Shape Feature Extraction for On-line Signature Evaluation

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***Abstract*—In the past few years, banks and companies have increased security by switching from simple static passwords to more dynamic security measures that offer greater protection for users of mobile and web commerce. The most personal method for authentication is analysis of handwritten signatures. Signature evaluation determines whether an individual's signature is considered "good" or "bad." A good signature is more complex and difficult to impersonate, whereas a bad signature is simple and easy to impersonate. A signature typically contains many angles, whether big or small. A signature with a higher number of angles is more complex and is considered "good"; therefore, the number of internal angles was calculated to determine the quality of the signature. In this paper, geometry was used to decide the kinds of angles to analyze. After the evaluation, verification was performed to analyze the EER (Equal Error Rate), and it has been concluded that it is best to use the Neighbor method to create the best signature evaluation system.**

Keywords-shape feature; signature verification; human–computer interaction

I. INTRODUCTION

Handwriting is the most natural way to enter text, and it allows users to replace the keyboard or mouse for input. Many kinds of input devices are available for handwriting, including the TouchPad, the pressure-sensitive tablet, the PDA touch panel, or other input panels. Online handwriting verification systems analyze the signature as a series of coordinate points, which are based on the writing movements made with a pen, in relation to the trajectory of the coordinates on the XY axis, including where the nib started to write, as well as the number of writing strokes [1]. The series of coordinates will first undergo pre-processing to remove noise in the handwriting and to reduce the variability of handwriting, including repetition of the coordinates of the point, smoothness, and size. Then, features are extracted around the contours of characters to identify illegible ligatures, with allowances for different strokes due to different writing habits of different users. Offline handwriting recognition systems allow users to write on paper, from which the image is scanned using a scanner or a camera. However, offline systems are unable to obtain any dynamic feature; therefore, it is more difficult to recognize the signature. The typical flow of the signature evaluation system includes image input, image recognition, and result output. Using images from devices such as digital cameras and digital scanners, image processing is performed in three steps: image pre-processing, feature extraction, and recognition. The available methods for offline signature recognition are based on a wide range of concepts. The research can be categorized according to the way that it handles the problem, as methods based on holistic, regional, and local properties.

Character feature extraction is the basis of character recognition. It is one of the most popular research topics in pattern recognition and is widely used in many areas, such as edge extraction, character learning, automatic letter sorting, and automatic license plate recognition. In license plate character recognition, some character feature extraction methods are used, including outline feature extraction and coarse grid feature extraction.

Signature verification is categorized into two main types: static and dynamic [2]. The static type, which is also known as offline verification, uses a scanner or a digital camera to obtain the image of the signature to be verified. The dynamic type, which is also known as online verification, verifies a signature that is entered using a digital pen and a tablet PC. The difficulty in signature recognition is that handwriting is affected by complex personal factors; therefore, the same character could have slightly different shapes.

Signature evaluation systems are used to analyze human signatures whether they are categorized as good or bad. If a signature is too simple or easy to replicate, it is considered a bad signature. A good signature must contain several angles or many strokes. In this paper, an evaluation system was used to determine if a signature is good or bad.

Online signature system can extract additional human-writing parametrics based on a time function (e.g., position trajectory, velocity, acceleration, pressure, direction of pen movement and azimuth); whereas, offline systems evaluate signatures using only scanned images. For this reason, online signature systems are much better than offline

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signature systems.

Most of previous research on signature evaluation focused on the development and the implementation of new algorithms. This paper discusses the analysis and evaluation of Chinese kanji from the "One Hundred Family Names" (百家姓), a collection of characters that are often used in Chinese family names.

If internal angles are used when evaluating good and bad signatures, a character could contain too many angles between 0° and 180°. In order to define the optimal angles, a method was used to determine how many angles usually appear in a character; therefore, 100 characters were selected and all of the angles that typically appeared in them were calculated.

II. RELATED WORK

Each person has a different signature, which could be slightly different in shape in different situations. To process these signatures, they need to be standardized based on some method.

Previous research usually focused on signature verification by using matching techniques based on dynamic time warping (DTW) [3], hidden Markov model (HMM) [4], and support vector machine (SVM) [5]. These techniques are useful for static signature verification, as well as dynamic verification when the signature image is combined with several features based on average speed XY, signature width, signature height, pen direction, number of strokes, pen azimuth [6], etc.

Figure 1. Eight principles of Yong

III. SIGNATURE EVALUATION METHODOLOGY

A. Eight Principles of Yong

The proposed kanji signature evaluation process is used to recognize an individual's handwritten signature whether it is considered good or bad, by applying the method only to internal angles. Twenty characters from the "One Hundred Family Names" collection were selected to calculate the averages on which to base the evaluations. Each character contains various angles, which were documented and compared. In the past, all characters were created with eight strokes; for example, this kanji contains eight strokes"永": 點, 横, 豎, 勾, 彎, 提, 撇, and 捺, where each stroke has different characteristics. Statistics on every stroke's angle can be obtained, as well as statistics on the angles between the lines (Figure 1).

B. "One Hundred Family Names" (百家姓)

The "One Hundred Family Names" (Chinese: 百家姓; pinyin: Bai jia xing) [7] is a classic Chinese book composed of common surnames in ancient China. Based on these family names, the average angles of the characters could be calculated.

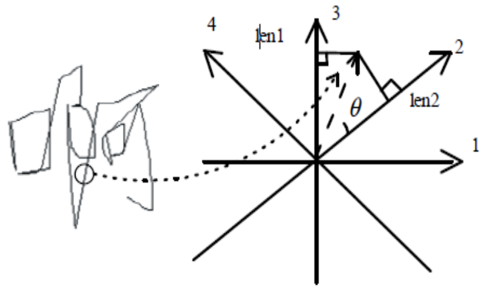

Figure 2. Internal angle

C. Internal Angle

An interior angle (or internal angle) of a kanji character is an angle formed by two connected lines [8] of a polygon stroke (Figure 3). Some people have a habit of writing kanji where the closed polygon is less than 180°; in that case, the polygon is called "convex." More complex signatures have more varied angles that were used for the calculations. The following are the different types of internal angles typically found in kanji:

- Equiangular: All angles are equal.
- Cyclic: All corners lie in a circular format.
- Vertex-transitive: All corners lie within the same symmetry orbit. The polygon is also cyclic and equiangular.
- Edge-transitive: All sides lie within the same symmetry orbit. The polygon is also equilateral.
- Tangential: All sides are tangential to an inscribed circle.
- Regular: The polygon is both cyclic and equilateral.

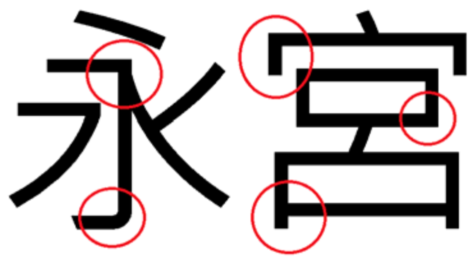

Figure 3. Internal angles in kanji

With simple characters and signatures, angles that were

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deemed important were manually searched for and selected. With complex signatures, a polygon algorithm was used to calculate the complex angles (Figure 2).

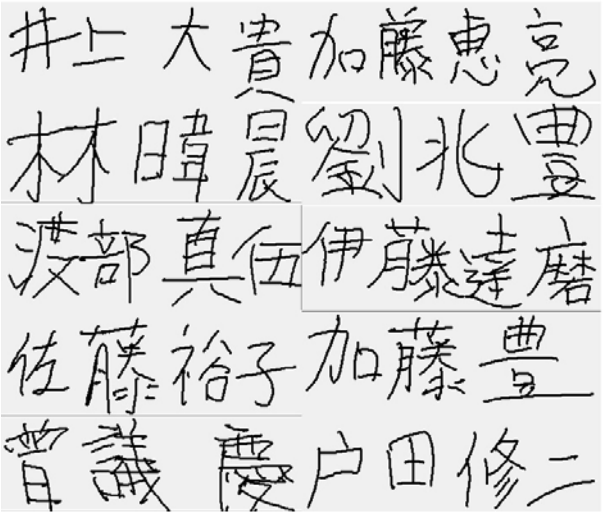


Figure 4. Example of signatures of twenty people

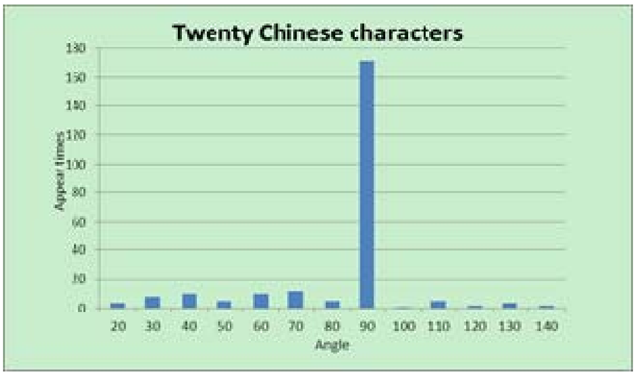


Figure 5. Analysis of internal angles occurring in twenty Chinese characters from “One Hundred Family Names”

D. Geometry

Geometric features [9][10] are based on multi-stroke recognizer techniques and are extracted to collect the internal features of the characters. Angles whose sum is a right angle (90°) are called “complementary.” Complementary angles are formed when one or more rays share the same vertex and are pointed in a direction between the two original rays that form the right angle. The number of rays between the two original rays is infinite.

Angles whose sum is a straight angle (180°) are called “supplementary.” Supplementary angles are formed when one or more rays share the same vertex and are pointed in a direction between the two original rays that form the straight angle. The number of rays between two original rays is also infinite.

Although the geometry method is a useful algorithm, the computer is unable to find some of the angles in a kanji character. In the end, all useful angles were manually collected.

E. Measuring Angle

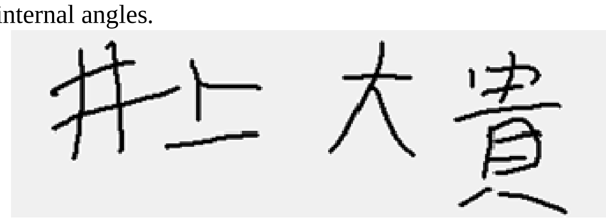
The following data were used in the analysis:

1) Eight Principles of Yong: This basic character set was used as a reference to obtain statistics on all the angles that usually appear in kanji characters.

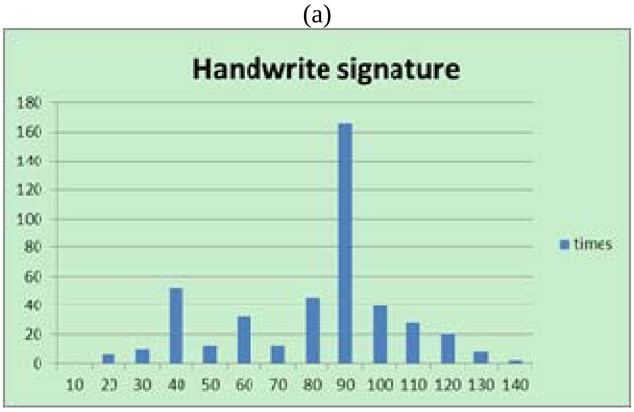
2) “One Hundred Family Names” (百家姓): Twenty characters were randomly selected, and statistics were generated on the most common angles found in them.

3) Own Individual Signatures: Twenty test subjects wrote their own signatures, and statistics were also generated on the most common angles found in them. In addition, the analyses on handwritten and printed characters were compared.

4) Unfamiliar Signatures: The same twenty test subjects were asked to handwrite newly designed signatures that were unfamiliar to them and to handprint other characters. This set of experimental data was used to determine whether copying an unfamiliar signature would create different internal angles.



(a)



(b)

Figure 6. (a) Handwritten samples of test subjects’ own signatures with simple patterns (b) The analysis of internal angles occurring in those signatures

III. EXPERIMENTAL RESULTS

Figure 4 shows an example from our database of signatures of people who handwrote their own names.

A. Analysis of Twenty Printed Chinese Characters

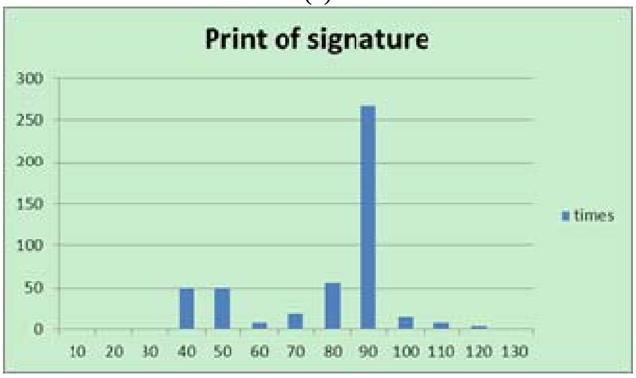
Twenty Chinese characters obtained from the “One

Hundred Family Names" collection were analyzed, as shown in Figure 5.

B. Analysis of Own Handwritten Signatures

The analysis of the handwritten signatures occurred in two steps. First, twenty people handwrote their own signatures and those were analyzed (Figure 6). Then the results were compared with the analysis of the computer-printed signatures (Figure 7).

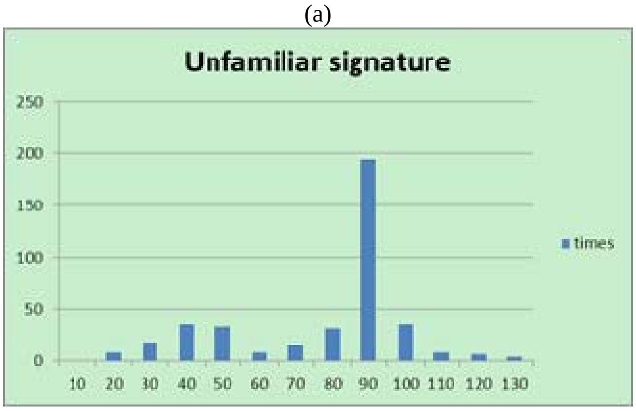
(a)



(b)

Figure 7. (a) Computer-printed samples of test subjects' own signatures with simple patterns (b) The analysis of internal angles occurring in those signatures

(a)



(b)

Figure 8. (a) Hand-copied samples of unfamiliar signatures (b) The analysis of internal angles occurring in those signatures

C. Analysis of Unfamiliar Signatures

Analyzing people's own signatures is not enough; therefore, in order to collect additional data about character angles, the research included an analysis of signatures that were unfamiliar to people who were writing them (Figures 8 and 9).

D. Chinese and English Character Angles

For this research to be more complete, the same analysis was performed not only on Chinese character signatures, but also on English characters from A to Z and English signatures, as shown in Tables 1 and 2.

(a)

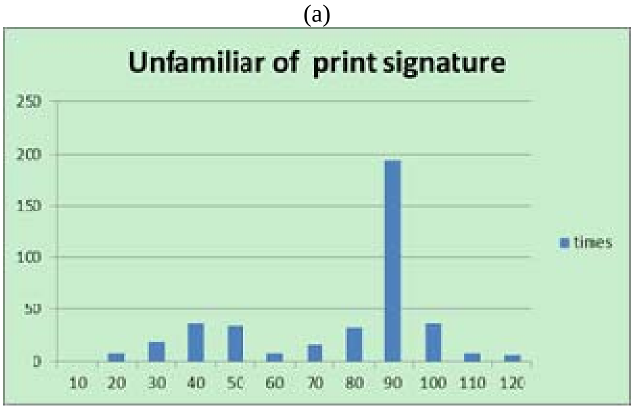


Figure 9. (a) Computer-printed samples of unfamiliar signature with simple patterns (b) The analysis of internal angles occurring in those signatures

TABLE I. ANALYSIS OF ALL ANGLES FOUND IN COMMON CHINESE CHARACTERS

	40°	50°	60°	70°	80°	90°	100°
Handwritten Sig.	52	12	32	12	46	166	40
Twenty Chinese	16	10	16	18	4	160	2
Print of Sig.	50	50	8	18	56	266	14
Unfamiliar Sig.	36	34	8	16	32	194	36
Print of Unfamiliar	2	5	0	0	1	12	0
Total	156	111	64	64	139	792	92

TABLE II. ANALYSIS OF ALL ANGLES FOUND IN COMMON ENGLISH CHARACTERS

	10°	20°	30°	40°	50°	90°	120°
English A–Z	80	46	12	54	80	120	50
English Sig.	30	43	50	20	18	200	20
Total	110	89	62	74	98	320	70

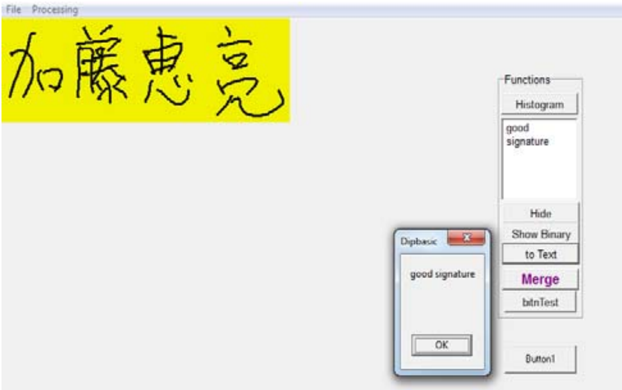


Figure 10. An example of a good signature

Figure 11. An example of a bad signature

V. EVALUATION SYSTEM

In the proposed evaluation system, the signature could be considered good and bad, as shown in Figures 10 and 11.

A. Comparison with Nearest Neighbor method and BPN

The analysis of the signatures was performed using the Neighbor method and the Neural Network BPN method. Although either of these methods would be effective, the two methods were still compared to find the best method. The results of the comparison are shown in Figure 12, Figure 13, and Table 3. We compared the Neighbor method and the Neural Network BPN method by analyzing Chinese basic characters, handwritten Chinese signatures, computer–printed signatures, unfamiliar Chinese signatures, and English signatures for analysis.

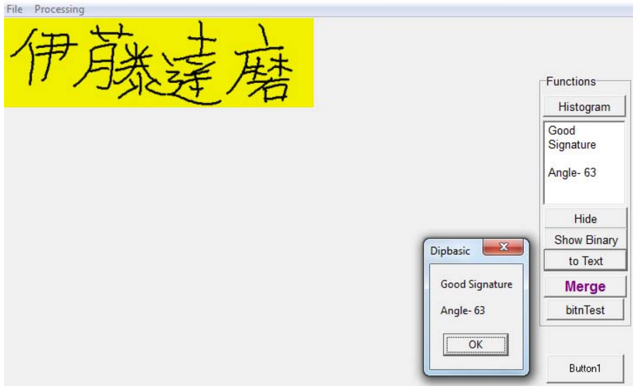


Figure 12. Angle of Neighbor method

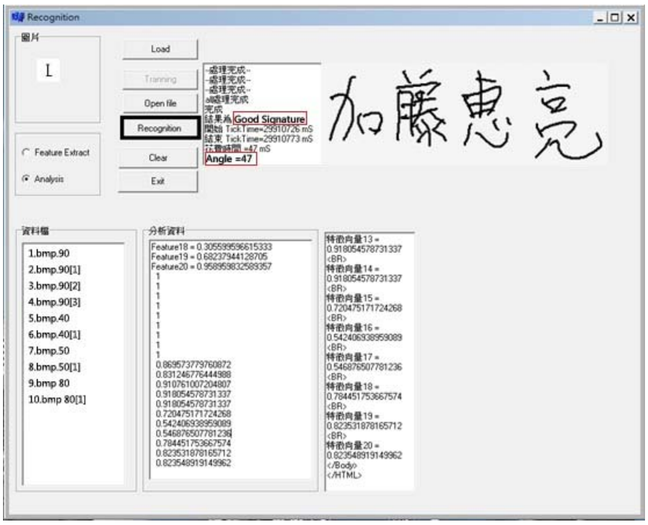


Figure 13. Angle of neural network BPN method

Table 3 illustrates that the Neighbor method can find more angles than the Neural Network BPN method, because the Neighbor method scans all pixels; therefore, it can be more accurate in extracting angles.

On the other hand, the Neural Network BPN method uses pattern recognition. In this research, the neural network was taught a total of 20 pattern designs, covering all angles (40°, 60°, 70°, and 90°). Because of the limited number of learned patterns, the neural network is unable to find all angles in an image. However, given additional patterns to learn, the Neural Network BPN system would require more processing time.

In a set of twenty randomly selected characters from "One Hundred Family Names," the most common angles are 40°, 60°, 70°, and 90°, as shown in Figure 5. In a set of twenty handwritten signatures, the most common angles are 40°, 60°, 80°, 90°, and 100°, as shown in Figure 6 (b). This set was also compared with the computer–printed versions of these characters to check whether these two categories would have similar analyses, as shown in Figure 7 (b).

TABLE III. COMPARISON RESULTS OF NUMBER OF ANGLES WITH NEIGHBOR AND BPN METHOD (A) CHINESE SIGNATURE (B) CHINESE CHAR. (C) COMPUTER PRINT (D) UNFAMILIAR AND (E) ENGLISH SIGNATURE

	(a)	**(b)**	**(c)**	**(d)**	**(e)**	**Total**
Neighbor	80	56	103	74	35	348
BPN	45	53	60	95	37	290

In order to increase the accuracy of the system, the same twenty people handwrote unfamiliar signatures that were not their own. Then those signatures were analyzed, as well as the computer-printed versions of the same characters, as shown in Figure 8 (b) and Figure 9 (b). In handwritten characters, the most common angles are 40°, 50°, 80°, 90°, and 100°.

To reduce the number of angles between 0° and 180° that the system would have to analyze, the analysis was focused on the five most common angles in Table 1: 40°, 50°, 80°, 90°, and 100°. In future work, the automatic signature verification system could use this research data to decide the best angles to analyze.

In addition to collecting and analyzing Chinese characters, computer-printed English characters (uppercase A to Z and lowercase a to z) and twenty handwritten English signatures were selected, and the most common angles in those samples are 10°, 20°, 30°, 40°, 50°, 90°, and 120°. Based on this result, the evaluation system could be designed to be more accurate, based on these angles and on the kind of characters that need to be evaluated.

TABLE IV. FRR AND FAR FOR RANDOMLY CHOSEN SIGNATURES

Total/Signature		**Good Signature**		**Bad Signature**	
60 Angles	FAR	2/20	10%	8/20	40%
	FRR	2/20	10%	6/20	30%
80 Angles	FAR	1/15	6%	3/25	12%
	FRR	2/15	13.3%	5/25	20%
100 Angles	FAR	0/8	0%	2/32	6.25%
	FRR	0/8	0%	2/32	6.25%
Average total FAR		5.33%		19.4%	
Average total FRR		7.76%		18.75%	

B. Calculate FRR and FAR from Nearest Neighbor

To determine whether the system was optimal, random signatures were evaluated and categorized as good or bad.

In Table 4, we determined the false acceptance rate (FAR) and false rejection rate (FRR) values for randomly selected signatures. FRR is affected when users write their own individual signature, and FAR is affected when people forge someone else's signature. With bad signatures, FAR and FRR are expected to be high. If the verification of a good signature reduces FRR and increases FAR, it means that the system performs good evaluations. If the verification of a bad signature raises the FAR higher than the FRR, the bad signature is easy to forge. However, a low FRR value with a bad signature is not sufficient for evaluation. In this system, the research focused on evaluating good signatures, whether they are easy to forge or not. Sometimes, signatures can be successfully copied; therefore, this system is not foolproof.

VI. CONCLUSION

This paper focused on Chinese characters and signatures for evaluation and discussed the analysis of the handwriting of twenty people who wrote familiar characters and unfamiliar characters. These two categories of samples were compared with characters that appear in family names to calculate which characters appear more often. After the evaluation, a verification system analyzed the EER, and it is concluded that the Neighbor method creates the best signature evaluation system.

REFERENCES

[1] D. Y. Yeung, H. Chang, Y. Xiong, S. George, R. Kashi, T. Matsumoto, and G. Rigoll, "SVC2004: First international signature verification competition," in: Proceedings of the International Conference on Biometric Authentication (ICBA), vol. 3072, Springer LNCS, China, pp. 16-22, 2004.

[2] D. S. Guru and H. N. Prakash, "Online signature verification and recognition: An approach based on symbolic representation," IEEE Transaction on Pattern Analysis and Intelligence, vol. 31, no. 6, pp. 1059–1073.

[3] M. I. Khalil, M. N. Moustafa, and H. Abbas, "Enhanced DTW-based on-line signature verification," in: Proceedings of ICIP 2009, 2009, pp. 2713–2716.

[4] S. M. A. Ahmad, A. Shakil, and R. M. Anwar, "Stability and repeatability of HMM based probability outputs across dynamic handwritten signature features," IEEE 2008 International Symposium on ITSim Information Technology,

[5] N. Abbas, "Combination of off-line and on-line signature verification systems based on SVM and DST," IEEE International Conference on Intelligent Systems Design and Applications, 2011, pp. 855–860.

[6] G. Taherzadeh, "Evaluation of online signature verification features," International Conference on 2011 Advanced Communication Technology (ICACT), pp. 772–777.

[7] Y. Nakamura and M. Kidoe, "Extraction of individual handwriting characteristics from handwritten Chinese characters based on knowledge of handwriting analysis," Technical Report of IEICE PRMU2004-23,MI2004-23,WIT-23 (2005405).

[8] S. Huang, L. Jin, and J. Lv, "A novel approach for rotation free online handwritten Chinese character recognition," International Conference on Document Analysis and Recognition, 2009. ICDAR, pp. 1136–1140.

[9] K. Franke, "Analysis of Authentic Signature and Forgeries," in: Proc. IWCF, 2009, pp. 150–164.

[10] B. Fang, C. H. Leung, Y. Y. Tang, K. W. Tse, P. C. K. Kwok, and Y. K. Wong, "Off-line signature verification by the tracking of feature and stroke positions," Pattern Recognition, 2003, pp. 91–101.