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Mobile devices handwritten Chinese character recognition based on template matching

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ABSTRACT

Currently, in the light of popular *xml* file storage format of handwritten Chinese characters on the mobile device, a new test matching algorithm between handwritten Chinese character stroke and Template word stroke is proposed. It is got through orientation, topology and shape - the three kinds of features to comprehensively measure matching degree, and has good experimental results. This algorithm is greatly used in adding and lacking stroke, judging the right order and neat discrimination of users.

KEYWORDS

Hausdorff distance; Topology similarity measurement; Direction chain code; The total similarity matrix.

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INTRODUCTION

The popularity of mobile Internet devices makes it possible to evaluate the online writing Chinese characters. It is different from the previous approach based on an offline image format, whose Chinese characters are saved in the file and composed of strokes point sets or its time stamp, shown in Figure 1.


```
<?xml version='1.0' encoding='UTF-8' standalone='yes' ?><property><stroke
strokeOrderID="1"><point><x>0.40865384615384615</x><y>0.28139859713040866</y>
<time>237449841101251</time></point><point><x>0.40442354642427886</x>
<y>0.28652625450721153</y><time>237449919098251</time></point><point>
<x>0.4048076923076923</x><y>0.2909107384314904</y><time>237450118971251</time>
```


Figure 1 : xml storage format of Chinese characters on the

Identifying the strokes of Chinese characters is the foundation of online assessment; similar to calligraphy educational software on the current mobile Internet devices, it often uses comparison evaluation method. In the article, on - line handwritten Chinese character strokes recognition is based on the comparison with Chinese character template of experts. Select users' handwritten character stroke $s_i^{'}$ from S' in xml file, and compare the similarities with S in Chinese character template of experts with this algorithm. If it occurs $sim(s_i^{'}, s_i) > sim(s_i^{'}, s_k), k \neq i, s_k \in S$ with $h \leq sim(s_i^{'}, s_i) \leq 1$ (h is threshold), strokes $s_i^{'}$ and s_i match. According to the above method, all strokes in user and standard template can be compared. By the correct recognition of strokes, writing errors can be identified, including adding and lacking stroke, judging the right stroke order and the writing style, and it can also be achieved with the above-mentioned strokes similarity strategy.

Intuitively, strokes similarities can be identified the orientation, topological relationships, shape, and many other indicators. The average matching methods are separate indicators comparison, calculate similarity of every indicator according to a certain order. Such strategy need to specify each threshold of the indicators, while there is often a different matching conclusion. Therefore, integrate a variety of indicators and calculate an overall similarity to determine the matching results. The basic idea of this paper is to identify the similarity of strokes : first, combining the characteristics of handwritten word, match the space of user and template words by geometric methods; second, according to the characteristics of handwriting strokes, select position, topological relationships and shape as the matching index to calculate the similarity of different sources; third, according to above characteristic, pay a weight to each indicator in order to increase differences between the matching and non-matching entities, and calculate the average weighted value of different indicators as the total similarity matching to find out the matching strokes.

SIMILARITY MEASUREMENT

Registration method for matching space

Prerequisite for similarity measurement of users and templates word is to match the two spatial registrations. Classic registration method must first calculate the minimum coverage area of matching objects, such as minimum convex closure (MCC), minimum bounding rectangle (MBR) and the minimum circumscribed circle (MBC)[1,2], and two matching spaces coincide after affine transformation or RST transform[3,4]. For the huge difference between the user word and template word and it is non- systemic, it is difficult to conduct spatial registration using the above method. Based on the characteristics of handwritten Chinese character strokes stored on mobile Internet devices, simplify this process: first, form a horizontal rectangular space as matching space with point sets x_{min} 、 x_{max} 、 y_{min} 、 y_{max}, and do the RST transformation of S', that is, $\begin{bmatrix} x_{new}^{'} \\ y_{new}^{'} \end{bmatrix} = \begin{bmatrix} s_x & 0 \\ 0 & s_y \end{bmatrix} \begin{bmatrix} x^{'} \\ y^{'} \end{bmatrix} + \begin{bmatrix} \Delta x_b \\ \Delta y_b \end{bmatrix}$, $\Delta x_b = (x_{min} - x^{'}{}_{min})$, $\Delta y_b = (y_{min} - y^{'}{}_{min})$, $s_x = (x_{max} - x^{'}{}_{max}) / x^{'}{}_{max}$, $s_y = (y_{max} - y^{'}{}_{max}) / y^{'}{}_{max}$ 。 It is easy to estimate the time efficiency of this registration operation: $O(n)$, which is much higher than the classical method of registration. At the same time, maintain the direction of handwriting because there is no rotational operation.

Directional similarity

Directional Similarity should examine two indicators: orientation and relative position. Guo Qingsheng proposes the descriptive model based on quadrant angle, do quantitative statistics of the relationship of the space target and make a corresponding direction rose-figure. Based on the above, propose similarity calculation model of three kinds of line-group direction with use of standard deviation ellipses and histogram, and at last validate experiments[5,6,7]. This method is complicated and more suitable to describe the similarities of spatial entity groups; Liu Dayou employs algebraic and logical approach to describe the spatial relationships and characteristics, and study reasoning problems of complex reasoning, constraint satisfaction and qualitative simulation, including directional relationship description. According to the reference plane of MBR, direction will be divided into nine parts: S, SW, W, NW, N, NE, E, SE, O to define nine atomic direction relationships corresponding to the geographic space of the South, southwest, west, northwest, north, northeast, east, southeast and central regions, and the regional relationship between these atoms is non- empty set[8]. Simple directional relationship can form qualitative reasoning models, but need a qualitative similarity comparison, so this approach clearly requires a more detailed description. Belongie employs a way similar to radar scan to describe shape contexts[9]. Inspired by this method, here construct a circle with horizontal rectangular diagonal crossing point p_0 as a center in article 1.1 and the length p_0A as radius. Among them, A is the farthest point from p_0. Equally divide into four concentric circles, and make each ray from starting point p_0 in 0^0、45^0、90^0、135^0、180^0、225^0、270^0, you will get 32 regions and eight directions, with each direction 4 relative positions and number gradually decreases from the outside. As shown in Figure 2, i in Encoding $C(i, j)$ indicate direction, and j indicates relative position.

Figure 2 : A coordinate system to depict the direction similarity in handwriting

This paper will employ modified Hausdorff distance(MHD)proposed by Dubuisson and Jain to measure the similarities between user word and template word stroke. Given two finite sets $A\{a_1, a_2, ..., a_m\}$ and $B\{b_1, b_2, ..., b_n\}$, then define the Hausdorff distance between A and B as $H(A,B) = max(h(A,B), h(B,A))$. Wherein, $h(A,B) = \max_{a_i \in A} \min_{b_j \in B} \|a_i - b_j\|$, $h(B,A) = \max_{b_j \in B} \min_{a_i \in A} \|b_j - a_i\|$。 Wherein $\|.\|$ expresses the distance between A and B. Hausdorff distance is a distance of two points for measuring the matching degree of sets, influenced little by object translation, rotation and scaling, and can more effectively characterize the similarity between entities.

MHD defines one-way Hausdorff distance as $h(A,B) = \frac{1}{N}\sum_{a \in A} \min_{b \in B} \|a - b\|$, $h(B,A) = \frac{1}{M}\sum_{b \in B} \min_{a \in A} \|b - a\|$. Expand the idea that individual element is representative of all elements in the collection to the average effect of all elements, which has greatly improved the algorithm to calculate adaptability of the noise and isolated points. User has considerable arbitrariness in the process of handwriting, and jitter and distortion often occur in finger or pen moving. MHD applications will improve the recognition rate of strokes in these circumstances.

The method uses a two-stage MHD to calculate similarity. Given stroke $s_h^{'}$ in $S^{'}$ of user encodes point sets as $s_h^{'} = \{c_1^{'}(i_1^{'}, j_1^{'}), c_2^{'}(i_2^{'}, j_2^{'}), ...c_m^{'}(i_m^{'}, j_m^{'})\}$, stroke s_k in templates words S encodes point sets as $s_k = \{c_1(i_1, j_1), c_2(i_2, j_2), ..., c_n(i_n, j_n)\}$。 The steps to calculate directional similarity are

(1)Calculate $H_{MHD}(s_1^{'}(i), s_1(i))$, $H_{MHD}(s_1^{'}(i), s_2(i))$, ……, $H_{MHD}(s_1^{'}(i), s_n(i))$, wherein $s_1^{'}(i)$ and $s_k(i)$ indicate direction encode in user stroke and template stroke. In $H_{MHD}(s_1^{'}(i), s_k(i))$,calculate distance between encode $s_1^{'}$ and s_k : $d(s_1^{'}, s_k) = |s_1^{'}(i) - s_k(i)| \quad mod \quad (M - m + 1)$。 the maximum direction coding M is 8, and m, the largest direction difference with M (minimum similarity), is encoded as 4, and thus need to take the remainder by $M - m + 1 = 5$.

(2)Calculate $H_{MHD}(s_1^{'}(j), s_1(j))$, $H_{MHD}(s_1^{'}(j), s_2(j))$, ……, $H_{MHD}(s_1^{'}(j), s_n(j))$, wherein $s_1^{'}(j)$ and $s_k(j)$ represent relative position coding between user stroke and template stroke, in $H_{MHD}(s_1^{'}(j), s_k(j))$, calculate distances of relative positions codes $s_1^{'}$ and s_k as follows: $l(s_1^{'}, s_k) = \left| s_1^{'}(j) - s_k(j) \right|$.

(3)According to the result of the calculation, show the similarity of $s_1^{'}$ 与and Number k template stroke : $sim_{pos}(s_1^{'}, s_k) = 1 - \frac{H(s_1^{'}(i), s_k(i)) \times H(s_1^{'}(j), s_k(j))}{L_{pos}}$. Wherein, L_{pos} is the value of the experience and $L_{pos} = \lceil \max\{H(s_h^{'}(i), s_k(i))\} \times \max\{H(s_h^{'}(j), s_k(j))\} \rceil$, $h = 1, 2, ..., m$, $k = 1, 2, ..., n$。Thus, the directional similarity vector may be formed : $P_1^{'}(s_1^{'}) = [sim_{pos}(s_1^{'}, s_1), ..., sim_{pos}(s_1^{'}, s_n)]$。

(4)According to steps (1) - (3), respectively calculate $s_2^{'}, ..., s_m^{'}$, and form similarity matrix.

$$P = \left| \begin{array}{ccc} sim_{pos}(s_1^{'}, s_1) & ... & sim_{pos}(s_1^{'}, s_n) \\ ... & ... & ... \\ sim_{pos}(s_m^{'}, s_1) & ... & sim_{pos}(s_m^{'}, s_n) \end{array} \right| \begin{array}{c} P_1^{'}(s_1^{'}) \\ ... \\ P_m^{'}(s_m^{'}) \end{array}$$

Each row of the matrix represents user stroke word and all template character, and the matrix lists the directional similarity of all user word and template strokes.

Spatial topological similarity

Spatial topological relation refers to the relationship satisfies all spatial data of the geometry principle. Topological relation of strokes sets can be briefly summarized as follows: phase integral, adjacent, phase intersecting and overlapping. There is a small probability of coincidence between user word and template word; therefore, there is no overlap relationship here. Topological relations are an important feature of spatial information, and it has great application importance in spatial information processing field: the visual object recognition, spatial data and spatial scene similarity descriptions. The history of spatial entities topological relationship research is not long, in 1991 Egenhofer established a four- post model theory (4IM) and 9-intersection model (9IM) based on point set topology theory, then expand them in order to distinguish the different dimensions of topological relationships, and get the dimension-expanded DE-4IM and DE-9IM[10,11]. Later, it was proposed that the V9I model[12,13,14,15] in figure Voronoi. These models have advantages and disadvantages, they have merits in qualitative reasoning of the spatial entity relationship, but it is difficult to apply to measure the similarity of stroke spatial topological relations. As an indicator of the topological similarity measure, satisfy the following two conditions: 1, can be compared among the depart, adjacent, phase and intersect relations ; 2, can quantify the results of this comparison.

Analyzing the depart, adjacent, phase and intersect spatial topological relations can discover that $sim(intersect, depart) > sim(intersect, phase)$, that is to say, phase and intersect are more similar than depart and adjacent, so are other relations, therefore, distinguish these similarities by weighting these relations, as shown in TABLE 1

TABLE 1 : The weight relationship of the depart, adjacent, phase and intersect

	depart	adjacent	phase	intersect
Weight	1	2	3	4

TABLE 1 shows that the greater the similarity of spatial topological relations are, the larger weighting values are; So these types of topological relations can be linearized, so that there occurs comparability between them and weights can also be used directly to quantify the similarity of spatial topological relations instead of quantified values. This method is particularly suitable in handwriting stroke recognition, because user often write arbitrarily, and the intersect relationship may be written in phase relationship. In this case, the algorithm may still provide similarity metric with template word topology relation; directly employing weights to calculate can simplify the operation process, and improve the operational efficiency. Topological similarity calculation steps are:

(1)Given set point of $s_h^{'}$ in $S^{'}$ of user stroke: $s_h^{'}=\{p_1^h, p_2^h,..., p_m^h\}$, set point of $s_k^{'}$ is $s_k^{'}=\{p_1^k, p_2^k,..., p_n^k\}$。 Let the user word strokes point set point set of strokes. First find out the closest point to original coordinates, the method is to compare distance: circularly compare $\sqrt{(p_i^h(x)-p_j^k(x))^2+(p_i^h(y)-p_j^k(y))^2}$ value, and take the least, and the corresponding coordinate $(p_i^h(x), p_i^h(y))$ and $(p_j^k(x), p_j^k(y))$ is the closest point between stroke $s_h^{'}$ and $s_k^{'}$.

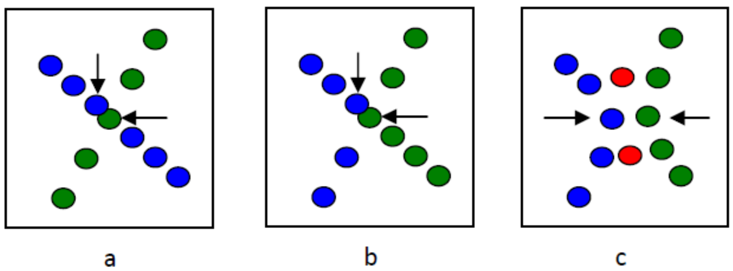


Figure 3 : Find the closest point between strokes

Figure 3 (a) is the correct intersection, of course, it may be the case shown in Fig 3 (b), it is necessary to further determine: take each point on both sides of $(p_i^h(x), p_i^h(y))$,you will get $(p_{i-1}^h(x), p_{i-1}^h(y))$ and $(p_{i+1}^h(x), p_{i+1}^h(y))$, take the two points and make a line $y=ax+b$; also take points on both sides of $(p_j^k(x), p_j^k(y)):(p_{j-1}^k(x), p_{j-1}^k(y))$ and $(p_{j+1}^k(x), p_{j+1}^k(y))$, take these two points in $y=ax+b$ and determine whether they are on the both sides of the line by determine whether $p_{j-1}^k(y)<ap_{j-1}^k(x)+b$ and $p_{j+1}^k(y)>ap_{j+1}^k(x)+b$ or $p_{j-1}^k(y)>ap_{j-1}^k(x)+b$ and $p_{j+1}^k(y)<ap_{j+1}^k(x)+b$ are both correct, if correct, they intersect; if not, they do not. If $s_h^{'}$ and $s_k^{'}$ interact, $\text{topology}(s_h^{'}, s_k^{'})=\text{topology}(s_h^{'}, s_k^{'})+4$, if $d((p_i^h(x), p_i^h(y)),(p_j^k(x), p_j^k(y)))<L_{dis}$, $s_h^{'}$ and $s_k^{'}$ phase, wherein L_{dis} is the experience value and take the length of template stroke. At this time, $\text{topology}(s_h^{'}, s_k^{'})=\text{topology}(s_h^{'}, s_k^{'})+3$. If $s_h^{'}$ and $s_k^{'}$ do not phase, based on Figure 3(c),determine whether $s_h^{'}$ and $s_k^{'}$ adjacent by : if $s_h^{'}$ and $s_k^{'}$ adjacent, there will be no stroke to cross the closest point. Given $s_l^{'}\subset S^{'}, s_l^{'}\neq s_h^{'}$, $s_l^{'}\neq s_k^{'}$, take the point $s_l^{'}$ and all turning points $\{p_1^l, p_2^l,..., p_s^l\}$。 Make a line: $y=ax+b$ by crossing $(p_i^h(x), p_i^h(y))$ and $(p_j^k(x), p_j^k(y))$, and determine in turn whether $p_i^l, p_{i+1}^l, i=1,2,...,s-1$ are on the both sides of the line; if yes, $s_h^{'}$ and $s_k^{'}$ do not adjacent, and stop calculating, $\text{topology}(s_h^{'}, s_k^{'})=\text{topology}(s_h^{'}, s_k^{'})+1$; if no, $s_h^{'}$ and $s_k^{'}$ adjacent, $\text{topology}(s_h^{'}, s_k^{'})=\text{topology}(s_h^{'}, s_k^{'})+2$.

(2)According to the method in (1) determine all $\text{topology}(s_h^{'}, s_i^{'}), i=1,2,...,m$, and accumulate all the results, you will the value of $\text{topology}(s_h^{'})$ and all $\text{topology}(s_i^{'}), i=1,2,...m$.

(3)Using the same method you can also get the value of all standard template word strokes: $\text{topology}(s_i), i=1,2,...n$, and user can calculate the similarity of user and template words stroke:

$$sim_{\text{topology}}(s_h^{'}, s_k)=1-\frac{\left|\text{topology}(s_h^{'})-\text{topology}(s_k)\right|}{L_{\text{topology}}}$$

Wherein L_{topology} is the experience value, and

$$L_{\text{topology}} = \max(\left|\text{topology}(s_h^{'}) - \text{topology}(s_k)\right|), h = 1, 2, ..., m, k = 1, 2, ..., n$$

Description: According to the analysis of the text, take different value of each character, you will get different L_{topology}; for convenience, take the max value of all Chinese characters in this experiments as L_{topology}.

(4)Form topology similarity matrix of user word $S^{'}$ and template word S :

$$U = \left| \begin{matrix} sim_{\text{topology}}(s_1^{'}, s_1) & \dots & sim_{\text{topology}}(s_1^{'}, s_n) \\ \dots & \dots & \dots \\ sim_{\text{topology}}(s_m^{'}, s_1) & \dots & sim_{\text{topology}}(s_m^{'}, s_n) \end{matrix} \right| \begin{matrix} P_1^{'}(s_1^{'}) \\ \dots \\ P_m^{'}(s_m^{'}) \end{matrix}$$

Each row in matrix represents the topological similarity of each user word stroke and all template word strokes, and it lists the topological similarity of all user word strokes and all template word strokes.

Shape Similarity

Methods commonly used to describe the shape similarity are Fourier descriptors operator[16] and shape description function[17], and to recognize shape through Hu 's " The same distance theory "[18], and to entity match through the direction of shape. As for the characteristics of handwriting, this paper describes the stroke with direction chain code shown in Figure 3, and employs the above improved Hausdorff distance to calculate the similarity between the user and the template word stroke.

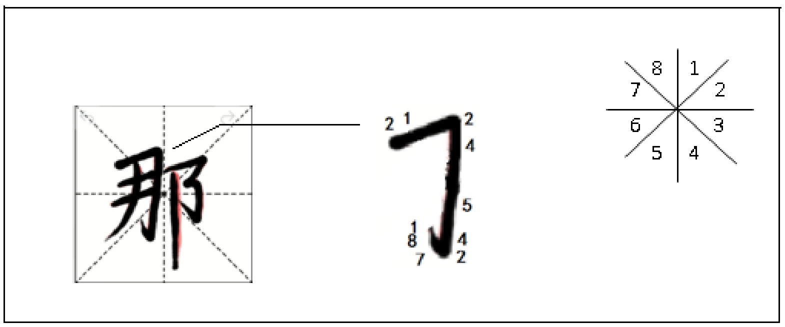


Figure 4 : Stroke direction chain code

First, track handwriting words stroke set point $S'\{s_1^{'}, s_2^{'}, ...s_m^{'}\}$ and template words stroke set point $S\{s_1, s_2, ...s_m\}$, and get their direction codes and calculate $H_{MHD}[s_h^{'}(p_1^{'}, p_2^{'}, ..., p_s^{'}), s_k(p_1, p_2, ..., p_t)]$ value; calculate the distance between the number i direction code in $s_h^{'}$ and the number j direction code in s_k by : $l[s_h^{'}(p_i^{'}), s_k(p_j)] = \left|p_i^{'} - p_j\right|$, wherein $s_h^{'}(p_1^{'}, p_2^{'}, ..., p_s^{'})$ indicates direction code of user stroke $s_h^{'}$, and $s_k(p_1, p_2, ..., p_t)$ indicates direction code of user stroke s_k; $sim_{shape}(s_h^{'}, s_k) = 1 - \dfrac{H_{MHD}[s_h^{'}(p_1^{'}, p_2^{'}, ..., p_s^{'}), s_k(p_1, p_2, ..., p_t)]}{L_{shape}}$, wherein L_{shape} is the experience value, and $L_{shape} = \max\{H_{MHD}[s_h^{'}(p_1^{'}, p_2^{'}, ..., p_s^{'}), s_k(p_1, p_2, ..., p_t)]\}$, $h = 1, 2, ..., m$, $k = 1, 2, ..., n$, similar to L_{topology} value of topology similarity, wherein L_{shape} is also the max integer of all Chinese Characters L_{shape} in experiment: $\left\lceil L_{shape}^{\max} \right\rceil$. At last, you can get user shape-similar matrix words of $S^{'}$ and template words S.

$$V=\begin{vmatrix} sim_{shape}(s_1^{'},s_1) & \dots & sim_{shape}(s_1^{'},s_n) \\ \dots & \dots & \dots \\ sim_{shape}(s_m^{'},s_1) & \dots & sim_{shape}(s_m^{'},s_n) \end{vmatrix} \begin{matrix} P_1^{'}(s_1^{'}) \\ \dots \\ P_m^{'}(s_m^{'}) \end{matrix}$$

Each row in matrix represents the topological similarity of each user word stroke and all template word strokes, and it lists the topological similarity of all user word strokes and all template word strokes.

Overall similarity

The overall similarity is determined by calculating the weighted average of similarity in the various features of the entity, and setting different weights can further embody the characteristics of handwriting, whose use increases the flexibility of some of the important features. As the user writes arbitrarily, it may occur severe deformation, so consider giving shape similarity smaller weights. The above P, U and V matrixes are dimensionless matrixes; doing matrix weighted average can obtain overall similarity matrix:

$S=\omega_1 P+\omega_2 U+\omega_3 V$, $\omega_1=\omega_2=0.4$, $\omega_3=0.2$.

S matrix is in shape "S", $S=\begin{vmatrix} sim(s_1^{'},s_1) & \dots & sim(s_1^{'},s_n) \\ \dots & \dots & \dots \\ sim(s_m^{'},s_1) & \dots & sim(s_m^{'},s_n) \end{vmatrix} \begin{matrix} P_1^{'}(s_1^{'}) \\ \dots \\ P_m^{'}(s_m^{'}) \end{matrix}$, wherein

$sim(s_h^{'},s_k)=\omega_1 sim_{pos}(s_h^{'},s_k)+\omega_2 sim_{\text{topology}}(s_h^{'},s_k)+\omega_3 sim_{shape}(s_h^{'},s_k)$. Each row of the S matrix represents the overall similarities of corresponding user's certain stroke and all the template strokes, and chooses the max:

$$\begin{vmatrix} sim(s_1^{'},s_1) & \dots & sim(s_1^{'},s_n) \\ \dots & \dots & \dots \\ sim(s_m^{'},s_1) & \dots & sim(s_m^{'},s_n) \end{vmatrix} \begin{matrix} \Rightarrow sim(s_1^{'},s_{k_1}) \\ \\ \Rightarrow sim(s_m^{'},s_{k_n}) \end{matrix}$$

Given $s_{k_1}\neq s_{k_2}\neq \dots \neq s_{k_n}$ and $sim(s_1^{'},s_{k_1})\geq L_{sim}$、$sim(s_1^{'},s_{k_2})\geq L_{sim}$ …… $sim(s_m^{'},s_{k_n})\geq L_{sim}$,(L_{sim} is threshold), user words stroke $s_1^{'}$ match with the template words stroke s_{k_1}, and so do $s_2^{'}$ and s_{k_2}, $s_m^{'}$ and s_{k_n}.

Usually when it does not occur user writing errors of the number of strokes, $m=n$; when it occurs, $m\neq n$. The user's mismatch word is wrong strokes or superfluous strokes

$s_{k_i}=s_{k_j}$ has not yet appeared in the trial, the reasons analyzed are fewer strokes of Chinese characters and more dispersed distribution. Generally, strokes of different users matching with the same template word stroke do not appear. But in the algorithm, you need to exclude it from happening, as follows:

(1)Given $s_{k_i}=s_{k_j}$, write s_{k_i} or s_{k_j} as s_k, select the larger one in $sim(s_{h_1}^{'},s_k)$ and $sim(s_{h_2}^{'},s_k)$ to match, if $sim(s_{h_1}^{'},s_k)>sim(s_{h_2}^{'},s_k)$, $s_{h_1}^{'}$ and s_k match.

(2)Match $s_{h_2}^{'}$: select the largest one except $sim(s_{h_2}^{'},s_k)$ in $P_{h_2}^{'}$, if selected, $sim(s_{h_2}^{'},s_{k_j})$ $k_j\neq k$ conform to $sim(s_{h_2}^{'},s_{k_j})\geq L_{sim}$ and $s_{k_j}\neq s_{k_1}$、$s_{k_j}\neq s_{k_2}$, ……, $s_{k_j}\neq s_{k_n}$, $s_{h_2}^{'}$ and s_{k_j} match ; if $sim(s_{h_2}^{'},s_{k_j})\geq L_{sim}$ and $s_{k_j}=s_{k_i}$, compare the values of $sim(s_{h_2}^{'},s_{k_j})$ and $sim(s_{h_i}^{'},s_{k_i})$, if $sim(s_{h_2}^{'},s_{k_j})>sim(s_{h_i}^{'},s_{k_i})$, $s_{h_2}^{'}$ and s_{k_j} (s_{k_i})match, $s_{h_i}^{'}$ needs to settle; match according to the method(2) ; if $sim(s_{h_2}^{'},s_{k_j})<sim(s_{h_i}^{'},s_{k_i})$, continue match $s_{h_2}^{'}$ with the subsequent method. If not satisfied, continue to select the larger one between $sim(s_{h_2}^{'},s_k)$ and $sim(s_{h_2}^{'},s_{k_j})$, and match

according to the above condition until find the matching stroke or all the optional strokes are removed. If the latter, $s_{h_2}^{'}$ is the stroke that loses.

EXPERIMENTS AND ANALYSIS

Matching experiment

The accuracy of matching handwriting strokes and template word is affected in two ways: character shape and writing habits. For this reason, three experiments were designed to verify the merits of the above algorithm. The first group contains the single characters (minimum stroke), with the word structure (fewer strokes) and structured strokes words with most strokes, and this experiments was to verify the effectiveness of the algorithm in the case of a different shape, the second group included the relatively simple structure and more complex structure and character of the same person; and the third group contains the relatively simple structure of different people and more complex structure and character of the same person. In order to form contrast, the latter two groups choose the same characters as shown in Figure 6, 7 and 8. To increase the experiment effect, increase the writers' randomness of the latter two groups;

Observation can be found that many words have different degrees of deformation in direction, topology and shape.

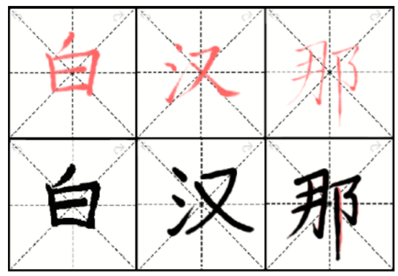
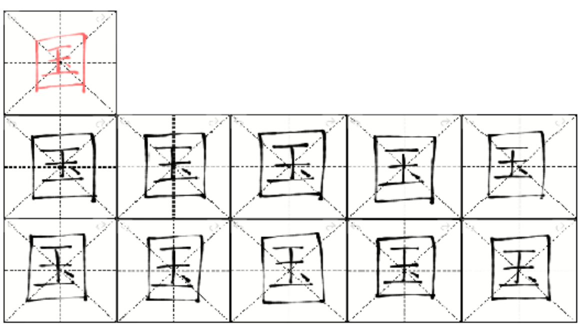


Figure 5 : Samsung GT-N8010 Handwriting device Fig.6 Template and Handwriting words in group one



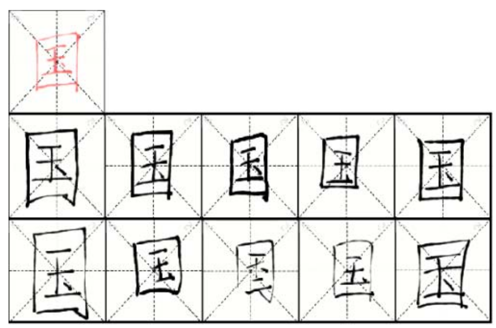


Figure 7 : Template and Handwriting Words in group two Fig.8 Template and Handwriting words in group three

Analysis of experimental results

Samsung GT-N8010 was chosen as the handwriting device, shown in Figure 4, its screen size is 10.1 inches with the screen pixel density of 149PPI, writing instruments are its own 1024 Samsung sensitivity S-Pen stylus, tablet use Android4.0 operating system, with a 4 -core processor, basic frequency 1.4GHz and 2GB memory. Before the experiment started, first set the threshold given in the text, and obtain the experience value based on calculation. This paper will assess performance of the algorithm based on two angles: precision and recall. Precision is the ratio of correct stroke and matching stroke to match, $precision \frac{\text{correct matching strokes}}{\text{all strokes - mismatching stroke}}$; Recall is also known as the recall rate, is the ratio of correct matching strokes and all strokes. $recall \frac{\text{correct matching strokes}}{\text{all strokes}}$. The higher recall rate is, the fewer of unmatched strokes are; the most ideal result is 100% precision rate and 100% recall rate, reflecting all the strokes are matching and the matching strokes are correct. When a user writes correctly, 100% precision rate and 100% recall rate indicate the good performance of the algorithm, but when a user makes an error, the recall rate is not 100%, and then the ability to identify mismatching strokes also reflects the good performance of the algorithm.

TABLE 2 : Experience values and thresholds in algorithm

L_{pos}	L_{topology}	L_{shape}	L_{sim}
12	21	7	0.75

Space limited, here list the similarity result of the character "white", as shown in TABLE 3.

TABLE 3 : sim_{pos} value of character "white"

	First stroke of template	Second stroke	Third stroke	Fourth stroke	Fifth stroke
First stroke of user	0.91 67	0.70 43	0.11 25	0.49 84	0.63 12
Second stroke	0.79 17	0.91 67	0.16 67	0.20 34	0.47 37
Third stroke	0.14 79	0.13 52	0.91 67	0.12 91	0.13 58
Fourth stroke	0.54 31	0.23 15	0.09 33	0.91 67	0.73 61
Fifth stroke	0.67 32	0.44 56	0.10 27	0.72 35	0.91 67

From the data, the value of the diagonal matrix in sim_{pos} is the peak, indicating a consistence of user and template word stroke order and the user's stroke is correct.

TABLE 4 : sim_{topology} value of character "white"

	First stroke of template	Second stroke	Third stroke	Fourth stroke	Fifth stroke
First stroke of user	1.00 00	0.42 85	0.76 19	0.90 48	0.76 19
Second stroke	0.52 38	0.95 24	0.85 71	0.52 38	0.71 43
Third stroke	0.61 90	0.85 71	0.90 48	0.85 71	0.95 24
Fourth stroke	0.85 71	0.57 14	0.85 71	1.00 00	0.85 71
Fifth stroke	0.76 19	0.71 43	0.95 24	0.85 71	1.00 00

From the data, the values of the diagonal matrix in sim_{topology} are much higher, discrimination data is not high, even it occurs the similarity between" Third stroke of User " and " Third stroke of Template " less than that between " Third stroke of User " and " Fifth stroke of Template ". This is because user writes the "white" more standardized, and there are differences in topology relation between template word and user word; when a user writes arbitrarily and word error of the topological relations appears, this similarity calculation will fully play its role.

TABLE 5 : sim_{shape} value of character "white"

	First stroke of template	Second stroke	Third stroke	Fourth stroke	Fifth stroke
First stroke of user	0.57 14	0.28 57	0.07 44	0.22 85	0.01 53
Second stroke	0.21 43	0.71 43	0.14 29	0.12 38	0.01 53
Third stroke	0.04 35	0.07 14	0.57 14	0.18 27	0.05 24
Fourth stroke	0.22 85	0.26 23	0.15 24	0.71 43	0.61 43
Fifth stroke	0.02 11	0.71 43	0.05 24	0.58 57	0.64 29

From the data, the values of the diagonal matrix in sim_{shape} are a little smaller, because there may be " hand-shake ", " pause " during user writes; even if the stroke is similar in shape, the similarity value is not too high.

TABLE 6 : sim value of character "white"

	First stroke of template	Second stroke	Third stroke	Fourth stroke	Fifth stroke
First stroke of user	0.88 10	0.51 03	0.36 46	0.60 70	0.56 03
Second stroke	0.56 91	0.89 05	0.43 81	0.31 56	0.47 83
Third stroke	0.31 55	0.41 12	0.84 29	0.43 10	0.44 58
Fourth stroke	0.60 58	0.37 36	0.41 06	0.90 95	0.76 01
Fifth stroke	0.57 63	0.60 68	0.43 25	0.75 04	0.89 53

Table 7 : $precision$ and $recall$ in the first set of experiments

	$precision$	$recall$
"White"	5/5	5/5
Chinese Character "Guo"(equal to English word "country")	5/5	5/5
Chinese Character "Na"	5/5	5/5

In the "white" word matrix, take the maximum value (given in TABLE 6, in red) in each row, the max values are much higher than threshold value L_{sim}, indicating the user's word order is correct and all strokes are matched successfully.

TABLE 8 : $precision$ and $recall$ in the second set of experiments $precision$ and $recall$

	$precision$	$recall$
Country 1	8/8	8/8
Country 2	8/8	8/8
Country 3	8/8	8/8
Country 4	7/7	7/8
Country 5	8/8	8/8
Country 6	8/8	8/8
Country 7	8/8	8/8
Country 8	8/8	8/8
Country 9	8/8	8/8
Country 10	8/8	8/8
Total	100%	98.75%

TABLE 9 : $precision$ and $recall$ in the third set of experiments

	$precision$	$recall$
Country 1	8/8	8/8
Country 2	7/7	7/8
Country 3	8/8	8/8
Country 4	8/8	8/8
Country 5	8/8	8/8
Country 6	8/8	8/8
Country 7	8/8	8/8
Country 8	8/8	8/8
Country 9	6/7	6/8

Country 10	8/8	8/8
Total	98.71%	96.25%

Through the recall and precision analysis, you can see when the user writes specifically, the algorithm has high recognition rate; when writing with increased arbitrariness or by the multi-user, recognition rate will decrease. Analysis of specific data, you can see recall and precision rate have obvious consistency in the algorithm, and select an indicator to evaluate.

CONCLUSIONS

Widely using of mobile devices makes it possible to write anywhere. Related software such as “ready to learn writing" and "ready to learn calligraphy" should be applied broadly. However, handwriting arbitrariness will seriously affect the determination of writing quality with such software. A variety of non-standard cases will inevitably appear in the handwriting process. There exists some similarity between 3 features: direction, handwriting on the orientation, topology and shape and standard word, and employing the overall similarity to measure handwriting strokes matching has good experimental results. The algorithm can support other types of software by judging the right order of handwriting stroke and neat discrimination of users.

This paper employs a novel coding technique in getting value of stroke direction and shape, while improves coding Hausdorff distance. In dealing with the topological relationship of strokes, propose the idea of quantified topological relations and integration of a variety of topological relations.

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