# Application of Improved SVM Image Segmentation Algorithm in Computer Tomography Image Analysis

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***Abstract:*** *Medical imaging is becoming increasingly important in clinical diagnosis. Ultrasound imaging, computed tomography, magnetic resonance imaging (MRI) and other new medical imaging technology greatly broadens the imaging diagnostic methods. Animal Computer Tomography (CT) imaging, as an animal model, is of great significance to guide the experimental research of clinical diagnosis, and the treatment of pet disease also has a pioneering significance. Image segmentation, as the basis of medical image processing and analysis, has played a vital role in clinical diagnosis and treatment from doctors. In this paper, the existing segmentation algorithm is improved based on the characteristics of CT images of animals. In this paper, we use the global optimization of the genetic algorithm to improve the traditional support vector machine classification algorithm. At the same time, the kernel function of the support vector machine algorithm is improved to promote the segmentation results. The experiments show that the algorithm in this paper has a better segmentation effect in the processing of CT images of animals.*

***Keywords****: Computer tomography, Animal, Support vector machine, Genetic algorithm, Kernel function.*

## Introduction

Medical Computer Tomography (CT) image processing is widely used in medicine, and arouses more and more scholars' attention as a new research field. In 1895, the German physicist Roentgen discovered X-rays [12]. CT appeared in the 1970s which created a digital imaging precedent. However, CT is different from the ordinary X-ray imaging, for CT shows the sectional anatomical images, and its density resolution is much higher than that of an X-ray image. Its advent was another revolution in medical imaging technology. CT has been widely used for the central nervous system, head and neck, lungs, heart and large blood vessels and other systems and organ disease diagnosis [8]. The use of animals in medical experiments is a necessity for many medical institutions and research institutes. It is important in guiding clinical diagnosis and treatment by analyzing the CT scan and obtaining the medical image of the relevant parts of the animal. The emergence of medical imaging equipment and the improvement of medical imaging technology have multiplied the number of obtained medical images, which makes it impossible for doctors to determine the type and extent of disease through piecemeal reading of medical images. Thus the application of medical imaging equipment in clinical practice is limited. Image processing technology and medical imaging technology can greatly reduce the workload of doctors, and improve the accuracy and effectiveness of doctors' diagnosis and treatment. Medical image processing and analysis mainly includes medical image segmentation, registration, 3D reconstruction, structure analysis and motion analysis. Among these, medical image segmentation is the basis of other research directions.

Most of the algorithms used in medical image segmentation can be divided into the following types, algorithms based on the statistical method, information theory, the neural network method, and fuzzy segmentation. The threshold algorithm was first proposed by Doyle in 1962 [5]. Ant Colony Clustering Algorithm in image segmentation was studied in [14]. Zhang [11] and Zhang et al. [10] studied fingerprint image segmentation. The statistical learning theory proposed by Vapnik is a theory of the machine learning rule under the condition of a small sample [7]. Based on the statistical learning method, Support Vector Machine (SVM) [4] learning theory has attracted increasing attention in recent years, and has gained broad and intense interest as a research topic in the field of machine learning, because it no longer needs to meet the requirement of a large sample as in traditional methods. Chew et al. [3] put forward the weighted support vector machine through using various parameters of C to eliminate differences in degrees of risk. Zhou et al. [13] studied the osteoporosis based on SVM. Lin and Wang [6] combined fuzzy theory with SVM, and proposed the fuzzy support vector machine. Xue and Li [9] used the support vector machine algorithm to segment virtual human slices. Chapelle et al. [2] extracted gray histogram images as the training samples, then used the SVM method for image segmentation. The genetic algorithm is based on the theory of the evolution mechanism of natural selection, and it is a paralleled, statistical, and randomly searching method. The genetic algorithm is good at global searching, but lacks local search capability, so the genetic algorithm is always combined with other algorithms when it is applied [1].

On the basis of the research of various image segmentation algorithms and CT image features, this paper conducts in-depth research on using image segmentation algorithms to process CT images, particularly CT images of animals. In this paper, firstly, the CT image is analyzed. Secondly, this study focuses on the SVM algorithm. Then, the genetic algorithm is discussed. Finally, the SVM algorithm is improved by using the improved kernel function and genetic algorithm, which improves the operation speed and segmentation results. At the end of this paper, some experiments are designed to test the effect of the algorithm. The experiment results show that the algorithm has a fast segmentation speed. At the same time, the effect of segmentation is greatly improved compared with the traditional algorithm.

## Materials and methods

### *Principle and characteristics of CT images*

Computer X-ray tomography technology is a medical image contrast technology which combines computer technology with ray scanning technology. A CT image is composed of two parts: pixel intensity and pixel size. Among these, the pixel intensity reflects the organs' or tissues' absorption degree of X-ray, and the size of the pixel reflects the fine degree of fineness of the image, i.e., the spatial resolution of the image. A CT image is a gray distribution image. Compared with the X-ray image, its black region is a low density area with a low degree of absorption of X-rays. The white area of a CT image is a high density area with a strong degree of absorption of X-rays. In reality, for convenience the CT value is usually used to represent the absorption of X-rays of the organ or tissue. Fig. 1 presents the CT value of each element of the human body. A careful study of the map shows that the bone has the highest CT value, while air has the lowest, and the CT value of the other elements is between these two values.

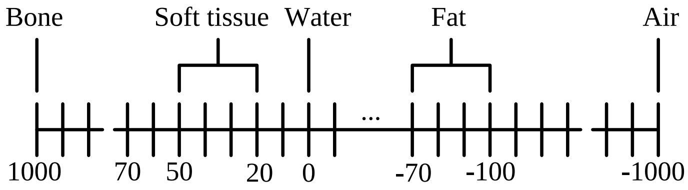


Fig. 1 CT value of each element of the human body

Compared with ordinary images, a CT image has the characteristics of anatomical structure, complexity, inherent fuzziness, uniformity of the internal gray level, and a massive amount of data. Therefore, research on a CT image segmentation method has the following characteristics:

(1) CT images belong to the category of anatomical images. In the process of CT image segmentation, the fusion of other types of functional images, such as positron emission tomography images, to guide the CT image segmentation has gradually become a new trend [7].

(2) Due to the complexity and diversity of CT images and the difficulty of segmentation, there has not been a segmentation method that is applicable to a variety of tasks to date.

## *SVC basic concept*

The support vector machine is a machine learning method based on statistical learning theory. It is based on the principle of Vapnik Chervonenkis (VC) dimension and minimal structural risk. The VC dimension is an important index to describe the function set or machine learning capabilities. Statistical learning theory is based on VC dimension, and deduces the relationship between the expected risk and the empirical risk, which is known as the generalized bound. The empirical risk minimization principle is to calculate the empirical risk through the known training data, and uses the empirical risk to gradually approach the minimum value of the expected risk. In the case of finite samples, the learning machine should not adopt the principle of empirical risk minimization, but should minimize the sum of the confidence range and the empirical risk. Researchers have put forward the structural risk minimization (SRM) principle.

For a given set of sample points $\{(x_i, y_i), i = 1, 2, \ldots, n\}$, $x_i \in R^d$, $y_i \in \{1, -1\}$ is the known classified identification corresponding to the sample point $x_i$. The purpose of classification is to find a classification hyperplane in the sample space

$$w^{\mathrm{T}} x + b = 0, \tag{1}$$

where, $w$ is the direction vector, and $b$ is the bias. This can separate the two types of points; that is:

$$\begin{aligned} w^{\mathrm{T}} x_i + b &\geq 0, \quad y_i = 1, \\ w^{\mathrm{T}} x_i + b &\leq 0, \quad y_i = -1. \end{aligned} \tag{2}$$

The schematic diagram is shown in Fig. 2.

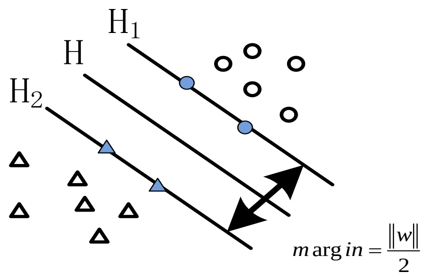


Fig. 2 The optimal classification hyperplane for linear separable cases

In this figure, solid rectangles and hollow circles represent two types of samples. $H_1$, $H_2$, and $H$ are parallel to each other. $H$ is the classification of hyperplane. $H_1$ and $H_2$ are the nearest samples to $H$ in the two types of samples and they are also parallel to $H$. The vertical distance between planes $H_1$ and $H_2$ is referred to as the classification interval. The sample points that go through planes $H_1$ and $H_2$ are the support vectors.

Because $w$ and $b$ multiply any non-zero number at the same time, the hyperplane has no change. To make it standardized, the requirements are:

$$\min_{i=1,2,..,n} \left| w^T x_i + b \right| = 1. \tag{3}$$

At this time, the classification interval is $m\arg in = \frac{\|w\|}{2}$, and the best classification is the one that makes the classification interval $m\arg in$ largest or $\frac{\|w\|}{2}$ smallest. The problem of two types of linear separable support vector machine is a two programming problem, which can be rewritten as the following optimization problem:

$$\begin{aligned} &\min \ \frac{\|w\|^2}{2} \\ &s.t. \quad (y_i(w \cdot x_i) + b) \geq 1 \quad i = 1,\ 2,\ ...,\ N \end{aligned} \tag{4}$$

Using $A = (a_1, a_2, ..., a_N)^{\mathrm{T}}$ as the Lagrange multiplier, the above formula can be expressed as:

$$L(w,b,a) = \frac{1}{2}\|w\|^2 - \sum_{i=1}^{N} a_i \left\{ y_i[(w \cdot x_i) + b] - 1 \right\}. \tag{5}$$

A partial derivative is made to $w$ and $b$, and the value of the partial derivative is assigned to zero, so that the minimum value of the function can be calculated. At the same time, the optimal classification face problem becomes a dual problem.

In the case of $\sum_{i=1}^{n} y_i a_i = 0$ and $a_i \geq 0$, find the value of $a_i$ when the maximum value of the following formula is obtained:

$$Q(a) = \sum_{i=1}^{n} a_i - \frac{1}{2}\sum_{i,j=1}^{n} a_i a_j y_i y_j \left(x_i, x_j\right). \tag{6}$$

If $a_i^*$ is the optimal solution, the weight vector $w*$ can be expressed as:

$$w* = \sum_{i=1}^{N} a_i^* y_i x_i \ . \tag{7}$$

In the case that $w*$ has been obtained, respectively choose any support vector from the two types of samples and then find the solution parameter $b*$ through the vector

$$b^* = \frac{1}{2}[w * x^*(1) + w * x^*(-1)], \tag{8}$$

where $x*(1)$ and $x*(-1)$ represent the support vectors selected from the two types of samples.

The optimal classification decision function is as follows:

$$f(x) = \operatorname{sgn}\left(w * x + b^*\right) = \operatorname{sgn}\left(\sum_{i=1}^{N} a_i^* y_i \left(x_i \cdot x\right) + b^*\right). \tag{9}$$

*Nonlinear support vector machine*
In practical applications, the data are mostly linear inseparable, instead of being nonlinear separable. A nonlinear support vector machine algorithm can be used to solve the problem. The nonlinear SVM firstly maps the input data in the original space to high dimensional feature space by nonlinear mapping, and then the optimal classification hyperplane is constructed in the feature space. In this way, the nonlinear classification of the data in the original space is transformed into a linear classification problem in the high dimensional space to look for a hybrid plane in the high dimension space.

*Kernel function*
The introduction of the kernel function gives the SVM a prominent advantage in solving the nonlinear problem. Low dimensional space vector sets are usually difficult to divide, and the solution is to map them to high dimensional space. But the kernel function is an effective way to solve this problem. In practical problems, the kernel function is usually given directly. Up to now, the following three kernel functions have been the most commonly used:

RBF kernel function: $k(x_i, x_j) = \exp\left(-\frac{\left\|x_i - x_j\right\|^2}{2\sigma^2}\right)$, (10)

Polynomial kernel function: $k(x_i, x_j) = [1 + (x_i \cdot x_j)]^d$, (11)

Sigmoid kernel function: $k(x_i, x_j) = \tanh[\gamma(x_i \cdot x_j) + c]$. (12)

Different kernel functions and their parameters have a great influence on the classification performance, so it is very important to select a suitable kernel function.

### *Operation process of genetic algorithm*

The genetic algorithm is based on natural selection and genetic theory. By simulating the process of natural evolution, the optimal solution in the target space is searched in the manner of a kind of artificial evolution. At present, as a kind of optimization and search technology based on statistical theory, the application of the genetic algorithm in the field of computer vision arouses increasing attention, such as application in feature extraction, image matching, and image segmentation. The genetic algorithm has five basic elements: encoding and decoding, the initial population setting, the setting of fitness function, genetic operation (selection, crossover and mutation), and the setting of control parameters. The specific implementation steps are shown in Fig. 3.

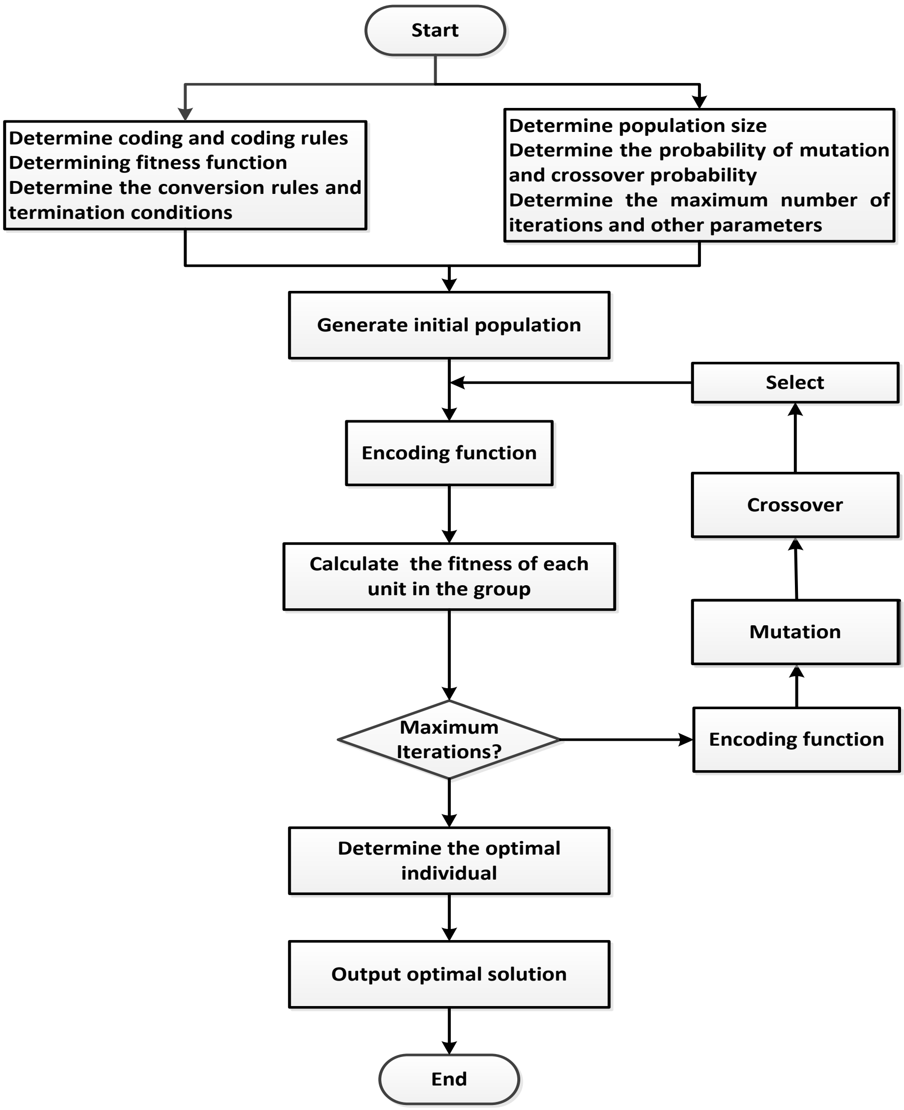


Fig. 3 Flow chart of genetic algorithm

### *Application of the improved SVM algorithm combined with genetic algorithm in the segmentation of animal CT image*

With its high resolution, low cost and mature technology, CT has become the primary method of examination and pathological study, and thus is widely used in clinical practice. Effective segmentation of CT images can rapidly diagnose and treat related cases, which is of great help in reducing the burden on doctors and improving the accuracy and effectiveness of diagnosis and treatment. As a classical image segmentation algorithm, SVM has been widely used. However, its segmentation results and computational time are not ideal. This paper presents a dual optimization improved algorithm which combines SVM of the improved kernel function with a genetic algorithm. This improved algorithm significantly improves the segmentation effect and operation time of the original SVM algorithm.

Firstly, the kernel function is improved. The RBF kernel function, polynomial kernel function, and Sigmoid kernel function are pairwise weighted to construct a new function, and through the optimization of the weights, the weight combination of the best segmentation results can be found. The form of the new weighted kernel function set in this paper is as follows:

$$K = \alpha K_1 + \beta K_2 + (1 - \alpha - \beta) K_3 \tag{13}$$

where $K_1$ is the RBF kernel function, $K_2$ is the polynomial kernel function, $K_3$ is the Sigmoid kernel function, $\alpha$ and $\beta$ are the weights of the weighted kernel function, $\alpha, \beta \in (0, 1)$.

If the ratio of the segmented animal CT image background in the whole image is $P$, and the test set accuracy returned by the support vector machine is $R$, each weight of the weighted kernel in the interval (0, 1) will be traversed to determine the weight making $\omega = |P - R|$ minimal; i.e., the best segmentation weight. The corresponding weighted kernel function is the one with the best segmentation effect.

In order to improve the efficiency of SVM classification, this paper introduces the concept of multi-classification into CT image segmentation, which can improve the efficiency of image segmentation. The two prong decision tree method and SVM are combined to form a multiple classifier, which can conduct multi-task processing at the same time. This increases the processing quantity of characteristics, and the most easily classified features can be classified first. Then, the genetic algorithm is used to improve the structure of SVM multi-classifier.

*Improved algorithm*

Genetic algorithm is adopted to optimize the SVM multi-classification decision tree structure. At each decision node of the decision tree, multi-class training samples are divided into two categories by using a real valued encoding genetic algorithm, under the rule of making a maximal class interval in the high-dimensional feature space, which can guarantee the best divisibility of the two samples. Then, an appropriate decision tree structure is generated. Combined with the improved kernel function, the classification algorithm in this paper can obtain excellent performance when dealing with animal images. The implementation steps of the algorithm are as follows:

(1) Input the image, and calculate $P$, the proportion of the background in the image.
(2) Transform the image into an HSI image, and extract the characteristics of pixels.
(3) Randomly select a certain number of samples from the original image as the training samples of the foreground and background.
(4) Design the operator of the genetic algorithm.
(5) Encode the training samples according to real value, and initialize the population.
(6) Filter each class of samples, constantly iteratively classify them, and finally obtain an optimal SVM classifier.
(7) Return the test accuracy set of the designed kernel function $\omega_i = |P - R_i|$.
(8) Calculate and determine the weight of the designed kernel function.

A method of using a genetic algorithm to optimize SVM is proposed in this paper. Its goal is to make the classification interval maximization of the nonlinear support vector machine in high dimensional feature space, and the training samples are divided into two categories which ensures that each of the two samples has better divisibility. When specifically implemented, the objective function for maximizing the classification interval is searched, and it is used as the fitness function of the genetic algorithm. Then a suitable kernel function is obtained, which reduces the computation time and improves the classification efficiency.

## Results and discussion

To verify the effectiveness of this algorithm, we collect a large number of CT images of different parts from different animals. The CT images are segmented by SVM based on the improved kernel function. Experimental results show that the proposed algorithm can quickly segment the diagnosis and treatment image, compared with the traditional SVM. The experimental platform used is the hardware Intel(R) Core(TM) i5-4300M @2.60GHz, 4G memory, and Windows 7 software, with MATLAB as the design language.

We select common animals such as chickens, ducks, rabbits, and dogs as experiment objects, and then conduct CT imaging studies on their brains, and joints. By comparing the new algorithm in this paper with the traditional SVM algorithm, the new algorithm has obvious advantages in anti-noise capability, computing speed and segmentation effect. Fig. 4 shows the original CT images of various animals.

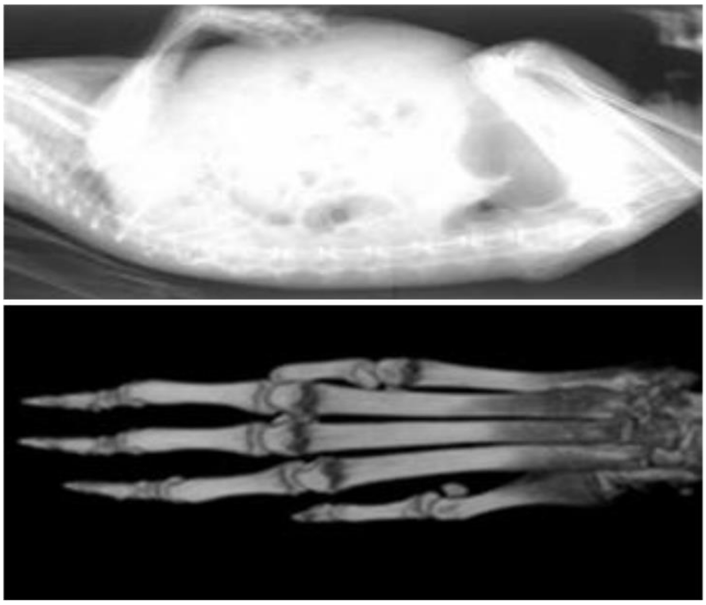

Fig. 4 Original CT images of various animals

Table 1 shows the time and segmentation results of different algorithms in the segmentation of CT images.

Table 1. Accuracy of segmentation of brain magnetic resonance images

| | **Run time, (ms)** | **Segmentation effect** |
|---|---|---|
| **GA** | 1327 | good |
| **SVM** | 893 | good |
| **Proposed method** | 407 | excellent |

As can be seen from Table 1, the algorithm proposed in this paper is superior to other algorithms both in time and in segmentation results.

## Conclusion

This paper conducts in-depth research on the segmentation of animal CT images, and proposes the use of a multi-classification algorithm to improve the calculation speed of the traditional algorithm. At the same time, this study further improves this algorithm by using a genetic algorithm, and designs an appropriate kernel function to enhance the segmentation results. In this paper, we first introduce the CT image. Secondly, the SVM algorithm is introduced in detail. At the end of this paper, the improved algorithm is used to carry out segment experiments on the CT images of animals. Experimental results show that the proposed algorithm achieves excellent segmentation results, and reduces the running time. Compared with the traditional algorithm, it has many obvious advantages.

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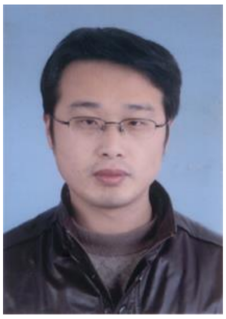

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