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# *Improved Hidden Markov Algorithm Based on Bayes in Low Dose CT Images*

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***Keywords:*** Improved Bayes, Improved Hidden Markov Algorithm, Low-dose CT Image, Visual Effects, Image Quality

***Abstract:*** In order to reduce the radiation exposure of patients during CT scan, low-dose CT images were produced, but the disadvantage was that the image quality was reduced. The Bayesian maximum posterior probability estimation (Bayesian MAP) method is an applied statistical method that can estimate the original noise-independent coefficients from the noise-contaminated image detail coefficients. This paper aims to study the application of bayesian based improved hidden markov algorithm in low-dose CT images, which has become the focus of CT research in recent years. In this experiment, hmrf-em, eHMRF algorithm and hmrf-msa-em algorithm were firstly analyzed by mathematical statistics within the experimental scope, and the superiority of this algorithm was compared by looking at different coefficients. The classification and statistical analysis of the re-data statistical method were carried out by using the naive bayesian algorithm and the improved hidden markov algorithm based on bayes. And the use of a single variable method to compare the use of bayesian based improved hidden markov algorithm in the low-dose CT image imaging whether there are different changes, and the degree of change. Experimental data show that the improved hidden markov algorithm based on bayes achieves higher values of Jaccard, Dice and CCR at different noise levels. The improved hidden markov algorithm based on bayes is clearer than the low-dose CT images obtained by the naive bayes algorithm. In various medical images, the improved hidden markov algorithm based on bayes plays an obvious role in changing the resolution of low-dose CT images. Experimental data show that compared with other denoising methods, the peak signal-to-noise ratio of the de-noised image can be improved, the detailed features of the image can be retained better, the visual effect can be improved by 46.78%, and the correct segmentation rate can reach 95.75%.

## 1. Introduction

As the main representative of modern radiology, CT has become an indispensable part of radiological diagnosis and is one of the most common methods of nondestructive testing in clinical diagnosis. After years of development, the speed and quality of CT images have been greatly improved. With the increasing popularity of CT technology in some clinical fields, more and more people are concerned about the radiation risk of CT to human body. Compared with other radiological diagnostic tools, CT is usually accompanied by high levels of X-ray radiation. Medical research shows that too much X-ray radiation can cause metabolic abnormalities or cancer, leukemia or other genetic diseases. A decrease in CT dose is usually accompanied by a decrease in image quality. The study of low-dose CT began in the late 20th century, when researchers conducted a large number of analytical studies on clinical CT, and we attempted to analyze the effect of dose control on the scanning results of diagnostic information in different locations. CT image navigation minimally invasive surgery robot motion control system is a high-precision surgical positioning for minimally invasive surgery, as a robot with three east and two degrees of freedom of rotation, and one degree of freedom of insertion for minimally invasive surgery. Among them, the main function of CT image is to provide doctors with an interface for planning surgery and operating robots, and to obtain the mapping calculation between the robot coordinate system and the image coordinate system, as well as the calculation of robot kinematics and inverse kinematics. CT images and robots cooperate to provide great help for minimally invasive surgery.

The "Hidden Markov Model" Model, which consists of the "Hidden Markov" process and the observation process, has recently become a subject of increasing attention. The model should include a discrete first-order market model and a continuous or discrete observation model that describes the relationship between a series of states and a series of observations. Basic models have been used in speech processing, biochemistry, biology, psycho-educational measures and many other disciplines. In recent years, with the advent of the era of big data, the application of hidden markov model in seismic exploration has aroused people's concern. From an economic point of view, the hidden markov model leads to the consumer price index. The hidden markov model is used to explore the information of Chinese stocks. The research on these aspects related to the macroeconomic forecast and the analysis of the financial market microstructure is an instructive example.

Niu S Z, on the basis of reconstruction of projection data with low-dose CT, obtains high-quality low-dose CT images with full generalized variational regularization method [1]. Methods the linear Anscombe transformation was used to transform the projected data of CT image from poisson distribution to gaussian distribution, and then an effective full generalized variation minimization algorithm was used to recover the transformed data. The SheppLogan image reconstructed by FBP algorithm was 17.752 dB and 19.379 dB, and the NMSE of the clock image reconstructed by FBP algorithm and shepp-logan image was 0.86% and 0.58%, respectively, which decreased to 0.2% and 0.23%, respectively. Conclusion the method can effectively suppress the noise and bar artifacts in low-dose CT images under the condition of impossible assumption of piecewise constant. Zhang H believes that the markov random field (MRF) model is widely used in the penalty of noise smoothing in the edge preserving region, and is used to reconstruct segmentation smooth images in the presence of noise, for example in low-dose computed tomography (LDCT) [2]. Although it retains the sharpness of the edges, its area smoothness may sacrifice the texture of the tissue image, which has been considered a useful imaging biomarker, so it may impair clinical tasks such as identifying malignant and benign lesions, such as pulmonary nodules or colonic polyps. The purpose of this study is to transform the edge preserving region noise smoothing mode into the texture preserving frame of LDCT image reconstruction, while retaining the edge preserving advantages of MRF neighborhood system. Specifically, we adjusted the MRF model and used the previously full-dose CT(FdCT) scan of muscle, fat, bone, lung and other image texture as the prior knowledge of bayesian reconstruction of LDCT image retention texture. To demonstrate the feasibility of the proposed reconstruction framework, we conducted a clinical patient scan trial. The experimental results show that the prior knowledge of LDCT image reconstruction using Haralick texture measure is gained significantly. Therefore, it is speculated that LDCT reconstruction with preserving texture has more advantages than the region smoothing method with preserving edge in the clinical application of texture specificity.

Due to the lack of attention to the intrinsic relationship of pixels, many traditional image separation algorithms still have a lot of room for improvement[3-4]. The purpose of this paper is to study the application of improved bayesian hidden markov algorithm in low dose CT images. In recent years, this algorithm has become a key research field of TCP. In this experiment, hmrf-em, eHMRF algorithm and hmrf-msa-em algorithm were firstly analyzed by mathematical statistics within the experimental scope, and the superiority of this algorithm was compared by looking at different coefficients. The classification and statistical analysis of the re-data statistical method were carried out by using the naive bayesian algorithm and the improved hidden markov algorithm based on bayes. And the use of a single variable method to compare the use of bayesian based improved hidden markov algorithm in the low-dose CT image imaging whether there are different changes, and the degree of change.

## 2. Programs Method

### 2.1. Improving the Introduction of Hidden Markov

(1) Definition of hidden markov model

The hidden markov model is developed from the markov model, which can be regarded as a double-random process, and is defined as follows:

The first part is the unobservable state sequence $\{C_t: \ t=1,2, \ldots\}$, which satisfies the markov property, i.e

$$p\left(C_t \middle| C^{(t-1)}\right)=p\left(C_t \middle| C_{t-1}\right), \ t=2,3, \ldots, \ C_t \in \{1,2, \ldots, K\} \tag{1}$$

Among them, K represents the maximum number of states that can be obtained, and the distribution of the initial state C1 is denoted as π1. The second part is the state-dependent process $\{X_t: \ t=1,2, \ldots\}$, and the conditional distribution of Xt is only related to the state Ct, that is:

$$p\left(X_t \middle| X^{(t-1)}, \ C^{(t)}, \pi_1, \Gamma\Gamma,\right)=p\left(X_t \middle| C_t, \theta\right), t=1,2, \ldots \tag{2}$$

θ is a parameter of the conditional distribution $p\left(X_t \middle| C_t\right)$, and the structural dependence of the hidden Markov model can be represented by FIG. 1.

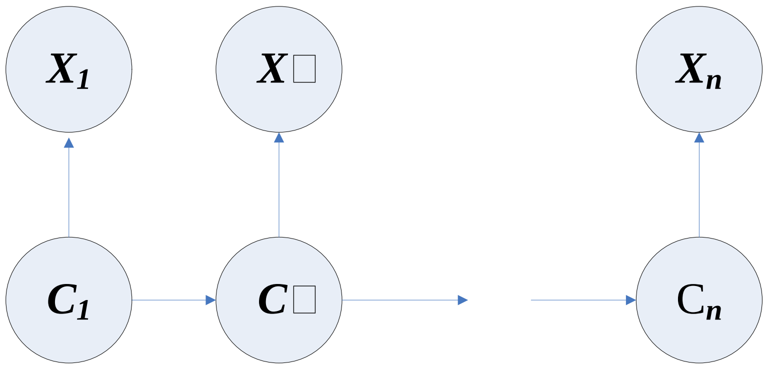


*Figure 1. Schematic diagram of the structure of the hidden Markov model*

(2) Research status at home and abroad

The hidden markov model has been applied to the word recognition system for the first time. After years of development, the hidden markov model has been widely used in various fields [5]. The research on implicit model mainly focuses on the method of estimating model parameters and the practical application of the model. The estimation methods of hidden markov model parameters are mainly based on the most probable method and bayesian method. The methods to evaluate the most possible parameters are mainly numerical and maximum elasticity algorithm (EM). Since the markov chain in the hidden model cannot be observed, the natural approach to parameter estimation is to treat it as a missing value and use the EM algorithm to estimate the parameter. The EM algorithm is simple and numerically stable, but when the initial parameters deviate from the actual parameters and the algorithm converges slowly, the EM algorithm needs more iterations. Altmanetal also pointed out that when estimating the maximum probability of the estimated parameter, the maximum numerical method was faster than the EM algorithm [6-8]. The integration of the hidden model and the prior algorithm reduces the computation of EM algorithm and improves the efficiency. Although the bayesian method is superior, it can also be used to estimate the parameters of the hidden markov model. The Reversibel Jump Makov ChainMonte Carlo Method(RJMCMC) algorithm is proposed to estimate the parameters of the hidden markov model. The RJMCMC algorithm is a special Metropolis Hastings(MH) algorithm, whose particularity is to realize dynamic sampling Jump of different parameters in the spatial position, so that the RJMCMC algorithm can effectively reach the hidden markov number model, and avoid the "swap indication" of the sampling parameters. The Makov Chain Monte Carlo(MCMC) method allows direct sampling of the inverse distribution of hidden markov model parameters, while in fact, when the sample size is large, more states are taken, which slows the convergence rate of the conventional markov algorithm. The gibbs sampling algorithm is used to track the entire edge chain using the forward-backward gibbs (FB) sampling algorithm. The results show that this method can accelerate the attenuation of sample autocorrelation and improve the efficiency of the sampling algorithm.

## 2.2. Composition of Bayesian Algorithm

(1) Introduction to bayes

The problem of pattern recognition and classification is to extract the observed values from the identified objects and then classify them according to the observed values. Firstly, the training set of the recognition object is established, where the category of each point is known. According to these conditions, the discriminant function is established, the parameters in the discriminant function are estimated through the existing samples, and then the discriminant function is used to determine the samples whose category is unknown.

1) Bayes' rule

Bayesian method is a method to correct subjective judgment. When sampling is sufficient, it involves approximating the sampling probability with the population probability. In general, the probability of event A under the condition of event B is not equal to that of event B under the condition of event A, but there is a specific relationship between them, which is described by bayes' rule.

2) Bayesian decision making

Bayes' rule is just one way to break it down in a big way into a lot of implementation-specific decisions. If the statistical knowledge is complete, bayesian decision theory is an optimal classifier. Bayes classifier is the classifier with the lowest probability of classification error or the lowest average risk [9]. Its design method belongs to a basic statistical classification method.

3) Bayesian decision based on the minimum error probability

If each sample belongs to $P(X|\omega_1)$, $P(X|\omega_2)$ of ω1,ω2, we know that the prior probability of the two classes is P(ω1) and P(ω2) respectively, and the class density function of the two classes is $P(X|\omega_1)$, $P(X|\omega_2)$. I'm going to give you an X, and I'm going to determine the category of X. We know that by bayes' formula

$$P(\omega_j|X)=\frac{P(X|\omega_j)P(\omega_j)}{P(X)} \tag{3}$$

We know it by the full probability formula

$$P(X)=\sum_{j=1}^{M}P(X|\omega_j)P(\omega_j) \tag{4}$$

Where M is the number of categories. For both types of problems,

$$P(X)=P(X|\omega_1)P(\omega_1)+P(X|\omega_2)P(\omega_2) \tag{5}$$

So we're going to use a posteriori probability

$$P(\omega_1|X) > P(\omega_2|X) \Rightarrow X \in \omega_1 \tag{6}$$

$$P(\omega_1|X) < P(\omega_2|X) \Rightarrow X \in \omega_2 \tag{7}$$

(2) Feature extraction based on bayes

Can be regarded as a characteristic of low dose CT image text, appear in the vector space consists of all the words of low-dose CT image of the original vector feature, if every word represent itself as vector characteristics, the characteristic vector space is usually too much, if direct in spatial dimension classification, and the training of a large number of samples to calculate the redundancy will need a lot of information about features, and useless calculation can cause child categories of [10]. In general, unnecessary characterization should be avoided as far as possible before the sample is formed without affecting the accuracy of classification. Before extracting the feature, the artificial size of the feature vector is used to eliminate some common noises. This type of CT image has no effect on the classification results, but it will incur considerable computational cost.

### 2.3. Features of Low-dose CT Images

(1) System modeling and scattering noise suppression

Under low dose scanning condition, the electronic noise of the system will have a great influence on the quality of low dose CT imaging. A large number of studies have shown that under the condition of normal data processing dose, satisfying CT before the data distribution is made up of projection, but from the modern CT system to get data from pluripotent detector ray is the process of identity, rather than the consistent response, and the photon can not work consistently electronically reflect a variety of factors, such as the noise of the reconstruction imaging before, calibration can be used in projection of a large number of data pretreatment, etc[11]. The CT statistical properties of the original measurement data can be mined, a new method for statistical modeling of the predicted CT data has been established, and a new conventional mixing model of Poisson has been created based on the measurement results of the CT data processing system.

Due to the existence of collation system, the observed data of CT images are generally regarded as random variables independent of the same distribution. However, the actual scanning object often has a high adjacent correlation in the image space, which will lead to the observation data to show a certain adjacent correlation. By analyzing the data obtained from the CT system, the researchers modeled the correlation between the observations received from adjacent detectors, thereby eliminating the random noise of the acquired data [12-14].

In addition to developing more accurate observation models, some researchers have improved the text-to-noise ratio of the observed data through a number of extensive calibration links. The distribution of dispersion noise is estimated and corrected by using grid attenuation plate, which not only improves the noise signal ratio of the observed data, but also improves the suppression of the dispersion noise of the low-energy gamma ray component and improves the noise. The system density resolution, at the same time eliminates the random noise.

(2) Low-dose CT reconstruction algorithm structure

1) Projection data filtering

Since the introduction of CT system, the reconstruction algorithm of anatomical structure represented by filtered backprojection (FBP) has become the main algorithm in 2d CT system because of its fast computation speed and easy operation. However, the resolution algorithm cannot effectively eliminate the noise, and the reconstruction results are easy to be forged and noisy under the low dose scanning condition. Some researchers eliminated the noise in the projection data by modifying and retrieving the projection data, so the SNR of the low-dose projection data was as close to the SNR of the normal projection as possible, thus solving the problem of the lack of noise attenuation ability in the method. Reframe the composition class. The data filter directly corrects the projected data, making the filtering process and reconstruction process independent of each other, facilitating system integration [15-16]. The computation is usually much smaller than the iterative reconstruction, which has obvious advantages in the following aspects: calculation speed.

2) Iterative reconstruction algorithm

Iterative reconstruction algorithm is of great significance in the research field of CT reconstruction because the expected maximum likelihood expectation maximization (MLEM) algorithm has been introduced into the reconstruction field of alternative images. Based on the physical model of the image processing system and the statistical characteristics of the detection data, the iterative reconstruction algorithm creates a statistical model of gaussian or pumm subdistribution. In the rear of the training will be estimated based on the theory of bayesian Maximum probability density (Maximum a posterior, MAP), preventive information space is introduced in the reconstruction of the image as a punishment, effectively dispersed noise and stay on the edge, in terms of the dispersion and pseudo noise eliminated obviously superior type algorithm, very suitable for the reconstruction condition and low dose CT scan images [17-19]. One of the focuses of iterative reconstruction algorithm research is the method that can be priori designed to improve the quality of reconstruction. Iterative image reconstruction algorithm is usually used on traditional neighborhood space, prior correlation recognition model, and then from the same serious influence of data in the projection of markov, to noise and pseudo thorn and serious data projection noise level reduces the capacity constraints, and some by a set of previously agreed the potential constraints, may introduce other fake thorns. Based on the diffusion constraint, a complete reconstruction method is proposed to minimize the total low dose variation of CT, thus eliminating the total variation of pseudo-conventional blocks.

3) Sparse Angle reconstruction

In addition to the intensity of the X-ray, the scanning time is a direct factor affecting the radiation dose. The reduction in scanning time is usually achieved by reducing the sampling Angle (obscuring Angle or incomplete Angle) of the projection. Since the projected data of CT system is usually highly redundant, the complete projected data set can be obtained under reduced sampling conditions by reducing the estimation of lost data. The dictionary learning method was used to evaluate the lost projection data, and the results were better than the television method. The Betram method is used to obtain missing data for the projection, and it produces better experimental results than traditional linear values.

4) Low-dose CT post-processing algorithm

Noise analysis, pseudo-photographic characteristics and improved post-processing algorithm in reconstructed images are also important guidelines for low-dose CT research. The characteristics of these algorithms are that they do not rely on projection data, can be transferred, and can be processed directly by improving existing CT images without improving or replacing existing equipment to facilitate their use and promotion [21]. In order to ensure the reliability of diagnosis, the post-processing algorithm should retain or improve the details of the original image as much as possible, while effectively reducing the noise of the low-dose CT image and canceling its forgery. Postprocessing algorithms are usually used in the image space. Later working algorithm helps to improve CT image by constructing image space filter. By using nonlinear or low dose anisotropic filter to filter the image reconstructed by CT, the image can be adjusted effectively while maintaining a certain limit effect [22-25]. However, the disadvantage is that it is easy to reduce the contrast of the image and blur the edges. In addition, because these filters are usually confined to a small area, it is impossible to effectively suppress high-frequency noise in the projected data.

## 3. The Experiments

### 3.1. Experimental Settings

(1) Experimental background

This experiment detects the application of bayesian improved hidden markov algorithm in low-dose CT images [26-28]. In order to verify the feasibility and effectiveness of the improved algorithm, the enhanced mutual information selection function in this paper is designed and tested, and the enhanced tf-idf is used to assign different weights to the selected function. The final result of the classification is obtained by the enhanced probability of the hidden markov algorithm based on bayes. Low-dose CT, which reduces the radiation dose to a quarter of the initial dose, is better suited for suspicious lung cancer detection or large-scale testing without necessarily having a disease[29]. However, due to the increase of image noise caused by the reduction of radiation dose, the contrast between the target area and the background area decreases, which affects the accuracy of separation. In order to improve the location and detection speed of the damaged sites of lung diseases, it is urgent to study the high-precision extraction method of lung reburning to provide low-dose CT images.

(2) Experimental setting process

Experimental data were collected from various medical image databases. To verify the effectiveness of the algorithm in this study, low-dose CT pulmonary clinical data from 50 screeners in the medical image database were selected for the experiment[30]. The current of the tube is 40mA, the data of each layer is 512×512 pixels, and the thickness of the layer is 1.25mm. Of the 50 clinical data sets, each group had more than 200 layers, with a minimum of 219 layers and a maximum of 304 layers.

### 3.2. Experimental Steps

(1) Based on improved hidden markov algorithm based on bayesian applications, use of image HMRF - EM, eHMRF algorithm, HMRF - MSA - EM algorithm segmentation experiments, using Tohka processing method for medical image data after the different levels of noise, respectively in three segmentation algorithm for processing, the processed image is to the Jaccard, Dice and CCR coefficient were compared.

(2) According to different types of medical image data, investigate the changing application ability of naive bayes and bayesian based improved hidden markov algorithm in low-dose CT images.

(3) According to different types of medical image data, investigate the imaging noise comparison between the improved bayesian hidden markov algorithm and the normal low-dose CT image, and observe whether the improved bayesian hidden markov algorithm has the correct application to the low-dose CT image.

(4)According to the experimental phenomenon, various data were recorded, and the Excel software owned by the computer was used for data statistics. The one-way ANOVA program of SPSS19.0 analysis software was used for data variance analysis and comparison, and the data results were expressed in the form of average value.

### 3.3. Matters Needing Attention in the Experiment

(1) The principle of contrast

In setting up the experiment, usually create two group, one is to use the improved hidden markov algorithm based on bayesian application in the low dose CT image of the experimental group, one is to use the traditional hidden markov algorithm applied in low dose CT image of the control group, and then through the intervention or control of low-dose CT images in order to eliminate or reduce data error, after can see more clear, more comparative improved hidden markov algorithm based on bayesian precision in the low-dose CT image effects. Among them, the use of a lot of control methods, by positive control, standard control, self-control, etc., but the most commonly used is the blank control method.

(2) Randomness principle

The randomness principle of the improved hidden markov algorithm based on bayes in the low-dose CT image experiment refers to the random and arbitrary sampling of samples to be studied in the monitoring of the improved hidden markov algorithm based on bayes in the experimental range of low-dose CT image parameters. Only in this way can we ensure the significance of low-dose CT image experiment, reduce the unnecessary result errors brought by low-dose CT image experiment system, and balance the conditions brought by each application.

(3) The principle of parallel repetition

That is, it shows the difference between the improved bayesian hidden markov algorithm in low-dose CT images and the ordinary low-dose CT images in one of the application range of data to observe the temperature in the improved bayesian hidden markov algorithm in low-dose CT images and the ordinary low-dose CT images. For the sake of scientific rigor, this experiment must be repeated many times. In order to minimize the data errors caused by unnecessary factors, samples must be randomly selected. Of course, this cannot guarantee that all the influences caused by unnecessary factors can be completely eliminated. The principle of parallel repetition is the answer to this confusion.

(4) Single factor variable principle

Namely, the control variable, which highlights one application data of the experiment in the low-dose CT image, while the other variables remain unchanged. To observe the effect of this data on the experimental results of the improved bayesian hidden markov algorithm in low-dose CT images, that is, the consistency of other variables must be maintained without changing control. It is precisely because when doing experiments, we may habitually forget some basic principles, which leads to errors in solving or designing experiments. Therefore, in the experiment of low dose CT image, we must pay attention to the essential and critical principle of the experiment.

## 4. Discussion

### 4.1. Effectiveness of Improved Hidden Markov Algorithm Based on Bayes

(1) Three evaluation indexes, Jaccard, Dice and Correct classification ration(CCR), were used for experimental evaluation. The data show that table 1, table 2 and table 3 show that the improved hidden markov algorithm based on bayes achieves higher values of Jaccard, Dice and CCR at different noise levels. With the increase of noise levels, the value of Jaccard coefficient of eHMRF algorithm decreased by 0.0871, while that of the improved hidden markov algorithm based on bayes decreased by 0.0869, indicating that the improved hidden markov algorithm based on bayes not only has higher accuracy but also better stability. The data acquisition table is shown in table 1 and figure 2.

*Table 1. Jaccard coefficient comparison*

| Noise level /% | HMRF-EM | eHMRF | HMRF-MSA-EM |
|---|---|---|---|
| 1 | 0.9472 | 0.9714 | 0.9584 |
| 5 | 0.8232 | 0.8914 | 0.8923 |
| 9 | 0.7823 | 0.8432 | 0.8343 |

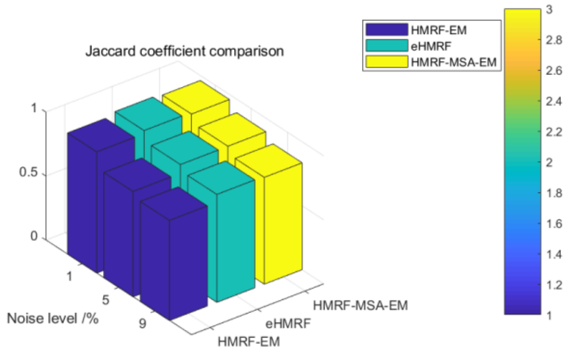


*Figure 2. Jaccard coefficient comparison*

The data show that the improved hidden markov algorithm based on bayes increases the noise at different levels and gets higher data parameter values for each value. Contrast HMRF - eHMRF algorithm and the EM algorithm, an improved algorithm of hidden markov based on bayesian in one layer, 5, 9 layers of parameter values are higher than the previous two algorithms about 0.01, 0.0072, 0.006, prove that the improved hidden markov algorithm based on bayesian in low dose CT image will be more clear than HMRF - EM algorithm and eHMRF algorithm of images, and more accurate numerical. The data acquisition table is shown in table 2 and figure 3.

*Table 2. Dice coefficient comparison*

| Noise level /% | HMRF-EM | eHMRF | HMRF-MSA-EM |
|---|---|---|---|
| 1 | 0.9743 | 0.9784 | 0.9793 |
| 5 | 0.8355 | 0.9355 | 0.9427 |
| 9 | 0.8645 | 0.8943 | 0.8949 |

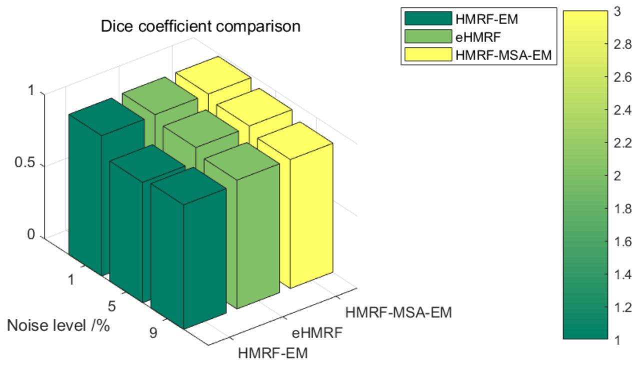


*Figure 3. Dice coefficient comparison*

The data show that the improved hidden markov algorithm based on bayes increases the noise at different levels after using CCR coefficient comparison algorithm in the three segmentation algorithms, and each value gets higher data parameter value. In the first layer, the improved hidden markov algorithm based on bayes was compared with hmrf-em algorithm and eHMRF algorithm, and the data were improved by 0.0045 and 0.004 respectively. In the fifth layer, compared with the first two algorithms, the data increased by 0.0033 and 0.0003, respectively. In the nine layers, the data increased by 0.0217 and 0.0004, respectively. It is proved that the algorithm in this paper is more accurate and effective than the previous two algorithms. The data acquisition table is shown in table 3 and figure 4.

*Table 3. CCR coefficient comparison*

| Noise level /% | HMRF-EM | eHMRF | HMRF-MSA-EM |
|---|---|---|---|
| 1 | 0.9733 | 0.9774 | 0.9778 |
| 5 | 0.9426 | 0.9456 | 0.9459 |
| 9 | 0.9033 | 0.9246 | 0.9250 |

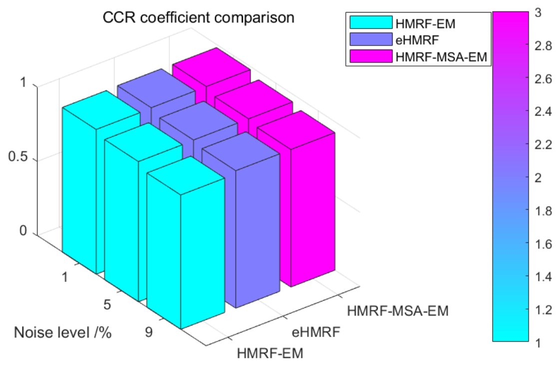


*Figure 4. CCR coefficient comparison*

## 4.2. Convenience of Using Improved Hidden Markov Algorithm Based on Bayes

(1) Data show that in the use of simple bayesian algorithm and improved markov algorithm based on bayesian, the application of low-dose CT image can be seen in all database on medical images, change has obvious differences, using the markov algorithm based on bayesian get basic parameter value is 23.22% higher than that of using naive bayesian algorithm of data. It is proved that the application of improved markov algorithm based on bayes is positive and has optimization effect. The data acquisition table is shown in table 4 and figure 5.

*Table 4. Naive Bayes and improved Bayes in image application*

| Algorithm /% | Umbilical cord around the neck | Lung parenchyma | Pulmonary nodule | Spine | Bone tissue |
|---|---|---|---|---|---|
| Naive Bayes | 20.34 | 22.36 | 21.46 | 24.39 | 23.52 |
| Improved Bayes | 48.45 | 49.25 | 47.95 | 50.05 | 48.77 |

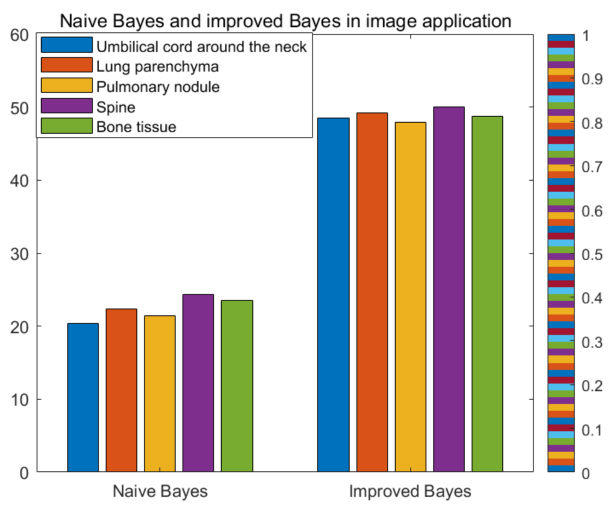


*Figure 5. Naive Bayes and improved Bayes in image application*

(2) This experiment detects whether the improved hidden markov algorithm based on bayes helps to improve the noise of CT images in low-dose CT images. The data showed that in various medical applications, such as CT images of infant umbilical cord around the neck, pulmonary tuberculosis, pulmonary nodules, spine and bone tissues, the improved bayesian hidden markov algorithm was significantly clearer than the image comparison of direct low-quality CT image operation, which was more than 46.87%. It shows that the improved hidden markov algorithm based on bayes is more accurate and effective in the application of low dose CT images. The data acquisition table is shown in table 5 and figure 6.

*Table 5. Application of improved Bayes in low dose CT image*

| Algorithm /% | Umbilical cord around the neck | Lung parenchyma | Pulmonary nodule | Spine | Bone tissue |
|---|---|---|---|---|---|
| Low dose CT image | 1.63 | 2.76 | 1.26 | 4.36 | 3.53 |
| Improved Bayes | 48.45 | 49.25 | 47.95 | 50.05 | 48.77 |

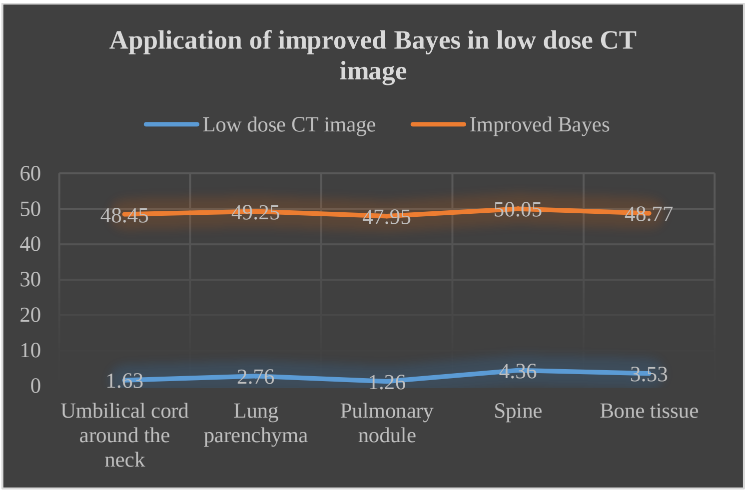


*Figure 6. Application of improved Bayes in low dose CT image*

## 5. Conclusion

(1) At present, the establishment and optimization of simple theoretical model algorithm is no longer the focus of researchers, and the ever-changing hardware development level continues to inject new vitality into the study of low-dose CT imaging. The research of low dose CT imaging is mainly carried out from three directions: system model, reconstruction algorithm improvement and post-processing algorithm. The scattering noise estimation and scattering correction of CT imaging system will help to establish more accurate statistical model of projection data and improve the scattering artifact correction ability of CT system.

(2)This paper improves the random medical image segmentation algorithm based on bayesian improved hidden markov algorithm. The improved hidden markov algorithm based on bayesian improves the accuracy of spinal segmentation to a certain extent, achieves reproducibility, and has a good feasibility. Although CT imaging is widely used at present, it still has some insuperable disadvantages in local links due to the imaging principle and other reasons. Therefore, how to integrate the advantages of multiple types of images and explore the segmentation of multiple modal images will be the next research focus.

(3) This paper aims to study the application of bayesian based improved hidden markov algorithm in low-dose CT images, which has become the focus of CT research in recent years. In this experiment, hmrf-em, eHMRF algorithm and hmrf-msa-em algorithm were firstly analyzed by mathematical statistics within the experimental scope, and the superiority of this algorithm was compared by looking at different coefficients. The classification and statistical analysis of the re-data statistical method were carried out by using the naive bayesian algorithm and the improved hidden markov algorithm based on bayes. And the use of a single variable method to compare the use of bayesian based improved hidden markov algorithm in the low-dose CT image imaging whether there are different changes, and the degree of change. Experimental data show that the improved hidden markov algorithm based on bayes achieves higher values of Jaccard, Dice and CCR at different noise levels. The improved hidden markov algorithm based on bayes is clearer than the low-dose CT images obtained by the naive bayes algorithm. In various medical images, the improved hidden markov algorithm based on bayes plays an obvious role in changing the resolution of low-dose CT images. Experimental data show that compared with other denoising methods, the peak signal-to-noise ratio of the de-noised image can be improved, the details of the image can be retained better, and the visual effect can be improved by 46.78%.

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## Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

## Conflict of Interest

The author states that this article has no conflict of interest.

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