

## D-15 Reconstructing Dynamic Font Control Points via Deep Learning Approach

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## 1. Introduction

Dynamic Font is a framework that models characters as the result of three-dimensional writing motions, represented by a virtual writing device and a writing plane (e.g., [1]). In this framework, the writing motion of a character is expressed as a sequence of B-spline control points, which formally define its shape. This representation is particularly powerful for applications such as Japanese calligraphy, where stroke thickness and stylistic variation are essential. However, manually selecting these control points is labor-intensive, even with specialized software [2], and the process does not easily generalize across diverse font styles.

In this study, we propose a deep learning-based approach that predicts B-spline control points directly from character images. The model outputs both the sequence of control points and their effective length.

## 2. Proposed Method

Figure 1 illustrates the dynamic font model. A sequence of control points defines the weights of cubic B-spline basis functions, and their combination produces the trajectory of a character (i.e. the writing motion). This writing motion provides a parametric representation that can be modified or regenerated. The mathematical formulation of this process is given as

$$x_d(t) = \sum_{i=3}^{m-1} p_i B_3(\alpha(t - t_i)), \quad (1)$$

where  $B_3(\cdot)$  denotes the cubic B-spline as basis function. Also,  $p_i, i = -3, -2, \dots, m-1$  are B-spline control points. In this work, we fix  $\alpha = 1$  and formulate the problem as estimating the sequence of control points  $p_i$  from input character images via a CNN.

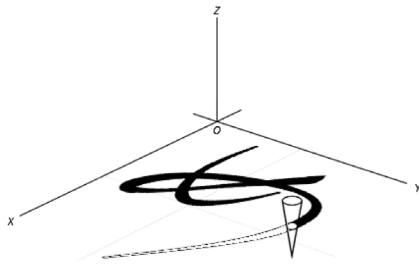


Figure 1: Dynamic font model.

Training data are prepared by perturbing the x, y, and z coordinates of existing font control points with a fixed standard deviation  $\sigma = 0.15$ , generating 60 synthetic samples per character for 48 characters (2,880 samples in total). Each set of perturbed control points is rendered as character images using the dynamic font framework. These images are then used as input to a CNN. The task is formulated not only as regressing the 3D control point coordinates but also as predicting the effective number of control points simultaneously.

The CNN consists of three convolutional blocks (32–64–128 channels, ReLU activation) followed by fully connected layers (128 → 94 units). The network is trained to regress the 3D control points using mean squared error (MSE) loss and the Adam optimizer.

## 3. Experimental Method and Results

Experiments are conducted on all Japanese Kana characters

from “あ” to “ん”. The CNN predicts a sequence of B-spline control points from character images, together with their effective number. Using these predicted control points, we reconstruct both the writing motion and the rendered character shape through (1).

Figure 2 shows an example of the results for “あ”. The predicted control points (red cross marks) are plotted together with the corresponding writing trajectory (red lines), while the original control points and trajectory are indicated by blue crosses and lines for comparison. In Figure 3, we show the generated character obtained by substituting them into (1). The comparison indicates that the proposed method is able to reproduce the structural features of the target character with reasonable accuracy, although some distortions remain in certain cases.

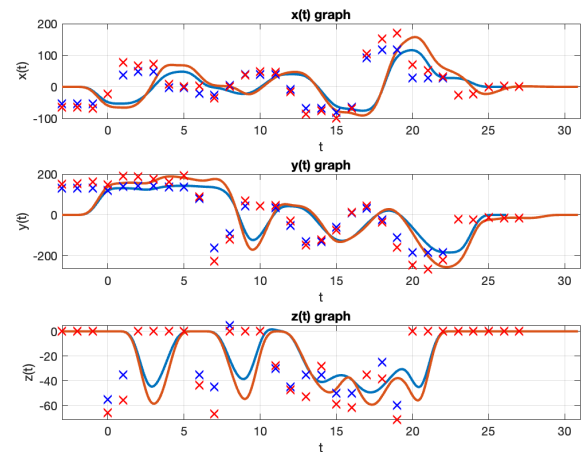


Figure 2: The predicted control points and writing motions for “あ”.

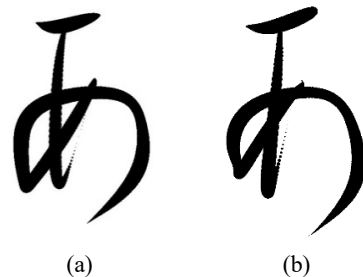


Figure 3: Generated characters using (a) original control points and (b) predicted control points.

## References

- [1] H. Fujioka and H. Kano, “Constructing and Reconstructing Characters, Words and Sentences by Synthesizing Writing Motions,” *IEEE Transactions on Systems, Man and Cybernetics, Part A*, vol. 36, no. 4, pp. 661–670, 2006.
- [2] H. Nakata and H. Kano, “Generation of Japanese cursive sentences using optimal smoothing splines,” *IPSJ Journal*, vol. 44, no. 1, pp. 134–142, Jan. 2003.