Mining Vibrational Effects on Offline Handwriting Recognition

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***Abstract*—An individual's handwriting exhibits variation under external factors, such as writing surface, writing pen, and writing force. Recent studies on handwriting recognition emphasised on interpretation techniques using feature extraction, pattern recognition, and classification approaches. However, no study has evaluated the effects of external source vibrations on handwriting patterns. Hence, this study analyses offline handwritings features on two conditions: with vibrational (V) and without vibrational (N) stresses using the data mining approach. The goal was mainly to recognise individual handwriting features characterised by vibrational conditions. This research was performed on experimental and public offline handwriting databases consisting of English phrases written under (V) and (N) conditions. Vibrational stresses impact was simulated with Mondial Slim Beauty Fitness Massager strapped onto the writing table and Parkinson's Disease (PD) patient with hand tremor symptom. Nine handwriting size metrics with demographic data were extracted as the data attributes. PART and J48 classification algorithms in Waikato Environment for Knowledge Analysis (WEKA) tool were employed on cross-validation and full training set modes to classify the handwriting data into two predefined classes: (V) and (N). Further significant attributes that distinguish data classes were examined on the decision list and tree diagram constructed from PART and J48. Findings showed that size of "short" letter and "tail" letter were dominant to determine handwriting classes at accuracies: 55.3%- 66.7% (cross-validation) and 86.0% - 100.0% (training set). The study suggests that the size of "short" letter and "tail" letter are the dominant features to distinguish between the (V) and (N) handwriting.**

***Index Terms*—Classification; Handwriting Recognition; Offline Handwriting; Parkinson's Disease; Vibrational Stress.**

I. INTRODUCTION

Offline handwriting recognition refers to the transformation of handwritten text on paper into symbolic representation from its visual marks [1]. The recognition has captured diverse research attention from the Forensic Biometrics, Psychology, Human-Computer Interaction, or Biometric Security perspectives. Early research interests were concentrated on the text recognition and interpretation to discriminate handwriting characters between the original and forged versions. Recent works have demonstrated higher level analysis such as personality characteristics traits of an individual through handwriting patterns.

In the past, most related studies were focused on the effectiveness of different classifiers, Neural Network (NN), Hidden Markov Model (HMM), Support Vector Machine (SVM) in distinguishing the handwriting patterns [2]–[4]. Another focused research area was on the rectangle histogram-oriented grid and poset-oriented grid for efficient feature extraction [4-5]. Moreover, biomechanical variables which affect the handwriting patterns were reported in some studies, such as soreness, writing force, pain, grasp pattern and pen-grip force [6]-[8]. There have been no general good handwriting features to account for accurate classification of handwriting features. The common handwriting features adopted in the previous works include the speed of writing, writing pressure, and size of writing. Better features to well distinguish between individualistic handwriting differ case-by-case.

Handwriting developed from the same individual may appear different resulting from variations during the brain writing process. The handwriting recognition presents difficulties when writing in the presence of external perturbations like under the vibrational stress. A better handwriting recognition feature and prediction can impact the behaviour of handwriting patterns under such effects. Despite successful handwriting recognition works reported, no studies had distinguished vibration with the normal handwriting patterns. Besides, data mining applications to derive informative knowledge from the off-line handwriting attributing features is lacking in the existing body of knowledge. Therefore, this project attempts to fill the gap by considering offline handwriting features under vibrational stress using a data mining approach. The goals are to recognise individual handwriting features characterised by the effects of vibrational stress.

The remainder of the paper is organised as follows. Section II presents the state-of-the-art literature on the existing techniques used for handwriting pattern recognition in different languages. The methodology involving data collection, preprocessing, classification and knowledge discovery are described in Section III. The results obtained are discussed in Section IV and concluded in Section V.

II. RELATED WORKS

The qualities of the training data sample, feature extraction technique and efficient classifier are the important aspects to determine the accuracy of a handwriting recognition system [9]. The handwriting sample quality is commonly accessed after the writing process is completed through the application of handwriting recognition techniques [10]. The quality of handwriting is measurable by legibility, alignment, slant, shape and size of letters, as well as the spacing between words. Agrawal et al. [11] estimate the slant angle features for better emotional recognition, writer identification, and skew correction. Meanwhile, Joshi et al. [12] considered slant, baseline and margin features to detect the personality traits of an individual.

In Surinta et al. [13], the local gradient feature descriptors were used to extract a high dimensional feature vector from handwritten characters of three different languages such as Thai, Bangla, and Latin. In addition, the comparison between K-Nearest Neighbour (K-NN) and SVM classifiers was also conducted. Recent researches in [4], [5], [9] on off-line handwriting recognition focused on feature extraction techniques: Rectangle Histogram Oriented Gradient (R-HOG), poset-oriented grid, and binarisation.

Efficient classifiers essentially support handwritten character recognition. As such, researchers had adopted various classifiers for high recognition accuracies and shorter processing time. Choudhary et al. [9] used the binarisation technique and multi-layered feedforward Artificial Neural Network (ANN) to extract and classify the handwriting data features. In Morera et al. [14], convolutional NN to several automatic demographic classifications of handwriting was used to predict the gender and handedness of study subjects. Joshi et al. [12] used a machine learning approach to predict the personal traits of subjects, such as optimism, and level of self-esteem.

Kamble et al. [4] applied the R-HOG technique for feature extraction. The authors have also compared the feed-forward ANN with the SVM and found that the former classifier is more effective with increased speed and accuracy. A common concept shared in [4], [9], and [13] was on the accuracy of feature extraction with the classifier techniques used to recognise and predict forged handwritings in comparison to the actual. On the other hand, Chherawala et al. [15] studied the recognition accuracy between Marti and Bunke, local gradient histogram, and column gradient histogram features with bidirectional long short-term memory classifier (BLSTM). The authors concluded that the recognition rate is higher for context-dependent models, indicating that BLSTM classifier is capable of dealing with tons of character models.

Handwriting analysis was also studied from external perturbation basis. In Chang et al. [6], the effects of soreness and perceived discomfort (pain) on the handwriting were considered. Their study results implied that both external disturbances caused lower efficiency in pen tip movement and hand muscle activation.

Recent works presented efficiency of feature extraction techniques and classifiers applied in handwriting recognition analyses [4], [5], [9], [12], [14], [15]. Other works have additionally considered external disturbances such as soreness and discomfort that may affect the quality of handwriting [6]. The main highlight was that both feature extraction and classifier determines the better prediction in handwriting classification.

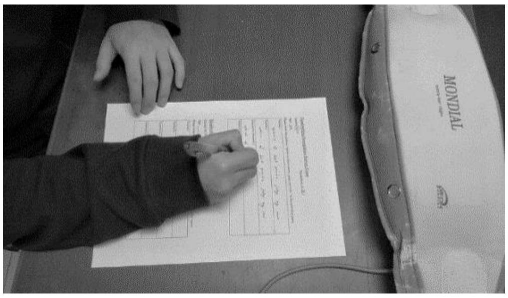
III. METHODOLOGY

A. Data Collection

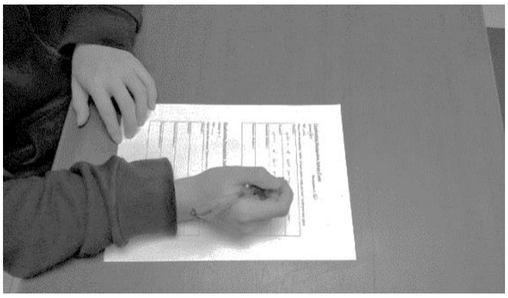
1) Case 1

The experimental study involved 25 right and left-handed university students (15 males, 10 females, 22 ± 2 years old) on voluntary bases. The informed consents were obtained from all participants prior to the experiment. The participants were instructed to write the phrase "Sphinx of black quartz, judge my vow" under normal and vibrational impact with a provided Pilot G2 05 gel ink rollerball pen. The handwritings were executed on a desk at 0.74 m height (elbow height) with a sheet of survey form on it as shown in Figure 1. The participants were required to write the phrase “Sphinx of black quartz, judge my vow” using their dominant hands in normal handwriting condition for two repetitions in columns labelled "Normal 1" and "Normal 2" (N).

Subsequently, the same task was executed on the desk strapped with Mondial Slim Beauty Fitness Massager (100V – 240AC50/60HZ) belt in columns labelled as “With vibration 1” and “With vibration 2” (V) for the vibrational condition as shown in Figure 1. In order to simulate just sufficient effect of vibrations to the writing surface without letting the form fall off, the belt was set “low” throughout the experiment. The entire experimental procedures under normal and vibrational conditions impact were performed on a single session for two repeats in each task. The demographic information of the participants (gender and handedness) were also recorded in the form. A sample of handwritings under both (V) and (N) conditions are written by the same individual is as shown in Figure 2. Note that the style of writing differs despite being written by the same individual.



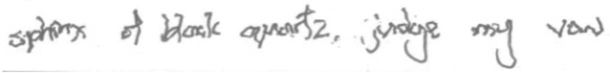
(a)



(b)

Figure 1: Participant writing under (a) with vibration (V) and (b) without vibration (N).

(a)



(b)

Figure 2: Sample handwritten phrase under (a) with vibration (V) and (b) without vibration (N).

2) Case 2

The data for the second case study was retrieved from Zhi [16] and Ribaudo [17] to benchmark. The obtained dataset were handwritten phrases of “The quick brown fox jumps over the lazy dog.” by three PD patients in a survey form to reflect handwriting V. The PD patients were recruited on three sessions of therapeutic Amplified Air Writing (AAW) exercises for 30 to 45 minutes per day. In each AAW session, patients were asked to grip a ‘remote-control-size’ object using the dominant hand, stretched the arm on the dominant side and repeated handwriting phrases and words with giant strokes vertically in the air (≥ 2 feet). The purpose of AAW was to improve PD affected subjects' handwriting performances. The improved PD patients' handwritings were collected as the simulated normal handwriting (N).

B. Preprocessing

Nine study attributes were computed through data transformation from image to numeric. Handwriting size metrics features include average alphabet width (W), average spacing (S), inclined angle (IA), slant (SL), and size (SZ1-SZ3) were extracted as the data attributes as shown in Figure 3. W and S attributes were computed as in Equations (1) and (2). In Case 1, the recorded data were essentially made up of 25 samples of handwritings with nine attributes and 50 instances (Table 1). As for Case 2, there were three handwriting samples with similar nine attributes of 6 instances extracted for benchmarking purpose (Table 1).

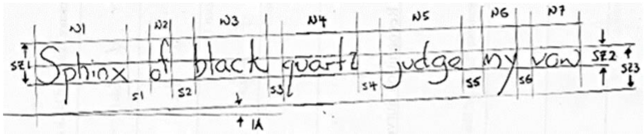


Figure 3: Handwriting size metrics (w_i, s_i, IA, SZ1-SZ3) features

$$W = \frac{\sum_{i=1}^{n} w_i}{k}, \quad n = 7\ (Exp), 10\ (Public), \ k = 29\ (Exp), 44\ (Public) \tag{1}$$

$$S = \frac{\sum_{i=1}^{N} s_i}{N}, \qquad N = n - 1 \tag{2}$$

where: w_i= width word number i
s_i= spacing between word number i

Table 1
Descriptive Summary of Data Attributes

Attributes	Description	Range	
		Case 1	Case 2
W	Average alphabet width (cm)	[0.23 – 0.44]	[0.62 – 1.66]
S	Average spacing width (cm)	[0.22 – 0.57]	[0.05 – 0.54]
IA	Inclined angle (°)	[-2.00 – 3.00]	[-2.50 – 2.50]
SL	Slanting of writing	{L, S, R}	{S, R}
SZ1	Size of "tall" letter (cm)	[0.30 – 0.78]	[0.45 – 0.55]
SZ2	Size of "short" letter (cm)	[0.20 – 0.55]	[0.20 – 0.30]
SZ3	Size of "tail" letter (cm)	[0.40 – 0.91]	[0.33 – 0.65]
G	Gender of participant	{M, F}	{M, F}
H	Handedness of participant	{L, R}	{R}

C. Data Classification

This process involved recognising handwriting features extracted into predefined data classes; (V), and (N) using the WEKA tool. PART and J48 algorithms were adopted to classify the handwriting data on two test modes: cross-validation and training set. PART and J48 enables the display of decision list and tree diagram structures in which significant attributes to classify the data can be easily identified. The cross-validation determines the robustness of general models to predict classes of new 'non-observed' handwriting data. The training set, though rarely used in the literature, allows a primary indication of the algorithms' performance when being trained on the existing 'observed' study data. The classification performances were evaluated by comparisons against the standard baseline measures: OneR (training set) and ZeroR (cross-validation).

D. Knowledge Discovery

At this level, the significant attributes were mined by inspecting the decision list and tree diagram developed from PART and J48 classifications. The decision list model and the tree-like graph were built on attributes to depict the chances of classification outcomes. The attributes employed and its frequency in the classification structures was considered. Among the attributes observed, a plausible hypothesis assumed that the attributes might be inter-related. Hence, the Pearson's correlation was used to investigate the relationship between the attributes identified, to determine the significant attribute that decides the data classes.

IV. Results and Discussion

The PART and J48 algorithms were employed to categorise the handwriting data into two pre-defined classes: (V) and (N) based on two attribute selection modes: the cross-validation and full training set. The baseline classifier; ZeroR and OneR were included as the reference points to determine the reliable performance of the algorithms.

Figure 4 depicts a summary of classification accuracies (as the performance evaluation metric), on the experimental data (Exp), exclusive preference experiment for the right-handed participants (R) and the public domain data (Public). It can be observed that both PART and J48 algorithms performed well with consistent results shown for each case, reflecting merely a small difference of 0% - 7.9% accuracies between the attribute selection modes.

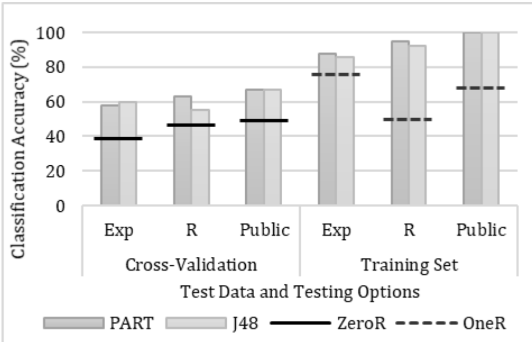


Figure 4: Classification accuracy on PART and J48 algorithms for the Exp, R and Public with cross-validation and training set mode

The performances of PART and J48 algorithms were reportedly reliable, achieving classification accuracies above the baselines - ZeroR and OneR as shown in Figure 4. The results showed different classification accuracies reflected on the training and cross-validation mode. The training set mode yield accuracies range from 86.0% to 100.0% for Exp, R and Public while the cross-validation mode accuracies range from 55.3% to 66.7%. This effect was expected as the training set mode tested the classification models trained with the existing study cases' (observed) data. In the different occasion where the prediction of new (non-observed) data is required, the cross-validation mode ought to be a more reliable option. As the prediction of the future data class was not major in this study, the training mode was included on purpose to exhibit how well the generated model predicts the current data class outcome.

```
Word > 0.32 AND
H = R AND
G = F AND
SZ2 > 0.35: V (4.0)

Word > 0.32 AND
H = R AND
G = M AND
SL = R AND
IA <= 0.5: V (3.0)

SL = S AND
G = F: N (8.0)

G = F AND
SL = L: V (4.0)

H = R AND
SZ2 <= 0.3: N (12.0/2.0)

G = M AND
IA <= 1.5 AND
SL = R AND
SZ3 <= 0.7: N (4.0/1.0)

SZ2 <= 0.4: V (8.0)

: N (7.0/3.0)
```

(a)

```
Word > 0.34 AND
Word <= 0.37: V (10.0)

IA > 0.75: N (13.0/1.0)

SZ3 <= 0.76 AND
SpaciNg <= 0.47: N (6.0)

: V (9.0/1.0)
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(b)

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SZ3 <= 0.45: V (3.0)

: N (3.0)
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(c)

Figure 5: Decision list of cross-validation classification with the PART algorithm on the (a) Exp (b) R and (c) Public

```
Word <= 0.32
|   SL = R
|   |   SZ3 <= 0.6: N (4.0)
|   |   SZ3 > 0.6: V (4.0/1.0)
|   SL = L
|   |   SZ2 <= 0.3
|   |   |   SZ3 <= 0.46: V (2.0)
|   |   |   SZ3 > 0.46: N (5.0)
|   |   SZ2 > 0.3: V (2.0)
|   SL = S: N (11.0/1.0)
Word > 0.32: V (22.0/5.0)
```

(a)

```
Word <= 0.34
|   IA <= 0.75
|   |   SL = R: N (4.0/1.0)
|   |   SL = L: V (4.0/1.0)
|   |   SL = S
|   |   |   SpaciNg <= 0.39: N (2.0)
|   |   |   SpaciNg > 0.39: V (2.0)
|   IA > 0.75: N (10.0)
Word > 0.34
|   Word <= 0.37: V (10.0)
|   Word > 0.37
|   |   SZ3 <= 0.73: N (2.0)
|   |   SZ3 > 0.73: V (4.0/1.0)
```

(b)

```
SZ3 <= 0.45: V (3.0)
SZ3 > 0.45: N (3.0)
```

(c)

Figure 6: Tree diagram of cross-validation classification with the J48 algorithm on the (a) Exp (b) R (c) Public

In order to determine the main attribute which describes and distinguishes handwriting data accurately into classes, the decision list and tree diagram obtained from the PART and J48 algorithm were examined as depicted in Figures 5 and 6. The tree structure combines the attributes at each internal node linking between dominant features and the predicted classes. The model developed from decision rules can be expressed in the form of a tree structure or vice versa. The major attributes for the Exp rest on SZ2 and SZ3, observed at the decision list as shown in Figure 5(a)) and the tree diagram as presented in Figure 6(a)). Meanwhile, only the SZ2 appeared in the decision list and tree diagram for the Public as shown in Figures 5(c) and 6(c)). It can be argued at this point that only the right-handed participants were considered in the Public. Therefore, to confirm the influence of handedness on the main attributes for classification, a secondary analysis excluding the left-handed participants from Exp was conducted, (R). Interestingly, the findings showed that SZ2 was no longer important. Instead, the SZ3 was considered in the classification for R as shown in (Figures 5(b) and 6(b)).

Hence, the main attributes of the Exp were SZ2 and SZ3, while for both R and Public, only the SZ3 dominates. The SZ2 and SZ3 attributes were the indicators for the size of "short" letter and "tail" letter respectively as discussed in Section II. There were fundamental assumptions made on this basis; SZ2 captures the distinctive features of variation of handedness in individual's handwriting while SZ3 further distinguishes the presence of the external factor (V).

This led us to explore the Pearson's correlation between SZ2 and SZ3 and whether this correlation is significantly different from zero as listed in Table 2. Results showed there were moderate positive correlations between the SZ2 and SZ3 ($r > 0.5$) for Exp, R and Public. The correlations were statistically significant ($p < 0.05$), which signifies that out of the nine attributes measured, only SZ2 and SZ3 were dominant to classify the handwriting data. A plausible explanation was that the remaining seven study attributes (W, S, IA, SL, SZ1, G and H) contained insufficient distinctive or crucial information to establish a clear variation between classes.

Table 2
Correlation and Significances Between SZ2 and SZ3 for Experimental, Right and Public Data

SZ3	SZ2		
	Exp	R	Public
Correlation	0.691	0.633	0.789
Significance	5.08E-27	3.21E-22	1.72 E-4

The width of each written word was measured and divided by the number of letters to retrieve average alphabet width (W) (Equation (1)). The major challenge was that some words were written too close to the other words in the phrase resulting in similar W measures among subjects. The average spacing width (S), whereas, would be dominant only if there were significant S between subjects, which failed in this case study [18]. The Inclined Angle (IA) is sometimes known as the baseline or skew slope to consider the alignment of handwritten text from the horizontal line [12], [19]. However, according to Bal and Saha [19], IA is difficult to be interpreted accurately due to the individual's mental condition varies during the process of writing.

Although the slant (SL) attribute could well distinguish a personal handwriting mechanism, better detection results could be achieved if the slant angle is estimated for each word [11], [20]. Unfortunately, in our study context, SL was considered by means of inclination direction, i.e. towards the right, left or straight (Section II) following [12]. Meanwhile, the size of the "tall" letter (SZ1) measures the highest letter from the horizontal line either the uppercase or lowercase or whichever taller. The uppercase should appear a bit taller than the lowercase. However, there were occasions when the lowercase letters like ‘h’, ‘f’, ’l’, ‘k’, ‘t’ appear more like the same height or even taller than the uppercase. The weak point was that the SZ1 hardly show a distinctive difference to distinguish the unique handwriting between lowercase letters and uppercase letters. The demographic data: gender (G) and handedness (H) were commonly valued as the class attributes in existing studies [14]. In other words, G and H ultimately contribute minimal relevant information to distinguish handwriting into classes.

V. Conclusion

This study considered experimental and public benchmark offline handwriting data, (V) and (N) conditions. In particular, handwriting attribute recognitions under two conditions were addressed considering seven handwriting size metrics (W, S, IA, SL, SZ1, SZ2 and SZ3) and two demographic data (G and H) attributes. Classification analyses were performed on two algorithms: PART and J48 with cross-validation and full training set techniques supported by the WEKA tool. Both algorithms showed consistencies on the cross-validation and full training modes and proven reliable with accuracies higher than the classification baselines (40% - 74%). Main findings from decision list and tree diagram developed from PART and J48 at accuracies 58% and 60% respectively exhibit SZ2 and SZ3 being the dominating attributes to distinguish the handwriting classes. The size of the “short” letter (SZ2) and size of the “tail” letter (SZ3) are the height of letters like “a, c, e, m, o” and “g, p, q, y” respectively. While SZ2 establish distinctive information on the variation between the handedness, the SZ3 by itself recognises the variation for the right-handed writings to distinguish the vibration (V) and without vibration (N) handwriting conditions. Pearson’s correlation analysis on SZ2 and SZ3 attributes show that both attributes were significant on the moderate positive relationship. Thus, both SZ2 and SZ3 were informative as the dominant attributes for case study handwriting classifications. The main contribution of this study is that both SZ2 and SZ3 are crucial features in distinguishing the individualistic handwriting under vibrational stress. Future studies could address the weaknesses of the non-dominant attribute identified in order to extract better data features that reflects personality handwritings. Another extension is to include more handwriting datasets to consider different levels of vibrational effect for the handwriting recognition process.

Acknowledgement

The authors gratefully acknowledge the financial support provided by Universiti Sains Malaysia (USM), through the Geran Pembangunan Siswazah (308.AIMEKANIK.415403), Research University (RUI) Scheme (1001/ PMEKANIK/ 814271) and Bridging Fund Programme (USM/IPS/BF2017).

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