Signature Sample Synthesis

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Synonyms

Signature synthesis, Handwriting synthesis, Handwriting sample synthesis

Definition

Signature sample synthesis is the generation of synthetic signature from a user's signature samples. It is a special case of handwriting sample synthesis which generates novel handwriting in a particular person's handwriting style. A handwriting or signature synthesis system has two basic modules: the modeling module and the synthesis module. In the modeling module, the system collects handwriting/signature samples of a specific writer (online or offline), and identifies and stores the basic characteristics of samples (for example, shape and spatial layout). In the synthesis module, synthetic glyphs are generated from the stored templates, and they may be further aligned and connected to form synthetic handwriting data.

Main Body Text

Introduction

Like many biometric characteristics, such as face, fingerprint and iris, signature/handwriting has been widely accepted by people as an effective way to identify a specific writer. Historically, signatures and forged handwritings have always been of interest to forensic experts. Many signature verification technologies have been reported in the literature to detect handwriting forgeries [1, 2]. Signature sample synthesis [3], as an inverse biometrics problem, is the process of generating synthetic signatures that mimic real signature samples. The literature on signature sample synthesis is quite rare. However, it is a special case of handwriting sample synthesis [4, 5], which generates novel artificial handwriting in a person's handwriting style. So we may start with handwriting sample synthesis techniques and then narrow down to signature sample synthesis.

Handwriting sample synthesis has become active in recent years, because the flourish of pen-based devices, such as Tablet PCs, touch-screen mobile phones, personal digital assistants (PDAs), and electronic white-boards, has brought users more natural communication ways in human-computer interaction. In many situations, writing with a pen on the screen is more convenient than typing on the keyboard. Yet, many users find that keyboards are more efficient than handwriting because typing is faster than writing, and his/her handwriting may become illegible after long-time writing. Handwriting sample synthesis addresses this dilemma by converting ASCII text to handwriting that is close to the user's personal handwriting. For those people who prefer handwriting personal letters, greetings and compliments, handwriting sample synthesis adds a personal touch to communications. Like wallpapers and favorite software settings, synthesized handwriting also contributes to the personalization of one's computing devices. Moreover, it can always generate legible handwriting and free the user from lengthy and stressful writing, e.g., when preparing many handwritten documents such as greeting cards with different content [6].

Handwriting sample synthesis is helpful to build a signature/handwriting recognizer which heavily depends on the size and quality of the training set [7]. It can generate a large database of handwriting/signature samples that look natural. This not only greatly reduces the manual intervention in handwritten sample preparation, but also provides the ability to perform operational testing in a laboratory environment. The automated synthesis is also useful to evaluate existing signature/handwriting verification methods [8], including the accuracy and reliability against fraudulent signature/handwriting. In addition, this technique can help forensic examiners [9] to understand the key factors that affect a person's handwriting or signature.

Characteristics of Handwriting/Signature

As a behaviorial biometrics characteristics, handwriting/signature is affected by various factors which the synthesis process should consider. For instance, the signatures are quite different when the specific writer writes in different languages (here we mainly consider English language, which contains a small set of single characters, and the combination of individual characters in a linear fashion forms various words). Writing with different digital pen devices can also cause direct changes in the appearance of handwriting. Likewise, the person's mood, his/her hand health and the surrounding environment are also possible factors to affect the acquisition process of handwriting samples. Despite of those factors, signatures from a single individual tend to be different even using the same digitizing device. For different people, the character shapes can vary greatly and the amount of shape variation in one person's handwriting may also differ from person to person. In addition, people may tend to write handwriting/signature in a cursive style or in a partially cursive and partially handprint style, which makes the problem of synthesis more difficult.

As suggested by handwriting analysis techniques in forensic inspection [10], the specific features that are easily noticeable to ordinary people to distinguish different handwriting styles include: 1. the glyph and the size of single characters; 2. the pressure distribution and the slant of handwriting; 3. the relative sizes of the middle, the upper, and the lower **zones** of letters; 4. the existence and the shape of head, connecting, and tail parts; 5. the letter, the word, and the line spacings; 6. the embellishment in strokes or character glyphs; and 7. the simplified or neglected strokes. These features can be roughly classified into three types: features of character glyphs, spatial layout of characters, and connection between characters. Different from English language, the oriental languages, such as Korean and Indian, often contain a large number of characters that share the same small set of strokes, and the characters are usually unconnected. Therefore, the handwriting characteristics of the oriental languages are depicted by two types of features: features of strokes and spatial layout of strokes to form characters [11, 12]. For simplicity, the following discussion focuses on synthesis of English scripts.

Modeling Process

To generate signatures that look natural, it is important to model the characteristics of signatures/handwriting samples. Fig. 1 shows the general outline of the modeling process. It collects handwriting data of a specific user and learns his/her handwriting model. In the modeling process, the handwriting samples are first obtained by acquisition devices. For example, digitizing pen-based devices capture the handwriting sample by a sequence of discrete 2D points. Kinematic information such as pressure and duration of writing can be recorded during the acquisition. Handwriting samples may also be acquired via scanning the off-line sample images, but all kinematic characteristics will be lost.

The general handwriting model consists of three parts: a character model which captures the shapes and variations in single characters; an alignment model which controls the spatial layout of the individual characters that form words; and a connection model which simulates how two characters are connected together. The simplest form to represent the signature/handwriting is a planar curve. Hence, the character model often extracts a set of control points to represent the handwritten character **glyph** [1, 13, 3, 14, 15, 16, 17]. Bezier curves or polynomials are then used for curve approximation. The shape variation such as scale, position and slant can be learnt from multiple samples of one character. Besides the geometry information, physically plausible models have been proposed to model the speed and acceleration in the writing [4, 5]. These kinematic-based models are capable of representing, compressing and reconstructing input handwriting data, but they do not target on synthesizing new handwriting. In contrast, geometry-based models can generate handwriting with natural shape variations and support different handwriting styles, i.e., from **handprint** style to fully **cursive** style. The alignment model records the horizontal letter spacings and the relative vertical positions of characters with respect to a horizontal baseline [17]. The connection model may record which character pairs are likely to connect to each other. It may also extract the distribution of concatenation strokes which are formed by the tail and the head parts of adjacent characters [14].

In the modeling process, the system usually requires users to provide adequate handwriting samples, so a practical concern is to keep user involvement at a reasonable level. In fact, the burden of user involvement in the sample collection process depends upon the handwriting models that the systems use. For example, users are asked to write more than one thousand letter groups in [13]. Besides writing 80 to 200 words, the work in [14, 15] may need user interaction in order to get good segmentation results. In contrast, the user is only required to input each single character three times, several special pairs of letters and several multi-letter words (Fig. 2) in [17].

Synthesis Process

The synthesis process should have synthetic data be visually similar to the samples and incorporate sufficient variability in synthetic data. This objective, however, is not easily achieved, especially when considering cursive writing styles. Fig. 3 shows the basic flowchart of handwriting synthesis systems. For an input ASCII text, each individual character glyph is first generated from the character model. Then the glyphs are arranged and adjacent characters are connected when needed to form a cursive word. The words are further aligned into lines and paragraphs. In the following, we detail each step of synthesis.

Character selection generates glyphs based on the stored character models. In [4], the handwriting sample is modeled by the writing velocity equations. Then a similar synthetic data is generated by setting initial conditions to the equations. In [14, 15], the character model is the statistical distribution of control points that are learnt from multiple glyph samples for each character. By randomly sampling the distribution, new handwriting trajectory can be generated. In [17], three instances of characters are stored as the templates which are supposed to appear at the beginning, the middle and the end of words, respectively. Then according to the character position in the word one of the three templates is chosen as the initial glyph. After selection, affine transformation (scale, rotation and slant) is applied to the character glyphs. To mimic the variability in the natural handwriting/signature, some randomness is often added in the transformation.

Character alignment then places the glyphs with respect to the baseline, both vertically and horizontally. Vertical alignment is necessary for smooth handwriting generation. For example, middle-zone letters (‘a’, ‘c’, ‘e’, etc.), ascendent letters (‘b’, ‘d’, etc.) and digits are expected to have their glyph bottoms meet the baseline. Horizontal alignment, on the other hand, separates the bodies of adjacent letters at a distance along the horizontal baseline. However, the adjacent character glyphs may have severe overlapping when their head or the tail parts are too long. As a result, the synthesized handwriting may look weird or it may be hard to produce smooth connection part. Hence, redundant portions of heads/tails may be trimmed to alleviate the overlapping problem [17].

Character connection is developed to simulate cursive handwriting, in which adjacent letters are connected by smooth ligature parts (the head and tail parts of adjacent characters). In [14], a statistical ligature generative model is learnt from handwriting samples. When synthesis, a ligature stroke is generated for every pair of adjacent letters. The final ligature part is determined by jointly deforming the letter strokes and the ligature stroke. This method needs sufficient samples for training. In [15], a delta log-normal model is employed to represent the head/tail parts as pieces of arcs. By changing the arc parameters, the trajectories of letters are deformed to create a smooth ligature part. This model may be interfered by too long overlaps in head/tail parts. The work [17] adopts a high-order polynomial to fit the ligature part. The problem becomes to determine the control points given the head/tail parts of adjacent glyphs. To solve the fitting problem, three constraints are imposed on the ligature: similarity to the original ligature, deformation energy from the original ligature and smoothness of the ligature. The control points should minimize the sum of these three energy terms.

After the above processes, an ASCII word is converted to a handwritten word. Then it is natural to synthesize handwriting text by rendering multiple words one by one. Fig. 4 shows an example of the communication via emails with handwriting synthesis. The sender types in a text email. The handwriting synthesizer automatically converts it into a handwriting email and sends it to the receiver. Then the receiver finally reads the letter in the sender’s personal handwriting style.

Since signature is a special type of handwriting, handwriting synthesis techniques can be adapted for signature sample synthesis. Instead of representing each character in handwriting synthesis, the whole signature can be taken as a single glyph. Then the character modeling is applied to the signature glyphs, e.g., extracting the control points or estimating the writing speed. During synthesis, the process of character selection is applied to the learnt models of signature glyphs. By this way, a large database of synthetic signatures can be obtained to study the robustness of an existing handwriting/signature verification or recognition method.

Summary

As an inverse biometrics problem, signature/handwriting sample synthesis has been studied in recent years. Existing synthesis systems can help common users to produce personal signature/handwriting with pleasing visual quality. However, they do not capture all aspects of the handwriting style. For example, the handwriting of people may evolve gradually with their ages. It may add more liveness to the handwriting if the effect of time is considered. Furthermore, the research on synthesis in languages other than English needs more investigation before it becomes accessible to people in different countries.

Related Entries

Signature Features, Handwriting Structure, Sample Synthesis from Templates, Signature Recognition.

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Definitional Entries

Glyph

A glyph is the shape of a handwriting sample. In Roman scripts, it may contain one letter or even a group of letters depending on the content of the sample. In oriental scripts, a glyph corresponds to a character which consists of a set of strokes.

Handprint

In a handprint writing style, the writer is inclined to write each individual character in an isolated fashion. In other words, there is no connection between adjacent letters.

Cursive

In a fully cursive handwriting style, the writer is inclined to connect all adjacent letters in a smooth way. What makes it more complex is that different people may have different habits to connect even the same character pair. For example, some people like to connect the t-bar with other letters, while others may connect the t-stem to neighboring characters. Real-world handwriting is often in a mixture of cursive and handprint styles.

Zone

The print Roman characters usually occupy three zones: the upper, the middle and the bottom zones. For instance, letters ‘a’, ‘c’, ‘e’, ‘m’, etc., appear in the middle zone; ascendent letters ‘b’, ‘d’, ‘h’, etc., occupy both the upper zone and the middle zone; descendent letters ‘g’, ‘p’, etc., occupy both the middle zone and the bottom zone. There are some letters that may cover all the three zones such as ‘f’ and ‘j’.

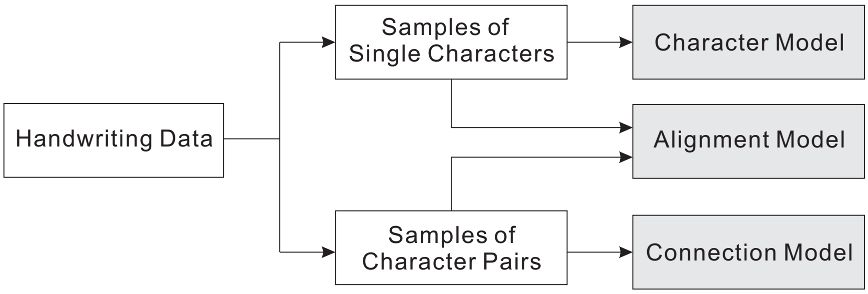


Fig. 1. Block diagram of the model training process.

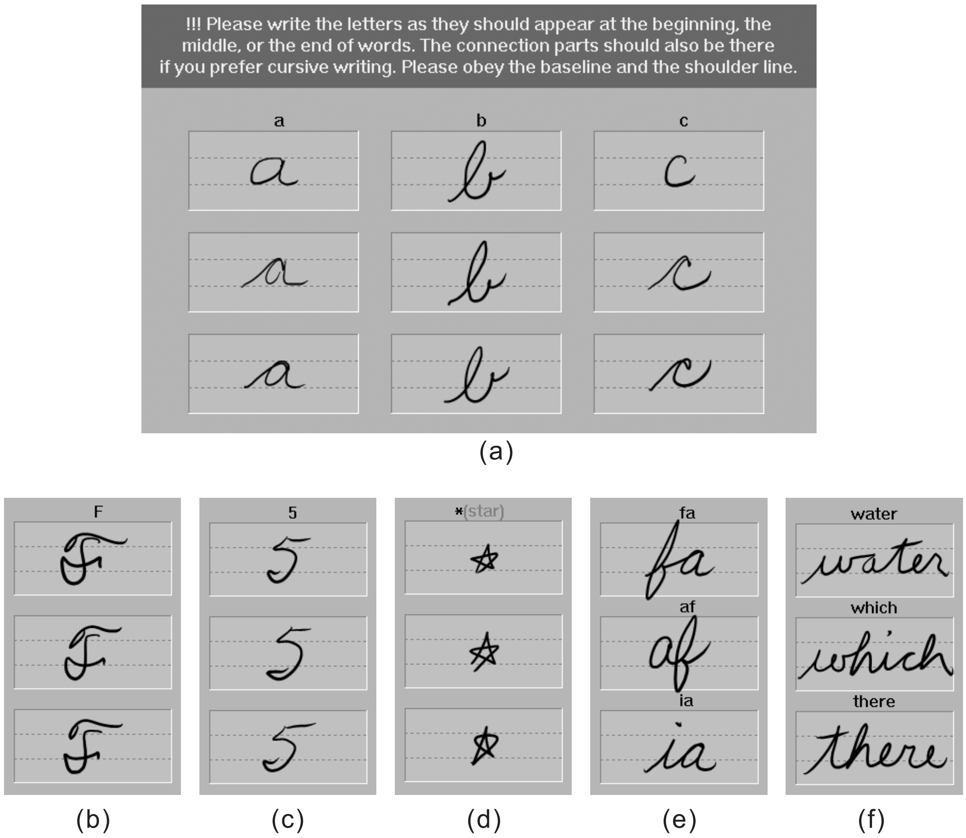


Fig. 2. The user interface in [17] to collect user handwriting samples: samples of lowercase letters, capital letters, digits, punctuations, special letter pairs, and multi-letter words.

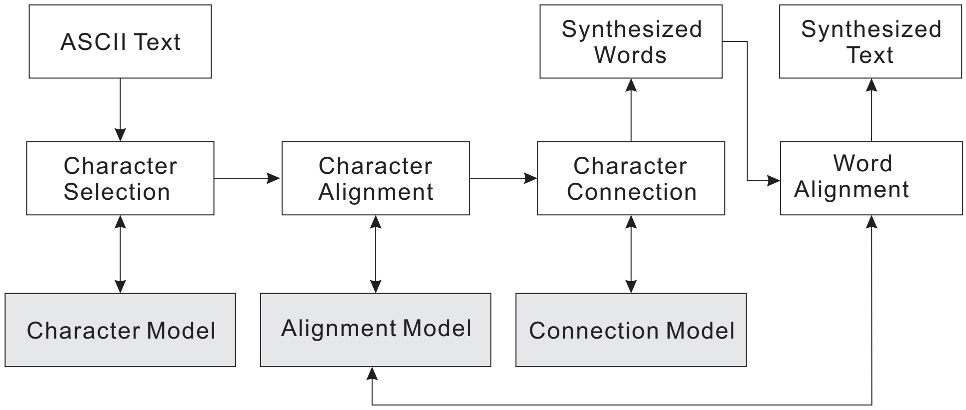
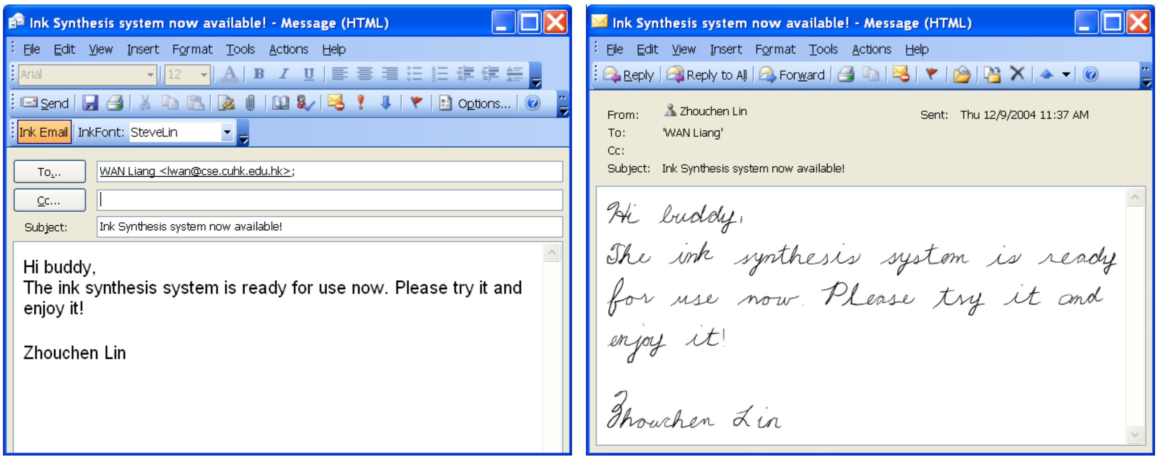


Fig. 3. Block diagram of the handwriting sample synthesis process.



(a) (b)

Fig. 4. Integration of handwriting sample synthesis system with Microsoft® Office Outlook®.