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Historical Document Image Denoising by Ising Model

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***Abstract*—In this paper, we propose a historical document image denoising method based on Ising-like model and Anisotropic filter. Physical statistics and morphological smooth process are combined together to improve image particulars. We first apply an Ising model to the 8-th bit plane of the original historical document image, then the image energy field and density is through Ising dynamic evolution. After the image is processed, it has been smoothed by Anisotropic morphological for several times. At last, we get the restored image document. We compare the visual quality changes before and after Ising evolution in different Anisotropic morphological condition respectively. Experimental results demonstrate that the Ising evolved image can better restore the local area details of the degraded historical document image.**

Keywords*—*Historical Document ;Image Denoising; Ising Model;

I. INTRODUCTION

Historical documents are the image records where we can understand the history and the cultural heritage. The protection of ancient image is significant. Most of the historical images have suffered from noise. Although traditional method can denoise the image, it has a deficiency in missing the detail of the image, and causes the image distortion. Therefore, a novel image denoise method is proposed to improve the image contrast and enhance image visual quality.

Cohen [1] proposed a method for noise estimation and image denoising. They found affinity between statistical mechanics and image processing will rise and put forward a framework where denoising algorithms could be derived: the Ising evolution models and simulated annealing techniques. It is said that Ising like methods can be used for images and video denoising. Results convince an important performance gain for PSNR and SSIM when compared to other filters, especially in cases of low impulse noise. When Ising models and other image processing method are bound together they will be even more effective.

Liaghati [2] et al. proposed a statistical model to compare some compression methods on binary images. To find the tendency of compression ability, they discovered that the improved Ising model with Metropolis can produce many binary images iteratively. In this way, they could learn the way the compression ratio change gradually when the image changes slightly.

Qin[3] et al. proposed an Ising model where the label of this physical model can be used to represent the image segmentation. In this model, statistical physics and computer image have been combined closely. The minimum energy of the Ising model has been taken advantage of to segment images. Each pixel of an image can be assigned a label and the pixels of the same label have the same visual features.

Lu[4] et al. proposed a model for brain sensory coding. It is assumed that neuron activity is independent and the interactions and correlations between neurons are all over the retina and cortex vortex. Ising model is used to reveal the pairwise correlation of neural activity. This kind of biological spike neural network model is adapted to the statistical characteristics of natural images.

Gavrilov[5] et al. proposed a combination of the statistical characteristics in both convolutional neural network and the Ising model to avoid the deficiencies of overfitting and underfitting. The Ising model contains of a magnetic dipole moment, which will be represented as one of two states, +1 or -1. Under the influence of the two-dimensional grid and neural network parameters, especially the learning rate and regularization rate, the image training sets have a good classification adaptability of the convolutional neural network which not only help better comprehend the neural network, but also provide a method for preventing both of overfit and underfit in image recognition.

Risser[6] et al. proposed a symmetric Ising model for image segmentation based on discrete Markov random field. To set the temperature parameters of the Ising field in unsupervised segmentation, they inferred the future, according to the development trend of the past for partial function evaluation in three-dimensional Ising fields. It is applied to brain regions of different sizes and topologies. Meanwhile, Ising model can also be used for combined detection and evaluation of functional magnetic resonance brain activity.

Tanaka[7] et al. proposed an Ising model for Bayesian multi-valued image restoration. Hyper parameters in the probabilistic model are designed to obtain the maximum marginal likelihood. Their method is based on traditional mean field approximation and chaotic belief propagation which are of superiority when compared with the conventional filters.

Liu [8] et al. proposed a study on the image layers of scale-invariant natural images are relevant to phase transfer. Phase transformation from disordered to ordered will increase the image perception quality and will improve the performance of the image. A two-dimensional Ising model parameters of images from the Kodak database show that the phase transition occurs approximately at the 4-th bitplane can perform visual quality

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assessments. The visual perception and structure information of image quality can by assessed by different combinations of intensity layers. The phase shift is used to decompose the image, extract the structural information of the image and evaluate the perceived quality of the image.

It is reasonable to describe a system with correlation in its parts. We employ physical many particle interaction mechanism to adjacent pixels in image denoising. The particles in physical systems are similar to the number of pixels in the image. The analogy between energy of a thermodynamical system and image high quality, smoothness is studied to some extent in this paper.

II. Ising Model

Ising model is a statistical physical model which describes the phase transition of ferromagnetic materials. When it is heated above a certain critical temperature, the system will lose its magnetism, while after it is cooled down below the critical temperature, the system will show magnetism. The transition between magnetic and non-magnetic phases is called a phase transition. Ising model assumes that ferromagnetic materials are composed of many small magnetic needles, each of which has only two rotation directions. The neighbor needles interact with each other by some energy constraints. Meanwhile, they undergo random magnetic transformation due to external influence. Degree of reversals are determined by the key parameters, e.g. temperature. When the temperature rises, it is more likely that the small magnetic needle is in disorder and the magnetism disappears. If the temperature is low, the system is in a state of high energy, a large number of small needles are in the same direction, and the system shows strong magnetism. When the system is at the critical temperature, Ising model shows a self similar phenomena.

Ising model can be applied to many fields. If smaller magnetic needle is considered as the neuron cell, the up-down state is the activation and inhibition of the neuron, the interaction of the small magnetic needle is associated with signal transmission in neurons, so the variance of Ising model can also be used to build the neural network system, such as Hopfield network or Boltzmann machine in machine learning. The interaction between adjacent needles is similar, and the temperature of the environment indicates that the system is at different scales. In the critical system, different components interact with each other locally, which leads to a certain regularity of the whole in the process of Ising evolution.

We use Monte Carlo Markov chain method to simulate two dimensional Ising spin model in some temperature. The Ising Hamiltonian can be shown below:

$$H(S) = -J \sum_{<i,j>} S_i S_j - H \sum_{i=1}^{N} S_i \tag{1}$$

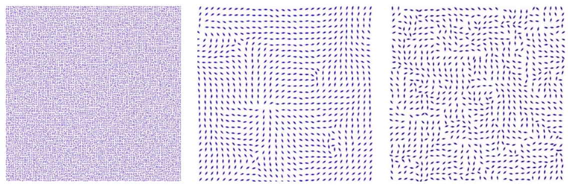
In Eqn.1, S_i is the spin of the i-th lattice position which takes the values +1 or -1, corresponding to spin orientation up or down respectively. $\sum_{<i,j>}$ means to the sum of all possible neighbors. J is the coupling constant. H an external magnetic field. Let L denote the linear size of the square lattice under consideration, where N = L x L are the number of these spins of some kind of orientation distribution. That is, a spin state is recorded as $S = S_i, i = 1, 2, ..., N$, the temperature here is represented by KT / J,where T is the absolute temperature in the general sense, J is the coupling constant, and K is the Boltzmann constant. The critical temperature is $KT_c/J = 2.269$,the Monte Carlo method with Metroplis sampling technique can make a random initial spin state reach the equilibrium state after the Markov process. Firstly, randomly select a spin state S_i, i.e. the initial configuration (t = 0)S_0, then construct a Markov chain . A former state S_t is transfered to a state S_{t+1} through an appropriate transition probability W, the transition probability is represented by:

$$W\left(S_t \rightarrow S_{t+1}\right) = \begin{cases} e^{-\frac{\Delta H}{KT}} & \text{if } \Delta H > 0 \\ 1 & \text{if } \Delta H < 0 \end{cases} \tag{2}$$

$$\Delta H = H\left(S_{t+1}\right) - H\left(S_t\right) \tag{3}$$

Eqn.2 and Eqn.3 determine together the direction of Markov processes, that is, when the energy difference between the adjacent states $\Delta H \leq 0$, state S_t is allowed to be transferred to S_{t+1},if $\Delta H > 0$ then proceed as follows:

$$e^{-\frac{\Delta H}{KT}} \begin{cases} < Z\left(t\right) \; Do\ not\ change\ spin\ state\ S_t \rightarrow S_{t+1} \\ \geq Z\left(t\right) Change\ spin\ state\ S_t \rightarrow S_{t+1} \end{cases} \tag{4}$$



(a) ising:size (b) ising: temperature (c) ising:iterations

Fig. 1: Ising Evolution with different parameters

III. Smoothing Via Anisotropic Diffusion

It has been years since the classical Anisotropic diffusion model was first proposed, the method has been widely used in image denoising. It controls the smoothness degree of an image by a diffusion function about the image gradient, which makes the image point spread on a large scale in the region with small gradient modulus, and on a small scale in the region with large gradient modulus. The variety character of image energy evolution to the the effect of historical document image restoration is concerned. We assume that the image field before Ising evolution satisfies a certain probability distribution while after the Ising evolution satisfies another distribution. We study image smoothing and denoising effect by anisotropic smoothing, and compare the differences between the two different image processing before and after the Ising evolution. Anisotropic smoothing is based on distance transformation and image geodesic morphological. It calculates the direction and the magnitude of image gradients by using eigen value analysis. The distance is estimated from the nearest neighbor by the threshold. In each pixel of the image, the distance represents as a pixel value is propagated from adjacent pixels that have already been scanned. For an input image, it enables considering up to nearest neighbor 3×3 to a central pixel, from which the gradient directions is calculated. We employ a non-adaptive thresholding filter like pixel-wise adaptive thresholding,dilation and erosion. It can remove the noise of the image and preserve the edge texture of an image. At each pixel p, let Θ_1,Θ_2 be the tangent and normal vectors of an image edge, λ_1,λ_2 be gradients of the vector. We use singular value decomlsition of the tensor G $\in R^{2\times2}$ to get D_x,D_y The binarized image is converted to the distance image D.

$$U\sum U^T = svd(G), where G = \begin{bmatrix} KD_x^2 & KD_xD_y \\ KD_xD_y & KD_x^2 \end{bmatrix} \quad (5)$$

where K represents Gaussian filtering to smooth the gradient images.$\sum$=diag(λ_1,λ_2) is the maximal and minimal eigenvalues of G, [Θ_1,Θ_2]=U is the corresponding eigenvectors. Through edge direction vectors Θ_1,Θ_2,and gradients λ_1,λ_2, the gradient tensor T $\in R^{2\times2}$is computed as follows:

$$T = f(\sqrt{\lambda_1+\lambda_2})\theta_1\theta_1^T + g(\sqrt{\lambda_1+\lambda_2})\theta_1\theta_1^T \quad (6)$$

where f,g is defined to control the smoothness of the image:

$$f(x) = \frac{1}{1+x^2}, \quad g(x) = \frac{1}{\sqrt{1+x^2}} \quad (7)$$

From the gradient tensor T and a Hessian matrix H

$$H = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix} \quad (8)$$

We set the iterative smoothing equation:

$$D^{t+1} = D^t + \eta Tr(TH) \quad (9)$$

where t is the number of iteration and η is the parameter to control the convergence.

IV. EXPERIMENTAL RESULTS

In the first we slice the original historical document image as Fig.2 (a) into eight bit planes. We get the 8-th bit plane as Fig.2(b) shows that the important structural information about the image is mainly contained in the high bit plane. Then we take Fig.2 (b) as an initialized energy magnetic field. The Monte Carlo method is utilized in learning dynamic evolution, behavior of two-dimensional Ising model under the temperature gradient. When the phase transition is reached at the critical temperature. The spontaneous magnetization and the effect of phase transformation from disordered to ordered will affect the image perception quality and has something to do with the performance of the image. After Ising evolution, we get Fig.2 (c).

According to image Anisotropic diffusion filter, we take Fig.2 (c) as the input image which is the result of the Ising evolution, then the image is smoothed by Anisotropic diffusion morphology operation, with the adjustment of the parameters in Anisotropic diffusion model and the number of iterations increasing, the image smoothing effect changes dramatically after Ising evolution. The smoother the image effect as Fig.3 can be shown, smoothing effect of the images without Ising evolution tends to be stable as Fig. 3. During the process of image restoration, the selection of parameters to adjust the gradient is conducive to the local information enhancement. When the smoothing operation is carried out, with the repeatedly increasing of the number of iterations, the image noise is gradually removed, making the improved model adaptive to the image contrast enhancement and keeping the details of the main content of the document. Finally, the restorable image effect of the smoothing output is accumulated, and the result shows that local details of the image evolved from Ising are better than that of the one without the evolution of Ising via visual quality assessments.

In this method, Anisotropic diffusion is based on image gradient and image local features. We try to use different strategy to improve different local areas of the image, preferably repair the image, making up for the defective part of the image respectively. The Anisotropic diffusion smoothing method is the traditional approach. Generally speaking, the diffusion function with large diffuse intensity is tend to be homogeneous area. Gradient information is used in Anisotropic diffusion image denoising methods. When the local area is seriously polluted by noise, these methods may be invalid to detect and recover. By utilizing Ising evolution and image morphology, the detail information of local areas about the image is retained. From a local image visual effect of view, as shown in Fig. 3 (b) ,Fig. 3 (d) ,Fig. 3 (f),Fig. 3 (h), when the range of the scale reduction ratio in distance image shifts from 1/2,1/3,1/4,1/5, Ising model has certain smoothing effect in different local areas of the historical document image. From Fig.3, we can see more clearly that some parts of details such as corners, spikes, narrow strokes and textures are smoothed out, the image details are polished. The proposed method can overcome the disadvantage of the noise fluctuation in the homogeneous region, highlight the gradient value difference and better reflect the change of the image. But at the same time, there are disadvantages such as a side effect of increasing the noise of other local areas, and other details are lost as also shown in the Fig.3.

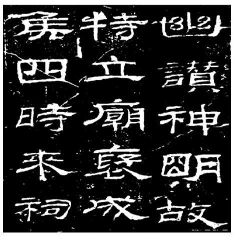
In addition, in order to explain the image field evolution performance by Ising model, we use different parameters such as the scale reduction ratio of distance image,window size of the Gaussian,direction,the magnitude of gradients,standard deviation and time step etc. in Tschumperle's Anisotropic diffusion to observe the performance of each model. With the repeatedly iterative adjustment of parameters, especially for scale reduction ratio of distance image λ, image sharpness drastic changes after Ising evolution, while the original image without evolution as shown in Fig. 3 (a) ,Fig. 3 (c) ,Fig. 3 (e),Fig. 3 (g) has little change in multiple iterative adjustment. The sharpness of local details in Ising model is higher than that of the one without Ising evolution, but accompanied by the side effect of the noise in other image parts, and some details will deteriorate, which shows that the image processed by the Ising model maintain some part of the local detail contrast and texture features better. It may be on the cards that texture image evolved by Ising can resist the influence of small changes in amplitude to a certain extent. By Ising, we may overcome the disadvantage of only using gradient as the operator; with adjusting parameters to control the diffusion intensity, we may improve the noise of the local area on historical document image. They are benefiting from the combination of global features and local features where Ising model and Anisotropic diffusion work together.

(a) Original image

(b) The 8−th bit plane of (a)

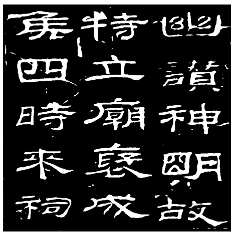
(c) Ising Evolution on (b)

Fig. 2: Visual Quality of the process in Ising Model

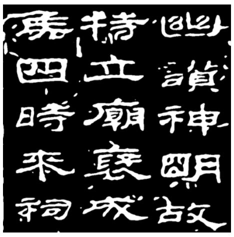


(a) original:λ=1

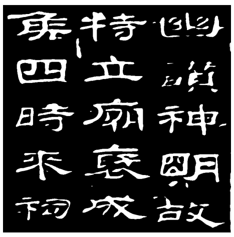
(b) ising:λ=1



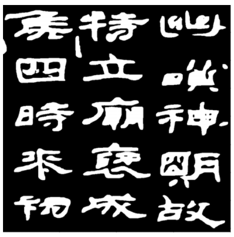
(c) original:λ=1,1/5



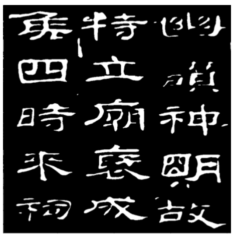
(d) ising:λ=1,1/5



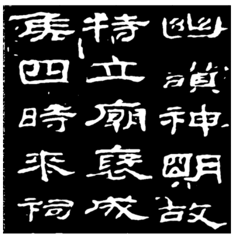
(e) original:λ=1/3,1/4



(f) ising:λ=1/3,1/4



(g) original:λ=1/3,1/5



(h) ising:λ=1/3,1/5

Fig. 3: Visual quality comparison with original image and Ising evolution image by Anisotropic Diffusion

V. CONCLUSIONS

In this paper, we suggest a study on improvement of the noisy historical image quality by integrating Ising-like model and Anisotropic filter. In this process, Ising evolution and morphological smooth process are combined together to improve image particulars. The randomness of the image particles will also change in the process of the interaction and evolution of adjacent pixel points. Furthermore, the high bit plane has a stronger correlation than the low bit plane, different bit plane has diverse texture spatial distribution and different frequency and direction intensity. Low bitplane means more randomness, high bit-plane has more visual, meaningful information and more image structure characteristics. Considering the influence of the evolution of image energy field and density on the image quality, we apply the obtained image via Anisotropic morphological smoothing for several iterations to get the restored image documents. We make a comparison of visual quality performance before and after Ising evolution in different condition respectively. Experimental results demonstrate that the Ising evolved image can better restore the local area details of the degraded historical document image.

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