



Using Augmented Cognition to Examine Differences in Online Handwriting Recognition for Native and Non-native Writers

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Abstract. The handwritten recognition (HWR) is a complex task with variety of challenges associated with natural language, variety in the styles of writing, variety and nuances of alphabets etc. The core research in handwritten recognition focuses around Latin alphabet and corresponding languages. However, differences between the languages using Latin as their main script are still major: from changed letter frequencies to additional letters. Additionally, handwriting practices and styles are not developed consistently within the same language; for example - cursive vs print calligraphy. As a result of globalization estimated 50% of world's population speaks second language [1]. Researching characteristics of non-native handwriting has been done by various educational and second language research purposes but remains largely unaddressed in the context of augmented cognition using online handwritten recognition. We researched differences and similarities of online handwriting between native and non-native speakers of English, Georgian, Chinese and Korean speakers. We have also examined related research for Arabic, Italian and Malay handwritings. As a result, we have identified key characteristics of non-native speakers' distinguishing from the native ones. In addition, we have identified differences based on writers' individual maturity with the second language.

Keywords: Handwritten recognition · Dynamic handwriting · Natural language processing

1 Introduction

For the world's languages, there are four broad classes of writing systems [2], also known as - orthographies. An "alphabet" is a type of writing system that includes a symbol for each sound in a language that is, for both consonants and vowels. European languages utilize the Greek, Cyrillic - Ukrainian, Bulgarian, etc., or Latin (Roman) alphabets - English, German, French, etc. The Latin alphabet is exceptionally broad and is used for numerous languages all over the world, not simply those spoken in Europe. The name "alphabet" itself is derived from the first two letters of the Greek alphabet, alpha and beta. Which are derived from Phoenician/Arabic words for "ox" and "home" respectively [3].

Second category of languages just depict the language's consonants. Abjad is a form of writing system that belongs to this category. Two well-known examples with numerous

speakers are Hebrew and Arabic. In truth, vowels are only partially represented in these systems, and they are derived by additional constructions. These systems came to form the limitations on representation of vowels because most languages have a limited or smaller number of vowels compared to consonants.

Third type of writing system include languages that use a single symbol to indicate syllables. For example, a symbol for groups of consonant and vowel (CV), a consonant followed with a vowel and a consonant (CVC), a consonant followed with a vowel that's followed with two consonants (CVCC), etc. This type of system is known as a syllabary. The most well-known are Japanese and Korean. For example, in Korean 뉴스(news) contains two CV syllables, 꽃(flower) contains one CVC syllable, etc. As a matter of fact, Japanese uses two such writing systems, Hiragana and Katakana. In addition, Japanese is based on number of Chinese-derived characters known as Kanji. Syllabaries operate effectively given that such languages tend to have a small number of syllables. These languages do not enable complicated consonant clusters at the beginning or end of a syllable, the writing system usually cannot accommodate such complications [4]. In addition, there are less number of vowels and consonants used overall (Fig. 1).



Fig. 1. Syllable creation in Korean language

As for the fourth category of writing systems - Chinese is the best example to describe this type. This form of system is known as logographic, from “logo” which in Greek means “word”. Logographic writing system expresses each word with a symbol. A logographic system, used for a language expression, comprises thousands of symbols - also referred to as “characters”. Chinese letters, in fact, are a blend of word meaning and pronunciation (Fig. 2).



Fig. 2. The evolution of the Chinese writing system [5]

Latin alphabet, also called Roman alphabet, is the most widely used alphabetic writing system in the world. It is the standard script of the English language and is used in more than 100 other languages [6].

Non-native handwriting is a term used to describe writing that does not originate from the country in which the language being written is spoken. In many cases, non-native handwriting can be difficult to read for native speakers of the language. This is often due to differences in spelling conventions and grammar usage between the two languages.

There are several differences between native and non-native handwriting when it comes to people being native to different writing systems from their second language proficiency. One of the most noticeable differences is the way that people write letters. Non-native writers often have a tendency to write letters that are more block-like, while native writers have a tendency to write letters that are more connected and fluid [7]. Another difference is the way that people form letters. Non-native writers often have a tendency to form letters that are more rigid and angular, while native writers have a tendency to form letters that are more curved and flowing. Additionally, non-native writers often have a tendency to write in a smaller font size, while native writers often have a tendency to write in a larger font size. Additionally, non-native speakers may have a more difficult time with grammar and spelling, which can also be reflected in their handwriting.

The Roman alphabet was developed from the Etruscan alphabet about 500 BC. The earliest inscription in the Roman alphabet is the graffito on the wall of a men's lavatory at the Temple of Apollo. Studying languages based on the same writing system and the same alphabet gives us the opportunity to study some of the common characteristics of bilingual writers. However, as we discuss in the following chapters, there are some similarities between native and non-native online or dynamic handwriting for writers using different writing systems as well. One similarity is that they are both written in a cursive style. Another similarity is that they both involve a lot of movement and are not very precise. There are many similarities in writing different languages using the same alphabet. For example, the letter "a" is always written as "a" in any language and the letter "z" is always written as "z" in most languages. Additionally, there are slight or no variations for majority of the letters from the Latin alphabet. Occasionally, new letters are introduced.

Advantages of analyzing the differences for native and non-native writers come from the various factors regarding online handwriting that records and provides more information to analyze compared to static handwriting:

1. Static handwriting recognition is performed by scanning a physical piece of paper with a hand-written note on it. Online handwriting recognition is performed by a tablet, mobile phone, or another digital device.
2. Online/Dynamic (performed on an electronic device) handwriting recognition is a more accurate recognition process because it takes into account the features describing the individuals writing style, by capturing the angle and inclination of the pen, and the pressure of the pen on the device [8]. Static handwriting recognition is not as accurate because it does not take into account all of these factors and there

could be additional factors about the physical conditions of the paper hindering the recognition process.

3. Static handwriting recognition can only recognize handwritten notes that are written on a specific type of paper. Online handwriting recognition can recognize handwritten notes that are written on any type of device.
4. Static handwriting recognition is a slower recognition process, as it needs pre-processing for extracting the relevant data [9].

To sum up, there are drastic differences between different writing systems indicating vastly different expected behavior of writers. However, given that the writers have unique individual habits there are still similarities between their handwriting in different writing systems. Additionally, even though some of the languages use same type of writing systems, the variety of the alphabets within the writing system poses additional challenge for handwritten recognition. The later also helps to study important similarities of non-native and native writing that we can utilize for better performance of recognition algorithms. As a part of the novel augmented cognition research, we utilize the advantages of researching online handwriting over static handwriting to recognize the key factors useful for handwriting recognition.

2 Background

Online handwritten recognition can be influenced various factors, especially regarding the writing style and speed of the process. Observations show that these factors are influenced by:

1. How long the writer has been practicing writing using this specific language
2. The complexity of transition from the previous language
3. The difficulty level of the language acquisition for the specific language, etc.

Given that examining native vs non-native speakers' writing style is a novel direction there is still need for researching the individual nuances of the way each language affects to the writers' style development. However, we can examine the similarities across several languages utilizing different alphabets and/or writing systems. To achieve this goal, we have surveyed the research related to differences in native vs. non-native speakers pronunciation and the way they form sentences [10]. Additionally we have examined handwritten character recognition methods for Arabic [11], Chinese [12], Pashto [13] and English languages.

Children learn languages with no prior experience. In the early stage of language learning when children start speaking about 50 words are acquired. At this point there is no syntax (word order) or grammar (plurals, verb tenses, etc.) being expressed yet. Some languages have more complex syntax or morphology that takes longer for children to master. For example Danish children learn language much slower compared to other languages [14]. Similarly, the impact of a non-native language on the writing process may be greater for students who are less proficient in the target language. Therefore, to understand the effect of second language or non-native behavior on writing diverse experience group of writers as well as cross-language examination is necessary.

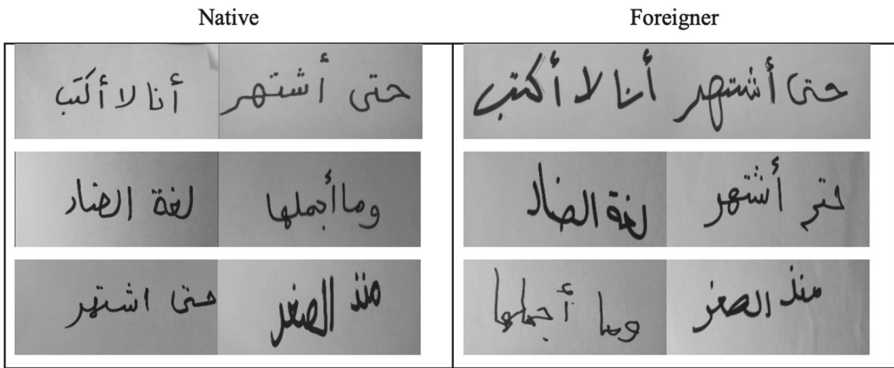


Fig. 3. Arabic handwriting of native vs non-native writers [11]

Arabic alphabet and calligraphy are a good example to study, as its uniqueness makes the learners go through various steps for developing their handwriting style (Fig. 3) [15].

The stages of written language learning and handwriting acquisition place different demands on the writer, and the relationship between body functions and handwriting performance varies between languages and stages of learning. The paper - “Relationship between body functions and Arabic handwriting performance at different acquisition stages” investigated the link between linguistic, visual-motor integration (VMI), and motor coordination (MC) functions and Arabic handwriting by analyzing two levels of handwriting acquisition [15]. The variation in handwriting speed in both grades was explained by handwriting automaticity. Improved VMI performance increased the likelihood of having good legibility in second grade but not in fourth grade. The body functions associated with Arabic handwriting differ depending on the stage of acquisition. As a result, the handwriting evaluation should be tailored to the students’ developmental stage [15].

A research paper from 2005 investigated the class characteristics in English handwriting of three ethnic groups in Singapore: Chinese, Malay, and Indian. They looked at letter designs, letter spacing, pen lifts, and decorative elements, among other factors. They used a two-by-three chi-square analysis to compare the frequency with which each feature occurred in the groups in order to identify the distinctive features unique to each group. Their findings confirmed the influence of the native language writing system on English handwriting [16]. Six class factors have been recognized, and they were attributed to the habitual effect of writing in their own native language: Chinese, Tamil, and Arabic. Not only they were able to determine the class characteristics in English handwriting of different groups, they have implicated the ability of identifying nationality or ethnic origins of writers.

3 Motivation

Researching differences and similarities for native and non-native writers can substantially aid in online handwriting recognition. Handwriting recognition is a complex task with numerous variables affecting the accuracy of the outcome. Factors such as the size,

stroke directions, shapes, and slant of letters; the spacing between letters and words; and the presence or absence of flourishes can all affect how well a handwriting recognition system works.

Nowadays common method used to improve the accuracy of handwriting recognition is to use a large database of handwritten samples to train the system. Most of the recent solutions are based on deep learning algorithms. This allows the system to learn the specific characteristics of the writer's handwriting. There are also various hybrid methods of using deep learning with more traditional natural language processing methods [17].

Latest developments in technology made tablets, phones and other widely available devices equipped with pen and other writing means. There is also significant amount of software offering online handwriting services. Therefore, there are more and more opportunities for studying handwriting characteristics that were not available just for static writing (pen on paper). The study of fine motor movements is carried out using intrinsic properties that measure precise motion features extracted from digitally recorded phrases. For hand motor performance quantification, we factor the basic elements of writing, such as strokes, letters and components.

Enriching the databases with additional descriptive information about the writers writing history and affiliation with other languages, gives an excellent opportunity for improving the model outcome with less information to be extracted by the HWR systems. Considering that our previous study on handwriting signature showed that there is significant information to gain whether the writing is done by the original signature author or it is a learned behavior for performing a skilled forgery, this study also focuses on analyzing the pen pressure as writing second language can be considered in the same angle of learned behaviors to imitate others' writing [8].

Additionally, to aiding with HWR task, differences between writing styles of non-native speakers and native speakers is standalone fascinating research topic for Augmented cognition. Given the fact that there are numerous studies focusing on speech/accents differences for native and non-native speakers and its demonstrated applicability to a diverse set of tasks from speech recognition to aiding with improving clarity for non-native speakers. Non-native accents can pose a challenge for listeners when trying to understand what is being said. Non-native accents have been demonstrated in studies to have a negative impact on speech recognition accuracy [18], speech comprehension [19], and listener perceptions of speakers' comprehensibility [20]. Non-native accents are generally less understandable than native accents due to more pronunciation problems and unfamiliar phonetic elements. According to the research, there are a number of factors that contribute to listeners' difficulties comprehending non-native speakers. This provides us with a strong incentive to search for such elements in handwriting, characterize them, and indicate their influence levels on handwriting recognition.

Moreover, the paper about "Detecting English Writing Styles For Non Native Speakers" [10] shows some interesting observations on the similarity between different languages measured by the similarity of their users English typing styles. This technique could be used to show some well-known facts about languages as in grouping them into families, which our experiments also include.

4 Analysis/Methodology

Examining the online handwriting of population including languages from the all three writing systems as well as the ones belonging to the same writing system but different alphabets is not possible by currently available dynamic handwriting datasets. We are anticipating that the wide distribution and popularity of technological devices like tablets and phones will naturally lead to making more samples of online handwriting available for research. For this preliminary study we opt in to collect dataset from wider range of writing styles, rather than collecting more samples for the same popular languages that are already widely studied for handwritten recognition tasks.

For this study we have managed to collect dataset for four different languages both from native and non-native speakers: English, Chinese, Korean and Georgian.

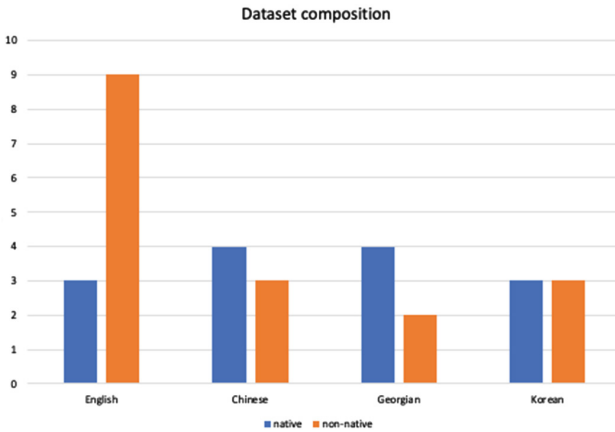


Fig. 4. Sample population

On Fig. 4 the size of population sample is shown. It includes three writing systems. Additionally Georgian and English both use alphabets though Georgian writing system is based on Georgian alphabet while English is based on Latin.

It is also worth mentioning that the writers of different language had different experiences and maturity with their non-native languages.

5 Results

We discussed in the analysis section the advantages given by analyzing dynamic handwriting over static handwriting. Therefore, we measured the features available for the online handwriting component: speed, pen pressure, letter/character size, pen ups, stroke count.

We compared the native and non-native speakers on two tasks:

1. Writing a simple word (<5 letters length or 1 character)
2. Writing a simple paragraph (<5 lines length, <25 words)

A stroke is the basic component of writing movements, defined by points of minimal curvilinear velocity [21], a component is the segment between two successive pen lifts, letter does not need a definition for alphabet and for the sake of this experiment we also considered one kanji character as a letter. The dynamic handwriting parameters associated with strokes, components, and letters - such as duration, length, pen pressure, and so on - may also reveal information about a writer's level of automation and fluency.

The three main types of online handwriting differences for second language speakers: speed, pen ups, stroke count. We have also included letter or character size in our measurements.

The first task showed similar results for all the characteristics besides the speed, by Chinese being slower to perform for all the non-native writers. 1.6 speed of the native writer.

Second task results are shown in the Fig. 5. Each number on the y scale represents the ratio of non-native speakers' measurement over the native speakers measurement.

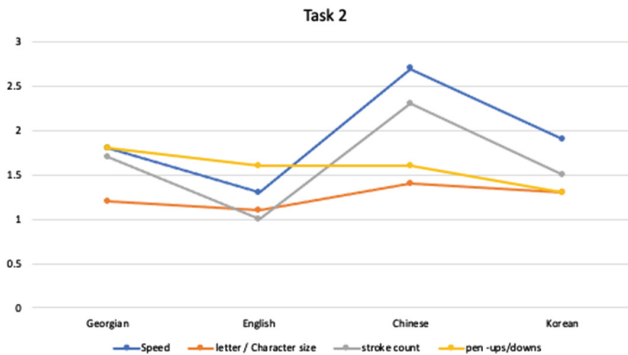


Fig. 5. Comparison of the handwriting characteristics of (non-native writers)/(native writers)

The most drastically difference is shown for non-native speakers writing speed against the native speakers of Chinese – 2.7, however the ratio between the stroke amount is 1.5. This can be explained with Kanji being based on short strokes. The native speakers also have to use the equal amount of pen ups, if they follow the writing rules. However, because of the speed of writing sometimes they omit a few pen-ups. It is important to notice that Handwriting recognition systems for Chinese do take into account the stroke count. Therefore, knowing the writer is non-native and given the ratio, we can accurately calculate the stroke count that otherwise would be obscured.

Korean being was the second language by having the most differences between the native and non-native writers speed - 1.9. This could be explained by using both letters, and syllables made of letters in Korean writing system. Stroke count and difference in

speed can be explained with similar reasons as the ones for Chinese. Though Korean native writers used less strokes compared to non-natives per syllable. It did not show as much difference as the Chinese writers overall, as one Korean syllable needs significantly less strokes than a Chinese character.

Georgian had the most difference between pen-ups. Georgian writing system is taught through alphabet at first and as a second step cursive handwriting is introduced. The native writers in our sample had an influence of the cursive writing, however the non-native speakers have not.

English had the least difference in ratios that can also be biased since most of the individuals from our experiment sample had the longest experience with English as a second language.

For each language in our sample population non-native speakers used larger letters and characters, which leads us to conclude that scaling should be done separately for native and non-native handwriting for it to not affect the recognition task negatively.

The only scenario where there was no noticeable difference between native and non-native speakers was for the 1st task and from writers of the same writing system (Georgian and English).

We have also examined pen pressure graphs between native and non-native writers. For the languages based on short strokes like Chinese and Korean, the pressure value is high in the beginning of the stroke and decreases gradually. The flow was natural for both of these languages. The most pressure fluctuations were visible with Georgian language. Our implicated explanation for this was the non-native writers short experience with the alphabet (<2 years). We have not observed similar differences with English writing.

It is also notable that letter size turned out to be harder to scale as syllables/Characters tend to be larger in appearance. If any conclusions can be drawn from our observations of the letter size, the writers from whose native and non-native writing system is same do not show any difference in letter size, while the ones for different writing system tend to be larger. However, as we did not have a writer with an experience with two logographic systems, we will leave this as an open question for future research.

6 Conclusion

Our research addressed the differences for non-native writers' motion characteristics, opposed to the ones of the native writers of a language. We have approached the problem from Augmented Cognition perspective, and we have used the features of online/dynamic handwriting performed on a tablet. There are three main types of online handwriting differences for second language speakers: speed, pen ups, stroke count. Since these features are used in handwriting recognition, we conclude that speakers' origin (native vs non-native) can affect the handwriting recognition process negatively if not being processed separately. As we examined the pen pressure, pen inclination, etc. does not affect in the context of second language writing skills. The most difference between the writing speed distinguished the native speakers of logographic writing system from the non-native ones. The least differences were shown for the languages in alphabetic group. As the handwritten datasets are becoming more available in different corners of the world, we expect to have more resources to continue researching the differences for non-native speakers of the languages that are not yet studied.

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