Visual Improvement for Bad Handwriting based on Monte-Carlo Method

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ABSTRACT

A visual improvement algorithm based on Monte Carlo simulation is proposed in this paper, in order to enhance visual effects for bad handwriting. The whole improvement process is to use well designed typeface so as to optimize bad handwriting image. In this process, a series of linear operators for image transformation are defined for transforming typeface image to approach handwriting image. And specific parameters of linear operators are estimated by Monte Carlo method. Visual improvement experiments illustrate that the proposed algorithm can effectively enhance visual effect for handwriting image as well as maintain the original handwriting features, such as tilt, stroke order and drawing direction etc. The proposed visual improvement algorithm, in this paper, has a huge potential to be applied in tablet computer and Mobile Internet, in order to improve user experience on handwriting.

Keywords: Visual improvement, handwriting, Monte Carlo simulation, typeface

1. INTRODUCTION

Along with the increasing use of personal computer, people tend to apply typing on a keyboard more frequently than handwriting on paper. Interestingly, the proliferation of mobile devices like tablets and smartphones brings back the use of handwriting on touch screen. However, writing letters on touch screen is significantly different from handwriting on paper. To ensure user smooth experience, it is of our concern to enhance visual effect of handwriting on touch screen.

Utilizing advanced modern digital algorithms, a series algorithms is proposed to generate beautiful glyph. These algorithms can be roughly grouped into three aspects: layout between characters, stroke structure and stroke itself. Lin and Wan[1] analyzed layout between two adjacent characters, investigating connection style from collected handwriting samples, to align automatically generated characters given to connection features from layout analysis. Considering handwriting motions and store motion data as a 3D time series, Miyata[2] and Fujioka[3] made well use of an esthetic viewpoint and utilized cursive theory to connect neighbor generated characters.

An ideal layout of characters displays the global beauty, whereas, a good topology of glyph represents structural beauty inside a glyph. Analyzing glyph structure and influence from traditional culture, Lai et al.[4-5] proposed glyph beauty metrics and a novel structure representation for glyph. Xu et al.[6-7] explored topology beauty under influence of glyph contour and developed an algorithm to generate elegant contour for improvement of glyph topology. Shi et al.[8] proposed an automatic glyph generation framework based on human vision and structural prior knowledge of glyph.

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Compared with layout between characters and stroke structure, stroke itself provides more local details. Several researches focus on writing tools. Through analyzing physical properties of writing tools, Mi et al.[9-10] developed a new concept of digital droplet for a virtual brush model, and redrew ink droplets along pen trajectory. To further investigate geometric deformation of writing brush under external force, Bai et al.[11-12] built a dynamic model and geometry model for brush, achieving imitation of redrawing strokes and obtaining more vivid visual effect. For aforementioned brush models, high computational complexity hinders their practical application. Instead of imitating physical writing tool, Yao et al.[13] employed spline curves. By controlling parameter of spline curves, glyph was generated automatically. Adopting machine learning methodology, Xu et al.[14] utilized more robust parameters to reconstruct stroke drawing process. Similarly, Yang and Li[15] employed inherent geometric features of glyph and prior knowledge to parameterize pen trajectory. Shi et al.[16] propose an effectively algorithm to generate a new hybrid glyph type by means of integrating local stroke contour feature from calligraphy.

As described above, many researches on generation of glyph with good visual accept have been done at three aspects: layout between characters, stroke structure and stroke itself. However, few consider making use of computer font to improve visual effect of handwriting. Unlike previous work, a visual improvement algorithm based on Monte Carlo simulation is proposed in this paper, in order to develop visual effects for bad handwriting. The remainder of this paper is organized as follows. An algorithm based on Monte-Carlo method to improve visual effect for bad handwriting is proposed in next section. In section 3, experiments and discussion are presented, and Section 4 concludes this paper.

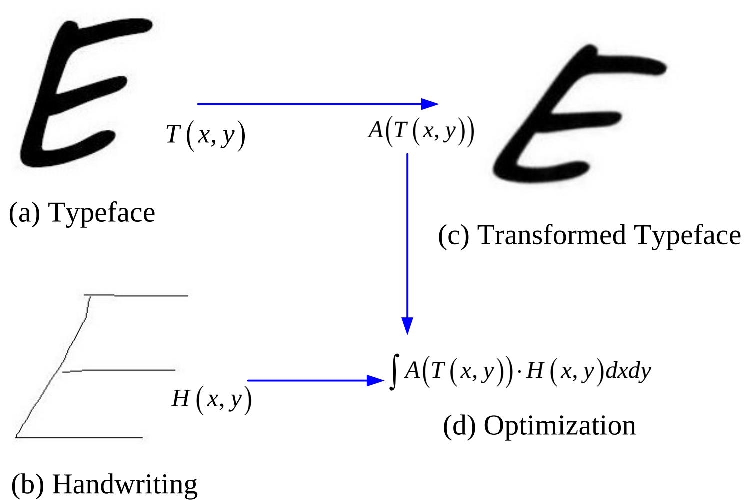

Fig. 1. Optimizing match between typeface and handwriting.

2. MONTE-CARLO METHOD TO IMPROVE VISUAL EFFECT FOR BAD HANDWRITING

The idea of visual improvement for handwriting in this paper is to optimize the match between well designed typeface and bad handwriting. As shown in Fig. 1(b), the handwriting image is obtained and represented as

$$H(x,y) \tag{1}$$

And the typeface (Fig. 1(a)) is also can be represented as a 2-D function:

$$T(x,y) \tag{2}$$

The visual improvement process is to transform $T(x,y)$, as shown in Fig. 1(c), using function $A(\cdot)$:

$$A\left(T\left(x,y\right)\right) \tag{3}$$

So as to maximize the integrals of the form:

$$\int A\left(T\left(x,y\right)\right)\cdot H\left(x,y\right)dxdy \tag{4}$$

Intuitively, (4) calculates the overlap area between handwriting image and transformed typeface. It is seemed as an optimization problem:

$$\max\left(\int A\left(T\left(x,y\right)\right)\cdot H\left(x,y\right)dxdy\right) \tag{5}$$

which subjects to (3). In this paper, affine transformation is used for $A(\cdot)$. Seven parameters: Horizontal Translation parameter, Vertical Translation parameter, Rotation parameter, Horizontal Scaling parameter, Vertical Scaling parameter, Horizontal Shear parameter and Vertical Shear parameter are grouped as a parameter vector:

$$\mathbf{p}=\left[p_1,p_2,p_3,p_4,p_5,p_6,p_7\right]^T \tag{6}$$

and then (5) is rewritten as:

$$\max\left(\int\left(\int_\Omega A\left(T\left(x,y\right)\right)\frac{1}{\rho\left(\mathbf{p}\right)}\rho\left(\mathbf{p}\right)d\mathbf{p}\right)\cdot H\left(x,y\right)dxdy\right) \tag{7}$$

where the random variable $\mathbf{p}$ distributes on Ω with density $\rho(\mathbf{p})$. Based on statistical sampling, Monte-Carlo Methods provide estimation for $\mathbf{p}$, such as Particle Filter[17], Sequential Importance Sampling (SIS)[18] algorithm, Markov Chain Monte Carlo (MCMC)[19] method, and Sampling Importance Resampling (SIR)[20] filter etc are used to approximate the optimal solution. In this paper, SIS[18] algorithm is employed to approximate the best $\mathbf{p}$ for the optimization problem described in (5).

3. EXPERIMENTS AND DISCUSSION

3.1 Handwriting Image Preprocessing

The preprocessing of visual improvement for handwriting includes two steps: handwriting captures and image normalization. Handwriting image is captured with mouse, scanner, digital camera, tablet, etc. and then size and format of captured handwriting image are normalized. Character is extracted from original handwriting by bounding-box technology. The size normalization ratio is determined by $\max\{Height, Width\}$ of extracted character image divided by corresponding Height or Width of typeface image. Naturally, character should be recognized, however, this topic is beyond the scope of this paper. The reorganization result is just treated as a parameter in the handwriting beautification process.

In the process of visual improvement, well designed typeface according to pen handwriting is preferred to approximate handwriting image. Such as Segoe Script (SS), Comic Sans MS (CSMS), Gabriola (GAB), Monotype Corsiva (MC) and MV Boli (MVB) etc., as shown in Fig. 2, this sort of typeface is more like handwriting than others typeface for publishing use only.

To evaluate the proposed visual improvement algorithm, attendees were invited to write down character in a 400×400 pixels area, as shown Fig. 3. And the visual improve results is size of 300×300 pixels.

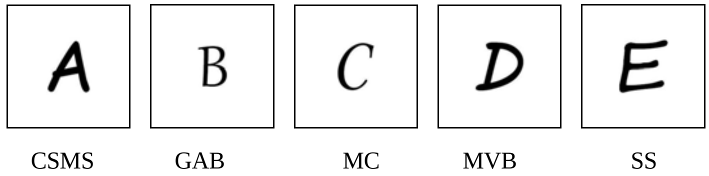

Fig. 2. Samples of typeface.

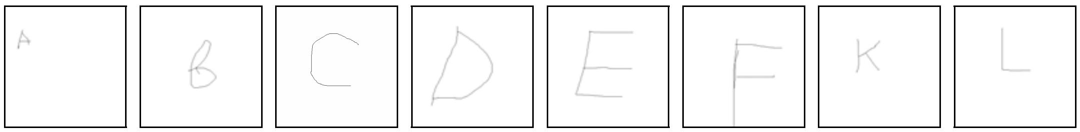

Fig. 3. Samples of captured handwriting.

3.2 Visual Improvement Result and Analysis

Fig. 4 shows visual improvement results of six characters. The whole figure is divided into two parts: the left part and the right part. Each part has three columns, the fist column exhibits captured original handwriting images, the second column presents normalized handwriting, and the last column shows the visual improvement results using typeface. Visual effects of six characters "A", "D", "A", "A", "E" and "A" are improved using typeface GAB, GAB, SS, SS, MVB and CSMS respectively. The dotted line on each normalized character image represents the slope by which character tilts, and it match the dotted line on the transformed typeface with great degree. In a extremely situation, the last character "A" has a blended left vertical stroke, and the visual improvement result also has a blended left vertical stroke. That means the proposed visual improvement methodology keeps the original tilt feature, and it is obviously the visual improvement results looks better than original handwriting.

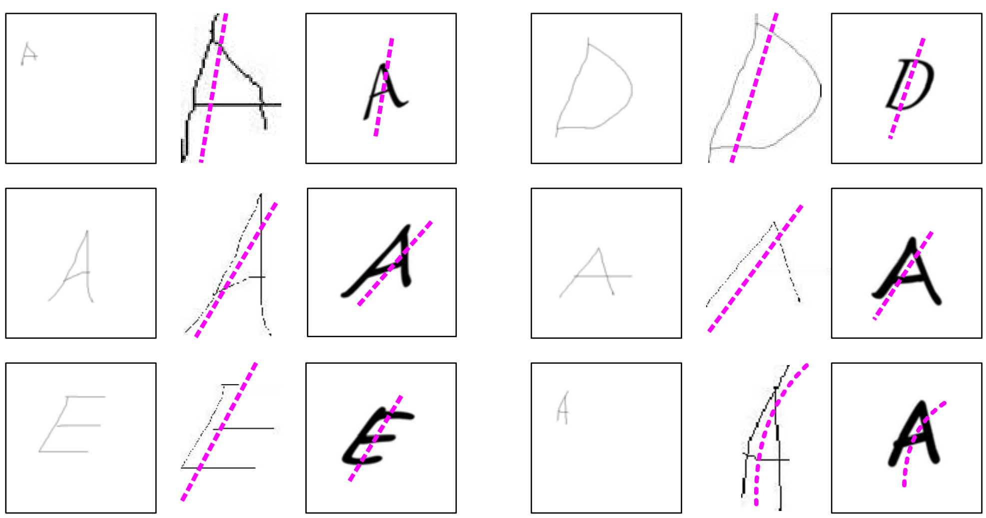

Fig. 4. Visual improvement for handwriting letters using GAB ("A"), GAB ("D"), SS ("A"), SS ("A"), MVB ("E"), CSMS ("A"). And transformed typeface, as visual improvement result, tilt the same slope corresponding to original handwriting image.

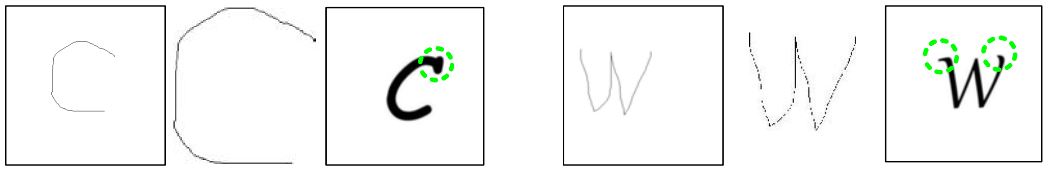

Fig. 5. Visual improvement for handwriting letters using CSMS ("C"), GAB ("W"). Marked with dot circle, serif of typeface typeface make visual improvement more vivid.

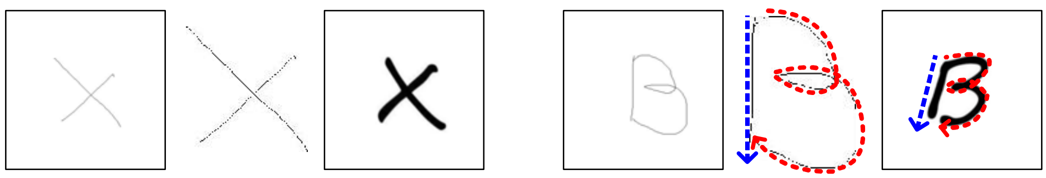

Fig. 6. Visual improvement for handwriting letters using SS ("X"), SS ("B"). In the typeface SS "X", the stroke from upper left corner to lower right corner is longer than the stroke from upper right cornor to lower left corner, which is the same situation in original handwriting image. The two strokes in typeface SS "B" keep the same trend corresponding to the original handwriting image. Especially, the second stroke of typeface SS "B" has a circle in the middle, which also occurs in the original handwriting image.

Two typefaces CSMS "C" and GAB "W" with serif are used to improve visual effect for handwriting images. In Fig.5, the handwriting image "C" looks stiff and tedious, whereas, the typeface CSMS "C" overcomes this drawback and makes the result more vivid. The strokes in original handwriting "W" are unsmooth. The GAB "W" generated smooth strokes using the proposed visual improvement methodology. In these two cases of visual improvement for handwriting, both CSMS "C" and GAB "W" have serif. Actually, the serif was designed at first for publishing usage. The serif on the end of stroke could avoid the lack of ink at the end of stroke in the printing process. And then in the digital era, the serif is kept for monitor display to provide vivid visual effect. In brief, the proposed visual improvement algorithm can make handwriting more vivid using the inherent serif in typeface.

The cases are shown in Fig. 6 concerning maintenance of stroke structure in visual improvement according to original structure in handwriting character. In handwriting character "X", the second stroke draws from upper left corner to lower right corner, which is longer than the first stroke from upper right corner to lower left corner. This feature about length difference between two strokes are kept in visual improvement result. Moreover, the random variation of curvature along the contour of typeface SS "X" let the improvement result gain the randomicity from handwriting. The stroke order and drawing direction along each stroke in handwriting character "B" are maintained in the typeface SS "B". In particular, the circle in the middle of the second stroke is kept in typeface SS "B".

Handwriting visual improvement experiments conclude that the proposed methodology in this paper can maintain the handwriting features, such as tilt, stroke order and drawing direction etc, as well as improve visual acceptance, especially using serif in the well designed typeface.

4. CONCLUSION

A Monte Carlo simulation based visual improvement algorithm is proposed in this work. The whole improvement process can be seen as a matching optimization between well designed typeface and handwriting image. The typeface is transformed using a series of linear operators, and the best parameters for linear operators are estimated by Monte Carlo method. The experiments show that improvement results maintain handwriting habits e.g. tilt, stroke order and drawing direction. And the proposed algorithm effectively enhance visual effect. It has a huge potential to applied in tablet computer in order to improve user experience on handwriting with touch screen.

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