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Discrete Meyer Wavelet Transform Features For online Hangul Script Recognition

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Abstract: Online hangul script recognition is important when writers input characters into computer and communication apparatus (such as PDA, Mobile Phone). In this study, a Wavelet Transform Features-based method for performance improvement of online handwritten hangul character recognition is proposed. The main idea is applying the Discrete Wavelet Transform (DWT) spectral analysis to the recognition of online hangul script. This method is based on the fact that online scripts offer space and time information. Locations of sample points belonging to a script give only space information and the order of occurrences of sample points provides time information. Given an online handwritten character sample, after a series of preprocessing, we obtain a 64×64 normalized online hangul handwritten script with the time information. The order of sample points can be the index of sequences. One sequence is the vertical coordinate of sample points. The second sequence is the horizontal coordinate of sample points. The third sequence is the product of the vertical coordinate and horizontal coordinate of sample points. The fourth sequence is the ratio between the vertical coordinate difference and horizontal coordinate difference of two sample points. The four sequences are combined as a vector whose size is 512. The vector is convoluted with the Meyer Wavelet and its dimension is reduced from 512 to 128 by Linear Discriminant Analysis (LDA) scheme. Modified Quadratic Discriminant Functions (MQDF) is utilized as the classifier for charter recognition. The Experiment results demonstrate that the method can improve the accuracy of character recognition.

Keywords: Discrete wavelet transform, handwritten recognition, hangul character, meyer wavelet, modified quadratic discriminant functions, on-line direction feature, pattern recognition

INTRODUCTION

In pattern recognition, feature extraction is an important process. The extracted features should have these properties: features extracted from the same class should be close to each other and those extracted from different classes should be relatively farther away. How to extract effective features strongly depends on idiographic domain and practical task, so it is important and necessary to utilize the knowledge of the specific task.

Given the trait of hangul's structure, some researchers propose the recognition method based on structure (Kang and Kim, 2003; Kang and Kim, 2004; Kim and Kim, 2001). But this method needs high quality cursive and its recognition accuracy will suffer from illegible script. On the other hand, this method relies on the unique structure of hangul that 51 jamo constitute 2350 hangul, so the expansibility is limited.

Motivated by the success of applying Hidden Markov Models (HMM) in voice recognition, some researchers use the HMM in the online script recognition and achieve satisfactory result (Ma and Huo, 2009; Bocchieri and Mak, 2001; Lee, 1998). The key point of this method is effectively utilizing the time information of online handwritten script, the hidden states depict the relation of sample points accord with writing habit. But this method have some drawbacks:

- The selection of the structure of HMM is so difficult and need the researcher's experience.
- The training process is time-consuming.
- The general ability is lower when the number of parameters is more.
- It is difficult to discriminate classes when these classes are similar to each other.
- The recognition speed is slow when the classes are more.

In statistical Online Handwritten Script recognition, the direction feature is the best so far, which reflects the distribution of the strokes's directions of cursive script in the two-dimensional space.

An online handwritten script is a sequence of sample points arranged according to their sample order. The main steps of extracting direction feature are as follow:

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Firstly, the angle between the line that connect two adjacent sample points and the horizontal line is calculated.

Secondly, the points are mapped to one or more sub images of n according to the angle, which include two adjacent points and the points in the connecting line (Ma and Huo, 2009; Kang and Kim, 2004; Kim and Kim, 2001). The sub images are the same size as script and they share the same coordinates with the two neighbor sample points and the points in connecting line. The intensity in sub images depends on particular method. n is number of parts in 0~360ºC where different parts are allowed to have common area, larger n denotes the higher resolution with the increase in computing. We usually set n to 4 or 8 and 8-directions is an extension to 4-directions. The difference between them is that 8-directions can distinguish two angles that the discrepancy of two angles is just 180ºC. In the online handwritten script recognition, because the occurrence order of two neighbor sample points is known, two angles can be distinguished, for instance, 45 and 225ºC, the difference between them is just 180˚C. Researchers usually use 8-directions feature when the task does not require high computing speed and the computer's hardware resource is not limited. In the study (Kawamura, 1992), proposed the method that extracting the feature of free writing script and achieve good experiment result. In the study (Nakagawa, 1996), Nakagawa proposed the method which is more robust that the complement of study (Kawamura, 1992). In the study (Bai and Huo, 2005; Bai and Huo, 2005) propose a more available method and this method achieves better result than others. The steps are the same in above three methods, which are mapping two neighbor sample points and the points in the connecting line to 2 of 8 sub images according to the angle between the connecting line and horizontal line. The angle will lie in one and only one of four regions which is [0, 90), [90,180), [180, 270), [270.360) and is mapped to 0th, 1th, 2th and 3th sub image corresponding. The angle will lie in one and only one of four regions consisting of [45, 135), [135, 225), [22, 315) and [-45, 45) and is mapped to 4th, 5th, 6th and 7th sub image corresponding. We call the 0th, 1th, 2th and 3th sub images the first sub images group and 4th, 5th, 6th and 7th sub images the second sub image group. Any angle can be mapped one and only sub image of the first group sub images and so do in the second sub image group. The different between the above 3 methods is using different way to calculate the sub images's intensity. In the study (Kawamura, 1992), the intensity of sub image in the first sub images group is the ratio between the absolute value which difference of horizontal distance and vertical distance between two sample points and the distance of two sample points. The intensity of sub image in the second sub images group is the ratio between the minimum value in horizontal distance and vertical distance and the distance of two sample points. In the study (Nakagawa, 1996), the intensity of sub image in the first sub images group is the ratio between the sum of horizontal distance and vertical distance and the distance of two sample points, The intensity of sub image in the second sub images group is the ratio between the maximal value in horizontal distance and vertical distance and the distance of two sample points. In the study (Bai and Huo, 2005), researcher simply set the intensity as 1 in both sub images. The process of mapping is also a lowpass procedure.

After mapping process, the 8 sub images are resampled based on 2-dimensional Gauss filter, the positions of sample points and the parameters of Gauss filter are relation to the feature dimensions and the size of sub image. The vector consisting of result of resampling is feature vector of online handwritten script.

After subsequent research (Ding *et al*., 2009; Liu and Zhou, 2006; Bai and Huo, 2006), the method proposed in the study (Bai and Huo, 2005) is proved to perform the best in online handwritten script recognition.

The essential of the above methods (Kawamura, 1992; Nakagawa, 1996; Bai and Huo, 2005) is counting the space distribute of feature on the image, different characters have different distribute. But the writing is a time course. Comparing with offline handwritten script, the online handwritten script has the time information which the script is not only an image but also we can know the occurrence order of sample points in time.

Beside distinguishing two angles whose difference is just 180ºC (Kawamura, 1992; Nakagawa, 1996; Bai and Huo, 2005), the occurrence order of sample points and the relations of the sample points can also provide useful information for recognition. So we can analyse the online handwritten script in time, which is more suit to person' writing. But the methods proposed in the study (Kawamura, 1992; Nakagawa, 1996; Bai and Huo, 2005) only consider the direction's distribution on space without taking the script signal as an time signal, so they lack of using online handwritten script signal.

The study (Pisit and Chom, 2002) proposed the method recognizes online handwritten script based on Fourier coefficients. Encouraged by this study, integrating the strong points of direction feature and HMM, we propose the method extracting the feature of online hangul handwritten scrip based on Discrete Wavelet Transform.

On the one hand, this method analyse the online handwritten script signal based on the time sequence of sample points. On the other hand, the horizontal and vertical coordinates determine the script's space position and the essence of direction feature is the ratio between the difference of horizontal coordinates and the difference of vertical coordinates of two neighbor sample points.

We use 4 sequences to describe the online handwritten script. The order of sample points can be an index of sequences in each sequence. One sequence is the vertical coordinate of sample points. The second sequence

is the horizontal coordinate of sample points. The third sequence is the product of the vertical coordinate and horizontal coordinate of sample points. The fourth sequence is the ratio between the vertical coordinate difference and horizontal coordinate difference of two sample points. The feature vector is convoluted with the Meyer Wavelet and its dimension is reduced from 512 to 128 by Linear Discriminant Analysis (LDA) scheme. The results of the experiments show the method we proposed can achieve ideal recognized result in on-line Hangul recognition.

THE FEATURES BASED ON WAVELET TRANSFORM

Preprocessed: Before extracting features, we must to do some preprocess on handwriting sequence. The main steps of preprocess include normalizing size of handwriting in order to avoid the influence of the difference size and setting the length of difference handwriting sequence to equal for the sake of reducing the influence of writing's speeding. The detailed steps as follows:

- Given a character sample, it is normalized to a fixed size of 64×64 using an aspect-ratio preserving linear mapping. We do this step in order to make the patterns with difference sizes can be normalized to one size for the sake of guide line.
- Imaginary strokes are those pen moving trajectories in pen-up states that are not recorded in the original character sample. We define an imaginary stroke as a straight line from the end point of a pen-down stroke to the start point of its next pen down stroke. All such constructed imaginary strokes are added into the stroke set of a character sample (Bai and Huo, 2005).
- NSN is used to normalize shape variability. The online character sample after the above two steps is first transformed into a bitmap that is then normalized by a dot density equalization approach reported originally in study (Narcowich, 2001). Using the derived NSN warping functions, the online character sample after the above step (2) is transformed into a new sample such that the temporal order of the original points is maintained.
- Extract sample points.

We assume that the writing length is L, we partition writing sequence into 255 portions averagely and every portion has L/255 length. Every portion has both a start point and an end point and we call these points as sample point. The end point of currently portion is the start point of next portion, so we can obtain 256 sample points in whole letters, noting the 256 sample as, S_1 (x_1, y_1),...,S_{256} (x_{256}, y_{256}) where, (x, y) is a coordinate of sample point. Then the time sequence of X-coordinate is defined as: X (t) = {x_1, ..., x_{256}}and the time sequence of Y-coordinate is defined as Y (t) = {y_1, ..., y_{256}}.

The features extraction:

Discrete wavelet transform and discrete meyer wavelet: Wavelets (Sun, 1998; Chiu *et al*., 2008; Qian, 2001) are mathematical functions that satisfy certain criteria, like a zero mean and are used for analyzing representing signals or other functions. A set of dilations and translations $\Psi_{i,k}(t)$ of a chosen mother wavelet Ψ(t) is used for signal analysis. In Discrete Wavelet Transform (DWT), dilation factors are chosen at a power of 2 and set of dilation and translation of the mother wavelet.

In the discrete wavelet transform, we can use filter bank to simplify the algorithm, the step of the filter bank algorithm is define as $\Psi_{i,k}(t) = 2^{-j/2}\,\Psi(2^{j/2}t - k)$. Where j is scaling factor and k is the translation factor. It is obvious that the dilation factor is a power of 2. A scaling function $\phi(t)$ is defined as:

$$\phi(t)\begin{cases}1 & if\ t \in [0, 1)\\ 0 & otherwise\end{cases} \tag{1}$$

And the set of dilation and translation of scaling function is:

$$\phi(t) = \sqrt{2^j}\,\phi(2^j t - k) \tag{2}$$

To span our data domain at different resolutions, the wavelet is represented in a scaling equation:

$$\psi_{j,k}(t)\sum_k C_k\phi(2^j t - k) \tag{3}$$

where C_k are the wavelet coefficients and they must satisfy linear and quadratic constraints with scaling basis $\phi_{i,k}(t)$ and wavelet basis $\Psi_{i,k}$(t).
we can decompose any function $f(t)$ as:

$$f(t) = C_{00}\phi(t) + \sum_{j=0}^{n-1} C_{j,k}\psi_{j,k}(t) \tag{4}$$

The coefficients C_∞ and $C_{j,,k}$ are selected as features for personal identity verification approach.

The Meyer wavelet not only has rapid decay and infinite differentiability, but also has compact support in the frequency domain. Due to the above feature, the meyer wavelet is used in many domain. In this study, we use it to extract feature.

The filter bank algorithm: In the discrete wavelet transform, it turns out that the discrete wavelet transform can be simply achieved by a tree of digital filter banks, with no need of computing mother wavelets. Hence, the

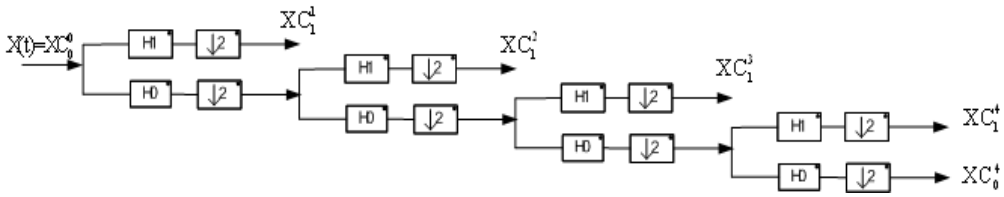


Fig. 1: The filter bank algorithm

filter banks have been playing a central role in the area of wavelet analysis (Kimura and Takashina, 1987). We can compute the discrete wavelet transform through the tree of filter banks, as shown in Fig. 1 and the steps as follow:

- i = 0, $XC^0{}_0\ X(t)$
- Firstly, we let inputting sequence $XC^0{}_0$ pass a high-pass filter h_1 and down sampled by 2 and record the even index of filtering result as $XC^{i+1}{}_1$
- Secondly, we let inputting sequence $XC^0{}_0$ pass a low-pass filter h_0 and record the even index of filtering result as $XC^{i+1}{}_0$
- i = i+1
- If i = n, end. Otherwise return to step 2

In our experiment, we let n = 7.
h_1 and h_0 determine the mother wavelet function Ψ(t).

Feature extraction: After decomposing $X(t)$, the high frequent $XC^0{}_0$ are considered as noise and eliminate. So we get $\{XC_0^7, XC_1^7, XC_1^6, XC_1^5, XC_1^4 XC_1^3 XC_1^2\}$ as feature which it's dimensions is 128 where we think $XC^1{}_1$ as noise. We do the same work on $Y(t)$, $Z(t)$ $X(t)\times Y(t)$ and $D(t) = \Delta X(t)/\Delta Y(t)$, we define $\Delta X(t) = X(t) - X(t-1)$, $\Delta Y(t) = Y(t) - Y(t-1)$ if $Y(t) - Y(t-1) \neq 0$ else $\Delta Y(t) = \sigma$ where σ is a small number, in this study we set $\sigma = 0.01$ $X(0) = 0 Y(t) = 0$. In finally, we can get 4×128 = 512 dimensions raw feature. Because the dimensions of feature:

$$\{XC_0^7, XC_1^7, XC_1^6, XC_1^5, XC_1^4, XC_1^3 XC_1^2,$$
$$YC_0^7, YC_1^7, YC_1^6, YC_1^5, YC_1^4, YC_1^3, YC_1^2,$$
$$ZC_0^7, ZC_1^7, ZC_1^6, ZC_1^5, ZC_1^4, ZC_1^3, ZC_1^2,$$
$$DC_0^7, DC_1^7, DC_1^6, DC_1^5, DC_1^4, DC_1^3, DC_1^2\}$$

are comparative higher, so we compress feature dimensions by LDA and we acquire 128-dimensions feature for a on-line script finally.

The recognize algorithm: After extracting feature, we use the Modifity QDF that Fumitaka Kimura propose IEEE, MQDF has the formula as follow:

$$g_k(x) = \sum_{i=1}^{n} \frac{1}{\lambda_{ki} + h^2} \{\varphi_{ki}^t (x - \mu_k)\}^2 + \log \prod_{i=1}^{n} (\lambda_{ki} + h^2) \quad (5)$$

Fig. 2: Hangul character "뚜"and"석"

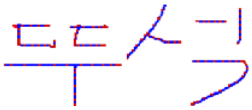
where, λ_{ki} is the eigen value of the kth class and φ_{ki} is corresponding eigenvector. μ_k is a mean of feature of the kth class, n is a dimensions of feature, in our experiment, we set n = 128.

The result of recognizing is $C = arg_k\ max\ (gi_k(x))$, where, x is feature.

EXPERIMENTAL RESULTS

In order to validate the effect of the algorithm, we design two experiments in this study. We use the Hanvon Company's Online Handwritten Hangul Characters database. This database has 2350 classes hangul characters which every class have 200 patterns in training set and 30 patterns in testing set, So there are 350×(200+30) = 540500 online hangul handwritten scripts in database. In these two experiments, we use MQDF as classifier.

There are two common use online hangul handwritten scripts " " and " " in Fig. 2. The normalized scripts of these two characters are shown in Fig. 3b. Figure 3c shows normalized scripts that added Imaginary strokes. We take a pattern " " as an example to compare the x and y coordinate sequences that are added imaginary strokes and resampled or not. There are two online hangul handwritten scripts image that only be normalized in size as shown in Fig. 4. The x and y sequences of these two patterns are shown in Fig. 5. Comparing Fig. 5a, b, c and d, we find two patterns are variance in X and Y sequence, although these two pattern come from the same class. For the sake of eliminating this variance, which can adversely influence on the result of discrete wavelet transform, the pattern will be preprocessed which include adding image stroke and resampling, The preprocessed patterns are shown in Fig. 6 and their x, y sequences are shown in Fig. 7. We can see that the x, y sequences of difference patterns of same class become more approximate when the patterns after added imaginary stroke and resampling. Farther, the sample points of pattern are arranged equidistance so as to reinforce the robust of the algorithm.



(a) The sample points in hangul characters

(b) The characters is normalized in 64×64

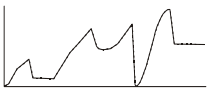
(c) The character are added imaginary strokes

(d) The resample points in two hangul characters

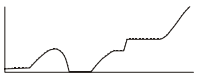
Fig. 3: Preprocessed on on-line handwritten hangul character

(a) (b)

Fig. 4: Tow patterns of hangul without "ㅜ" preproc essed

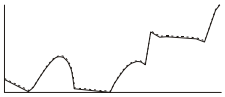


(a) The x coordinates trajectory of pattern as Fig. 4a shows



(b) The y coordinates trajectory of pattern as Fig. 4a shows

(c) The x coordinates trajectory of pattern as Fig. 4b shows

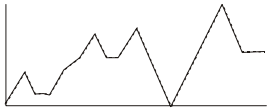


(d) The y coordinates trajectory of pattern as Fig. 4b shows

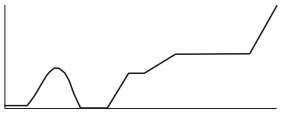
Fig. 5: Coordinates trajectory of two hangul patterns whithout preprocess as Fig. 4 shows

(a) (b)

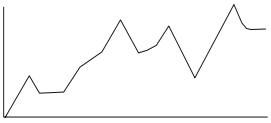
Fig. 6: Two hangul patterns that Fig. 4 shows after preprocess



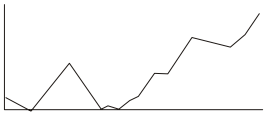
(a) The x coordinates trajectory of pattern as Fig. 6a shows



(b) The ycoordinates trajectory of pattern as Fig. 6a shows



(c) The x coordinates trajectory of pattern as Fig. 6b shows



(d) The y coordinates trajectory of pattern as Fig. 6b shows

Fig. 7: Coordinates trajectory of two hangul

Table 1: The results of the method we roposed, direction feature and feature based on daubechies wavelet

	Featuredi mansi	Recoganization rate in train set (%)	Recoganization rate in test set (%)
Direction features	128	85.12	81.31
Meyer wavelet	128	90.21	85.92
Daubechi es wavelet (k = 3)	128	87.82	83.15

Table 2: The result when we use meyer wavelet, direction feature and combation of both methods

	Featuredi mansi	Recoganization rate in train set (%)	Recoganization rate in test set (%)
Direction features	128	75.12	80.31
Meyer wavelet	128	89.21	84.92
Daubechi es wavelet (k = 3)	128	83.82	82.15

We compare the direction features, the feature extracted by Daubechies (k = 3) Wavelet and the feature

extracted by Meyer Wavelet in first experiment. The direction feature is extracted according to the method proposed in study (Ma and Huo, 2009). All methods extract 128-dimensions feature. The result as Table 1 shows.

In the second experiment, we want to prove the complementation of direction features and the feature we proposed. We extract combination 256-dimension s features which composed of 128 dimensions direction features and 128-dimension we proposed, Finally, we compress 256 combination features to 128-dimensions by LDA. The experiment result as Table 2 illustrates.

CONCLUSION

In this study, the result of the first experiment shows the feature we proposed can achieve better recognition accuracy than direction feature in Online Handwritten Hangul Script and the features extracted by Daubechies (k = 3) Wavelet. The second experiment shows the direction feature and the feature we proposed are complement in some sense. In our future study, we will try other mother wavelet and find the best mother wavelet for feature extraction.

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REFERENCES

Bai, Z.L. and Q. Huo, 2005. A study on the use of 8-directional features for online handwritten Chinese character recognition. 8th International Conference on Document Analysis and Recognition,1: 262-266.

Bai, Z.L. and Q. Huo, 2006. A Study of Nonlinear Shape Normalization for Online Handwritten Chinese Character Recognition: Dot Density vs. Line Density Equalization. Pattern Recognition, ICPR. 18th International Conference on Issue Date, pp: 921-924.

Bocchieri, E. and B. Mak, 2001. Subspace distribution clustering hidden Markov model. IEEE Trans. Speech Audio Proc., 9(3): 264-275.

Chiu, C.C., C.M. Chuang and C.Y. Hsu, 2008. A novel personal identity verification approach using a discrete wavelet transform of the ecg signal. International Conference on Multimdia and Ubiquitous Engineering, 24-26 April, pp: 201-206.

Ding, K., G.Q. Deng and L.W. Jin, 2009. An investigation of imaginary stroke techinique for cursive online handwriting chinese character recognition. Proceedings of the 10th International Conference on Document Analysis and Recognition ICDAR, pp: 531-535.

Kang, K.W. and J.H. Kim, 2003. Handwritten Hangul Character Recognition with Hierarchical Stochastic Character Representation. Proceedings of the 7th International Conference on Document Analysis and Recognition, South Korea, 1: 212-216.

Kang, K.W. and J.H. Kim, 2004. Utilization of hierarchical, stochastic relationship modeling for hangul character recognition. IEEE Trans. Pattern Anal. Mach. Intell., 26(9).

Kim, H.Y. and J.H. Kim, 2001. Hierarchical random graph representation of handwritten characters and its application to Hangul recognition. Pattern Recogn., 34: 187-201.

Kawamura, A., 1992. On-line recognition of freely handwritten japanese characters using directional feature densities. Proc.11th Int'l Conf. Pattern Recognition, 2: 183-186.

Kimura, F. and K. Takashina, (1987). Modified quadratic nctions and theapplication to chinese character recognition. IEEE Trans. Pattern Anal. Mach. Intell., 9(1): 149-153.

Lee, J.J., 1998. A hierarchical HMM network-based approach for on-line recognition of multi-lingual cursive handwritings. IEICE Trans. INF and Syst., E81-D(8).

Liu, C.L. and X.D. Zhou, 2006. Online Japanese character recognition using trajectory-based normalization and direction feature extraction. 10th International Workshop on Frontiers in Handwriting Recognition.

Ma, L. and Q. Huo, 2009. A study of feature design for online handwritten chinese character recognition based on continuous-density hidden markov models. 10th International Conference on Document Analysis and Recognition.

Nakagawa, M., 1996. Robust and highly customizable recognition of on-line handwritten japanese characters. Proc. 13th Int'l Conf. Pattern Recogn., 3: 269-273.

Narcowich, F.J., 2001. A First Course in Wavelets with Fourier Analysis. Prentice-Hall, Upper Saddle River, NJ.

Pisit, P. and K. Chom, 2002. Handwritten thai character recognition using fourier descriptors and genetic neural networks. Gen. Introd. Comput. Sci., 18(3): 270-293.

Qian, S.E., 2001. Introduction to Time-Frequence and Wavelet Transforms. 1st Edn., Practice Hall, Upper Saddle River, NJ. ISBN: 0130303607.

Sun, W.C., 1998. The Fundamentals of Wavelet. Chuan-Hwa Publishing Co.