Online Slant Signature Algorithm Analysis

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Abstract: - A vector rule-based approach and analysis to on-line slant signature recognition algorithm is presented. Extracting features in signature is an intense area due to complex human behavior, which is developed through repetition. Features such as direction, slant, baseline, pressure, speed and numbers of pen ups and downs are some of the dynamic information signature that can be extracted from an online method. This paper presents the variables involve in designing the algorithm for extracting the slant feature. Signature Extraction Features System (SEFS) is used to extract the slant features in signature automatically for analysis purposes. The system uses both local and global slant characteristics in extracting the feature. Local slant is the longest slant among the detected slant while the global slant represents the highest quantity of classified slant whether the slant are leftward, upright or rightward. Development and analysis are reported on a database comprises of 20 signatures from 20 subjects. The system is compared to human expert evaluation. The results demonstrate a competitive performance with 85% accuracy.

Key-Words: - Slant feature, Online signature, Signature recognition, Signature analysis, Dynamic signature

1 Introduction

Signature is a complex behavior, which is developed through repetition and tends to remain constant once it becomes someone's routine. It is a special class of handwriting and among the most widely accepted personal attributes for identity verification. They reflect not only the semantic information related to the name of the signer, but also intrinsic and unique features related to the specificity of the biomechanical system used to produce the message, physiological and even the psychological state of the signer [9, 18]. However, checking and analyzing signatures as a means of establishing or verifying identity is both a challenge for technology especially to formulate robust algorithms for automatic signature verification and for the powers of human perception [5].

There are many features in handwriting signature. Some of them are direction, slant, stroke, pressure, baseline, caliber and shape of individual's signature. The slant of writing is perhaps one of the easiest features to recognize and to assess but difficult to interpret accurately. This is because the basic meaning is very broad that it can have many different applications. Furthermore, there is no universal definition for similarity measure satisfying wide range of characteristics such as slant, deformation or other invariant constraints [3]. Signature is usually slant in nature due to the mechanism of handwritten and one's personality. Details of slant feature such as slant definition and assessment are discussed in the next section.

There are various applications that applied signature recognition ranges from simple to complex activities. The applications include signature authentication [6], credit card authentication [13], forensic authentication [2], and *etc*. In signature authentication for example, the users are usually required to provide signature samples to be used as reference and will be kept in a database for later used. If there are differences to a certain threshold that has been identified, the user signature would be rejected or otherwise it would be authenticated [6].

This paper discusses the variable that involves in extracting the slant features in signature. The organization of the paper is as follows: Section 2 presents the overview of signature recognition and some related works on signature recognition in particular slant features. In section 3, the variables that involve in slant algorithms are presented. Next in section 4 the methodology that was employed is discussed followed by results and findings in section 5. The results from the implementation of slant algorithm produced by the SEFS are compared to the human experts' evaluation. The paper ends by giving some conclusions in section 6.

2 Signature Recognition

Generally, signature recognition are broadly divided into online and offline, depending on the sensing modality. In offline mode, signatures are usually scanned from paper documents where they were written. Some of the features that can be extracted are image of the signature, maximum distance between the highest and lowest points, signature length, standard different in *x*-axis and *y*-axis, caliber, baseline and shape of individual's signature.

In online method, pressure-sensitive tablets can capture and extract the dynamic information signature features with its shape. It consists of digitizing the signature as it is being produced. The information obtained not only contains the signature image, but also time domain information, such as signing speed and acceleration. Other features or characteristics are initial and final point signature, writing order, direction, slant, baseline, pressure changes in *x*-axis and *y*-axis and numbers of pen ups and downs. These features will make the signature more unique and more difficult to forge. Thus by taking into consideration these features it will make online signature verification more reliable and have a higher level of accuracy than offline signature. In corresponding to this, each of these features requires a method or algorithm to extract the raw data of the signature [7, 10, 11, 12, 16, 19].

A slant is the angle of inclination between the vertical directions of the strokes of signatures. Slant angle can be rightward slant, leftward and upright (vertical) slant. A rightward slant is where the signature is inclining towards the right while the leftward slant is when the signature leans towards the left. The upright slant is where the signature is vertical. The example of slant directions is shown in Figure 1.

(a) (b) (c)

Figure 1(a) Rightward slant (b) Upright (Vertical) (c) Leftward slant)

In slant assessment, measurement is taken by the angle of the stroke in relation to the baseline of the signature. Manual measurement is made in degrees by using a protector and ruler, while for online measurement computer is used for calculating the degree. A basic rule can be applied in the classification of slants. Rightward slant is measured, as being between 0 and 89 degrees and left slope as more than 91 degrees to 180 degrees and the upright is 90 degrees.

However, for upright there is variance of degrees to clarify the upright because it is not often and quite difficult to get exactly 90 degrees. The common slant measurement is defined as below [13]:

- Upright slant - between 85^0 to 95^0;
- Right slope slant - between 60^0 and 85^0;
- Normal left slant - between 95^0 to 100^0

A method of using chain code contour processing for handwriting word recognition was described in [14]. The handwriting slant is corrected before the process of segmentation and recognition. The vertical line elements from contours are extracted by tracing chain code components using a pair of one-dimensional filter I which each filter is an eight element array of different weights used for detecting vertical lines having opposite directions. A convolution operation between the filter and five consecutive components is applied iteratively by sliding the filter one component at a time. The coordinates of the start and end points of each line element extracted provide the slant angle. Global slant angle is taken as the average of all angles of all the line elements. The angles are given weights proportional to the length of the line elements in the vertical direction [8, 9].

A paper by Ding and friends [4] describes three methods for local slant estimation. The result from their experiments shows that their proposed methods can estimate and correct slant more accurately than the average slant correction. In their paper the local slant estimator is defined as a function of horizontal coordinate *x* by

$$\theta(x) = tan^{-1}\left[\frac{n1(x) - n3(x)}{n1(x) + n2(x) + n3(x)}\right] \qquad (1)$$

where $ni(x)(i = 1, 2, 3)$ is the frequency distribution of chain code elements at direction of $i \times 45^\circ$ in $[x-\delta x, x + \delta x]$. Figure 2a illustrates the calculation of local slant for a chain code sequence, where $n1(x) = 4$, $n2(x) = 3$, and $n3(x) = 1$.

A parameter δx is determined experimentally depending on the input image. The frequency distribution $ni(x)(i = 1, 2, 3)$ can be calculated as follows:

$$ni(x) = si(x + \delta x) - si(x - \delta x - 1) \qquad (2)$$

where $si(x)$ is cumulative frequency distribution number of chain code elements at direction of $i \times 45^\circ$ in $[0, x]$, as shown in Figure 2b. Then tan $\theta(x)$ is smoothed by the mean filter of adjacent three pixels.

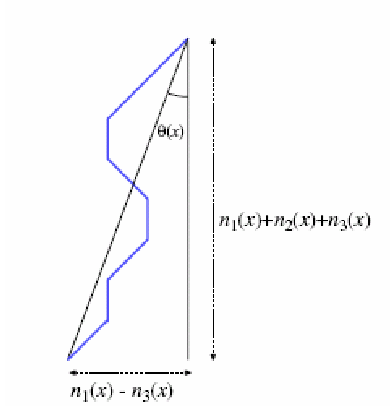


Figure 2a Local Slant tan θ(x) (Source of Figure 2: Ding et al., 2004)

The calculation of tan θ in this paper is based on coordinate x only and then it will proceed to find the next adjacent x point based on direction of $i \times 45^o$ in [0, x]. When the absolute local slant exceeds 45^o, the estimation is incorrect and not valid.

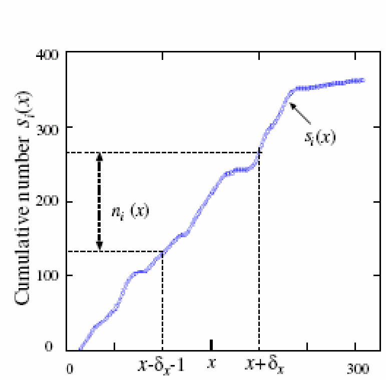


Figure 2b Example of Frequency Distribution of Chaincode (Source of Figure 2: Ding et al., 2004)

Ding and his co-workers [4] further proposed three improvement methods for local slant namely simple iterative chain code method, high-speed iterative chain code method and local slant estimation by 8-directional chain code. Their experiments result showed that their proposed methods could estimate and correct slant more accurately than the average slant correction. In interactive chain code method, the accuracy improves by repeating the process of local slant estimation and correction 2 or 3 times. In a high-speed iteration chain code method, the local slant correction and the smoothing are applied to the chain code. This paper shows the result of estimation of local slant where the estimation accuracy of 8-directional method is close to that of the simple interactive method or higher speed iterative method. However, all these methods need a higher processing time because it increases proportional to the number of iteration.

Meanwhile a good work on slant manipulation and character segmentation for forensic document examination can be referred in Sagar [17], which looks into the area of software tools for forensic document analysis. The study used a system called FOX (forensic document examination toolset) to extract global and local features of handwriting automatically for analysis purpose. The slant angle θ of each component is approximated using $\theta = \tan^{-1} x/y$ where y is window's height and x is windows width. The final angle, θ of the word is calculated by taking the average of θ for all components. Since the average of θ is taken, it could not represent each slant in the word and each slant need to be treated as local slant for each character of the word.

In another paper on writer identification based on handwritten text line was described in Andreas and co-workers [1] using Hidden Markov Model [15]. They use a few normalization operations on a handwritten text line before feature extractions are conducted. The normalization operations are slant correction, width normalization and vertical scaling. For slant correction, the normalization operation is to bring the handwriting into an upright position. To conduct correction to the slant, the angle between the actual, quasi-vertical strokes and the y-axis has to be known. In order to calculate this angle, the angle distribution of the writing's contour points is accumulated in an angle histogram. The maximum value of the histogram is the slant angle where the angle is then used to normalize the slant of a text line.

While a paper which presents a Relative Slope Based algorithm for online and offline signature verification is described in [7]. The paper used a slope based model in which the input signature is divided into many segments using optimized Hidden Markov Models method and then the slope of every segment are calculated with respect to its previous segment after the normalization process of a signature. The first step is data acquisition where pressure tablet and pen are used. At each sample the X(t), Y(t) and P(t) where t =1,2,3,4,5….T is the data obtained where X(t) represent the x-coordinate and y coordinate of a point at time T. P(t) represent pressure at time t and was not represented in this algorithm. After raw data has been gathered, preprocessing steps are applied where the redundant points are removed to speed up the comparisons and obtain a shape-based representation in which time dependencies are removed. However, when the researcher does the sampling of data, there were possibilities that the critical points of the signature were lost. They found that the benefits of not re-sampling significantly outweigh the disadvantage of not normalizing for speed. In feature extraction process, the segments are combined to create a line segment. The number of segments combined is decided based on the level of accuracy required however the paper does not mentioned the required level of accuracy. After the line segments are obtained the relative slope are then calculated. The relative slope of each line segment with respect to the previous line segments values is then stored. Then the length value associated with each time unit is calculated and stored as a profile signature values. This relative slope stored data and length value associated with time unit will be used as profile signature values to compare with the validation signature from user.

Furthermore, work by Tong et al. [19] present a stroke-based algorithm for dynamic signature verification. Their algorithm is developed to convert sample signatures to a template by considering their spatial and time domain characteristic and also by extracting features in term of individual strokes. Their proposed system call Dynamic Signature Verification (DSV) that consists of four subsystems which is data acquisition, signature preprocessing, feature extraction and signature verification. In their [19] data acquisition subsystem, signatures are acquired and digitalized by a digital pad using the modified standard Windows Tablet input API by measuring the data every millisecond. The measured data are sampling time, x position, y position and pressure. In the preprocessing subsystem, the dynamic signature signals are re-sampled and normalized to a standard length and missing data points interpolated. After that the features information are extracted from the input dynamic signature. Some of the features extracted are pen-up time, mean or variance of the x and y displacement signal in a number of pen ups and downs.

Next extraction method used by Madabusi et al. [7] is two tier time metric to extract length value associated with each time unit from the signature. The steps involve calculation of total time required to put the signature followed by preprocessing and normalizing of the signature data. The total length of the signature are calculated and then divided into equal time units. The length of signature completed in each time unit are calculated by combining all the segments associated with that time duration. The step before would be carried out until all the segments are processed. The length value associated with each time unit will be stored for verification process.

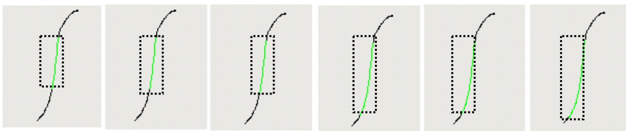
These past studies suggest the use global or local features in signature features extraction. This study would propose the use of both global and local features in extracting signature slant.

3 Variables in Slant Algorithm

This section presents three variables that involve in slant algorithm classification, namely reference degrees, percentage of reference height and slant classes. The details of slant algorithm can be referred in Rohayu *et al.* [20].

3.1 Acceptable Difference in Reference Degrees

Algorithm in Signature Extraction Features System (SEFS) has a variable called difference degree. This difference degree is the value of degrees that are acceptable to differ with Reference Degree. By having these difference degrees, the range of extracted slant of the signature can be adjusted accordingly. Figure 3 shows the extracted slants are in the dotted boxes with difference degree between 5º to 30º. It shows that acceptable slope of slant depend on the slant range required on the application. With this capability of the algorithm, users can choose the appropriate difference degree depending on the application of the extracted slant to be used.

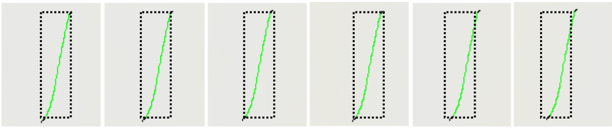


5º 10º 15º 20º 25º 30º

Figure 3 Extracted Slant for Signatures with difference degree between 5º to 30º

For signature, which has almost straight line, the variable difference degree does not give significant impact on the extracted slant as shown in Figure 4. Therefore the capability of the SEFS to extract slant is useful depending on the characteristic of the signature and application.

In application where the degree of a particular slant is needed, the SEFS can be used to extract the slant degree of a selected part of the signature by adjusting the variable of difference degree in the algorithm.

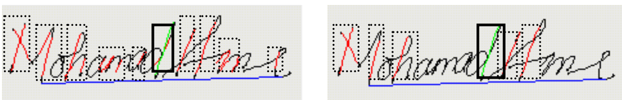


5º 10º 15º 20º 25º 30º

Figure 4 Extracted Slant for Signatures that Almost Straight Line with difference degree between 5º to 30º

3.2 Percentage of Reference Height

The percentage of reference height is a variable that is used for comparison with the height of extracted slant. In this algorithm, thirty percent of the overall height of the signature is set as reference height. With this setting, we can ensure that only slant which is higher than the normal overall slant height is extracted. If the application requirement needs more slant range of the overall character, the reference height can be adjusted to a lower value. Figure 5 shows examples of extracted slants in different percentages in which the slant height is set between 15 to 40 percent. When the slant reference is set to 40%, dominant slants will be extracted. Whereas if the slant reference is set to 15%, more slants are extracted which are comprised of dominant (i.e. black box) or non-dominant slants (i.e. black dotted box) as shown in Figure 5.



15% 40%

Figure 5 Image of Extracted Slant with Difference Reference Height of the Signature

3.3 Classification of Slant

The third variable is the slant classes in which slant features are groups based on its characteristic. In this study, the algorithm defines a leftward slant as a slant with an angle between 97 degrees to 135 degrees (with 0 degrees to the right of the protractor and 180 degrees to the left).

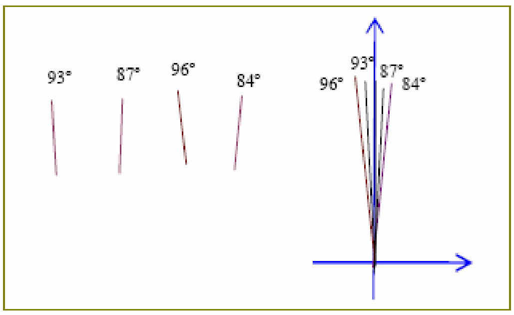


Figure 6 Classification of Upright Degree Selection

If the degree of slant falls between 84 degrees to 96 degrees then the slant would be categorized, as upright slant while rightward slant is when the degree is between 45 degrees to 83 degrees. Figure 6 shows that the degrees of vertical line which fall into upright category.

4 Methodology

4.1 Data Acquisition and Preprocessing

The WACOM Model CTE-440 tablet and pen is used in this study. The tablet is capable of sampling data at 100 samples per second. The Wacom's pen captured samples during the interaction of the pen tip with the tablet. The raw data available from a tablet pen consists of two dimensional series data which are *x* and *y* coordinates of signature's route which are recorded and representing the pen position.

In the preprocessing phase, the position points are counted from when the pen is down until it is lifted up. If the amount of points of data is less than 10 points then the set points of data would be discarded from the process of extracting features. It would reduce processing time where only the possible set points of data that have the extracted features would be processed.

4.2 Features Extraction and Classifications of Slant

Features are extracted from the pen position with respect to the *x*-axis and *y*-axis. The first feature is based on the slant angle of the signature, which is determined by the overriding value. This value is based on the global slant that was extracted in the signature whether their attributes is left slant signature, right slant signature or upright (vertical signature). Meanwhile, the global slant is calculated based on the maximum numbers of slant attributes. The local slant determination in this study is based on the longest length slant that was extracted from the signature.

4.3 Evaluations and Analysis

Twenty individuals are randomly selected to have their signature taken. These people would have to sign their signatures on the tablet and the SEFS would eventually gather the raw data. The data would be stored in binary files that are readable by the SEFS for future analysis. The image of the signature is created by the SEFS based on its signature. The images would be used as samples in questionnaire to identify the features of slant, where the questionnaire would be given to human expert for manual evaluation purposes.

The SEFS would analyze the binary data. It would then store the extracted features of the slant. The next step is where the results of the questionnaire would be gathered for analysis and comparison. Analyzed result from expert thru the questionnaire would be used to adjust the classification of slant in order to suite as close as possible with the human expert's judgment. The testing would be done several times until a satisfactory classification results are produced. In the final process of analyzing the data, the results on the features of slant from the SEFS are compared with the results from the human expert. The analysis is made based on the number of similarity and differences between the results from the SEFS and the expert. Details of these results are presented in the following section.

5 Result and Findings

The results of slant extraction from SEFS are presented in Table 1. The results show the value of local and global slant for every sample signature data. One can see that the results of sample number six give the same result for upright and rightward slant. In this case, global slant is chosen as upright due to the result from local slant, which is also upright slant. Similar results for sample eleven where the number of all type of classified slant is the same. Upright slant is chosen for global slant due to the result from local slant, which is also upright slant.

Table 1 The Slant Extraction Result from SEFS

No.	Signature Extraction Features System (SEFS)				
	Local Slant	L	U	R	Global Slant
S1	R:75°	0	0	2	R: Max =75°, Min= 64°
S2	L:99°	3	0	0	L: Max =99°, Min= 97°
S3	R:80 °	0	0	2	R: Max =80°, Min= 78°
S4	R:65°	0	0	2	R: Max =65°, Min= 49°
S5	U:95°	0	1	2	R:Max =73°, Min= 60°
S6	U:96°	0	1	1	U&R: **Decide to be Upright**
S7	U:96°	0	2	1	U: Max =96°, Min= 92°
S8	L:100 °	1	0	0	L: Max =Min= 100°
S9	U:90 °	0	5	2	U: Max = 92°, Min= 84°
S10	R:60 °	0	5	3	U: Max = 96°, Min= 85°
S11	U:94°	1	1	1	L,U & R **Decide to be Upright**
S12	R-81 °	1	0	2	R: Max =81°, Min= 54°
S13	R:82 °	0	1	2	R: Max =82°, Min= 82°
S14	R:49 °	0	0	5	R: Max = 64°, Min= 49°
S15	U:84 °	0	1	0	U: Max = Min= 84°
S16	U:90°	4	2	0	L: Max =110°, Min= 99°
S17	R:45°	0	0	2	R: Max =51°, Min= 46°
S18	R:46°	0	0	1	R: Max = Min= 46°
S19	R:58°	0	0	1	R: Max = Min= 58°
S20	R:101°	1	0	0	L: Max = Min= 101°

S: Sample; L: Leftward; R:Rightward; U:Upright

Table 2 shows the comparison slant results between SEFS and human expert analysis. Out of the twenty samples, three answers are not identical. They are samples number five, eleven and sixteen.

Table 2 Result of Comparison Between SEFS vs Expert Analysis

No.	SEFS	Questionnaire Result (%)			SEFS vs Questionnaire
	GS	L	U	R	
S1	R	4.17	4.17	91.67	Identical
S2	L	58.33	33.33	8.33	Identical
S3	R	12.5	41.67	45.83	Identical
S4	R	0	8.33	91.67	Identical
S5	R	37.0	29.17	33.33	Not Identical
S6	U	0	91.67	8.33	Identical
S7	U	16.67	70.83	12.50	Identical
S8	L	83.33	4.17	12.50	Identical
S9	U	16.67	75.00	8.33	Identical
S10	U	25.0	58.33	16.67	Identical
S11	U	45.83	37.50	16.67	Not Identical
S12	R	16.67	50.00	33.33	Identical
S13	R	12.5	8.33	79.17	Identical
S14	R	25.0	4.17	70.83	Identical
S15	U	33.33	33.33	33.33	Identical
S16	L	25.0	45.83	29.17	Not Identical
S17	R	20.83	25.00	54.17	Identical
S18	R	12.50	12.50	75.00	Identical
S19	R	4.17	12.50	83.33	Identical
S20	L	41.67	20.83	37.50	Identical

S: Sample; GS:Global Slant; L:Leftward; U:Upright; and R:Rightward

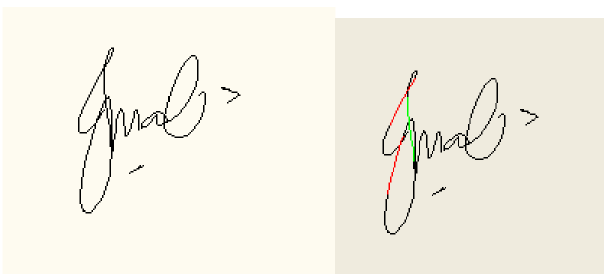


Figure 7 The Image of Sample 5 and Image Result From SEFS

For samples number five the SEFS has classified the signature as rightward slant but majority of human expert defined it as leftward slant. Although the results are not identical, the next highest result from the human expert is rightward slant, which is only 3.67% different from the highest result as extracted in table 3.

This is visible in figure 7 where the SEF system shows that most of the slant of the signature tends to slant to the right. There is one dominant slant which is slanted to the upright where the SEFS measured the dominant slant as having 95 degrees, which means that the slant is 5 degree from vertical slanting towards the left and falls in the upright categories which is from 84 degrees to 96 degrees.

Table 3 Comparison Result from Analysis for Sample 5

No.	SEFS	Questionnaire Result (%)			SEFS vs Questionnaire
	GS	L	U	R	
S5	R:Max =73°, Min= 60°	37.00	29.17	33.33	Not Identical

S: Sample; GS:Global Slant; L:Leftward; U:Upright; and R:Rightward

Overall the result from SEFS shows that the global slant is towards the rightward slant while the local slant is on the upright. The result from the questionnaire shows that human expert give almost the same result for leftward, upright and rightward slant but the highest score is towards leftward slant.

Figure 8 The Image of Signature of Sample 11 and Image Result From SEFS

As for sample eleven as extracted in table 4, the SEFS classified the signature as upright while the human expert classified sample eleven as leftward slant.

Table 4 Comparison Result from Analysis for Signature 11

No.	SEFS	Questionnaire Result (%)			SEFS vs Questionnaire
	GS	L	U	R	
S11	L, U & R : Equal Degrees	45.83	37.50	16.67	Not Identical

S: Sample; GS:Global Slant; L:Leftward; U:Upright; and R:Rightward

The SEFS system shows identical results for leftward, rightward and upright slant where for each category there is one features extracted as in figure 8. In SEFS system, when two categories or all categories have the same higher quantity, then the SEFS will chose one of them based on the local slant categories and in this case local slant is an upright which make the SEFS chose the upright as the global slant for this signature. Unfortunately from the questionnaire, leftward slant is the highest chosen by participants. The SEFS system chose upright because the dominant or local slant is 94 degrees where the slant is 4 degree from vertical towards the left. In SEFS system 94 degree falls into the upright slant categories while leftward slant only happens when the slant is more than 96 degrees.

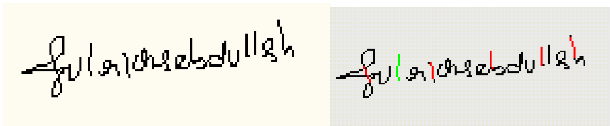


Figure 9 The Image of Signature of Sample 16 and Image Result From SEFS

As for sample sixteen shown in table 5, the SEFS classified the signatures as leftward slant while the human expert classified sample sixteen as upright slant.

Table 5 Comparison Result from Analysis for Sample 16

No.	SEFS	Questionnaire Result (%)			SEFS vs Questionnaire
	GS	L	U	R	
S16	L: Max =110°, Min= 99°	25.00	45.83	29.17	Not Identical

S: Sample; GS:Global Slant; L:Leftward; U:Upright; and R:Rightward

From the image shown in figure 9, the SEFS system extracted four leftward slants and two upright slants. The local slant for the signature is upright slant with an angle of 90 degree while the global slant is leftward slant. While from the results of the questionnaire, upright slant gives the highest results. The differences in results are due to the complexity of this particular signature, careful examination shows that the signature comprises of many combinations of slants where the letters sometimes seems to be on the left, right and upright.

In conclusion, there are a few cases where inconsistencies happen. However, the overall results of this study show 85% identical answers of slant features between the SEFS and the human expert.

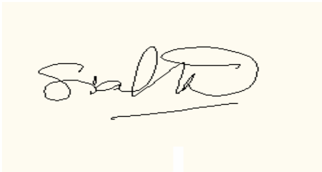


Figure 10 Signature Image of Sample 3

Next we look at the analysis of exact identical result taken from human expert. The result from figure 10 shows that the human expert gives higher and almost similar results for upright and rightward slant but the highest chosen answer is rightward slant. This shows that the two types of slants are dominant for the signature and it is quite difficult for an individual to differentiate between both of them.

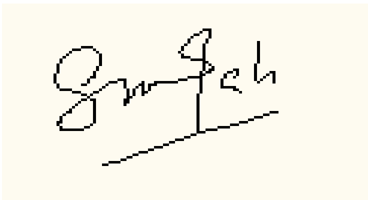


Figure 11 Signature Image of Sample 15

Figure 11 shows identical results for every type of slants. The participants of the questionnaire choose equal percentage of 33.33% for leftward, upright and rightward slant. This result is due to the fact that the signature seems to have equally all the three slant types and the participant could not decide on the slant type.

5.1 Tablet Sensitivity

This section discusses the sensitivity of the devices used in this study. These devices are very sensitive to any movement during the signing process whereby any small changes of direction or any jitter occurrences can be detected during signing session. With this sensitivity, there is a possibility that the results of the extracting slant will be slightly different because the degree and the direction have already changes. For example if the current point moves toward the right and downward to the destination point, this movement will produce a degree between 270 to 360 degrees. Any accidental hand movement will make the signature move towards the left and downward for a few moments before it moves back to its original intended track. If this happen the degree of signature will fall between 180 degrees to 270 degrees for that short moment. Consequently, the comparison between current degree and reference degree will fail due to the changes in the signing direction.

In order to compensate the sensibility issues of the pen tablet, the algorithm allows two subsequent errors (if error occurs) and proceeds to the next point. If it still fails then it assumed that the slant extraction has ended at the point when the first detected differs happened. But if the next point after two subsequent errors still happened then the slant extraction will continue and assume that this is only a part of jitter. This means that during extraction of slant, if the current direction and current degree fall outside the specified rules, the process will provide two more chances after the first process fail in order to know whether the next two subsequent degree and direction will follow the specified rules. Figure 12 shows example of occurrence of jitter.

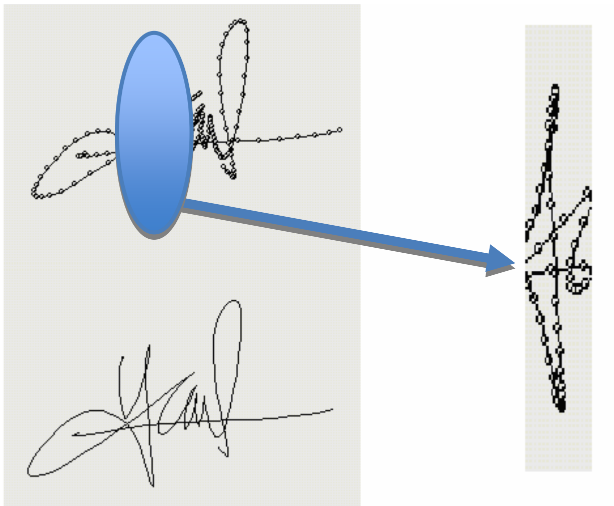


Figure 12 The Signature Effect due to Tablet Sensitivity

6 Conclusion

An analysis and discussion on some interesting findings of the new algorithm for extracting slant in signature to solve online signature recognition problem has been presented. The algorithm for extracting slant has been successfully implemented as demonstrated by the SEFS using both local and global slant characteristics where the local slant is the longest slant among the detected slant while the global slant represent the highest quantity of classified slant whether the slant are leftward, upright or rightward.

The demonstrated algorithm in extracting slant has variable values that can be adjusted to work according to the required application. These variables are acceptable difference in reference degrees, percentage of reference height and slant classes. The recognition performance result compared with the human experts analysis gives 85% accuracy, thus shows that the algorithm works and produced acceptable results.

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