Nonlinear and Non-Gaussian Bayesian Based Handwriting Beautification

Cao Shi*[ab], Jianguo Xiao[a], Canhui Xu[abcd], Wenhua Jia[a]
[a]Institute of Computer Science & Technology of Peking University, Beijing, China, 100080; [b]School of Information Science and Technology, Qingdao University of Science and Technology, Qingdao, China, 266061; [c]State Key Laboratory of Digital Publishing Technology (Peking University Founder Group), Beijing, China, 100080; [d]Postdoctoral Workstation of the Zhongguancun Haidian Science Park, Beijing, China, 100871

ABSTRACT

A framework is proposed in this paper to effectively and efficiently beautify handwriting by means of a novel nonlinear and non-Gaussian Bayesian algorithm. In the proposed framework, format and size of handwriting image are firstly normalized, and then typeface in computer system is applied to optimize vision effect of handwriting. The Bayesian statistics is exploited to characterize the handwriting beautification process as a Bayesian dynamic model. The model parameters to translate, rotate and scale typeface in computer system are controlled by state equation, and the matching optimization between handwriting and transformed typeface is employed by measurement equation. Finally, the new typeface, which is transformed from the original one and gains the best nonlinear and non-Gaussian optimization, is the beautification result of handwriting. Experimental results demonstrate the proposed framework provides a creative handwriting beautification methodology to improve visual acceptance.

Keywords: Handwriting, beautification, Bayesian statistics, optimization, typeface

1. INTRODUCTION

Handwriting has been partly replaced by typing in daily life, due to the increasing usage of personal computer. Interestingly, the evolution progress of personal computer results in the popularity of handwriting on tablet computer. People has become familiar with typing even more than handwriting skills, especially in the office. And writing letters on touch screen is significantly different with handwriting on paper. To improve user experience and realize handwriting using computer system, it is urgent to assist user in enhancing visual effect of handwriting in computer system.

Recently, there has been intensive research on glyph by utilizing advanced modern digital algorithms. It is significant to explore glyph, which influences human cognition and vision. A natural methodology to generate glyph according to given handwriting is to imitate handwriting process depending on pen trajectory. Through analyzing influence over handwriting from physical properties of writing tools, Mi et al.[1-2] build a virtual brush model which operates digital droplet to redraw pen trajectory. In order to beautify pen trajectory with more vivid visual effect, Bai et al.[3-4] explore geometric deformation of writing tools under external force, and propose a geometry model and dynamic model for writing tools, achieving imitation of handwriting process and painting process. An inevitable problem on the above models is high computational complexity. To reduce computational cost, Yao et al.[5] utilize mechanical parameter to adjust spline curves which compose glyph. To improve visual beauty of generated glyph, Xu et al.[6] employ a more robust parametric representation of drawing trajectories utilizing supervised machine learning algorithm. Similarly, Yang and Li[7] exploit prior knowledge and inherent geometric features of sample characters to parameterize pen trajectory. Shi et al.[8] propose an effectively algorithm to generate a new hybrid glyph type by means of integrating local contour feature of calligraphy.

*caoshi@yeah.net; shicao@pku.edu.cn; phone 86-10-82529244; pku.edu.cn

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As pen trajectory characterizes curve beauty, topology of glyph reflects structural beauty. Through analyzing internal structure of glyph, Lai et al.[9-10] present a structural expression and glyph beauty metrics from traditional culture background, in order to automatically generate glyph. Considering more about contour of glyph as well as topology, Xu et al.[11-12] develop an algorithm for automatic character generation depending on both contour of glyph which presents local style and geometry topology indicating global structural feature of glyph. Shi et al.[13] propose an automatic glyph generation framework based on human vision and prior knowledge of glyph.

To further investigate layout beauty between two adjacent letters, Lin and Wan[14] collect handwriting features such as special connection style and letter spacing from user's handwriting samples, exploit collected features to generate word by aligning character glyphs, through trimming heads and tails of letters, and facilitating possible connections between neighboring letters. Similarly, Miyata[15] and Fujioka[16] measure handwriting motions and store motion data as a 3D time series, construct character employing an esthetic viewpoint, and connect characters adopting cursive theory. A number of researches on handwriting synthesis have been done. However, few consider making use of computer font to beautify handwriting. Unlike previous work, a handwriting beautification strategy is proposed in this paper by exploiting Bayesian dynamic model to adjust typeface so as to gain the best nonlinear and non-Gaussian approximation of handwriting.

The remainder of this paper is organized as follows. A novel framework of handwriting beautification is proposed in next section, which includes three sub-sections: Handwriting Normalization, Typeface Selection, and Parameter Estimation. In section 3, experiments and discussion are presented, and Section 4 concludes this paper.

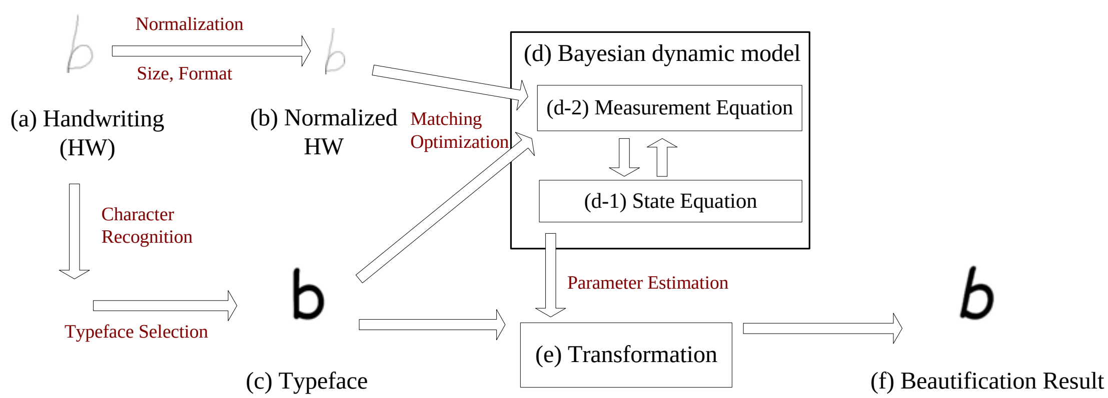

Fig. 1. Framework of handwriting beautification.

2. FRAMEWORK OF HANDWRITING BEAUTIFICATION

The preliminary step to beautify handwriting is handwriting capture and image normalization. As is shown in Fig. 1(a), handwriting image is captured, of which the size and the format are normalized in Fig. 1(b). After obtaining handwriting image, the second step is to recognize the character and select typeface. In practice, research on character recognition has been developed for several decades and remains as a challenging task. In this paper, character recognition is skipped, and the recognition result is a manual parameter. And then a typeface, shown in Fig. 1(c), is selected to beautify handwriting. The third step is called Parameter Estimation, in which Bayesian dynamic model is employed in Fig. 1(d). The Measurement Equation (Fig. 1(d-2)) calculates the likelihood between normalized HW (Fig. 1(b)) and selected typeface (Fig. 1(c)), and the State Equation (Fig. 1(d-1)) estimates the affine transformation parameters to transform typeface, resulting in handwriting beautification (Fig. 1(f)). The above three steps will be described elaborately in the following three sub-sections:

2.1 Handwriting Normalization

Original handwriting (HW) can be captured from touch screen computer, mouse, scan device etc., and each single character can be extracted by bounding-box technology. The size of HW $W_{HW} \times H_{HW}$ is normalized to $W_{NHW} \times H_{NHW}$ according to zoom ratio zr, described in (1)~(3):

$$W_{NHW} = W_{HW} / zr \tag{1}$$

$$H_{NHW} = H_{HW} / zr \tag{2}$$

$$zr = \begin{cases} W_{HW} / W_T\,, & W_{HW} \geq H_{HW} \\ H_{HW} / H_T\,, & W_{HW} < H_{HW} \end{cases} \tag{3}$$

where W_T and H_T are width and height of selected typeface, and zr is determined by $\max\{W_{HW}, H_{HW}\}$. Both Normalized HW (Fig. 1(b)) and selected Typeface (Fig. 1(c)) are converted to binary image.

2.2 Typeface Selection

As mentioned previously, the result of character recognition is a manual parameter. And typeface designed according to pen handwriting is preferred in this work. This kind of typeface is more similar to handwriting than printed typeface. Moreover, it is better to select typeface with the same style of handwriting, so as to obtain beautification result.

2.3 Parameter Estimation

In Bayesian dynamic model (Fig. 1(d)), the State Equation (Fig. 1(d-1)) recursively predicts and updates affine transformation parameters to transform typeface:

$$\mathbf{x}_{k+1} = \mathbf{x}_k \tag{4}$$

where $\mathbf{x} = [x_1, x_2, x_3, x_4, x_5, x_6, x_7]$, seven elements in $\mathbf{x}$ are Horizontal Scaling parameter, Vertical Scaling parameter, Rotation parameter, Horizontal Shear parameter, Vertical Shear parameter, Horizontal Translation parameter, and Vertical Translation parameter, respectively. N weights $\{w_k^1, w_k^2, \cdots, w_k^N\}$ are assigned to N samples $\{\mathbf{x}_k^1, \mathbf{x}_k^2, \cdots, \mathbf{x}_k^N\}$ of $\mathbf{x}_k$, using the Measurement Equation (Fig. 1(d-1)):

$$w_k^i = \frac{\mathrm{sum}\left(I \cap \mathrm{AF}\left(I_T, \mathbf{x}_k^i\right)\right)}{\sum_{j=1}^{N}\left(\mathrm{sum}\left(I \cap \mathrm{AF}\left(I_T, \mathbf{x}_k^j\right)\right)\right)} \tag{5}$$

where I, I_T are the binary images of Normalized HW (Fig. 1(b)) and selected Typeface (Fig. 1(c)). $\mathrm{AF}\left(I_T, \mathbf{x}_k^i\right)$ is the affine transformation result with the transformation order $x_1 \sim x_7$, and $\mathrm{sum}\left(I \cap \mathrm{AF}\left(I_T, \mathbf{x}_k^i\right)\right)$ gives the number of elements in the section $I \cap \mathrm{AF}\left(I_T, \mathbf{x}_k^i\right)$. Obviously, $\sum_{i=1}^{N} w_k^i = 1$ in the form of probability. $\{w_k^1, w_k^2, \cdots, w_k^N\}$ are sorted in descending order: $w_k^{1\prime} \geq w_k^{2\prime} \geq \cdots \geq w_k^{N\prime}$. And the corresponding samples of $\mathbf{x}_k$ are rearranged as $\{\mathbf{x}_k^{1\prime}, \mathbf{x}_k^{2\prime}, \cdots, \mathbf{x}_k^{N\prime}\}$. A threshold is set to keep M samples of $\mathbf{x}_k$ with relative high weights: $\{\mathbf{x}_k^{1\prime}, \mathbf{x}_k^{2\prime}, \cdots, \mathbf{x}_k^{M\prime}\}$, $M \leq N$, and $w_k^{1\prime} \geq w_k^{2\prime} \geq \cdots \geq w_k^{M\prime} \geq \mathit{threshold}$. $\mathbf{x}_k$ and its weights are updated. Samples of $\mathbf{x}_{k+1}$ $\{\mathbf{x}_{k+1}^1, \mathbf{x}_{k+1}^2, \cdots, \mathbf{x}_{k+1}^N\}$ consist of two parts:

- $\mathbf{x}_{k+1}^i = \mathbf{x}_k^{i\prime}$, $w_{k+1}^i = w_k^{i\prime}$, $i = 1, 2, \cdots, M$;
- $\mathbf{x}_{k+1}^i = \mathbf{x}_k^{1\prime}$, $w_{k+1}^i = w_k^{1\prime}$, $i = M+1,\ M+2, \cdots,\ N$.

Finally, parameters of Transformation (Fig. 1(d-1)) are estimated using $\mathbf{x}^i$ with the highest weight.

3. EXPERIMENTS AND DISCUSSION

To evaluate the proposed framework of handwriting beautification, a software was developed for Demonstration Session of IS&T/SPIE 2013 Electronic Imaging Symposium. During two hours (5:30 to 7:30pm, Feb. 5th, 2013), attendees were invited to test our software. And the setup is as follows: the size of Handwriting (Fig. 1(a)) is 400×400 pixels, and the size of Beautification Result (Fig. 1(f)) is 300×300 pixels. $k = 1$ in (4), $N = 5$ in (5), and $\mathbf{x}^i$ with the highest weight is used to estimate affine transformation parameters. Five typefaces in computer system are exploited to beautify handwriting, including Segoe Script (SS), Comic Sans MS (CSMS), Gabriola (GAB), Monotype Corsiva (MC) and MV Boli (MVB).

Fig. 2 shows that four handwriting “A”s are beautified. The first row includes four captured handwriting letters. Obviously, the first and the third are in the top left of image, that indicates the writing habit of left-to-right and top-to-bottom. The sizes of the two letters are smaller than the sizes of the others two. Hence, it is necessary to normalize their sizes, as is explained in Fig. 1(b). The normalized letters are illustrated in the second row of Fig. 2. Four letters in the second row are not well acceptable. The right vertical stroke of the first letter is too short to keep the balance, and the pen trajectory is unsmooth. However the beautification result in the third row using typeface GAB greatly improves visual acceptance. The serif of the right vertical stroke makes the whole letter look more beautiful. The second letter in row two tilts rightwards and it is beautified with SS so that the beautification result keeps the tilt feature. The top triangle of the third letter in row two is sharper than others, and this sharper triangle is kept in the beautification result using typeface CSMS. All horizontal strokes of the first letter, the third letter and the fourth letter in handwriting cross through their two vertical strokes, which is the case especially in the fourth letter. The reasons are various, including bad writing habits, slip of a pen, etc. Fortunately, well designed typeface is able to satisfy these drawbacks of handwriting. The improper horizontal stroke of the fourth letter is cut using the typeface SS.

To further investigate effect of beautification for different letters, Fig. 3 shows thirteen letters. The left column presents the original handwriting images, the middle column presents the normalized handwriting, and the right column shows the beautification results. In total, thirteen letters “B”, “C”, “D”, “E”, “F”, “K”, “L”, “R”, “S”, “W”, “X” “y” and “z” are beautified using typefaces SS, GAB, GAB, GAB, GAB, CSMS, CSMS, MVB, MVB, GAB, SS, SS, and SS, respectively.

Two handwriting letters “B” and “R” have only one stroke. “R” looks better than “B”. These two letters are beautified using typefaces SS and MVB. The “B” from SS and the “R” from MVB have just one stroke respectively. The beautification results keep well the number of stroke. Especially, the visual effect of “B” is greatly improved. To enhance 3D visual effect, the vertical strokes of the handwriting “R” has two vertical lines. However, the two line effect disappears after beautification process. The vertical stroke of the “R” from MVB doesn’t have two vertical lines. Consequently, the style of typeface influence the beautification result.

A big difference between handwriting and typeface is the serif in typeface. The original usage of typeface is for publishing. The serif is adopted to avoid the lack of ink at the end of stroke in the printing process. And then the serif is kept for monitor display to provide vivid visual effect. In Fig. 3, the serif is added to the beautification results of “C”, “D” and “W”, which are all beautified using the typeface GAB. The design of GAB already exploited the serif to improve visual experience, so that the serif is kept in the beautification results, which looks more vivid than other letters.

The strokes in the handwriting “K” are unsmooth. Generally, anti-aliasing is a challenging task. Whereas, the proposed beautification framework avoids anti-aliasing by exploiting well designed typeface to beautify handwriting. The Bayesian dynamic model optimize recursively the matching between handwriting and selected typeface until recursive process ends. Hence, complicated and time-consuming anti-aliasing algorithms are not necessary in the proposed framework.

It is easy to find that the beautification result of “X” looks more like handwriting than others letters. The random variation of curvature, along the contour of “X” from SS, let the beautification result obtain the randomicity from handwriting. It achieve successfully the imitation work of handwriting using typeface SS due to the creative design of typeface contour.

A problem appeared in Fig. 3 shows that some normalized handwriting strokes fade out partially, such as "R", "S", "W", "y" and "z". This phenomenon is caused in the conversion process from gray image to binary image. The conversion process is unable to guarantee the threshold is suitable for all handwriting images. Actually, when the binary image doesn't lose structural information of strokes and a fraction of strokes is lost, this problem doesn't influence essentially the beautification result.

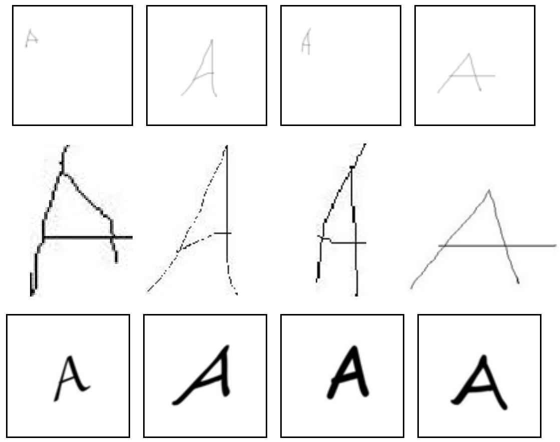

Fig. 2. Beautify four handwriting "A"s using GAB, SS, CSMS and SS, respectively. The first row includes four captured handwriting letters, the second row illustrates normalized letters, and beautification results are shown in the third row.

4. CONCLUSION

Bayesian dynamic model based handwriting beautification framework is proposed in this work. Captured handwriting images are normalized to reduce negative effect from bad writing habits or slip of a pen. The matching optimization between normalized handwriting image and selected typeface is employed in the measurement equation of Bayesian dynamic model, and the state equation realizes the estimation of parameters which are exploited to control affine transformation of selected typeface. Finally, the transformed typeface fulfills the handwriting beautification. Experiments illustrate the performances of handwriting results using the proposed framework. In the beautification process, not only the pen trajectory is smoothed, but also the serif of typeface is exploited to obtain more vivid visual effect. Additionally, the tilt feature of handwriting as well as the number of stroke are kept in the beautification results.

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Fig. 3. Beautify thirteen different letters using SS ("B"), GAB ("C"), GAB ("D"), GAB ("E"), GAB ("F"), CSMS ("K"), CSMS ("L"), MVB ("R"), MVB ("S"), GAB ("W"), SS ("X"), SS ("y"), SS ("z").

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