Robotic Calligraphy: Learning From Character Images

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I. INTRODUCTION

Known as the 'art of combining strokes to form complex letters', the Chinese and Korean Calligraphy can be learned by assimilating the skill of drawing these strokes. Once this dexterity is mastered, it can be used to compose a calligraphic letter afterwards. The very notion of calligraphy is endeavored to be implemented on robots in this research. Korean calligraphy is the nucleus of this research and the image of the calligraphic character is used as an input. Unlike humans or calligraphers, the robots are unacquainted with combination of various strokes used to draw a calligraphic letter. Hence it is quite cardinal and arduous to fragment the calligraphic letter into diverse strokes used to draw it. Therefore this has been the area of interest for many researchers which led to couple of unalike approaches like in [1], [2] and [3] but with some drawbacks. Authors in [1] used geometric properties of contour of the character to extract the stroke which fails in even very simple case like shown in Figure 13 in [1]. Hence a novel approach ensuing Gaussian Mixture Model (GMM) is proposed in this research to segregate the input image into assorted strokes. Once the strokes are extracted, they are combined to reproduce the same character using Gaussian Mixture Regression (GMR). The resulted learned strokes are then implemented on KUKA Light Weight Robot and further improved using RL.

II. PROCEDURE FOR STROKE EXTRACTION

A. Image Pre-processing

First, the image is pre-processed to make it compatible to be estimated by GMM. This phase comprises thinning of input image. The image is thinned to prevent the GMM from modeling the thickness of the strokes.

B. Gaussian Mixture Model

In the second phase, the GMM as mentioned in [5] is learned on the data points obtained in the first phase. Its parameters are estimated using Expectation Maximization algorithm and Bayesian Information Criteria is used to determine the number of clusters required to fit the data set.

C. Extraction Algorithm and Gaussian Mixture Regression

The third phase is the core of this research. In this step, a novel stroke extraction algorithm is proposed. The algorithm combines the clusters that represent the respective stroke based on the following rules. The components represent one stroke if:

1) Distance between intersecting point of two adjacent GMM components and the end point of the under-observed Gaussian is less than a threshold.
2) Angle between intersecting axes of GMM components is less than a threshold.
3) The end point of an intersecting axis of a GMM component lies with in the Gaussian distribution of intersecting cluster.

Once the corresponding clusters are combined to represent a stroke, GMR is used to get the smooth trajectory of the stroke. The information regarding the thickness of the stroke is extracted directly from the original image of the calligraphic letter.

D. Dynamic Moment Primitives (DMP) and Reinforcement Learning (RL)

A stroke encoded using GMM has a high number of free parameters which become problematic when applying RL. Hence, to reduce the number of parameters, the trajectories extracted using GMR are re-encoded using DMPs. The resulting character is implemented on a robot i.e. KUKA LWR. Its parameters are updated by using EM based RL [4] which results in iterative improvement of the learned skill. The update policy is shown by Equation1

$$\theta_{new} = \theta_{old} + \frac{\sum_{j=1}^{K} \gamma_j \epsilon_j}{\sum_{j=1}^{K} \gamma_j} \tag{1}$$

where θ_{new} = learned parameters of DMP, θ_{old} = old parameters of DMP, γ_j = Correlation between original image and image reproduced by robot and ϵ_j = exploration terms.

III. RESULTS

Results are shown in form of Figure 1 explicitly. The Figure 1 shows step-wise procedure of extracting stroke from original image. The characters reproduced by robot after several iterations are shown in Figure 2. The Figure 2c shows the character reproduced by robot after 7th iteration of RL. It has the highest correlation with original image which is shown in Figure 2d. The parameter update is performed after every ten reproductions with the importance sampling factor of five. The Figure 2d shows the correlation between reproduced character and original image and it is used as reward for RL.

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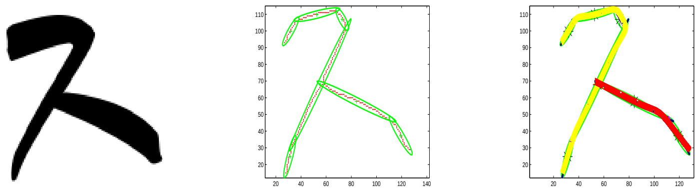

(a) (b) (c)

Fig. 1: (a) Shows the original image of calligraphic letter, (b) Shows the GMM fitted image of calligraphic letter, (c) Shows the extracted Strokes.

(a) (b) (c) (d)

Fig. 2: (a) Shows the character before reinforcement rearning, (b) Shows the character after 3 iterations, (c) Shows the character after 7 iterations (d) Reward against number of iterations. The higher the better.

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