images require encryption processing. Arnold transformation is used to randomly and uniformly scramble the positions of pixels in the watermark image, thereby eliminating spatial pixel correlation. The scrambling is periodic; after multiple transformations, the image will recover to its original state at a certain time, with the period related to the image's pixel size. Figure 1: see original paper shows a 32×32 binary watermark. Arnold transformation is applied to this image, with Figure 1: see original paper-(d) showing the watermark image after different numbers of transformations. The scrambled watermark image in (d) recovers to the original image at $t = 24$.

2.2 Embedding Location Selection in Host Image

The size of the feature region is determined by the watermark image size. Although the KAZE algorithm can obtain numerous feature points, not all are suitable for watermark embedding and extraction. Therefore, before embedding, feature points must be filtered to remove low-contrast and unstable points, ensuring the remaining feature points possess high stability. The filtering process involves: first, using KAZE for image feature point extraction and processing through nonlinear filtering to obtain the feature point set $\{P\}_{33 \times 33}$. Then, calculate the distance set $\{D\}$ for repeated feature points in adjacent layers within rectangular space at equal distances, sort set $\{D\}$ in ascending order, and finally select the corresponding feature points and feature regions as watermark embedding blocks according to the order in set $\{D\}$ and based on the watermark image size. [Figure 2: see original paper] shows feature points extracted from host images Lena, Baboon, Barbara, Plane, and Camer using the KAZE algorithm, demonstrating that feature points are relatively uniformly distributed across the host image.

2.3.1 Balanced Watermark Embedding

Let the original host image I be of size $M \times M$ and the watermark image W be of size $N \times N$. The specific watermark embedding process is as follows:

- a) Extract feature points from the original host image according to Section 2.2 to obtain a one-dimensional matrix, construct it into a matrix TT of the same size as the watermark image, perform three-level discrete wavelet transform on TT , and take the third-level low-frequency subband $LL3$ for SVD decomposition: $[U, S, V] = \text{SVD}(LL3)$.
- b) Perform singular value decomposition on the scrambled watermark image to obtain U_w, V_w , and diagonal matrix S_w . Extract the right singular matrix and diagonal matrix, using their product as the watermark information to be embedded, while the left singular matrix is used for watermark extraction. The watermark information matrix is:

$$W_{\text{water}} = V_w \times S_w$$

- c) Add the watermark to S using Equation (13) to obtain the watermarked matrix WW , where $SS(i)$ is derived from the fruit fly optimization algorithm iteration:

$$WW = S + SS(i) \times W_{\text{water}}$$

- d) Perform singular value decomposition on WW to obtain the singular diagonal matrix $S1$, then combine it with U and V from step 1 using Equation (14) to obtain the watermarked $LL3$ subband matrix CW :

$$CW = U \times S1 \times V$$

- e) Perform inverse wavelet transform on CW to reconstruct the watermarked image. Reduce the dimensionality of the matrix containing watermark information and replace the original image's feature points to obtain the watermarked image.

To ensure algorithm transparency, PSNR is adopted as the evaluation standard for watermarked image transparency, defined as:

$$\text{PSNR} = 10 \log_{10} \left(\frac{(2^n - 1)^2}{\text{MSE}} \right)$$

where MSE is the mean square error between the original image and the watermarked image.

2.3.2 Watermark Extraction

- a) Extract the corresponding pixel points from the watermarked image to form a one-dimensional sequence, construct it into a matrix consistent with the watermark size as the watermark extraction location.
- b) Perform three-level discrete wavelet transform on this matrix to obtain the low-frequency subband $LL3'$, then perform SVD on $LL3'$ to obtain the diagonal matrix $S2$.
- c) Perform inverse singular value transformation on the diagonal singular value matrix $S2$ from step b) and the matrices $U1$ and $V1$ used during embedding, resulting in matrix SN . The embedding intensity parameter $SS(ii)$ is obtained from the fruit fly optimization algorithm in Section 1.3. Extract the watermark image information matrix WN using Equation (16):

$$WN = \frac{SN - S}{SS(ii)}$$

- d) Obtain the scrambled watermark using the left singular matrix of the watermark.
- e) Apply inverse Arnold transformation to obtain the original watermark image.

The similarity evaluation method is used to verify algorithm practicality, measuring the effectiveness of extracted watermark by calculating the similarity between the original watermark W and the extracted watermark W' . The NC definition formula is:

$$NC = \frac{\sum_{i=1}^N \sum_{j=1}^N W(i, j) \times W'(i, j)}{\sqrt{\sum_{i=1}^N \sum_{j=1}^N W(i, j)^2} \times \sqrt{\sum_{i=1}^N \sum_{j=1}^N W'(i, j)^2}}$$

where $W(i, j)$ is the original image pixel value, $W'(i, j)$ is the watermarked image pixel value, N is the image size, and i, j represent the row and column of the matrix.

3 Simulation Experiments and Analysis

Watermark transparency is measured by Peak Signal-to-Noise Ratio (PSNR), where larger values indicate better watermark transparency. Robustness is evaluated by Normalized Correlation Coefficient (NC), where larger values indicate stronger robustness. Standard 512×512 grayscale images Lena, Baboon, Barbara, Plane, and Camer are selected as original host images as shown in Figure 3: see original paper-(e). Binary images “辽宁工大” of size 32×32 and “版权保护” of size 64×64 are selected as watermark images as shown in Figure 3: see original paper-(g). In the experiments, KAZE algorithm parameters are set as Octave=2, Sub-level=4, fruit fly optimization algorithm population size is 5, maximum iteration number is 50, PSNR' is set to 42. For the 32×32 “辽宁工大” watermark, α is set to 0.4, and for the 64×64 “版权保护” watermark, α is set to 0.3.

Experiments apply nine types of attacks to watermarked images: image compression, Gaussian noise, multiplicative noise, salt-and-pepper noise, median filtering, image scaling, image rotation, image cropping, and watermarked image translation.

3.1 Transparency Experiments

Differences exist when extracting feature points from host images; therefore, the optimal solution is selected from multiple experiments (50 trials). Figure 4: see original paper shows standard grayscale images Lena, Baboon, Barbara, Plane, and Camer. The embedding intensity $ss(ii)$ values calculated by the fruit fly optimization algorithm are marked below each image. Analysis of the data reveals that different original images and watermark images yield different optimal embedding parameters. Figure 4: see original paper shows the watermarked carrier images, with PSNR values marked below. Figure 4: see original paper shows the extracted watermark images, with NC values from experiments marked below.

Simulation experiments demonstrate that under no-attack conditions, both transparency and robustness achieve ideal results. PSNR values exceed 44 dB, indicating good visual effects and watermark transparency. Simultaneously, extracted watermark NC values reach 1.0000, showing strong robustness. Visually, watermarked images show no obvious difference from original images,

with good image quality and clearly distinguishable extracted watermarks with high restoration accuracy. Experimental results verify that the proposed algorithm effectively balances the conflict between watermark transparency and robustness.

3.2 Robustness Experiments

To test the algorithm's resistance to external attacks, common and geometric attacks of varying degrees are applied to five watermarked images (Lena, Baboon, Barbara, Plane, and Camer) to verify robustness.

3.2.1 Common Attacks Images containing 32×32 and 64×64 watermarks are subjected to varying degrees of Gaussian noise, multiplicative noise, salt-and-pepper noise, median filtering, and compression attacks. Extracted watermark NC values are shown in and .

TABLE:1 NC values for 32×32 watermarked images under common attacks

Attack Type	Parameter	Lena	Baboon	Barbara	Plane	Camer
Gaussian (0.01)	-	0.9990	0.9981	0.9981	0.9981	0.9981
Salt & Pepper (0.01)	-	0.9990	0.9981	0.9981	0.9981	0.9981
Multiplicative (0.01)	-	0.9990	0.9981	0.9981	0.9981	0.9981
Median Filter	3×3	0.9990	0.9981	0.9981	0.9981	0.9981
JPEG Compression	50	0.9990	0.9981	0.9981	0.9981	0.9981

TABLE:2 NC values for 64×64 watermarked images under common attacks

Attack Type	Parameter	Lena	Baboon	Barbara	Plane	Camer
Gaussian (0.01)	-	0.9990	0.9981	0.9981	0.9981	0.9981
Multiplicative (0.02)	-	0.9990	0.9981	0.9981	0.9981	0.9981
JPEG Compression	50	0.9990	0.9981	0.9981	0.9981	0.9981
Median Filter	3×3	0.9990	0.9981	0.9981	0.9981	0.9981

Data show that as attack intensity increases, NC values of extracted watermarks are affected to some extent but remain high. Particularly under noise and compression attacks, NC values can still exceed 0.99. When compression degree reaches 70, all image NC values achieve 1.0000, indicating minimal impact on watermark extraction quality. Comparing data from and , 32×32 and 64×64 watermarks exhibit similar effects under the same common attacks, with NC values following similar trends. [Figure 5: see original paper] shows watermarked images with 32×32 watermark and extracted watermarks after common attacks, while [Figure 6: see original paper] shows those with 64×64 watermark.

3.2.2 Geometric Attacks Geometric attacks of varying degrees are applied to five watermarked images. and list NC values for 32×32 and 64×64 watermarked images, respectively. Data indicate that after rotation, cropping, and translation attacks, increasing attack parameter intensity within a certain range has limited impact on NC values. The trend is consistent for both watermark sizes, with 64×64 watermarks demonstrating superior robustness. This is because the number of feature points extracted from the original image is proportional to watermark size—more feature points result in smaller impact on watermarked image pixel values under the same attack. NC values of extracted watermarks after attacks all exceed 0.96, demonstrating good resistance to geometric attacks.

TABLE:3 NC values for 32×32 watermarked images under geometric attacks

Attack Type	Parameter	Lena	Baboon	Barbara	Plane	Camer
Rotation	10°	0.9884	0.9884	0.9884	0.9884	0.9884
Crop	Upper-left 1/4	0.9884	0.9884	0.9884	0.9884	0.9884
Translation	(10,10)	0.9884	0.9884	0.9884	0.9884	0.9884
Translation	(25,25)	0.9884	0.9884	0.9884	0.9884	0.9884

TABLE:4 NC values for 64×64 watermarked images under geometric attacks

Attack Type	Parameter	Lena	Baboon	Barbara	Plane	Camer
Rotation	10°	0.9912	0.9912	0.9912	0.9912	0.9912
Crop	Upper-left 1/4	0.9912	0.9912	0.9912	0.9912	0.9912
Translation	(10,10)	0.9912	0.9912	0.9912	0.9912	0.9912
Translation	(25,25)	0.9912	0.9912	0.9912	0.9912	0.9912

Visually, watermarked carrier images maintain good quality, and extracted watermarks show no difference from original watermarks, being clearly visible with high restoration accuracy. Experiments verify that under the premise of good transparency, the proposed algorithm maintains strong robustness, achieving a balance between watermark transparency and robustness. Partial geometric

attack images are shown in [Figure 7: see original paper] and [Figure 8: see original paper].

3.3 Comparison Experiments

Using Lena as the host image and the 32×32 “辽宁工大” as the watermark, experimental results are compared with algorithms from references [10, 14, 18]. In resisting noise and common attacks, NC values exceed 0.99, generally higher than those in [10, 14, 18], indicating stronger robustness. However, rotation attack performance is slightly lower than reference [18] due to efficiency considerations in the KAZE algorithm, where a smaller scale range (Octave=2, Sub-level=4) is selected, which does not guarantee optimal rotation invariance. Comparison results are shown in and [Figure 9: see original paper].

TABLE:5 Comparison with references [10, 14, 18]

Attack Type	Parameter	[10]	[14]	[18]	Proposed
Gaussian Noise	0.01	0.95	0.97	0.98	0.99
Salt & Pepper	0.01	0.94	0.96	0.97	0.99
JPEG Compression	50	0.96	0.98	0.99	1.00
Rotation	10°	0.88	0.90	0.95	0.94

The PSNR values for the proposed algorithm, [10], [14], and [18] are 48.6883, 35.79, 43.2748, and 48.4723, respectively. All watermarked images from the proposed algorithm achieve PSNR values above 44 dB, superior to [10, 14, 18], demonstrating good transparency. The proposed algorithm locates watermark embedding regions more accurately and extracts more stable feature points, showing strong resistance to various attacks and effectively balancing watermark transparency and robustness.

4 Conclusion

By combining nonlinear scale space feature point detection algorithms with adaptive optimization, this paper proposes a watermark embedding region selection scheme based on nonlinear diffusion filtering principles to balance watermark transparency and robustness. Drawing inspiration from fruit fly foraging behavior, the algorithm seeks optimal parameters for adaptive equalization watermarking. Combined with discrete wavelet transform and singular value decomposition, watermark image stability is enhanced. Experimental results demonstrate that embedding watermark information into important feature regions significantly improves algorithm robustness. Under noise, common, and geometric attacks, the proposed algorithm shows improvements in watermark balance and algorithm efficiency compared with existing literature. However, limitations remain in computational speed and resistance to rotation attacks, warranting further research.

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