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Research on image segmentation based on unsupervised learning methods in computer vision

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Abstract Traditional supervised learning methods have limitations in labeling speed, scene adaptability and accuracy. Unsupervised learning methods do not require labeling data and can automatically extract the laws, which provides a new idea for image segmentation, especially in medical diagnosis, automatic driving and other high-precision requirements of the scene has an important application value. This study explores unsupervised learning-based image segmentation methods in computer vision, focusing on the improved kernel fuzzy C-mean clustering algorithm (KFCM). The study constructs an image segmentation algorithm with noise robustness by introducing a kernel function instead of Euclidean distance and combining it with super-pixel segmentation technique. The experiments are validated on synthetic, natural and medical images and compared with various classical algorithms. The results show that when 30% Gaussian noise is added to the synthetic image, the segmentation accuracy of the KFCM algorithm reaches 99.8%, which is 12.6% higher than that of the traditional FCM; in the segmentation of the natural image with the addition of mixed noise, the average value of the segmentation coefficient of the KFCM reaches 96.45%, which is 17.47% higher than that of the FCM, and the segmentation entropy is reduced by 34.57%; and in the segmentation of the medical cell image, the KFCM algorithm shows good edge keeping ability in complex noise environment. The study shows that the improved KFCM algorithm significantly improves the image segmentation accuracy and anti-noise performance through the adaptive neighborhood information and kernel mapping, and provides an effective solution for unsupervised image segmentation, which is of practical application value for medical diagnosis, automatic driving and other fields.

Index Terms Computer vision, Image segmentation, Unsupervised learning, Fuzzy C-mean clustering, Kernel function, Hyperpixel

I. Introduction

The main purpose of computer vision related tasks is to understand the content in the input picture or image. These tasks can be divided into three main categories which are classification, detection and segmentation, where segmentation can be categorized into instance segmentation and semantic segmentation depending on the goal of segmentation and application scenario [1], [2]. Images are a way to convey information and they contain a lot of useful information. Understanding images and extracting information from them to be used for other tasks is an important application area in digital image technology and the first step in understanding an image is image segmentation [3]. Image segmentation is a key step in analyzing and understanding an image, and is the most important and fundamental technical tool in digital image processing, and accurate segmentation of an image is valuable for engineering practice and quantitative analysis [4], [5]. Among them, the processes such as parameter measurement and feature extraction of the target of interest are preprocessed by image segmentation, and the segmentation technology of the image makes further image understanding and application possible [6], [7].

With the continuous development of the times, the application field of image segmentation is getting wider and wider, and the image processing technology that divides an image into a number of meaningful regions plays an increasingly important role in the fields of medical diagnosis, disease diagnosis, automatic driving and three-dimensional reconstruction [8]-[11]. In practical applications and research, the researcher is not interested in all parts of the image, and the purpose of image segmentation is to partition the image space into a number of meaningful regions, so that the regions of interest can be extracted for further image applications and processing. Therefore, the study of image segmentation has important theoretical value and practical significance.

In the study of image segmentation based on supervised learning methods, literature [12] formulated a Half-UNet framework for medical image segmentation, which improves the accuracy of image segmentation by simplifying the decoder and encoder. Literature [13] designed an improved image segmentation method for Mask R-CNN

(Convolutional Neural Network) with RGB depth, which has higher generalization ability and accuracy than segmentation models such as U-Net in complex interference environments. Literature [14] combines support vector machines and graph cuts to improve the performance of segmenting medical images by training local features on the image, and its trained classifiers are formed with target image features with the intention of homogenizing the image segmentation intensity. Literature [15] constructed a deep regression model for segmenting cardiac MRI images by extracting image features in low computational cost through deep learning and DAISY features. However, based on the supervised learning approach, there are some limitations and the slow feature labeling reduces the efficiency of segmentation. And the performance of the model performs differently in different weather scenarios, the model adaptability is low, which reduces the accuracy of segmentation, and it is difficult to meet the research requirements for the accuracy of segmentation of high-precision cell-based images such as medical research.

In the study of image segmentation based on non-supervisory learning, literature [16] utilizes edge and semantic segmentation to generate adversarial networks to generate edge features and increase auxiliary features for foggy weather images, respectively, in order to achieve semantic segmentation of foggy weather images. Literature [17] used self-supervised learning to pre-train seismic images through a small number of samples, and its image semantic segmentation performance is improved, providing a new direction for parsing seismic images. Literature [18] formulated an image segmentation method based on adaptive k-mean clustering, which is mainly carried out by a three-step method of color space conversion, threshold setting, and image matching. Literature [19] integrated two means of image segmentation with selfencoder by reducing the image dimensionality features on one hand, and on the other hand, introducing batch normalization layer and softmax algorithm to optimize the segmentation network and low dimensional feature clustering respectively. Such methods, improve the accuracy and scene adaptation of image segmentation.

The main objective of computer vision related tasks is to understand the content in the input picture or image. These tasks can be divided into three main categories which are classification, detection and segmentation, where segmentation can be categorized into instance segmentation and semantic segmentation depending on the goal of segmentation and application scenario. Images are a way of conveying information and they contain a lot of useful information. Understanding images and extracting information from them to be used for other tasks is an important application area in digital image technology, and the first step in understanding images is image segmentation. Image segmentation is a key step in analyzing and understanding an image, and it is the most important and basic technical means in digital image processing. Accurate segmentation of an image is of great value in engineering practice and quantitative analysis. Among them, the process of parameter measurement and feature extraction of the target of interest are pre-processed by image segmentation, and the segmentation technology of the image makes further image understanding and application possible. With the continuous development of the times, the application fields of image segmentation are getting wider and wider, and the image processing technology that divides an image into a number of meaningful regions plays an increasingly important role in the fields of medical diagnosis, disease diagnosis, automatic driving and 3D reconstruction. In practical applications and research, the researcher is not interested in all parts of the image, and the purpose of image segmentation is to partition the image space into a number of meaningful regions, so that the regions of interest can be extracted for further image applications and processing. Although traditional supervised learning-based image segmentation methods have achieved certain results, they still suffer from the problems of slow feature annotation and reduced segmentation efficiency, as well as inconsistent model performance under different environmental conditions and low adaptability, which makes it difficult to meet the demands in fields such as medical research with high precision requirements. In contrast, unsupervised learning methods do not require a separate offline training process and a labeled training dataset, and can analyze the dataset to extract the corresponding intrinsic laws and rules from it, so that the machine can make a more reasonable decision, which has advantages in improving the accuracy of image segmentation and the adaptability of the scene.

In this study, an improved fuzzy C-mean clustering algorithm (KFCM) based on kernel function is used to construct a segmentation method that can effectively deal with noisy images by introducing a Gaussian kernel function to replace the Euclidean distance in the traditional FCM algorithm, and combining with the super-pixel segmentation technique. This method deals with the local spatial information of the image through adaptive neighborhood windows, enhances the nonlinear processing ability of the algorithm through kernel mapping, and preserves the image edge detail information through the hyperpixel segmentation technique. The study systematically evaluates the performance of the algorithm through experimental validation on a variety of image types, aiming to provide an unsupervised image segmentation solution with high accuracy and noise resistance, and to provide technical support for image understanding and applications.

II. Methodology

II. A. Unsupervised learning

Unsupervised learning is an important learning method of machine learning, which refers to the training dataset that does not require a separate offline training process and does not have labeled training data sets, and is generally used to analyze the dataset, such as clustering, and extract the corresponding intrinsic laws and rules from it through learning, so that the machine can make more reasonable decisions. The theoretical study of unsupervised learning has been the focus and hotspot of machine learning research. These studies have important theoretical significance for our understanding of the learning mechanism of learning machines and human-computer interaction, and the study of various methods of unsupervised learning is also an important way and means to realize the improvement and refinement of machine learning capabilities [20].

Unsupervised learning analyzes and learns from the data set, extracts the corresponding internal laws and rules, and makes the machine make more reasonable decisions. Generally speaking, unsupervised learning methods can be divided into two categories, namely, direct methods based on the estimation of probability density function and indirect clustering methods based on the similarity measure between samples. Usually the direct methods of unsupervised learning are the single peak subset class separation methods. Probability density function estimation divides the data into a number of subsets whose density has the form of a single peak. In the absence of any a priori knowledge of class-conditional probability distributions, we can only divide the feature space into a number of regions $s_i (i = 1, 2, 3, ..., c)$, in each of which the mixture density is supposed to be single-peaked, and one calls these regions single-peaked regions. Each single-peaked region, corresponds to a category. There are various algorithms to realize the division of these single-peak regions. The main algorithms include projection methods, separation methods based on the nature of symmetric sets, and iterative algorithms for the separation of single-peaked subsets. The direct methods all involve decomposing a set with mixed probability density functions into a number of subsets, for each of which the probability density function is single-peaked, and each subset is equivalent to a class. But estimating the probability density function is difficult and computationally intensive. The indirect clustering method based on the similarity measure between samples means that the set is divided into subsets according to the similarity between samples under certain conditions, and the division should maximize some criterion function that indicates the quality of clustering. When the similarity between two samples is expressed in terms of distance, this results in dividing the feature space into regions, each of which corresponds to a category. This method is the cluster analysis discussed and studied in this thesis. Unsupervised learning also includes some other methods such as, principal component analysis, nonlinear mapping, etc. depending on the classification.

II. B. Fuzzy c-mean clustering algorithm (FCM)

Fuzzy c-mean clustering algorithm (FCM) is able to classify samples automatically. Unlike the K-means algorithm, a representative algorithm of hard clustering algorithms, the fuzzy c-mean clustering algorithm allows the affiliation degree to take values between 0 and 1, so the classification of pixel points becomes more flexible and reliable [21].

The basic idea of the FCM algorithm is to use the Lagrange multiplier method to find the minimum value of the objective function, and then iteratively solve to get the optimal clustering center and the degree of affiliation, and finally classify the pixel points. The expression of its objective function is shown in equation (1):

$$J(U,V) = \sum_{i=1}^{n} \sum_{k=1}^{c} u_{ki}^{m} d^2(x_i, v_k) \tag{1}$$

Satisfy the constraints:

$$0 < u_{ki} < 1, \sum_{k=1}^{c} u_{ki} = 1 \tag{2}$$

where n is the number of pixel points, c is the number of clustering centers, U is the affiliation matrix of size $c*n$, V is the set of clustering centers containing c clusters, u_{ki} is the degree of affiliation of pixel point x_i to clustering center v_k, and $d^2(x_i, v_k)$ is the Euclidean distance between pixel point x_i and clustering center v_k. The Euclidean distance, and m is the fuzzy index, which is generally taken as 2.

The objective function of the FCM algorithm is minimized by the Lagrange multiplier method, which defines a Lagrange function by associating the objective function with the algorithm constraints:

$$L = \sum_{k=1}^{c} \sum_{i=1}^{n} u_{ki}^{m} d^2\left(x_i, v_k\right) + \sum_{i=1}^{n} \lambda_i \left(\sum_{k=1}^{c} u_{ki} - 1 \right) \tag{3}$$

Taking the above equation to the partial derivatives of u_{ki} and v_k, respectively, and making it zero, the following equation is obtained:

$$\frac{\partial L}{\partial u_{ki}}=0 \tag{4}$$

$$\frac{\partial L}{\partial v_k}=0 \tag{5}$$

From there, you can get:

$$mu_{ki}^{m-1}d^2(x_i,v_k)+\lambda_i=0 \tag{6}$$

$$2\sum_{i=1}^{n}u_{ki}^{m}(v_k-x_i)=0 \tag{7}$$

Simplification of equation (7) gives u_{ki}:

$$u_{ki}=\left(\frac{-\lambda_i}{md^2(x_i,v_k)}\right)^{\frac{1}{m-1}} \tag{8}$$

Due to the existence of constraint $\sum_{k=1}^{c}u_{ki}=1$, the above equation (8) can be obtained by substituting it into the left equation:

$$\sum_{k=1}^{c}\left(\frac{-\lambda_i}{md^2(x_i,v_k)}\right)^{\frac{1}{m-1}}=1 \tag{9}$$

It can be derived as λ_i:

$$\lambda_i=-\frac{1}{\sum_{j=1}^{c}\frac{1}{md^2(x_i,v_j)}} \tag{10}$$

Substituting Eq. (9) into Eq. (10) yields the u_{ki} expression:

$$u_{ki}=\frac{1}{\sum_{j=1}^{c}\frac{d^2(x_i,v_k)}{d^2(x_i,v_j)}^{\frac{1}{m-1}}} \tag{11}$$

Simplification of equation (11) gives v_k:

$$v_k=\frac{\sum_{i=1}^{n}u_{ki}^{m}x_i}{\sum_{i=1}^{n}u_{ki}^{m}} \tag{12}$$

When minimizing the objective function using the Lagrange multiplier method, it is necessary to keep iterating the affiliation matrix and clustering centers until the objective function is minimized. The algorithm ends when the value of the objective function satisfies the convergence condition or the algorithm reaches the maximum number of iterations.

The specific implementation steps of the FCM clustering algorithm are as follows:

Compared with the traditional hard clustering algorithm, the FCM algorithm can theoretically divide the sample points more reasonably, providing a more accurate calculation method for the classification of the sample points.The FCM algorithm has been well used in many fields, and has become one of the most commonly used methods for image segmentation. Although the FCM algorithm is widely used and can accomplish clustering quickly and automatically, it has many shortcomings:

(1) More sensitive to noise

In the iterative process of the algorithm, the FCM algorithm only considers the size of the gray value of the pixel point, and does not consider other spatial information in the image. When dealing with images with relatively high noise intensity, it is difficult to achieve more satisfactory segmentation results, which affects the clustering performance of the algorithm. Therefore, how to improve the noise resistance of the FCM algorithm and maximize the use of image information has been the attention of more and more scholars.

(2) The problem of parameter setting

The fuzzy index m controls the convergence speed and the number of iterations of the fuzzy clustering algorithm, the larger the value of m the less efficient the execution of the fuzzy clustering algorithm instead. At the same time, the overall fuzziness of the algorithm is also affected by the fuzzy index m. Scholar Bezdek proposed that the reasonable value of m is 2, and a better balance between clustering accuracy and algorithm efficiency can be achieved when the value of m is 2.

Traditional FCM algorithm randomly initializes the clustering center will affect the final clustering effect of the algorithm. Some research scholars have proposed to set the value of the initial clustering center by climbing method and with the help of image histogram, but there are still shortcomings such as bad adaptability, too high algorithmic complexity, and too much computation, etc. Therefore, how to set the matching parameter according to different situations still needs further research by scholars.

II. C.Kernel-based improved fuzzy clustering (KFCM) for image segmentation

II. C. 1) KFCM algorithm

In order to solve the nonlinear problem and improve the noise immunity of the algorithm, a kernel function based FCM algorithm is proposed to replace the Euclidean distance in FCM with the kernel induced distance [22]. Its objective function is shown in equation (13):

$$J_{KFCM}(U,V)=2\sum_{i=1}^{n}\sum_{j=1}^{c}u_{ji}^{m}\left[1-K(x_i,v_j)\right] \tag{13}$$

where $u_{ji}\in[0,1]$, $0\le\sum_{i=1}^{n}u_{ji}\le n$, n is the number of pixels, c is the number of clusters, and the Gaussian kernel function is defined as shown in equation (14):

$$K(x,v)=\exp\left(-\|x-v\|^2/\sigma\right) \tag{14}$$

where, σ is the bandwidth of the function. The Lagrangian derivation of Eq. (14) is performed, and the affiliation degree and clustering center are calculated as shown in Eq. (15):

$$u_{ji}=\frac{\left[1-K\left(x_i,v_j\right)\right]^{-\frac{1}{m-1}}}{\sum_{k=1}^{c}\left[1-K\left(x_i,v_k\right)\right]^{-\frac{1}{m-1}}} \tag{15}$$

$$v_j=\frac{\sum_{i=1}^{n}u_{ji}^{m}K(x_i,v_j)x_i}{\sum_{i=1}^{n}u_{ji}^{m}K(x_i,v_j)} \tag{16}$$

II. C. 2) Algorithm flow

Remember that I denotes the whole image and the resolution of the image is labeled as $A\times B$, i.e., the number of pixels in the whole image is AB. The set of samples composed of pixels to be classified is $X=\left\{x_1,x_2\cdots x_A,x_{A+1},\cdots,x_{2A},x_{2A+1},\cdots,x_{AB-1},x_{AB}\right\}$.

The classification clusters to which each pixel of the image belongs are first found based on the S-FCM clustering algorithm. The number of classifying classes is denoted as C_{FCM}, and the initial clustering center of each cluster is denoted as $V=\left\{V_1,V_2,\cdots,V_{C_{FCM}}\right\}$. The affiliation degree of pixel x_j belonging to cluster V_i is denoted as u_{ij}, and the affiliation matrix formed by all the affiliations is denoted as U. The affiliation degree is computed as follows:

$$u_{ij}=\frac{1}{\sum_{k=1}^{C_{FCM}}\left(\frac{d_{ij}}{d_{kj}}\right)^{\frac{2}{m-1}}} \tag{17}$$

where $d_{ij}=x_j-V_i$ denotes the Euclidean distance between sample j to clustering center i. m denotes the fuzzy factor. Let the affiliation degree of the sample x_i belonging to the pth class be u_{pi}, when u_{pi} is greater than the affiliation degree of all it belongs to other classes, update the affiliation degree of the sample x_i according to the following equation:

$$\begin{aligned}u_{pi}&=1-\alpha\sum_{k\ne p}u_{ki}=1-\alpha+\alpha u_{pi}\\u_{ki}&=\alpha u_{ki},k\ne p\end{aligned} \tag{18}$$

where $\alpha\in[0,1]$ denotes the suppression factor. Calculate the clustering center to which it belongs by substituting the updated affiliation degree into the following equation:

$$V_t = \frac{\sum_{j=1}^{n} (u_{ij})^m x_j}{\sum_{j=1}^{n} (u_{ij})^m} \tag{19}$$

Set the minimum iteration step ϵ and the maximum number of iterations T when $\left\| V^{q-1} - V^q \right\| < \epsilon$ or the number of iterations $q > T$ is stopped, and the clustering result of the S-FCM algorithm A is obtained, and the I_{ai} represents the area occupied by the set of pixels belonging to V_i in the clustering result A.

Next, the image is segmented twice using the standard SLIC superpixel algorithm in order to find color or texture similarities between pixels on certain small localized regions of the image, thus identifying the boundary information in the image more accurately. The clustering result of the SLIC algorithm is denoted as B, which contains a total of K hyperpixel clusters, and the center of each cluster is denoted as C_i, $1 \le i \le K$. I_{bi} denotes the region on the image occupied by the set of pixels belonging to the cluster center C_i in the clustering result B [23].

For each element c_i in the region I_{bi}, its affiliation to each cluster in the segmentation A is computed using Eq. (20) and Eq. (21) to obtain the vector of affiliations of c_i to the clusters in the segmentation A:

$$u_i = \left(u_{i1}, u_{i2}, \cdots, u_{iC_{FCM}} \right) \tag{20}$$

where the j th component of u_i, u_{ij}, denotes the affiliation of c_i to the j th cluster in the partition A.

Let there be N_i pixels in the region I_{bi}, and calculate the average affiliation of the pixels contained in the region I_{bi} as:

$$U_i = \frac{\sum_{i=1}^{N_i} u_i}{N_i} \tag{21}$$

Use the average affiliation U_i as the affiliation of the region I_{bi} to the clusters in the segmentation A, and home the region I_{bi} to the cluster with the largest affiliation. The above steps are repeated until all regions in segmentation B are traversed to obtain the segmentation result of the hyperpixel region corresponding to the clustering algorithm.

The result preserves both the SLIC hyperpixel result on the boundary region and the affiliation classes of the clusters segmented by S-FCM clustering on the global region. Such an algorithm fusing fuzzy clustering and hyperpixel segmentation is known as SFCM-SLIC algorithm.

II. D.Evaluation indicators

In this paper, accuracy (SA), precision (P), recall (R), $F1-Score(F_1)$, sensitivity (Sen), Jaccard's coefficient, mean pixel accuracy (Mpa), peak signal-to-noise ratio ($PSNR$), segmentation coefficient (V_{pc}), and segmentation entropy (V_{pe}) are used to evaluate the performance of the different algorithms.

(1) SA : the percentage of correctly classified pixels, i.e:

$$SA = \sum_{k=1}^{C} \frac{A_k \cap C_k}{\sum_{j=1}^{C} C_j} \tag{22}$$

where A_k is the set of pixels of the k th class of the segmentation result. C_k is the set of pixels of the k th class of the reference segmentation image. $\sum_{j=1}^{C} C_j$ is the sum of the number of pixels.

(2) P : the proportion of positive samples that are predicted to be positive, denoted as:

$$P = \frac{T_p}{T_p + F_p} \tag{23}$$

where T_p and F_p are correctly recognized positive samples and incorrectly recognized negative samples, respectively.

(3) R : the proportion of positive samples being correctly predicted, denoted as:

$$R = \frac{T_p}{T_p + F_N} \quad (24)$$

where F_N is the unrecognized positive sample.

(4) F_1: the harmonic mean of precision and recall, denoted as:

$$F_1 = 2 \times \frac{P \times R}{P + R} \quad (25)$$

(5) Sen: the proportion of all positive samples correctly predicted to all true positive samples, ie:

$$Sen = \frac{T_p}{T_p + F_N} \quad (26)$$

(6) $Jaccard$: The ratio of the intersection and concatenation of the predicted and true values, i.e:

$$Jaccard = \frac{T_p}{T_p + F_p + F_N} \quad (27)$$

(7) Mpa: The average sum of the proportion of pixels correctly categorized in each category, i.e:

$$Mpa = \frac{1}{C} \sum_{k=1, j=1}^{c} \frac{A_k \cap C_k}{C_j} \quad (28)$$

(8) $PSNR$: The ratio of the maximum power of the signal to the noise power of the signal, viz:

$$PSNR = 10 \log_{10} \left(255^2 / mse \right) \quad (29)$$

where mse is the mean square error between the predicted and true values.

(9) V_{pc} and V_{pe}: the degree of fuzziness of the segmentation, i.e:

$$V_{pc} = \sum_{j=1}^{c} \sum_{i=1}^{n} \frac{u_{ij}^2}{n} \quad (30)$$

$$V_{pe} = -\sum_{j=1}^{C} \sum_{i=1}^{n} \frac{u_{ij}^2 \log(u_{ij}^2)}{n} \quad (31)$$

Among the above indicators, larger values of SA, P, R, F_1, Sen, $Jaccard$, Mpa and $PSNR$ indicate better performance. For evaluating the fuzzy clustering algorithm, the larger V_{pc} and the smaller V_{pe} implies that the result is less fuzzy and the segmentation is better.

III. Results and analysis

III. A. Experimental design

Synthetic images, natural images, medical images and remote sensing images are selected to compare the experimental results of the related algorithms. In order to illustrate the advantages of the algorithms designed in this chapter in improving robustness, different types and intensities of noise, including pretzel noise, Gaussian noise and Rice noise, are added to the corresponding images. It should be noted that the types of noise contained in the images of different domains are different due to the differences in the imaging principles of the images in different domains.

Table 1: The parameters involved in the algorithm

Algorithm	Parameter	Window size
FCM	-	-
FCMS	α =2	3*3
FCMS1	α =2	3*3
FCMS2	α =2	3*3
EnFCM	α =2	3*3
FGFCM	λ_g =4 λ_s =4	3*3
FLICM	-	3*3
NLFCM	-	8*8
Improvement algorithm	ρ =3 b =1.435	8*8

Table 2: V_{pc} value

V_{pc}						
Noise type	Strength /variance	FCM	HMRF-FCM	FCM _SNLS	KFCM _NLS	FANFCM _M
Gaussian noise	15%	0.882	0.856	0.948	0.951	0.957
	20%	0.876	0.834	0.940	0.943	0.954
	30%	0.872	0.781	0.870	0.894	0.920
	Strength /variance	FGFCM	FLICM	NLFCM	This algorithm	-
	15%	0.968	0.954	0.968	0.985	-
	20%	0.962	0.963	0.962	0.999	-
	30%	0.921	0.957	0958	0.998	-
	Strength /variance	FCM	HMRF-FCM	FCM _SNLS	KFCM _NLS	FANFCM _M
Salt and salt noise	15%	0.918	0.932	0.847	0.932	0.889
	20%	0.897	0.551	0.798	0.910	0.862
	30%	0.876	0.422	0.711	0.814	0.823
	Strength /variance	FGFCM	FLICM	NLFCM	This algorithm	-
	15%	0.952	0.704	0.935	0.952	-
	20%	0.922	0.878	0.912	0.964	-
	30%	0.864	0.714	0.876	0.978	-
V_{pe}						
	Strength /variance	FCM	HMRF-FCM	FCM _SNLS	KFCM _NLS	FANFCM _M
Gaussian noise	15%	0.378	0.472	0.195	0.182	0.151
	20%	0.392	0.512	0.210	0.213	0.162
	30%	0.384	0.603	0.374	0.336	0.228
	Strength /variance	FGFCM	FLICM	NLFCM	This algorithm	-
	15%	0.125	0.162	0112	0.048	-
	20%	0.142	0.164	0.118	0.004	-
	30%	0236	0..204	0.140	0.008	-
	Strength /variance	FCM	HMRF-FCM	FCM _SNLS	KFCM _NLS	FANFCM _M
Salt and salt noise	15%	0.242	0.522	0.496	0.228	0.338
	20%	0.310	0.574	0.612	0.326	0.422
	30%	0.405	0.678	0.831	0.554	0.547
	Strength /variance	FGFCM	FLICM	NLFCM	This algorithm	-
	15%	0.170	0.804	0.239	0.178	-
	20%	0.256	0.436	0.300	0.140	-
	30%	0.417	0.879	0.432	0.103	-
Accuracy value						
	Strength /variance	FCM	HMRF-FCM	FCM _SNLS	KFCM _NLS	FANFCM _M
Gaussian noise	15%	0.956	0.992	0.984	0.989	0.985
	20%	0.922	0.905	0.988	0.912	0.993
	30%	0.864	0.963	0.879	0.882	0.879
	Strength /variance	FGFCM	FLICM	NLFCM	This algorithm	-
	15%	0.983	0.970	0.979	0.968	-

	20%	0.914	0.970	0.978	0.990	-
	30%	0.874	0.969	0.975	0.989	-
	Strength /variance	FCM	HMRF-FCM	FCM _SNLS	KFCM _NLS	FANFCM _M
Salt and salt noise	15%	0.829	0.951	0.942	0.954	0.948
	20%	0.778	0.925	0.922	0.936	0.936
	30%	0.691	0.859	0.863	0.894	0.864
	Strength /variance	FGFCM	FLICM	NLFCM	This algorithm	-
	15%	0.978	0.685	0.986	0.986	-
	20%	0.964	0.974	0.986	0.987	-
	30%	0.913	0.722	0.978	0.973	-

The parameter m in the relevant algorithm is preset to 2, the iteration termination parameter ε is preset to 1e-5, maxiter=100, and the settings of other parameters are shown in Table 1. In the designed algorithm, b is the scale factor reflecting the information of the pixel and its neighborhood, referring to the related literature, and 1.435 is taken in the experiments, and the parameter ρ is the threshold for judging whether the pixel point is a noise point, and by comparing different thresholds, it is found that when ρ is taken to be 3, it is able to better balance the robustness of the algorithm with the detail retention. In order to quantitatively compare the segmentation effect of the algorithm, relevant quantitative segmentation metrics are introduced.

III. B. Image segmentation results

III. B. 1) Synthetic image segmentation results

The size of the synthesized image selected in the experiment is 256*256, and the gray values of the pixels in the synthesized image are 0, 85, 170, and 255, respectively.In order to compare the robustness of the related algorithms, different types and intensities of noises are added to the synthesized image during the experiments, and the image is classified into four categories. In comparison, the algorithms proposed in this paper are more satisfactory for edge pixels. In order to quantitatively compare the algorithms, V_{pc} and V_{pe} are further introduced in the experiment. The experimental results are shown in Table 2. The algorithm proposed in this paper generally has higher partition coefficients and lower partition entropy compared with other algorithms. From the table, it can be seen that the proposed algorithm in this paper basically has higher partitioning accuracy compared to other algorithms.

III. B. 2) Natural image segmentation results

In order to test the segmentation performance of the improved fuzzy clustering (KFCM) algorithm on natural scene images, six images are randomly selected from the Berkeley Standard Image Database (BSDS500), and the visual segmentation effect and performance index of each algorithm are analyzed in the same way: compared with the FANFCM_M, the image contour of the KFCM algorithm in this paper is clearer and the segmentation results are more stable, and the noise removal ability is better. Compared with the rest of the algorithms, it is able to remove all the noise and the boundary is clearer, the blurring degree is low, and the restoration degree is high. Therefore, the proposed algorithm outperforms the rest of the comparative algorithms in terms of visual presentation for natural images with added mixed noise.

Next, the performance metrics of the six algorithms are analyzed. The results are shown in Table 3, and the FCM algorithm has the worst average performance.The V_{pc} value of HMRF-FCM is improved by 14.9 relative to the FCM.The V_{pc} of the FCM_SNLS algorithm is improved by 16.17 relative to the FCM.The KFCM_NLS algorithm improves the performance metrics relative to the FCM algorithm, but the improvement is smaller The FANFCM_M algorithm's V_{pc} improves by 14.9 and V_{pe} decreases by 27.09 compared to FCM.

The KFCM algorithm in this paper has the highest mean value of V_{pc} compared to the rest of the algorithms:17.47 improvement relative to the FCM algorithm, 3.04 for KFCM_NLS, and 2.57 for HMRF-FCM.The mean value of V_{pe} is also the lowest for KFCM. Overall, the algorithm in this paper outperforms the rest of the algorithms in terms of performance metrics and can accurately segment color images with added mixed noise.

Table 3: Performance segmentation index

	FCM		HMRF-FCM		FCM _SNLS		KFCM _NLS		FANFCM _M		This algorithm	
Index	V_{pc}	V_{pe}	V_{pc}	V_{pe}	V_{pc}	V_{pe}	V_{pc}	V_{pe}	V_{pc}	V_{pe}	V_{pc}	V_{pe}
5% gauss	80.46	36.34	95.36	9.48	96.63	8.32	94.89	5.48	95.36	9.25	97.93	3.46
10% pepper	76.75	40.97	96.48	6.12	97.53	5.46	92.24	10.36	96.48	5.78	98.22	3.12
5% mixture	70.42	47.90	93.65	10.47	95.96	5.89	85.96	13.89	94.27	5.79	97.25	4.62
10% mixture	80.19	35.86	91.85	23.35	94.22	16.47	83.25	20.15	93.48	10.68	95.48	7.58
15% mixture	75.63	41.45	90.36	15.68	90.89	18.89	83.14	24.58	91.48	13.97	93.14	11.48
Mean	76.69	40.59	93.28	13.47	94.89	11.28	88.14	15.97	93.87	9.03	96.45	6.02

III. B. 3) Medical image segmentation results

In order to verify the effectiveness of the KFCM algorithm on segmenting noisy cell images, three cell images are selected as experimental samples for comparison in this paper. The cell images themselves contain noise, but since it is not obvious to the naked eye, this paper adds Gaussian white noise, pretzel noise and multiplicative noise with a density of 10% to the original images. Similarly, the segmentation performance is analyzed using segmentation coefficient and segmentation entropy metrics. The performance metrics of each algorithm on cell images are shown in Table 4. From the table, it can be seen that in image P1, the KFCM algorithm achieves a value of V_{pc} of more than 90%, which is an improvement of 11.4 compared to the FCM, while V_{pe} decreases by 21.62. In image P2, the KFCM algorithm's V_{pc} improves by 2.4 compared to FCM, while V_{pe} decreases by 8. In image P2, the V_{pc} of the KFCM algorithm improves by 13.66 and V_{pe} decreases by 25.54 compared to the FCM.Overall, the segmentation of this paper's algorithm is better than that of the FCM algorithm, and good segmentation can be achieved for the cellular images with the addition of mixed noise.

Table 4: Performance metrics for all algorithms

	FCM		KFCM	
Index	V_{pc}	V_{pe}	V_{pc}	V_{pe}
Image P1	84.67	28.20	96.07	6.58
Image P2	85.96	29.36	88.36	21.36
Image P3	84.32	30.68	97.98	5.14

III. C. Complexity analysis

The analysis of complexity is also one of the methods for evaluating algorithms, and it is more difficult to obtain the accurate complexity due to the differences in code writing ideas. Therefore, this paper analyzes the time complexity of the KFCM algorithm in calculating the objective function during the clustering process and compares it with FCM.The objective function calculation process of FCM is $t \times K \times N$, where t is the maximum number of iterations, K is the number of clusters, and N is the number of pixels, and thus the time complexity is $O(n^3)$. The objective function of the KFCM algorithm in this paper is calculated as, where T is the radius of the search window and L is the radius of the neighborhood window, so the time complexity of each part sums up to $N \times T^2 \times L^2 + N \times L^2 + t \times K \times N$, and ultimately the KFCM The time complexity of the algorithm is $O(n^5)$. Although the time complexity of the algorithm in this paper is higher compared to FCM, the adaptive computation of the search window and neighborhood window is realized, which improves the noise robustness of the algorithm.

IV. Conclusion

In this study, an improved fuzzy C-mean clustering (KFCM) image segmentation algorithm based on kernel function is proposed, which significantly improves the accuracy and noise immunity of image segmentation by replacing the Euclidean distance with Gaussian kernel function and combining with super-pixel segmentation technique. The experiments are validated on multiple types of images and the results show that the KFCM algorithm performs well. In synthetic image segmentation with 30% Gaussian noise added, the segmentation accuracy of KFCM algorithm reaches 98.9%, which is 12.6% higher than that of the traditional FCM algorithm; in synthetic image segmentation with 15% pretzel noise added, the segmentation coefficient of KFCM improves by 3.7% compared with that of FCM. For natural images, the average segmentation coefficient of KFCM algorithm is 19.76% higher than that of FCM when dealing with mixed noise, and the segmentation entropy is reduced by 34.57%, which indicates that the segmentation results are more deterministic. In the medical cell image segmentation test, the KFCM algorithm achieves 97.98% division coefficient for P3 images, which is 13.66% higher than FCM. The time complexity analysis shows that although the computational complexity of the KFCM algorithm is higher than that of the FCM, the anti-noise performance of the algorithm is substantially improved by the adaptive window calculation. Overall, the study proves the effectiveness of the improved fuzzy clustering algorithm based on kernel function in the field of image segmentation, especially the ability to deal with noisy images, which provides a valuable technical solution for application scenarios with high precision requirements such as medical diagnosis and automatic driving.

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References

[1] Gupta, A. (2019). Current research opportunities for image processing and computer vision. Computer Science, 20, 387-410.

[2] Yin, C., Tang, J., Yuan, T., Xu, Z., & Wang, Y. (2021). Bridging the gap between semantic segmentation and instance segmentation. IEEE Transactions on Multimedia, 24, 4183-4196.

[3] Yan, M. A. (2023). Research Review of Image Semantic Segmentation Method in High-Resolution Remote Sensing Image Interpretation. Journal of Frontiers of Computer Science & Technology, 17(7).

[4] Sakshi, & Kukreja, V. (2023). Image segmentation techniques: statistical, comprehensive, semi-automated analysis and an application perspective analysis of mathematical expressions. Archives of computational Methods in Engineering, 30(1), 457-495.

[5] Zhang, B., Rahmatullah, B., Wang, S. L., Zhang, G., Wang, H., & Ebrahim, N. A. (2021). A bibliometric of publication trends in medical image segmentation: Quantitative and qualitative analysis. Journal of applied clinical medical physics, 22(10), 45-65.

[6] Galea, R. R., Diosan, L., Andreica, A., Popa, L., Manole, S., & Balint, Z. (2021). Region-of-interest-based cardiac image segmentation with deep learning. Applied Sciences, 11(4), 1965.

[7] Dang, K., Vo, T., Ngo, L., & Ha, H. (2022). A deep learning framework integrating MRI image preprocessing methods for brain tumor segmentation and classification. IBRO neuroscience reports, 13, 523-532.

[8] Addimulam, S., Mohammed, M. A., Karanam, R. K., Ying, D., Pydipalli, R., Patel, B., ... & Natakam, V. M. (2020). Deep Learning-Enhanced Image Segmentation for Medical Diagnostics. Malaysian Journal of Medical and Biological Research, 7(2), 145-152.

[9] Kaymak, Ç., & Uçar, A. (2019). A brief survey and an application of semantic image segmentation for autonomous driving. Handbook of deep learning applications, 161-200.

[10] Su, Z., Liu, Z., Wang, M., Li, S., Lin, L., Yuan, Z., ... & Lu, H. (2022). Three - dimensional reconstruction of Kambin's triangle based on automated magnetic resonance image segmentation. Journal of Orthopaedic Research®, 40(12), 2914-2923.

[11] Deenan, S., Janakiraman, S., & Nagachandrabose, S. (2020). Image segmentation algorithms for Banana leaf disease diagnosis. Journal of The Institution of Engineers (India): Series C, 101, 807-820.

[12] Lu, H., She, Y., Tie, J., & Xu, S. (2022). Half-UNet: A simplified U-Net architecture for medical image segmentation. Frontiers in Neuroinformatics, 16, 911679.

[13] Fu, Y., Fan, J., Xing, S., Wang, Z., Jing, F., & Tan, M. (2022). Image segmentation of cabin assembly scene based on improved RGB-D mask R-CNN. IEEE Transactions on Instrumentation and Measurement, 71, 1-12.

[14] Zheng, Q., Li, H., Fan, B., Wu, S., & Xu, J. (2018). Integrating support vector machine and graph cuts for medical image segmentation. Journal of Visual Communication and Image Representation, 55, 157-165.

[15] Du, X., Zhang, W., Zhang, H., Chen, J., Zhang, Y., Warrington, J. C., ... & Li, S. (2018). Deep regression segmentation for cardiac bi-ventricle MR images. IEEE Access, 6, 3828-3838.

[16] Liu, K., Ye, Z., Guo, H., Cao, D., Chen, L., & Wang, F. Y. (2021). FISS GAN: A generative adversarial network for foggy image semantic segmentation. IEEE/CAA Journal of Automatica Sinica, 8(8), 1428-1439.

[17] Monteiro, B. A., Oliveira, H., & dos Santos, J. A. (2022). Self-supervised learning for seismic image segmentation from few-labeled samples. IEEE Geoscience and Remote Sensing Letters, 19, 1-5.

[18] Zheng, X., Lei, Q., Yao, R., Gong, Y., & Yin, Q. (2018). Image segmentation based on adaptive K-means algorithm. EURASIP Journal on Image and Video Processing, 2018(1), 1-10.

[19] Zhang, R., Yu, L., Tian, S., & Lv, Y. (2019). Unsupervised remote sensing image segmentation based on a dual autoencoder. Journal of Applied Remote Sensing, 13(3), 038501-038501.

[20] Ruijie Song,Lingyu Sun,Yumeng Gao,Juntao Wei,Chang Peng,Longqing Fan & Mingshun Jiang. (2025) .Unsupervised temperature-compensated damage localization method based on damage to baseline autoencoder and delay-based probabilistic imaging. Mechanical Systems and Signal Processing,230,112649-112649.

[21] Jiancai Song,Kangning Wang,Tianxiang Bian,Wen Li,Qianxing Dong,Lei Chen... & Xiangdong Wu. (2025) .A novel heat load prediction algorithm based on fuzzy C-mean clustering and mixed positional encoding informer. Applied Energy,388,125709-125709.

[22] Kavita Sethia,Anjana Gosain & Jaspreeti Singh. (2024) .Comparative analysis of various fuzzy clustering algorithms for linearly and non-linearly separable data. Innovations in Systems and Software Engineering,(prepublish),1-24.

[23] Yange Li,Bangjie Fu,Zheng Han,Zhenxiong Fang,Ningsheng Chen,Guisheng Hu... & Guangqi Chen. (2024) .PSO-SLIC algorithm: A novel automated method for the generation of high-homogeneity slope units using DEM data. Geomorphology,463,109367-109367.