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Applications of Multiscale Geometric Analysis in Image Texture Recognition and Classification

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ABSTRACT

With the rapid development of computer vision, the applications of image texture recognition and classification are increasingly prevalent across various domains, particularly in medical imaging, industrial inspection, and remote sensing image analysis, these applications hold significant practical importance. Traditional texture recognition techniques often rely on manually designed feature extraction methods, which tend to perform poorly in complex environments, are sensitive to noise and lighting variations, and are limited when dealing with non-uniform or multiscale textures. To address these shortcomings, this paper introduces two novel texture analysis methods that enhance the robustness of texture features and improve classification accuracy. The first part of the study presents the contourlet-kernel spectral regression (KSR) image texture feature extraction technique, which, by integrating Contourlet transform with Krawtchouk polynomials, effectively enhances the descriptive power and adaptability of features. The second part explores a texture image classification method based on domain-multiresolution co-occurrence matrices (MCM), which significantly improves the accuracy and robustness of the classification process by analyzing the co-occurrence characteristics of images at multiple resolutions. The introduction of these methods not only optimizes texture recognition performance but also advances the application of image processing technologies in complex scenarios.

1. INTRODUCTION

With the rapid development of computer vision technology, image texture recognition and classification has become an important research direction in the field of image processing [1-4]. Image texture contains rich structural information about the scene, making it one of the key elements in understanding image content. Traditional methods of texture recognition often rely on manually designed feature extraction techniques, which are usually limited to specific texture types and complexities [5, 6]. To address challenges in various practical application scenarios, researchers are increasingly inclined to develop intelligent analysis algorithms that can adapt to multiscale and diverse textures [7, 8].

The study of texture recognition and classification is not only of significant importance for scientific research but also has a profound impact on the applications in fields such as industrial automation, medical image analysis, and remote sensing image processing [9-13]. For example, accurate texture recognition in medical image analysis can help doctors better diagnose diseases; in the field of remote sensing, effective texture classification can improve the accuracy of identifying land cover types. Therefore, exploring more effective methods for texture recognition and classification can enhance the analytical capabilities of image data in these fields, thereby promoting the advancement and application of related technologies.

However, existing methods of texture analysis have some shortcomings. Firstly, many traditional texture feature extraction methods are sensitive to noise and lighting changes, easily affected by environmental factors, which impacts the accuracy of classification [14-17]. Secondly, these methods often perform poorly when dealing with highly non-uniform or multiscale textures, failing to adequately capture the details and layers within complex textures [18-20]. Therefore, developing new algorithms to improve the robustness of texture features and the efficiency of classification has significant practical importance for the advancement of texture analysis technology.

This paper addresses the limitations of existing technologies by proposing two new methods of texture analysis. The first part introduces the Contourlet-KSR image texture feature extraction technique, which combines the multiscale and multidirectional advantages of the Contourlet transform with the spectral response characteristics of Krawtchouk polynomials, effectively enhancing the descriptive power and interference resistance of features. The second part discusses a texture image classification method based on domain MCM, which further improves the accuracy and robustness of classification by analyzing the co-occurrence characteristics of images at multiple resolutions. Through the application of these two methods, this paper not only demonstrates effectiveness in diverse texture environments but also provides new research directions and an experimental basis for the future development of image texture recognition and classification technologies.

2. CONTOURLET-KSR IMAGE TEXTURE FEATURE EXTRACTION

Compared to traditional wavelet transform methods, although wavelet transforms can perform multiscale decomposition, their ability for directional decomposition is limited and often insufficient to capture complex texture directions in images. Therefore, this study introduces the Contourlet transform to optimize the image texture feature extraction process. Compared to wavelet transforms, the Contourlet transform not only retains the characteristics of multiscale decomposition but also provides richer directional information, which is crucial for revealing the subtle texture structures in images. This high directional sensitivity is especially important in complex image texture analysis, such as vegetation cover in natural scenes or pathological tissues in medical images, significantly enhancing the discriminability and efficiency of texture features.

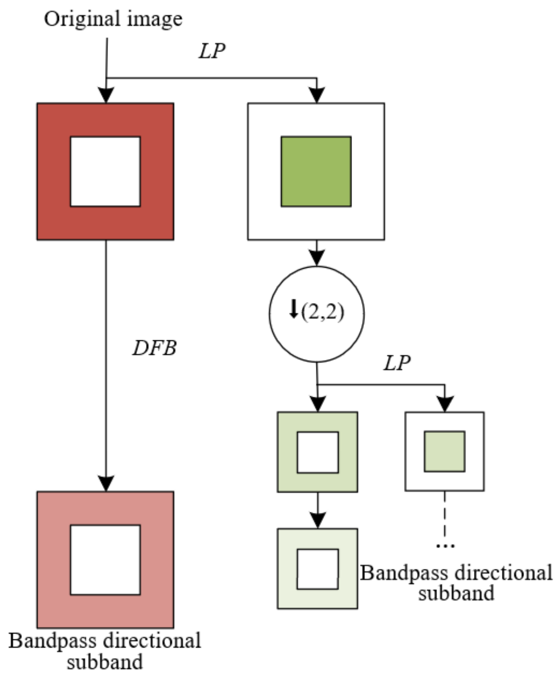

Figure 1. Principle of the discrete Contourlet transform filter bank decomposition

The discrete Contourlet transform, also known as the pyramidal directional filter bank (DFB), is a composite filter structure consisting of a Laplacian pyramid (LP) and a DFB. This transform is particularly important in the application of image texture feature extraction because it can effectively capture the texture information and local details in images. In the implementation of the Contourlet transform filter bank decomposition, the LP is used to decompose the original image into approximate low-frequency components and high-frequency detail components. This decomposition helps reveal the basic structures and singularities in the image, such as texture edges and breakpoints. By recursively decomposing the approximate component further with LP, the system can extract the texture and structural information of the image at multiple scales, which is crucial for complex texture analysis. Figure 1 shows the principle of the discrete Contourlet transform filter bank decomposition.

The implementation process of the Contourlet transform filter bank decomposition involves using the DFB to perform multi-directional decomposition on the high-frequency detail components obtained after LP decomposition. At this stage, singularities located in the same direction are merged into single coefficients, forming the Contourlet transform coefficients. As the scale increases, the number of directions in the Contourlet transform also increases, allowing the transform to capture finer texture details at various scales and directions. The coefficients in each direction have a gear-shaped support base, which is very suitable for capturing lines and curves in the image, such as texture stripes, thus effectively depicting the texture contours of the image. This method is particularly suitable for dealing with complex texture features in images, such as natural landscape tree textures or fabric detail textures.

Once the Contourlet transform is completed in the discrete domain, this transform can be extended to the square-integrable space of continuous functions, allowing for more detailed image analysis in the continuous domain. This process, through iterative filter bank operations, decomposes the image space into a sequence of multiscale and multidirectional subspaces, allowing for exhaustive extraction of texture features across various directions and scales. This decomposition method is particularly suitable for texture recognition and classification, as it captures the directionality and scale variations of textures, which is crucial for analyzing complex texture patterns in natural scenes such as trees, water ripple textures, or artificial environments such as fabrics and materials. Moreover, the multiscale and multidirectional processing capability of the Contourlet transform ensures that texture details from coarse to fine are effectively captured and described, greatly enhancing the effectiveness and application scope of image texture feature extraction. The orthogonal operation is denoted by $\oplus$, and the approximation component at the lowest level is denoted by N_0, while the detail component at scale 2^{mk-1} is denoted by $Q^{mk}_{k,j}$, then there is:

$$L^2\left(R^2\right)=N_0\oplus\left(\bigoplus_{k\le 0}\left(\bigoplus_{k\le 0}^{2^{m_k}} q_{k,j}^{m_k}\right)\right) \tag{1}$$

If the scale, direction, and position parameters are represented by k, j, and v respectively, the continuous domain Contourlet function is denoted by $\{\vartheta^{mk}_{k,j,v}(s)\}$, which gives the expression:

$$\vartheta_{k,j,v}^{m_k}(s)=\sum\nolimits_{l\in c^c} h_j^{m_k}\left(l-a_j^{m_k}v\right)\omega_{k,l}(s) \tag{2}$$

Assuming the low-pass analysis filter is represented by h^{mk}_{j}, the framework defined in the low-dimensional space R^2 is denoted by $\omega_{k,l}(s)$, and the oversampling matrix is represented by t^{mk}_{j}, the following definitions apply:

$$t_j^{m_k}=\begin{cases} DIAG\left(2^{m_k},2\right), 0\le j\le 2^{m_k-1} \\ DIAG\left(2,2^{m_k}\right), 2^{m_k}\le j\le 2^{m_k-1} \end{cases} \tag{3}$$

In the application of image texture feature extraction, the high dimensionality of features typically leads to a high model complexity, thereby affecting learning efficiency. To effectively address this challenge, this paper employs the Contourlet-KSR method, which is a technique that combines the Contourlet transform with the KSR. The Contourlet transform, with its capability for multiscale and multidirectional decomposition, can extract rich image texture information; while KSR, as a nonlinear dimensionality reduction technique, not only reduces redundant features but also preserves the local geometric structure of the data, i.e., the inherent manifold structure of image texture features. This method is particularly suitable for image texture feature extraction because it not only optimizes the representativeness and classification performance of the features but also simplifies the computational process through dimensionality reduction, enhancing processing speed. Compared to other application scenarios, image texture feature extraction places a greater emphasis on capturing and describing subtle texture differences within images, which is crucial for enhancing the accuracy and efficiency of image analysis.

In the process of image texture feature extraction, the first step of applying the KSR algorithm involves constructing a neighborhood graph H, which models the low-dimensional manifold structure of image data in high-dimensional space. In this process, the graph H contains v vertices, each representing an image sample a_u. If two samples a_u and a_k belong to the same texture category, they are connected by an edge in the neighborhood graph. Such a connection strategy is based on the assumption that samples of the same category have similar texture properties and therefore should remain close in the low-dimensional space. The construction of this neighborhood graph ensures that samples which are close to each other in the original high-dimensional space remain close when mapped to the low-dimensional space, effectively reflecting the intrinsic structure and texture patterns of the original data.

The second step involves determining the weight Q of the edges in the neighborhood graph. In graph H, if there is an edge connection between vertices u and k, the weight q_{uk} is set to $1/m_j$, where m_j is the number of samples belonging to the same category j, with z representing the total number of categories. This weighting design aims to balance the influence of each category's samples in the graph, preventing bias in the overall dimensionality reduction results due to a larger number of samples in certain categories. If there is no edge connection between vertices u and k, the corresponding weight q_{uk} is 0. This weighting helps maintain the cohesion of samples within the same category during the dimensionality reduction process while allowing samples from different categories to be appropriately separated in the low-dimensional space, thus enhancing the classifier's performance and accuracy in handling image texture features.

The third step of the KSR algorithm involves calculating the response vector b, which is central to the dimensionality reduction process. Initially, imagine projecting the neighborhood graph H onto a one-dimensional space, resulting in the response vector $y=[y_1,y_2....y_N]^T$.

$$\begin{aligned} & MIN\sum\nolimits_{u,k=1,u\neq k}^{v} q_{uk}\left(b_u-b_k\right)^2 \\ & s.t.\, b^S F b=1 \end{aligned} \tag{4}$$

To achieve this goal, we first construct a diagonal matrix F, where the diagonal element F_{uu} equals the weighted degree f_u of vertex u, with f_u being the sum of the weights q_{uk} between vertex u and all other vertices. Next, we define the Laplacian matrix M as M=F-Q, where Q is the weight matrix. This equation is obtained through a linear transformation:

$$\begin{aligned} b^* &= \underset{b^S Fb=1}{ARGMIN}\, b^S Mb = ARGMIN\frac{b^S}{b^S Fb} \\ &= ARGMIN\frac{n^S Qn}{n^S Fn} \end{aligned} \tag{5}$$

The Laplacian matrix crucially reflects the topological structure of the graph and is used to find a low-dimensional representation that preserves the local structure of the original data as much as possible. Solving the generalized eigenvalue problem of this matrix yields the first z largest generalized eigenvectors b_1, b_2, ..., b_z, which define the new coordinate axes mapped to the low-dimensional space. In the application of image texture feature extraction, these vectors help us capture the most representative texture features and maintain the relative positions and distances between samples in the original high-dimensional space, effectively revealing the internal texture structure and changes in the image. The corresponding generalized eigenvalue problem is:

$$Q_b=\eta Fb \tag{6}$$

The fourth step involves the implementation of regularized kernel least squares, which is used to optimize and precisely calculate the features expressed after dimensionality reduction. In this step, we construct a linear function $b_u=d(a_u)=\beta^S a_u$, where β is a coefficient vector obtained by solving a regularized least squares problem. x_j is the solution to the following regularized least squares problem:

$$x_j=\underset{x}{ARGMIN}\left(\sum\nolimits_{u=1}^{v}\left(x^S a_u-b_u^j\right)+\alpha\left\|x\right\|^2\right) \tag{7}$$

In practice, this optimization problem is converted into solving a set of linear equations, which are expressed in a kernelized form, transforming the original problem into a regularized kernel least squares problem:

$$\left(aa^T-\alpha U\right)x_j=ab_j \tag{8}$$

The kernel method, by introducing a kernel function $J(a,a_u)$, allows us to perform linear learning in a high-dimensional feature space while the actual calculations are still performed in the original dimensions.

$$\left(J+\alpha U\right)x_j=b_j \tag{9}$$

Thus, the final function $d(a)$ is expressed as $d(a)=\Sigma^v_{u=1}x^j_u J(a,a_u)$, where a^k_i is the solution to the regularized kernel least squares problem.

$$\underset{d\in G_j}{ARGMIN}\left(\sum\nolimits_{u=1}^{v}\left(d\left(a_u\right)-b_u^j\right)^2+\alpha\left\|d\right\|_{G_J}^2\right) \tag{10}$$

The fifth step involves using the eigenvectors obtained in previous steps to construct the projection matrix $\Phi=[x_1,x_2....,x_{z-1}]\in R^{v\times z-1}$, which is obtained by solving the least squares problem. This step is critical in the entire dimensionality reduction process, mapping the high-dimensional image data to a z-1 dimensional subspace:

$$a \rightarrow c = \Phi^S J(:,a) \tag{11}$$

This projection matrix Φ not only simplifies the dimensionality of the data but also preserves the important structural features of the original data, ensuring that the dimensionality-reduced data still retains key information about image texture. In this way, the sample data is embedded into a lower-dimensional space, effectively extracting the most critical features for classification recognition, while reducing computational complexity and enhancing processing efficiency.

In the application of the Contourlet-KSR feature extraction method to image texture feature extraction, parameter settings should be carefully considered to ensure the method can effectively process and analyze various texture types. First, for the setting of Contourlet transform parameters, adjustments need to be made based on the complexity and diversity of different image textures to optimize the performance of multiscale and multidirectional decomposition, thereby capturing more detailed and distinctive texture features. Second, in the implementation of the KSR algorithm, the construction of the neighborhood graph uses Euclidean distance to measure the distance between sample points, as Euclidean distance provides an intuitive and practical measure of similarity in most texture analysis scenarios. The weights of the edges are set using the heat kernel, with the kernel parameter set to 3, which helps to strengthen the connections within local neighborhoods, ensuring local continuity of texture structure and overall class cohesion in the image.

Finally, a support vector machine (SVM) is used for the final classification, where the SVM's kernel parameter is selected within a range from 0 to 4 in steps of 0.01. Such fine-tuning helps find the optimal model complexity, balancing the risks of overfitting and underfitting, while the penalty factor C remains default, providing a standard level of regularization. These parameter settings work together, aiming to maximize the recognition capability and classification accuracy of texture features extracted from complex image data while maintaining manageable computation.

In the experimental steps of applying the Contourlet-KSR feature extraction method for image texture feature recognition, the process can proceed as follows, as detailed in Figure 2:

(1) Perform a Contourlet transform on each image, decomposing it using multiscale and multidirectional methods to obtain several directional subbands and a low-pass subband.

(2) Calculate the mean and variance of each subband image and integrate these statistics into a one-dimensional long vector, see Figure 3 for the process.

(3) Vertically concatenate the statistical feature row vectors of all images to form a Contourlet feature matrix.

(4) Normalize the feature matrix and divide the samples into a training set and a test set, typically using even-numbered samples for training and odd-numbered samples for testing.

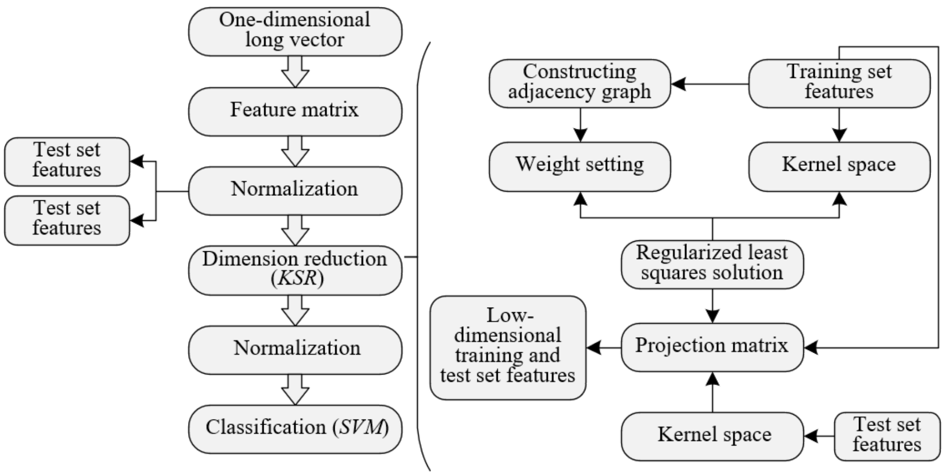

Figure 2. Flowchart of image texture feature recognition process

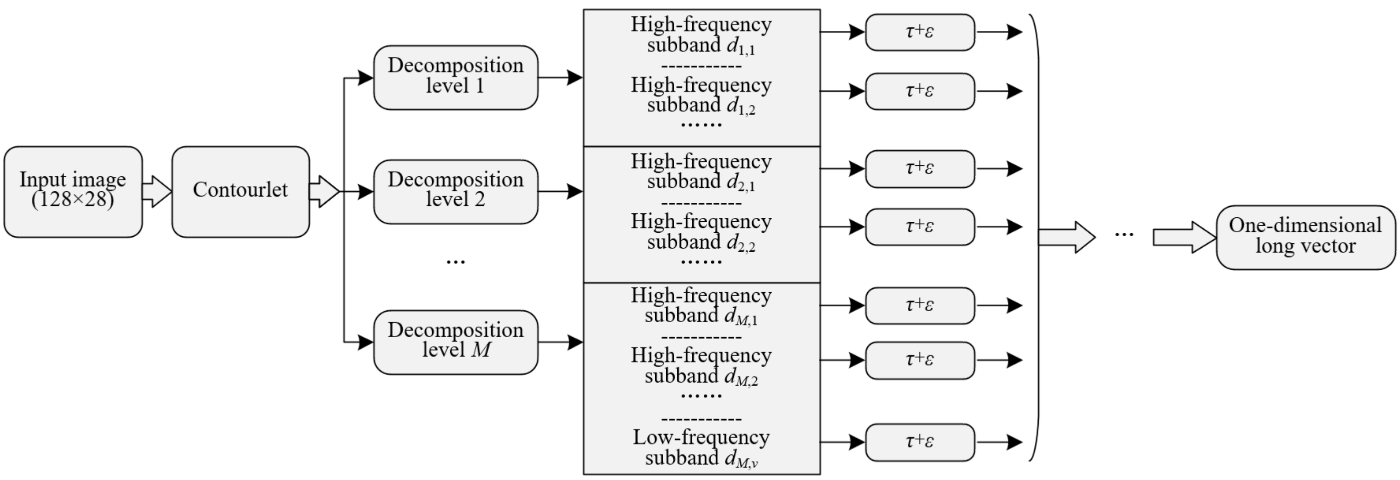

Figure 3. Flowchart of the process for acquiring a one-dimensional long vector

(5) Apply the KSR algorithm to perform dimensionality reduction on the feature matrix of the training set, and use the obtained projection matrix to perform the same reduction on the feature matrix of the test set.

(6) Normalize the feature matrices of the dimensionally reduced training and test sets to standardize the data input format, enhancing the performance of the classification algorithm.

(7) Finally, input the normalized features and their corresponding category labels into a SVM for final classification, with its efficient boundary decision function, SVM can accurately distinguish between different texture categories.

3. TEXTURE IMAGE CLASSIFICATION BASED ON DOMAIN MCM

In the application scenario of image texture classification, to overcome the limitations of traditional spatial domain gray-level co-occurrence matrices in describing texture features, this paper introduces a new feature extraction method—MCM. The core of this method lies in the use of non-subsampled wavelet transforms to maintain image translational invariance and ensure that the size of the processed subbands matches the original image size, which is crucial for maintaining the stability of statistical features of the image. Non-subsampled wavelet transforms allow the capture of texture information at different resolution levels, not only enhancing sensitivity to image texture details but also maintaining consistency of texture features across various scales. Compared to other feature analysis methods, MCM is particularly suited for texture image classification because it allows for a more comprehensive depiction of an image's texture structure and patterns by analyzing texture features at multiple resolution levels, thus improving classification accuracy and robustness.

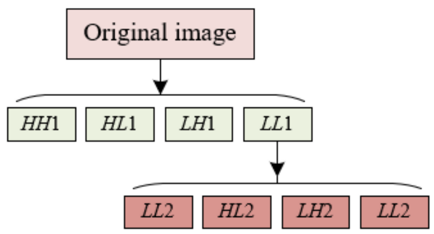

Figure 4. Schematic of non-subsampled wavelet decomposition

During the calculation process of MCM, the target image is first subjected to *M*-level non-subsampled wavelet transformation. This transformation strategy is particularly suitable for texture analysis because it maintains image translational invariance without losing any image information, and generates 3×*M*+1 subbands of the same size as the original image. Figure 4 provides a schematic of non-subsampled wavelet decomposition. This type of transformation allows us to analyze the image at different scales, thereby capturing more detailed texture features. Subsequently, a co-occurrence matrix is calculated for each subband, involving the setting of specific parameters such as direction, pixel distance, and quantization order. The choices of these parameters directly impact the sensitivity and descriptive power of the co-occurrence matrix. Ultimately, three key statistical measures are extracted from each co-occurrence matrix: contrast (*CON*), entropy (*ENT*), and correlation (*COR*). These metrics are selected as multiresolution co-occurrence features because they describe various aspects of texture roughness, complexity, and pattern similarity.

In the transformation domain co-occurrence matrices aimed at texture image classification, the choice of specific parameters is critical for accurately capturing and describing texture features. Below is a detailed analysis of three main issues to consider for transformation domain co-occurrence matrices:

(1) Choice of direction parameters: The non-subsampled wavelet transform produces horizontal, vertical, and diagonal subbands at each scale, which capture texture information in different directions of the image. Based on the physical meaning of the co-occurrence matrix, particularly the definition of correlation (*COR*), it is reasonable to choose direction parameter values consistent with the subband directions. For example, for a horizontal direction subband, a direction parameter of 0° is appropriate as it best describes the texture features in that direction; a vertical direction subband should select a direction parameter of 90°, and a diagonal direction subband should select a direction parameter of 45°. Such parameter matching ensures that the co-occurrence matrices can effectively reflect the texture details and structural differences in each direction.

(2) Determination of the distance parameter: The distance parameter t reflects the spatial interval of pixel pairs in the computation of the co-occurrence matrix, directly related to the frequency periodicity of the texture. Research indicates that setting t to 1 effectively substitutes for the high-frequency components in wavelet features, describing the fine structure of the image. In the context of non-subsampled wavelet transformation, this choice helps to effectively combine spatial features with transformation domain features, enhancing the expressive power of texture features while simplifying the feature extraction process, making the features extracted from the image more reflective of actual texture patterns.

$$t = 2^m, m = 1, 2, \cdots, M \tag{12}$$

(3) Application of quantization strategies: In co-occurrence matrix analysis, traditional methods require uniform quantization of gray levels within the range of 0 to 255, typically selecting 16 or 32 as the quantization order. However, the distribution of subband coefficients after wavelet transformation does not follow a uniform distribution, especially in the detail subbands, which are characterized by "high peaks, long tails, and zero mean", in contrast to the nearly uniform distribution of approximation subbands within the range of 0 to 1024. Therefore, the choice of quantization strategy needs to consider these distribution characteristics to more accurately capture and describe the texture information in each subband, avoiding the loss of important texture details due to inappropriate quantization. Assuming the quantization order for the *m*-th scale detail subband is represented by Δ*m*, the formula is as follows:

$$\Delta_m = \begin{cases} a & \left|a(l,v)\right| \le 3\delta_m \\ b & \left|a(l,v)\right| > 3\delta_m \end{cases}, m = 1, 2, \cdots M \tag{13}$$

In the research of image texture classification, effective feature selection is key to improving classification accuracy and reducing computational resource consumption. Faced with a large number of extracted features, such as those generated by MCM, direct feature extraction and reduction of feature redundancy through spatial transformations like *K-L* transformation or Principal Component Analysis are common strategies. Although these transformation methods can reduce feature dimensions by eliminating correlations among features, they typically sacrifice the interpretability of the features, which is undesirable in pattern recognition because features with strong interpretability are crucial for understanding the decision process and effectiveness of classifiers. To address this issue, a new feature selection method is proposed that aims to select features from MCMs, gray-level co-occurrence matrices, and wavelet energy features that are both physically meaningful and complementary. This method considers the redundancy and complementarity among features, optimizing the feature set by analyzing their correlations, ensuring that the selected features are not only statistically effective but also directly related to the physical properties of textures. Such a strategy not only maintains or even enhances classification accuracy but also provides a more intuitive understanding, aiding further analysis and interpretation of pattern recognition results. This feature selection method is particularly important in image texture feature analysis because texture features often have high complexity and subtle differences, requiring careful handling to ensure effective classification.

When using MCM for feature extraction in image texture classification, the feature selection strategy is crucial for effective classification. The statistical measures analyzed by MCM include contrast (*CON*), entropy (*ENT*), and correlation (*COR*), each with specific physical significance that aids in understanding different properties of image textures. *CON* mainly describes the smoothness and clarity of the image, while *ENT* reflects the complexity of the texture. Although *CON* and *ENT* show high correlation in different directional subbands at the same scale, *COR* exhibits lower correlation and can independently reflect the dominant direction of the texture. Therefore, in selecting features for texture classification, *COR* from each scale and direction is essential, while choosing one direction of *CON* and *ENT* per scale is sufficient. This strategy not only optimizes based on the physical significance of the measures and their correlations but also significantly reduces the feature dimensions, thus enhancing processing efficiency and classification performance. Specifically, by carefully selecting features, the dimensionality of multiresolution co-occurrence features can be reduced to about half of the original, which is particularly important when dealing with large data sets and complex image textures. This feature selection method not only considers the complementarity and redundancy of features but also fully utilizes the independent information of each feature, ensuring that the final feature set used for model training and classification is both compact and effective.

In applications aimed at texture image classification, the combined use of MCM and wavelet energy features can more effectively improve classification accuracy, although this method increases the dimensionality of features. Wavelet energy features, composed of the energy of wavelet transform subbands, are widely used in the field of image analysis due to their simplicity and effectiveness. Specifically for texture analysis, the energy and entropy (*ENT*) of wavelet detail subbands have some redundancy, as *ENT*, in describing the complexity of the texture, correlates with the energy of wavelet detail subbands; the more complex the texture in the image, the higher the energy typically is in the detail subbands. However, as the approximation subbands represent the low-frequency components of the image, their energy reflects the overall brightness rather than the complexity of details, thus the energy of approximation subbands, with generally lower entropy values, displays different characteristics, making the energy of approximation subbands irreplaceable in texture description. This combination of MCM and wavelet energy features, making full use of the multiscale and multidirectional capabilities of wavelet analysis and the statistical analysis advantages of co-occurrence matrices, effectively captures both global and local characteristics of images. In texture classification, this feature combination not only provides a deeper understanding of texture structure but also, through complementary properties, reduces the potential for information omission by single features, ensuring the robustness and accuracy of classifiers when handling various complex textures. This demonstrates that in designing texture classification systems, the physical significance of features and their effectiveness in specific tasks should be comprehensively considered, thereby selecting the feature set that best represents the image texture attributes.

4. EXPERIMENTAL RESULTS AND ANALYSIS

In comparing the experimental results of different image texture feature extraction methods, we can observe that each technique performs variably in terms of feature dimension, time consumed, recognition rate, and recognition rate after KSR dimension reduction (see Table 1). Wavelet transformation, with a feature dimension of 31 and a time consumption of 28, achieved a recognition rate of 92.31%, which increased to 93.45% after KSR dimension reduction. Local Binary Patterns (LBP) had a higher feature dimension (245) and a time consumption of 31, with an original recognition rate of 81.2%, which improved to 87.56% after KSR reduction. Gabor filters showed the best time efficiency (21) and reached a recognition rate of 91.25% with a feature dimension of 241, slightly improving to 92.31% after KSR reduction. Dual-Tree Complex Wavelet Transform (DT-CWT), with the lowest feature dimension (25) and a slightly higher time consumption (33), achieved a recognition rate of 93.54%, which increased further to 95% after KSR reduction. The method discussed in this paper, although slightly higher in time consumption and feature dimension (51), approached the optimal recognition rate at 93.5%, reaching 95.69% after KSR reduction, showing excellent performance. From the data analysis, it is evident that the Contourlet-KSR image texture feature extraction technique effectively combines the multiscale and multidirectional properties of the Contourlet transform with the spectral response characteristics of Krawtchouk polynomials, significantly enhancing the feature's descriptive ability and interference resistance. Despite higher feature dimension and time consumption, the use of KSR dimension reduction technology maintained a high recognition rate and even improved it to 95.69%, surpassing other traditional methods in performance.

Table 2 displays the experimental results of the Contourlet-KSR image texture feature extraction method under different configurations of decomposition levels and direction numbers. The data shows that with the increase in decomposition levels and changes in direction numbers, feature dimension, feature extraction time, and classification time all increase, but the corresponding recognition rates also improve. With three decomposition levels and a direction number configuration of (8,8,8), the feature dimension was 51, feature extraction time was 62 milliseconds, classification time without dimension reduction was 152 milliseconds, and the recognition rate was 92.56%, which significantly increased to 96.82% after using KSR dimension reduction. In four decomposition levels, using a direction number configuration of (4,8,8,16), the feature extraction time reached 81 milliseconds, classification time without dimension reduction was 178 milliseconds, and the recognition rate was 93.68%, stabilizing at 96.87% after KSR reduction. These data suggest that by increasing decomposition levels and adjusting direction numbers, classification accuracy can be significantly improved at the expense of some computational efficiency. From these experimental results, it can be concluded that the application of Contourlet-KSR technology is very effective in image texture feature extraction. Although feature extraction and classification time slightly increase with the addition of decomposition levels and direction numbers, the significant improvement in recognition rates demonstrates the advantage of this method in enhancing image texture recognition accuracy. Particularly, the use of KSR dimension reduction technology not only substantially reduces the feature dimension but also maintains a lower classification time while achieving a very high recognition rate.

Table 1. Experimental results of different image texture feature extraction methods

Method	Feature Dimension	Time Consumed	Recognition Rate	Recognition Rate After KSR Dimension Reduction
wavelet	31	28	92.31%	93.45%
LBP	245	31	81.2%	87.56%
Gabor	241	21	91.25%	92.31%
DT-CWT	25	33	93.54%	95%
The proposed method	51	51	93.5%	95.69%

Table 2. Experimental results of the contourlet-KSR image texture feature extraction method

Decomposition Level	Direction Numbers	Feature Dimension	Feature Extraction Time	No Dimension Reduction		*KSR* Dimension Reduction		
				Classification Time (*ms*)	Recognition Rate (%)	Number of Features after Dimension Reduction	Classification Time (*ms*)	Recognition Rate (%)
3	(4,4,4)	25	41	88	92.15	8	35	96.32
	(2,4,8)	31	43	114	91.32	8	36	96.54
	(8,8,8)	51	62	152	92.56	8	37	96.82
	(4,8,16)	57	66	171	91.87	8	35	96.21
4	(4,4,4,4)	33	45	121	93.21	8	35	96.87
	(2,4,4,8)	37	48	136	93.15	8	37	96.25
	(4,8,8,16)	73	81	178	93.68	8	36	96.87

Figure 5 shows the result distribution after processing the test set data using the Contourlet-KSR feature extraction method, which is a visualization representing features projected onto a two-dimensional plane. In this figure, different colors represent different image texture categories. Observations show that the data points of smooth textures are highly concentrated, exhibiting the least intra-class dispersion, indicating that images of smooth textures have high similarity and consistency in feature space. Granular textures are slightly more dispersed but still concentrated. In contrast, line textures show the greatest intra-class dispersion, indicating significant variability in feature expression for this category. Despite this, the inter-class dispersion among the three texture categories is similar, indicating that although each texture type varies in intra-class similarity, they are distinctly distinguishable from each other in feature space. These observations validate the effectiveness of the Contourlet-KSR feature extraction technique in the task of image texture classification. This method not only clearly distinguishes between different categories of textures but also reveals the continuous variations within similar textures. Therefore, the multiscale and multidirectional characteristics of the Contourlet-KSR technique, combined with the spectral response characteristics of Krawtchouk polynomials, successfully enhance the descriptive power of texture features and strengthen the robustness of the classification model.

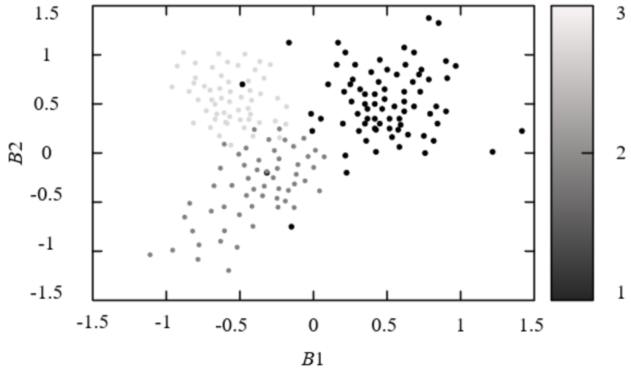

Figure 5. Data distribution after KSR dimension reduction

Table 3 details the image texture classification results using the texture image classification method based on domain MCM proposed in this paper. These data display the specific recognition effects of different texture types at an overall recognition rate of up to 97.8%. From the table, it is evident that the recognition rates for line and irregular textures reached

100%, demonstrating that the method is highly effective for these distinctly characterized texture types. The recognition rate for wave textures is also very high, at 98.58%. Although the recognition rates for smooth and regular textures are slightly lower, at 92.31%, they still perform well overall. Other texture types such as rough and mesh textures also showed high recognition rates exceeding 96%. These results indicate that the method maintains high accuracy even in complex texture classification scenarios. Analysis of the data in Table 3 allows us to conclude that the texture image classification method based on domain MCM performs with high precision and robustness in practical applications. This method effectively utilizes the multiresolution co-occurrence characteristics of images to improve classification accuracy, especially when dealing with images with complex texture features. Additionally, the high recognition rates and low misclassification rates demonstrated when processing various texture types confirm the practicality and reliability of this method in texture classification tasks.

Table 4 provides the correlation matrix data between non-subsampled wavelet subband energy and MCM features (entropy, contrast, and correlation), reflecting the degree of association between these features across different wavelet subbands. The data show that wavelet energy maintains high correlation with entropy across all subbands, especially in the *HH*1 and *HH*2 subbands, where the correlation coefficients are 0.9654 and 0.9574, respectively, indicating a very strong positive correlation. Although the overall correlation with contrast features is slightly lower, it also reaches 0.9321 and 0.9236 in the *HH*1 and *HH*2 subbands, respectively, indicating a strong association with energy features. In contrast, the correlation coefficients between wavelet energy and correlation are lower across all subbands, particularly lowest in the *HH*1 subband at only 0.3569. These data reveal the close relationship between wavelet energy and entropy and contrast in texture analysis, while the low correlation with correlation may point to the diversity and complementarity of feature extraction.

Table 3. Image texture classification results when recognition rate is 97.8%

Type of Texture	Smooth	Rough	Line	Regular	Irregular	Granular	Mesh	Stripe	Wave	Correct	Total	Recognition Rate
Smooth	38	0	0	0	1	0	1	1	0	38	41	92.31%
Rough	0	132	0	0	2	0	0	0	0	132	131	97.58%
Line	0	0	14	0	0	0	0	0	0	16	14	100%
Regular	1	0	0	12	0	0	0	0	0	14	13	92.31%
Irregular	0	0	0	0	52	0	0	0	0	52	52	100%
Granular	0	0	1	0	0	12	0	0	0	12	12	91.25%
Mesh	3	0	0	0	0	0	95	0	0	95	98	96.35%
Stripe	1	0	0	0	0	0	1	38	1	38	41	92.45%
Wave	0	0	1	0	0	0	0	0	232	232	225	98.58%

Table 4. Correlation matrix between non-subsampled wavelet subband energy and multiresolution co-occurrence features

Subband	First Scale			Second Scale			Approximation Subband
	*LH*1	*HL*1	*HH*1	*LH*2	*HL*2	*HH*2	*LL*2
Wavelet Energy-Entropy	0.8546	0.8234	0.9654	0.8851	0.8245	0.9574	0.5124
Wavelet Energy-Contrast	0.7458	0.7345	0.9321	0.7321	0.6896	0.9236	0.4326
Wavelet Energy-Correlation	0.4563	0.4265	0.3569	0.4356	0.4478	0.3269	0.5487

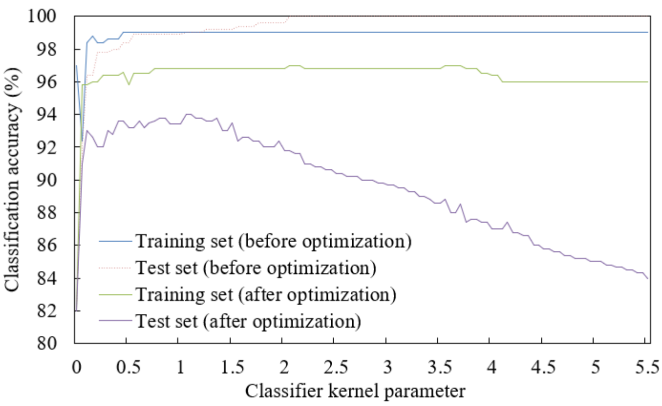

Figure 6. Image texture classification results before and after KSR dimension reduction

These experimental results emphasize the effectiveness of the non-subsampled wavelet transform in extracting image texture features, particularly its high correlation with entropy and contrast, providing a powerful tool for texture analysis. The high correlation of wavelet energy with entropy and contrast supports their capability to capture the complexity and clarity of image textures, which are key factors for effective texture classification. The texture image classification method based on domain MCM, by combining these strongly correlated features, can more accurately distinguish different texture types, enhancing classification precision and robustness.

Figure 6 details the recognition rates on the training and test sets in image texture classification tasks under different kernel parameter settings, before and after optimization. Before optimization, the recognition rate on the training set continually increased with the kernel parameter, eventually stabilizing at a high level of 99%. The test set also showed a similar trend, initially at 82% and gradually increasing to a peak of 100%. This indicates that as the kernel parameter is adjusted, the model becomes more precisely adapted to and predictive of different texture types. However, post-optimization data showed a different trend, with a slight decrease in the training set's recognition rate, mostly stabilizing around 96.8%, while the test set's recognition rate significantly dropped from an initial 93.8% to a low of 88.6%. This suggests that the optimization process may have led to overfitting, where the model is overly tuned to the training data, reducing its generalization ability on unknown data. These experimental results suggest that while the model's performance on the training set may slightly improve under some parameter settings after optimization, its performance on the test set indicates that the optimization strategies may not have effectively improved the model's generalization capability. This phenomenon emphasizes the need for careful handling of overfitting issues in model training and optimization in image texture classification tasks, especially when dealing with multiple parameters and high-dimensional feature spaces. The Contourlet-KSR technique and the method based on domain MCM, intended to enhance the descriptive power of features and robustness of classification, suggest that more detailed parameter adjustments and model validation processes might be necessary to ensure the practicality and effectiveness of the developed models.

Table 5. Comparison of texture image classification accuracy rates for various features

Feature Type	Spatial Gray-Level Co-occurrence Features	Wavelet Energy	Spatial Gray-Level Co-occurrence Features + Wavelet Energy	MCM Uniform Quantization	MCM Non-uniform Quantization	Wavelet Energy + MCM
Accuracy rate (%)	74.23	91.25	91.24	85.34	92.34	93.27
Standard deviation (%)	2.14	1.56	1.62	0.68	1.14	1.08

Table 5 compares the accuracy rates of various features in texture image classification tasks, including individual spatial gray-level co-occurrence features, wavelet energy features, their combinations, and MCM with uniform and non-uniform quantization. The data reveal that using spatial gray-level co-occurrence features alone resulted in the lowest accuracy rate of 74.23% with a standard deviation of 2.14%, indicating that while this method has a baseline effectiveness, it does not perform particularly well with complex texture images. Using wavelet energy features alone significantly improved the accuracy to 91.25%, showing a higher effectiveness. Combining spatial gray-level co-occurrence features with wavelet energy yielded an accuracy rate almost the same as using wavelet energy alone, indicating that adding spatial gray-level co-occurrence features did not bring additional improvements. The accuracy rates for MCM uniform quantization and non-uniform quantization were 85.34% and 92.34%, respectively, with non-uniform quantization performing better, showcasing the potential of this technology. The highest accuracy came from the combination of wavelet energy and MCM features, reaching 93.27%, also with a low standard deviation of 1.08%, indicating optimal stability and efficiency.

These experimental results highlight the effectiveness and superiority of the texture image classification method based on domain MCM proposed in this paper. In particular, the combination of wavelet energy and MCM features not only increased the classification accuracy but also ensured the stability of results, suggesting that integrating these two technologies can more effectively capture and utilize texture information for precise classification. Moreover, the performance of non-uniform quantization of MCM features being better than uniform quantization further proves the importance of considering non-uniform strategies in texture feature extraction and classification.

5. CONCLUSION

This paper successfully proposed and experimentally validated two innovative methods for texture analysis, designed to overcome the limitations of existing technologies and significantly enhance the accuracy and robustness of texture image classification. The first method, the Contourlet-KSR image texture feature extraction technique, effectively utilizes the multiscale and multidirectional characteristics of the Contourlet transform, along with the spectral response of Krawtchouk polynomials, to enhance the descriptive power of features and their resistance to interference. The second method, a texture image classification technique based on domain MCM, refines feature expression by analyzing the multiresolution co-occurrence characteristics of images, thereby improving the precision and efficiency of the classification process.

Experimental results demonstrated that various image texture feature extraction and classification methods display distinct advantages and limitations in different testing scenarios. In particular, the Contourlet-KSR method excels in feature dimension and computational efficiency, showing better classification accuracy and stability compared to traditional methods. The KSR dimension reduction technique further optimizes data distribution, enhancing processing efficiency and classification accuracy. Additionally, the high correlation coefficients between non-subsampled wavelet subband energy and MCM features validate the effectiveness of these features in capturing texture information. A comprehensive comparison of various features also confirms that combining wavelet energy with MCM features achieves the optimal accuracy rate for texture image classification.

Despite significant achievements in this study, there are still some limitations. For example, the current methods may still require further adjustments and optimizations for highly non-uniform texture images. Moreover, although the results indicate that the optimized methods might exhibit overfitting in some cases, affecting the model's generalization capability, this highlights the need for future research to focus more on the generalizability and practicality of models. Future research directions could include further exploration and development of new feature extraction and classification algorithms to address more complex texture classification challenges. Additionally, researching more effective dimension reduction techniques and noise resistance strategies will also be crucial for ensuring reliable and robust classification results in practical applications. By continuously optimizing and refining these technologies, we can anticipate broader applications in the field of image processing and machine vision in the future.

REFERENCES

[1] Yan, H.Y., Zheng, Z. (2024). Image cartoon-texture decomposition by a generalized non-convex low-rank minimization method. Journal of the Franklin Institute,

361(2): 796-815. https://doi.org/10.1016/j.jfranklin.2023.12.025
[2] Yan, N., Mei, Y., Yang, T., Yu, H., Chen, Y. (2024). RTHEN: Unsupervised deep homography estimation based on dynamic attention for repetitive texture image stitching. Displays, 82: 102670. https://doi.org/10.1016/j.displa.2024.102670
[3] Shi, J. (2024). High-resolution art recognition of modern packaging design and images based on texture image classification. Applied Mathematics and Nonlinear Sciences, 9(1): 1-17. https://doi.org/10.2478/amns.2023.2.00338
[4] Lyra, L.O., Fabris, A.E., Florindo, J.B. (2024). A multilevel pooling scheme in convolutional neural networks for texture image recognition. Applied Soft Computing, 152: 111282. https://doi.org/10.1016/j.asoc.2024.111282
[5] Yang, L., Zhang, T., Lu, F., Zhang, M. (2023). Multifractal image texture analysis combined with 2D empirical mode decomposition. In 2023 4th International Seminar on Artificial Intelligence, Networking and Information Technology (AINIT), Nanjing, China, pp. 764-770. https://doi.org/10.1109/AINIT59027.2023.10212874
[6] Feng, Y., Wu, J., Hu, X., Zhang, W., Wang, G., Zhou, X., Zhang, X. (2023). Medical image fusion using bilateral texture filtering. Biomedical Signal Processing and Control, 85: 105004. https://doi.org/10.1016/j.bspc.2023.105004
[7] Wang, Z., Zhang, X. (2024). Contextual recovery network for low-light image enhancement with texture recovery. Journal of Visual Communication and Image Representation, 99: 104050. https://doi.org/10.1016/j.jvcir.2024.104050
[8] Xu, Q., Jia, S., Jiang, X., Sun, T., Wang, Z., Yan, H. (2024). MDTL-NET: Computer-generated image detection based on multi-scale deep texture learning. Expert Systems with Applications, 248: 123368. https://doi.org/10.1016/j.eswa.2024.123368
[9] Zhang L.M., Cong Y., Meng F.Z., Wang Z.Q., Zhang P., Gao S. (2021). Energy evolution analysis and failure criteria for rock under different stress paths. Acta Geotechnica, 16(2): 569-580. https://doi.org/10.1007/s11440-020-01028-1
[10] Zhang, Y., Liu, H., Li, Z., Gao, X., Shi, G., Jiang, J. (2024). TCDM: Effective Large-Factor Image Super-Resolution via Texture Consistency Diffusion. IEEE Transactions on Geoscience and Remote Sensing, 62: 5609613. https://doi.org/10.1109/TGRS.2024.3358913
[11] Chen, L., Wang, T., Ge, H. (2023). TMTrans: Texture mixed transformers for medical image segmentation. AI Communications, 36(4): 325-340. https://doi.org/10.3233/AIC-230089
[12] Guan, Q., Chen, Y., Wei, Z., Heidari, A.A., Hu, H., Yang, X., Zheng, J., Zhou, Q., Chen, H., Chen, F. (2022). Medical image augmentation for lesion detection using a texture-constrained multichannel progressive GAN. Computers in Biology and Medicine, 145: 105444. https://doi.org/10.1016/j.compbiomed.2022.105444
[13] Rajangam, V., Kandikattu, D., Kumar, M., Raj, A.N.J. (2022). Texture aware deep feature map based linear weighted medical image fusion. IEEE Access, 10: 88787-88797. https://doi.org/10.1109/ACCESS.2022.3200752
[14] Li, W. (2023). Texture feature extraction of a landscape design image based on the contour wave transform. International Journal of Data Science, 8(1): 39-51. https://doi.org/10.1504/IJDS.2023.129456
[15] Xu, Z., Jiang, W., Geng, J. (2024). Texture-aware causal feature extraction network for multimodal remote sensing data classification. IEEE Transactions on Geoscience and Remote Sensing, 62: 5103512. https://doi.org/10.1109/TGRS.2024.3368091
[16] Feng, K., Zhang, R. (2022). Realization technology of texture feature extraction algorithm of remote sensing satellite image based on FPGA. In 2022 IEEE 2nd International Conference on Data Science and Computer Application (ICDSCA), Dalian, China, pp. 110-114. https://doi.org/10.1109/ICDSCA56264.2022.9987799
[17] Liu, M., Zhang, F. (2023). Texture feature extraction and classification based on improved LBP. In 2023 35th Chinese Control and Decision Conference (CCDC), Yichang, China, pp. 4189-4192. https://doi.org/10.1109/CCDC58219.2023.10327665
[18] Zhang L.M., Chao W.W., Liu Z.Y., Cong Y., Wang Z.Q., (2022). Crack propagation characteristics during progressive failure of circular tunnels and the early warning thereof based on multi-sensor data fusion. Geomechanics and Geophysics for Geo-Energy and Geo-Resources, 8: 172. https://doi.org/10.1007/s40948-022-00482-3
[19] Wang, Y., Shao, Z., Lu, T., Huang, X., Wang, J., Chen, X., Huang, H., Zuo, X. (2023). Remote sensing image super-resolution via multi-scale texture transfer network. Remote Sensing, 15(23): 5503. https://doi.org/10.3390/rs15235503
[20] Li, B., Li, Y., Wu, Q.J. (2023). A multi-scale threshold integration encoding strategy for texture classification. The Visual Computer, 39(11): 5747-5761. https://doi.org/10.1007/s00371-022-02693-x