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Image-based Handwriting Analysis for Disease Diagnosis

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Abstract: Handwriting movement is an activity dominated and controlled by human advanced nervous system, which depends on coordination and cooperation of multiple parts of the whole body, and the analysis of handwriting movement has been applied in many fields. In disease diagnosis, handwriting tremor is common in neurodegenerative diseases(NDs), such as Parkinson's disease(PD) and Alzheimer's disease(AD). In this paper, the image-based handwriting trajectories of mild and severe Parkinson's disease patients and healthy people with no tremor are collected, and the features of images are extracted. Utilizing corner detection method to judge the fluctuation of trajectory; 2-dimensional Discrete Fourier Transform (2D-DFT) is applied to transform it into frequency-domain space, and texture features of amplitude spectrum are extracted based on gray level co-occurrence matrix (GLCM). Finally, the machine learning method is used to classify the above features, so as to realize the diagnosis of diseases.

Key Words: handwriting image, 2D-DFT, GLCM, corner detection, disease diagnosis

1 Introduction

Handwriting movement is accomplished by multiple muscle groups through continuous or overlapping coordination activities, depends on the participation of multiple brain regions, muscle coordination and skeletal system. The process contains abundant cognitive, physiological and pathological information, which is widely used in the study of cognitive characteristics, fine motor control mechanism, human-computer interaction, visual motor control, movement disorders, dystonia, writing spasm, child development, developmental disorders, signature verification and recognition and many other fields.

Handwriting movement is affected by shaking in one limb or hand, which is usual in neurodegenerative diseases such as Alzheimer's disease, Huntington's disease and PD. With the advent of the era of big data, the diagnosis of diseases is not limited to doctors' professional knowledge and clinical experience, computer technology plays an important role in the auxiliary diagnosis of diseases. For neurodegenerative diseases, Tăuţan reviewed the artificial intelligence diagnosis methods, mainly including AD, PD, Huntington's Diseases, Amyotrophic Lateral Sclerosis, and Multiple System Atrophy[1]. Hand tremor, as one of the main symptoms of NDs, has also been deeply studied by many scholars, among which handwriting is a hot issue. Stefano analyzed the literature of handwriting-based diagnosis of NDs, such as AD, PD and mild cognitive impairment, provided the relevant researchers of the latest research results[2].

Nachum proposed a computer vision approach, which using ordinary cameras and videos to capture and analyze handwriting, and they achieved writing position estimation within 0.5mm with speed and acceleration errors of less than 1.1%[3]. Kuznetsov developed a handwriting peculiarities evaluation method, using laser speckle to contrast the motion and pressure, designing just a simple laser diode and camera for image acquisition, and proposed a handwriting pressure and kinematics evaluation method based on LSCI[4]. Taleb searched for handwriting features of PD patients from PD-MultiMC database, they focused on the pressure, energy, entropy and intrinsic features in kinematic and spatiotemporal characteristics of each task, and adopted two stages for features acquisition[5]. Cascarano asked subjects to write three different patterns on a flat plate with a Myo armband, which can collect muscle activation signals of the main forearm muscles, they extracted several features related to writing mode, such as pen movement, pressure and muscle activation, then applied an artificial neural network to classify[6].

In the process of writing motion, besides kinematic parameters, the hand-written trajectory image can also be analyzed. Razzak analyzed different writing tasks of PD, in order to choose an optimal task and improve the diagnostic performance, and they used different strategies and methods based on transfer learning to choose the optimal writing task[7]. Zhi analyzed the subtle and related changes in handwriting morphology, and they developed a set of evaluation indicators that are very sensitive to the changes of notes, these indicators can capture charactersize reduction, ink utilization rate and pixel density in handwriting samples[8]. Khatamino designed a deep learning system based on convolutional neural network to learn features from the handwriting drawings of Parkinson's patients, and evaluated the performance of the deep learning model using K-Fold cross validation and LOOCV technology[9].

In this paper, we propose an image-based handwriting feature analysis method for disease diagnosis, 2D-DFT is used to transform the handwriting images of subjects into frequency-domain space, and the texture features are calculated by GLCM. For the original trajectory images, the corner detection method is applied to identify the number of corners. Finally, the classification method based on machine learning is used to classify the above features. This method is based on computer technology to extract the features of handwriting images, and utilizes machine learning method to realize disease diagnosis, in order that the obtained result is more objective.

This paper is organized as follows. In Section 2, the prin-

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ciple of Fourier transform and the application of 2D-DFT in the direction of image filtering are introduced. Section 3 introduces two methods of image feature extraction, including corner detection method and texture feature extraction method based on gray co-occurrence matrix. Combining the collected handwriting images of patients with PD, the above mentioned methods are applied concretely, and the classification method based on machine learning is used to classify the features and realize the disease diagnosis in Section 4 in this paper. Section 5 summarizes this paper.

2 Mathematical Preliminaries

Digital image processing technology is utilizing computer to handle images according to requirements, which plays an important role in image restoration, image enhancement, image recognition and so on. In the filed of image processing, image filtering is a common way, including median filtering, Gaussian filtering and other time-domain filtering methods, spatial-domain filtering and frequency-domain filtering, etc. The following is the Fourier filtering method in frequency-domain.

2.1 Discrete Fourier Transform

Fourier transform is a usual signal processing method. Its idea is that any continuous signals can be decomposed into the superposition result of infinitely many sinusoidal signals with different frequencies. Fourier transform is commonly used to convert time-series signals into amplitudes and phases corresponding to different frequencies, amplitude represents the weight of each sinusoidal signal at a certain frequency, phase indicates the offset of each sinusoidal signal from the origin with a certain frequency. The time-domain representation of the signal is straightforward, but when it is converted into the frequency-domain, the representation of the signal will be more refined, convenient for subsequent processing. Therefore, Fourier transform is widely applied in modern acoustics, voice communication, biomedical process and other fields, gradually developed into Continuous Fourier Transform (CFT), Discrete Fourier Transform (DFT), Fast Fourier Transform (FFT) and other forms.

Discrete Fourier Transform (DFT) is a discrete form of Fourier transform in both time-domain and frequency-domain, the expression is as follows:

$$\hat{x}[k] = \sum_{n=0}^{N-1} e^{-i\frac{2\pi}{N}nk} x[n] \tag{1}$$

where $x[n]$ is a uniform sampling sequence, $n = 0, 1, \ldots, N-1$; $\hat{x}[k]$ is the kth coefficient, $k = 0, 1, \ldots, N-1$.

2.2 2-dimensional DFT

Suppose that the size of the original image is $M * N$, and the image can be regarded as a 2-dimensional discrete signal $f(x, y)$ with a period of $M * N$ obtained by equally spaced sampling in the spatial-domain, and Fourier transform is carried out on the x and y directions respectively, the expression is as follows:

$$\mathscr{F}(u, v) = \textstyle\sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) \mathrm{e}^{-j2\pi\left(\frac{ux}{M} + \frac{vy}{N}\right)} \tag{2}$$

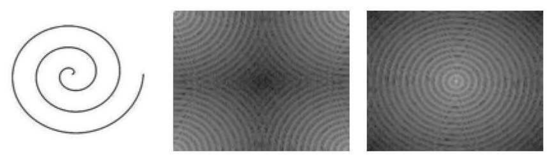
where $u = 0, 1, \cdots, M-1; v = 0, 1, \cdots, N-1$; u and v are frequency values; x and y are coordinate values in the spatial-domain. The polar coordinate expression is as follow:

$$\mathscr{F}(u, v) = |\mathscr{F}(u, v)| \mathrm{e}^{-j\cdot\varphi(u,v)} \tag{3}$$

where $|\mathscr{F}(u, v)|$ and $\varphi(u, v)$ are the amplitude spectrum and phase spectrum, respectively.

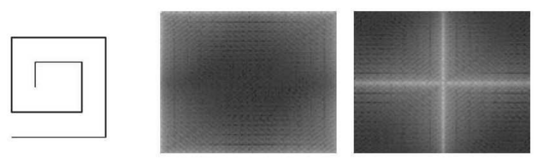
In fact, the spectrum obtained by 2-dimensional Fourier transform is the gradient distribution of the image. There is no one-to-one correspondence between the spectrum and the points in the original image, in which the point with different brightness in amplitude spectrum indicate the distinction between a certain point in the original image and its neighboring points, namely the magnitude of this point's gradient. Generally, the larger the gradient, the brighter the point in amplitude spectrum. Therefore, by observing the amplitude spectrum of image, we can know the energy distribution of it.

In this paper, we design two kinds of handwriting images, archimedes spiral and labyrinth lattice, as shown in Fig. 1(a) and Fig. 2(a), 2D-DFT is performed on original images and amplitude spectrums are obtained, as shown in Fig. 1(b) and Fig. 2(b). In the amplitude spectrums, the points at the four corners are brighter, that is, energy of the image are mainly concentrated in the low-frequency part. Translation transformation is carried out to sift the low-frequency information to the central position, as shown in Fig. 1(c) and Fig. 2(c).



(a) Original image (b) The image of 2D-DFT (c) The image of centralization

Fig. 1: The image of archimedes spiral



(a) Original image (b) The image of 2D-DFT (c) The image of centralization

Fig. 2: The image of labyrinth lattice

3 Image-based Feature Analysis Approach

Images often contain abundant information, but it is difficult for computer to process images directly. Therefore, we often reduce the dimension of image and extract the information we are interested in, that is, feature extraction of image. There are many features that can describe image information, including color feature, texture feature, shape feature, spatial relationship feature and so on.

3.1 Corner Detection

Corner is often regarded as the point where the brightness changes drastically in image, the curvature of image's edge curve is the maximum or the intersection of several edge curves. Corner detection is very important in image feature, which has been widely used in computer vision fields such as 3D scene reconstruction, motion estimation, target tracking, target recognition, image registration and matching, etc. Corner detection is usually divided into three methods based on gray image, binary image and contour curve.

Gray-based corner detection method can be divided into gradient-based, template-based and template-based gradient combination. In 1977, Moravec proposed Moravec corner detection operator, whose basic idea is to find the maximum value of the minimum gray value change by moving a binary rectangular window on the image in four directions: vertical, horizontal, diagonal and anti-diagonal[10]. Subsequently, Harris and Stephens invented Harris corner detection operator based on Moravec, expanded by Taylor series expansion method, to calculate the gray change of the window after moving in any direction, and further determined the feature points by mathematical analytic expression[11]. For the input image I, the first partial derivatives I_x and I_y along the x and y axes are calculated, and the isotropic Gaussian kernel G is used to smooth the image, and the autocorrelation matrix M is constructed as follow:

$$\begin{cases} I_x = \dfrac{\partial I}{\partial x}, I_y = \dfrac{\partial I}{\partial y} \\ \overline{I_x^2} = I_x^2 \otimes G, \overline{I_y^2} = I_y^2 \otimes G, \overline{I_x I_y} = I_x I_y \otimes G \\ G = \dfrac{1}{2\pi\sigma^2} \exp\left(-\left(x^2+y^2\right)/2\sigma^2\right) \\ \boldsymbol{M} = \begin{bmatrix} \overline{I_x^2} & \overline{I_x I_y} \\ I_x I_y & \overline{I_y^2} \end{bmatrix} \end{cases} \tag{4}$$

where $\otimes$ is the convolution operator, σ is the gaussian smoothing scale. Then, the corner response R is constructed and determined by the eigenvalues α and $\alpha, \beta(\alpha \geq \beta)$ of the autocorrelation matrix as follow:

$$R = \alpha\beta - k(\alpha+\beta)^2 \tag{5}$$

where k is the error corner response suppression constant.

3.2 Gray Level Co-occurrence Matrix

Gray level co-occurrence matrix is a feature extraction method based on texture, which is obtained by statistical analysis of the situation that two pixels in an image with some distance along a certain direction have a certain gray level.

For the element $P(a, b)$ in GLCM, Haralick [12] proposed 14 scalars to represent the texture features of the image, including homogeneity, contrast, dissimilarity, correlation, energy and entropy, etc. Three of them are briefly introduced below.

Dissimilarity is used to describe the difference degree of gray values between elements in the horizontal or vertical direction of gray co-occurrence matrix, which is a measure of gray linear relationship, the expression is as follows:

$$DIS = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} P(i,j)|i-j| \tag{6}$$

where L is the number of pixels in the image.

Contrast reflects the sharpness and depth of the image by measuring how the value of the matrix is distributed and how much the local changes is in the image. The deeper the groove of the texture, the greater its contrast, the clearer the effect, the expression is as follows:

$$CON = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} (i-j)^2 P(i,j) \tag{7}$$

Correlation reflects the similarity of image pixels in horizontal and vertical directions, so it can be used to measure the similarity of gray levels. When the values of matrix elements are uniformly equal, the larger the correlation value is, the more relevant the gray values of image pixels will be, the expression is as follows:

$$COR = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} \frac{ijP(i,j) - \mu_1\mu_2}{\sigma_1\sigma_2} \tag{8}$$

where $\mu_1, \mu_2, \sigma_1, \sigma_2$ are represented respectively:

$$\begin{cases} \mu_1 = \sum\limits_{i=0}^{L-1} i \sum\limits_{j=0}^{L-1} P(i,j) \\ \mu_2 = \sum\limits_{i=0}^{L-1} j \sum\limits_{j=0}^{L-1} P(i,j) \\ \sigma_1 = \sum\limits_{i=0}^{L-1} (i-\mu_1)^2 \sum\limits_{j=0}^{L-1} P(i,j) \\ \sigma_2 = \sum\limits_{i=0}^{L-1} (j-\mu_2)^2 \sum\limits_{j=0}^{L-1} P(i,j) \end{cases} \tag{9}$$

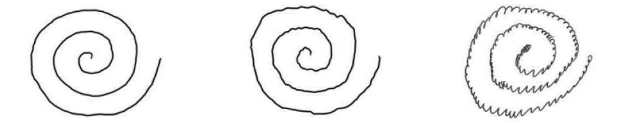
4 Feature-based Classification: An Application Example

We collect handwriting images including archimedes spiral and labyrinth lattice of Parkinson's patients with mild tremor, severe tremor, and healthy people with no tremor symptoms, respectively. The above three kinds of data are applied to feature analysis, and then, the classification method based on machine learning is utilized to diagnose disease.

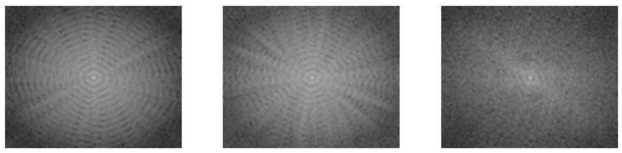
4.1 Results of Feature Extraction

4.1.1 Results of 2D-DFT

The results after 2D-DFT are shown in the Fig.3 and Fig.4. From that can be seen, for the images of the no tremor's subjects, the difference between each point and the neighborhood is small, and the edge presents a relatively regular distribution, so there are more dark points in the amplitude spectrum, and the distribution of bright points is regular. For patients with tremor, the images are more sharp and have more burrs, so there are more bright spots in the amplitude spectrum, but the brightness drops, and the distribution is messy. To sum up, the amplitude spectrum of handwriting image can better reflect the features contained in the original image.

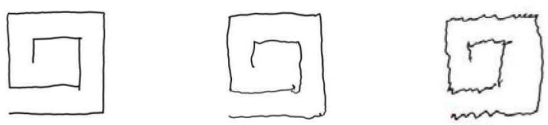


(a) Original image of no tremor (b) Original image of mild tremor (c) Original image of server tremor

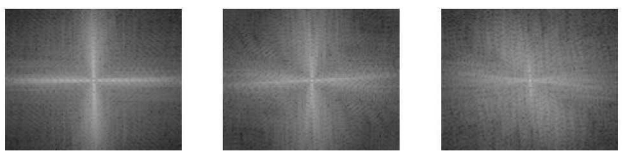


(d) 2D-DFT of no tremor (e) 2D-DFT of mild tremor (f) 2D-DFT of serve tremor

Fig. 3: Results of archimedes spiral



(a) Original image of no tremor (b) Original image of mild tremor (c) Original image of server tremor



(d) 2D-DFT of no tremor (e) 2D-DFT of mild tremor (f) 2D-DFT of serve tremor

Fig. 4: Results of labyrinth lattice

4.1.2 Results of Corner Detection

The handwriting image of the no tremor is relatively smooth, mild tremor image fluctuates to some extent, severe tremor image is volatile. Therefore, corner detection of three types of handwriting image can reflect the fluctuation of the trajectory to a certain degree, as shown in Figs. 5 and 6. The average number of corners detected for two kinds of image with three degrees are shown in Tables 1 and 2. We can see that the number of corner of handwriting image increases with the increase of tremor degree.

4.1.3 Results of GLCM

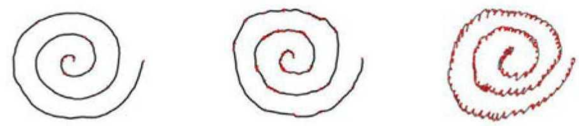
Binary the amplitude spectrum image obtained by 2D-DFT, retain the low frequency part with higher brightness, and flip the pixels of the image to make the low frequency part appear gray, as shown in Figs. 7 and 8.

Calculate the GLCM of the processed images, and their texture feature parameters. The average values of contrast, dissimilarity and correlation in four directions of 0, 45, 90, 135 degree are shown in Tables 1 and 2. It can be seen, as the tremor deepens, the number of corner increases, the image's contrast became high, the correlation decreased and the dissimilarity increased.

4.2 Classification Based on Machine Learning

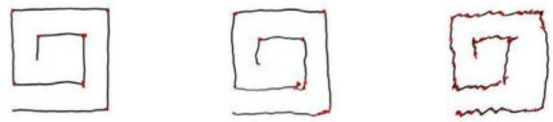
Disease diagnosis can be achieved by classification, and the degree of disease corresponds to the classification category. With the popularization of artificial intelligence, classification methods based on machine learning are becoming more and more mature, so they are widely used in various fields. In this paper, we choose decision tree to apply.

Decision tree is a tree structure composed of nodes and directed edges. To construct a decision tree model, a feature is selected as the splitting criterion of the current node according to the information entropy and information gain, and then the sub-nodes are generated recursively from top to



(a) No tremor (b) Mild tremor (c) Serve tremor

Fig. 5: Results of corner detection of archimedes spiral



(a) No tremor (b) Mild tremor (c) Server tremor

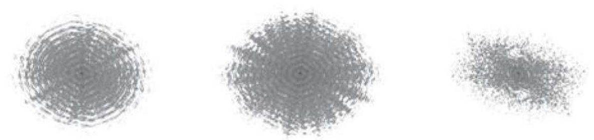
Fig. 6: Results of corner detection of labyrinth lattice

Table 1: The Average of Features Extracted from Archimedes Spiral

Features		No Tremor	Mild Tremor	Severe Tremor
Corners		15.37	31.86	102.76
DIS	$\theta = 0°$	0.42	0.43	0.50
	$\theta = 45°$	0.59	0.60	0.69
	$\theta = 90°$	0.42	0.43	0.51
	$\theta = 135°$	0.60	0.62	0.73
CON	$\theta = 0°$	2.72	2.91	3.38
	$\theta = 45°$	3.92	4.21	4.99
	$\theta = 90°$	2.72	2.92	3.52
	$\theta = 135°$	4.01	4.27	5.03
COR	$\theta = 0°$	0.93	0.92	0.89
	$\theta = 45°$	0.89	0.88	0.84
	$\theta = 90°$	0.93	0.92	0.89
	$\theta = 135°$	0.89	0.88	0.84

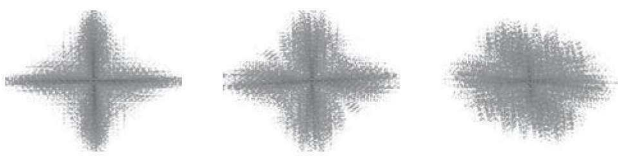
Table 2: The Average of Features Extracted from Labyrinth Lattice

Features		No Tremor	Mild Tremor	Severe Tremor
Corners		15.26	20.10	109.90
DIS	$\theta = 0°$	0.42	0.44	0.53
	$\theta = 45°$	0.61	0.64	0.79
	$\theta = 90°$	0.44	0.47	0.58
	$\theta = 135°$	0.60	0.65	0.79
CON	$\theta = 0°$	2.49	2.64	3.26
	$\theta = 45°$	3.74	3.98	4.95
	$\theta = 90°$	2.64	2.85	3.56
	$\theta = 135°$	3.69	4.00	4.93
COR	$\theta = 0°$	0.93	0.92	0.90
	$\theta = 45°$	0.89	0.88	0.85
	$\theta = 90°$	0.92	0.91	0.89
	$\theta = 135°$	0.89	0.88	0.85



(a) No tremor (b) Mild tremor (c) Serve tremor

Fig. 7: Results of binarization of archimedes spiral



(a) No tremor (b) Mild tremor (c) Server tremor

Fig. 8: Results of binarization of labyrinth lattice

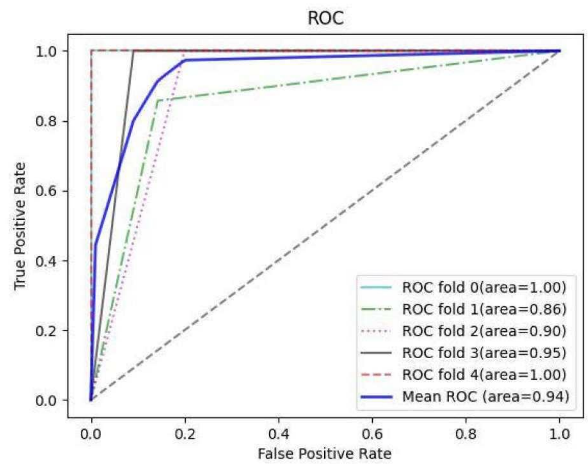


Fig. 9: ROC of decision tree's 5-fold cross validation

bottom according to the selected feature evaluation criterion, until the dataset is inseparable, the decision tree stops growing. Finally, the decision tree is optimized, such as pruning, missing value processing and so on.

The features extracted from handwriting images above are considered as dataset, a decision tree model is constructed to carry out three-classification processing, and 5-Fold cross validation is used to verify the classification accuracy. Fig. 9 shows the ROC curve of decision tree's 5-fold cross validation, and the area under the curve of ROC (AUC) reflects the accuracy of the classifier. It can be seen from Fig. 9 that the mean AUC of is 0.94, indicating that this method has excellent performance.

5 Conclusion and Future Work

In this paper, we design two trajectories, archimedes spiral and labyrinth lattice, carry out 2-dimensional discrete Fourier transform, detection corner and calculate gray co-occurrence matrix for corresponding handwriting images, and classify these features. We collect three kinds of handwriting images of Parkinson's patients with different degrees of disease and healthy subjects, and conduct example analysis. The results show that this method can be used for disease diagnosis.

Compared with the original method of disease diagnosis based on handwriting, our method avoids the extraction of complex kinematic parameters, and chooses the trajectory image which is easy to obtain and more intuitive. Feature analysis of image rather than image classified by deep learning can save computing resource and improve diagnosis speed to a certain extent. What's more, the characteristic parameters obtained have practical physical significance, which are convenient to record the current disease situation of patients, and helpful for the long-term work of patients' rehabilitation and drug efficacy evaluation.

In the future, we will collect more data to expand dataset and try more types of handwriting tasks to find better trajectories. We will also learn and optimize image processing methods to better reflect the information contained in handwriting images.

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