An Observation based Method for Human Robot Writing Skill Transfer

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***Abstract*—This paper proposes a novel method of Chinese character stroke extraction and a framework for human robot skill transfer through vision-based observation. By analyzing the structure of Chinese characters, a direction vector update rule and a pixel finding rule were proposed to find the basic strokes. Then we designed a basic stroke connection algorithm to achieve stroke extraction. Afterward, to adapt to human interference in real-time, we adopt dynamical movement primitives (DMPs) to model writing skills. Finally, the adaptive capability of the method was verified by experiments in which the robot writes Chinese characters on a randomly moved writing board.**

I. Introduction

With the rapid development of robotics, robots have entered every aspect of human life. The robot can easily cope with repetitive and unchanging tasks, such as assembly in industry. However, it is still difficult for the robot to complete the task whose goals and trajectories often change, such as handwriting under disturbance.

At present, some researchers have studied the handwriting skills of robots. For example, in [1], the authors used the 3D camera Kinect to track the movement of human hands, where the robot can imitate human beings and write in real time. In [2], the authors established the font database, and used the trajectory of human arm to train the classifier integration, and the robot can write according to it. However, these methods are hard to adapt to the changing environment during the writing.

Learning from demonstration (LfD) is an common and effective method for human-robot skill transfer. LfD enables robots to learn skills from demonstrations of the human tutors. Based on the teaching methods, there are mainly three approaches, kinesthetic demonstration, teleoperation based demonstration and observation based demonstration. Kinesthetic demonstration is demonstrated by humans dragging a robot to complete the task [3]. However, this teaching method requires the physical contact between robot and human, which is not safe for human demonstrators. Teleoperation based demonstration is demonstrated via human teleoperating a robot to complete the task [4]. However, wearing or operating teleoperation equipment makes this method hard to implement. Observation based demonstration enables robots to learn skills through perception information obtained from cameras, Optical marker, etc [5], [6]. Skill models for learning from demonstration mainly include dynamic system based model, such as dynamical movement primitives (DMPs) and statistic based method, such as Gaussian mixture model (GMM)/Gaussian mixture regression (GMR), probabilistic movement primitives (ProMPs) etc. This paper uses DMPs, an easily generalizable skills model, to encode the writing skill. DMPs proposed by Ijspert can generalize the learned trajectories by simply changing the position of the starting point and the target point [7]. Since then, many studies have been implemented to improve the generalisation capability of traditional DMPs [8]–[10], but these methods are still hard to adapt to the situation that the starting point and target point rotate at the same time. In order to enable the robot to adapt the dynamic tasks and human intervention, inspired by [11], we designed a frame independent DMP based on rotation matrix and translation matrix.

Inspired by the process of human imitating handwriting, we use observation based demonstration. Referring to the steps of human imitating others' writing, we first analyze the strokes of Chinese characters. In [12], the authors point out that there are two main ways of acquiring information about Chinese characters: computer font reproduction and human-computer collaboration/imitation learning. Computer font reproduction mainly consists of programming to obtain information on Chinese characters from existing font [13]–[15] and processing of character posters to obtain information on Chinese character strokes [16]–[20]. But computer font reproduction method cannot imitate random human handwritten Chinese characters. Human-computer collaboration/imitation learning includes both human-computer collaboration to obtain information on Chinese writing [21], [22] and imitation to obtain information on Chinese writing [23]–[26]. However, human-computer collaboration/imitation learning method relies on human teaching actions and it is not possible to imitate human handwritten Chinese characters simply by using a picture of a Chinese character. Stroke extraction of Chinese characters in picture has been studied by many researchers. In [27], the authors extracted Chinese strokes based on B-spline curve matching. In [28], the authors used point to boundary orientation distance (PBOD) of one triangular mesh to decompose the contour and singular regions of Chinese characters. In [29], the authors used video to extract stroke dynamic information. In [30], the authors presented a method of extracting strokes by using ambiguous zone information. In [31], cursive Chinese

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characters were segmented by using Stroke Speed Feature and Stroke Vector Feature. In [32], the authors used Optimum Paths to extract the strokes of handwritten Chinese characters. However, these methods require a lot of computation.

The main contributions of this paper are as follows:

- Based on the curve search with direction and sequential splicing, a new stroke extraction algorithm is developed.
- The stroke extraction method enhanced by DMPs could adapt the dynamic tasks and human intervention.
- A robot writing system is developed to evaluate the proposed observation based human robot skill transfer method.

The paper is organized as follows. Section II introduces the principle of framework independent DMPs. Section III proposes the stroke extraction algorithm, including basic stroke extraction and basic stroke connection. Section IV presents the experiments we designed and discusses the results. Section V is the conclusion.

II. Preliminary

DMPs is an LfD method that encodes the motion trajectory by a second-order dynamical system with a nonlinear forcing term. It is divided into discrete DMPs and rhythmic DMPs. This paper focuses on discrete trajectory. A single degree of freedom motion can be expressed as [7]:

$$\tau \dot{v} = \alpha_y (\beta_y (y_g - y) - v) + f \tag{1}$$

$$\tau \dot{y} = v \tag{2}$$

where, τ is temporal scaling parameter, α_y and β_y are constants, y_g is the goal, y is the current position, v is the scaled velocity. A set of radial basis functions can be used to approximate the forcing term f,

$$f(x, y_g) = \frac{\sum_{i=1}^{N} \psi_i \cdot \omega_i}{\sum_{i=1}^{N} \psi_i} \cdot x \cdot (y_g - y_0) \tag{3}$$

$$\psi_i = \exp(-h_i (x - c_i)^2) \tag{4}$$

$$\tau \dot{x} = -\alpha_x \cdot x \tag{5}$$

where, α_x is a positive gain coefficient.

Although the original DMPs model can well generalize the trajectory according to the position of the starting point and the target point, it can not deal with the situation that both the starting point and the target point rotate. Paper [11] proposes a new DMPs model for global and frame independent spatial scaling in the task space to solve the above problems. Inspired by [11], we regard the generalized space as the rotation of the original space, and design a new frame independent DMPs based on the rotation matrix. Equation (1) is rewritten as,

$$\tau \ddot{y} = \alpha_y (\beta_y (y_{g,1} - y) - \dot{y}) + s \cdot R \cdot f \tag{6}$$

$$y_{g,1} = R \cdot y_{g,0} + t \tag{7}$$

$$y_{0,1} = R \cdot y_{0,0} + t \tag{8}$$

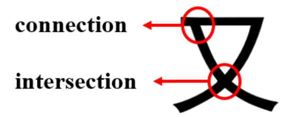


Fig. 1. Connection and intersection of the Chinese character "you".

$$s = \frac{\|y_{g,1} - y_{0,1}\|}{\|y_{g,0} - y_{0,0}\|} \tag{9}$$

where, $y_{g,1}$ and $y_{0,1}$ are the goal and starting point of generalized space, $y_{g,0}$ and $y_{0,0}$ are the goal and starting point of original space, s is the scaling constant, R and t are rotation matrix and translation matrix, respectively.

When the transformation relationship between two spaces can be detected directly, this method can smoothly and accurately generalize the trajectory in the original space to the new space.

III. Stroke Extraction

Stroke extraction has always been one of the major difficulties in the study of Chinese characters. The main difficulty lies in the fact that Chinese characters have many intersections and connections as shown in Fig. 1, making it difficult to accurately segment the correct strokes. For example, in the simple Chinese character "shi" as shown in Fig. 2(a), the strokes should be divided as shown in Fig. 2(b). However, because of the different treatment of the intersections, the strokes can easily be mistakenly divided into two other incorrect cases as shown in Fig. 2(c) and Fig. 2(d). Therefore, we need a method for extracting strokes of Chinese characters that can accurately and quickly deal with the problem of intersections and connections.

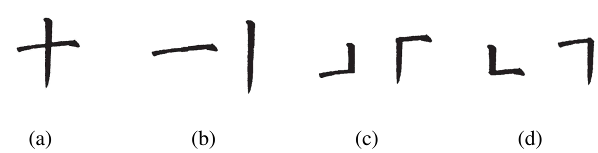


Fig. 2. Stroke division of Chinese character "shi".

Without regard to the direction of writing, it can be found that, the strokes of Chinese characters all consist of a combination of dots, horizontals, verticals, left-fallings, and right-fallings as shown in Fig. 3. For example, a vertical-turning can be seen as a combination of vertical and horizontal as shown in Fig. 4. Here we refer to dot, horizontal, vertical, left-falling, and right-falling as the basic strokes. As can be seen from Fig. 3, the basic strokes are all approximately straight, i.e. the direction of extension remains essentially unchanged. We note that the intersections usually occurs after the stroke has been extended for a period, when the direction of the stroke's extension has been fixed. When the direction is known, the extension of the strokes can easily and accurately cross the

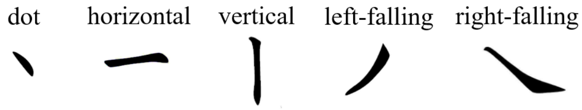


Fig. 3. Basic strokes of Chinese characters.

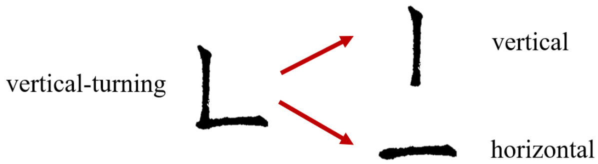


Fig. 4. The stroke vertical-turning is divided into the basic strokes horizontal and vertical.

intersection. The connections, on the other hand, usually occur at the beginning and end of the strokes and have no influence on the determination of the direction and extension of the basic strokes. Therefore, we can extract the basic strokes that approximate straight lines, then combine them into complete strokes.

A. Basic Stroke Extraction

As shown in Fig. 9, for a set of eight neighbourhoods, we assume that the central pixel is P_0 and starting from the pixel above the central pixel, the pixel points in a clockwise circle are $P_x(x = 1, \ldots, 8)$ respectively. Then we assume a direction vector $D = (v, h)$, where the positive and negative sides of v indicate vertical down and vertical up respectively, and the positive and negative sides of h indicate horizontal right and horizontal left respectively.

Take an example of a picture with black Chinese characters on a white background. First the image is refined. Then the basic stroke extraction algorithm is shown in Fig. 8, where P_0 is the central pixel of the current search, P_x is the searched black pixel around P_0, and $Img_*(P_*)$ is the pixel P_* in the image Img_*.

B. Basic stroke connection

After the basic strokes have been extracted, the points of the basic strokes need to be sorted and connected to form the strokes. According to the rules of Chinese character writing,

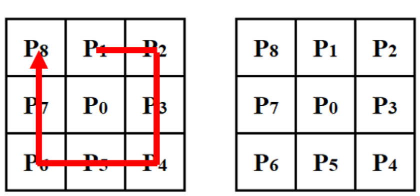


Fig. 5. Eight neighbourhoods with P_0 as the central pixel.

TABLE I: Update rules for direction vector.

x	$D = (v, h)$	
1	$v = v - 1$	$h = h$
2	$v = v - 1$	$h = h + 1$
3	$v = v$	$h = h + 1$
4	$v = v + 1$	$h = h + 1$
5	$v = v + 1$	$h = h$
6	$v = v + 1$	$h = h - 1$
7	$v = v$	$h = h - 1$
8	$v = v - 1$	$h = h - 1$

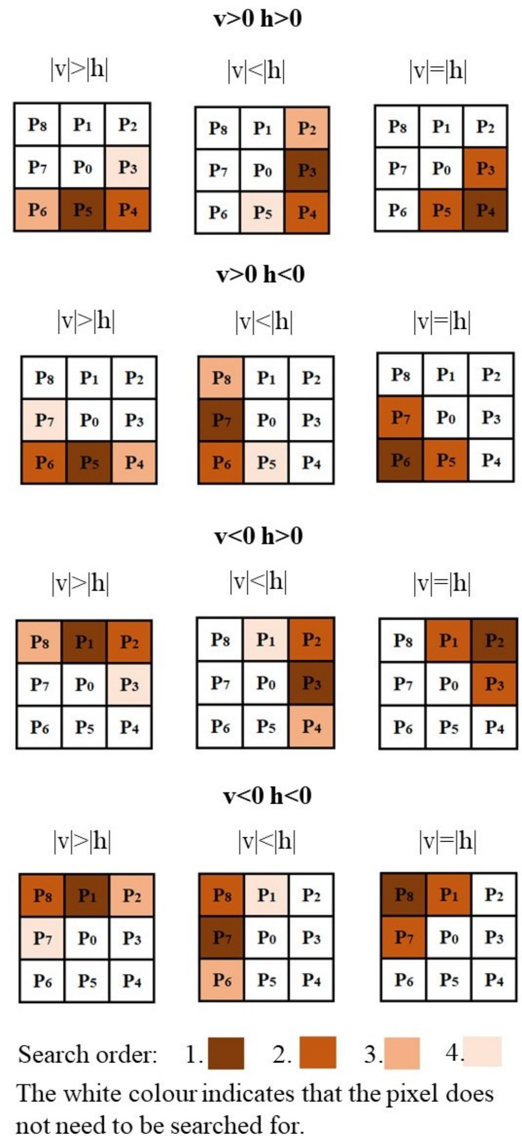


Fig. 6. Search rules of P_x when $D = (v, h)$

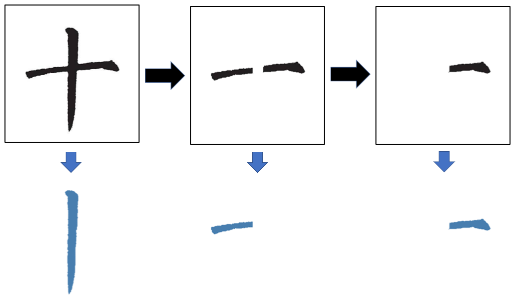


Fig. 7. The break in the horizontal in the Chinese character "shi". Black indicates variations of the Chinese character picture and blue indicates the extracted base strokes.

each stroke is generally written in a top-to-bottom, left-to-right order. Therefore, the points in the extracted basic strokes can be sorted first in a top-to-bottom or left-to-right writing order before connecting the basic strokes. However, it should be noted that many of the Chinese strokes have a hook, which travels from the bottom to the top. Its characteristic are that its length is much shorter than other basic strokes, and it is connected with other basic strokes. So for strokes that are much shorter than the other basic strokes, we check both their starting points and end points. If its starting point coincides with the end point of other basic strokes, it is connected with the basic stroke. If its end point coincides with other strokes, all its points are inversely sorted and connected with the basic stroke. If neither the start point nor the end point coincides with the end point of other strokes, the points are arranged from top to bottom or from left to right and regarded as a separate stroke (i.e. stroke "dot").

After these steps, as shown in Fig. 10, the strokes of Chinese characters writing in regular script and even writing in cursive script can be extracted.

IV. Experiment

In this experiment, we use the extracted strokes as the demonstration to make the robot write Chinese character on the writing board according to the correct strokes. In the process of robot writing, people move or rotate the writing board as shown in Fig. 10. The robot can adjust the writing trajectory online so that each point in the stroke is written in the accurate position on the writing board. As shown in Fig. 11, the experimental platform consists of Elite Collaborative Robot, Intel RealSense Depth Camera D435 and LCD Writing Board.

The experimental scheme is shown in Fig. 12. We start with hand-eye calibration, which enables the robot to adjust the manipulator position based on visual information. The strokes of the Chinese character are then extracted and the stroke trajectory is mapped from the picture plane to the writing board plane of the experimental scene. Afterwards, the trajectory is modelled using frame independent DMPs. Then, the robot detects the translation and rotation of the writing board in real time via the camera and generalizes

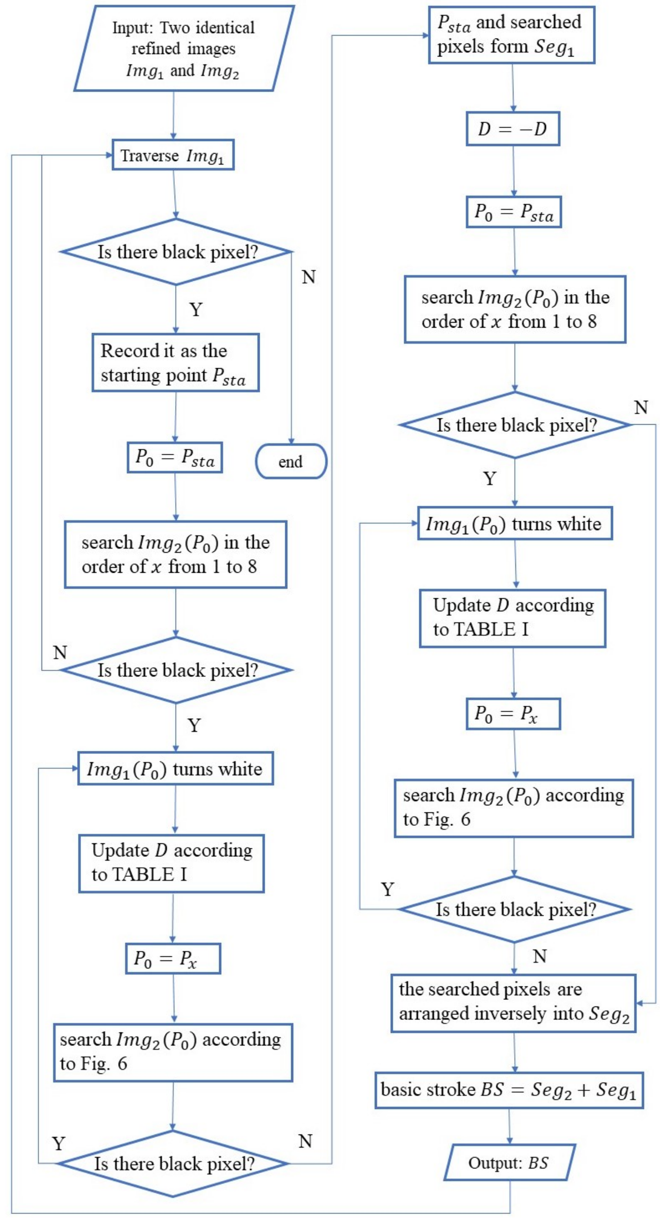


Fig. 8. The neighbouring pixels of P_0 are searched in a directional and sequential manner according to Fig. 6. When a black pixel is searched, the direction vector is updated according to TABLE I and the black pixel is treated as P_0. These steps are repeated until no black pixels are searched.

Fig. 9. Stroke extraction results. Different colours indicate different strokes.

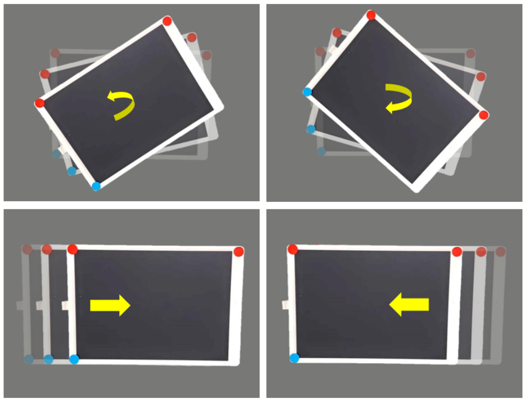


Fig. 10. In the process of robot writing, people rotate or move the writing board.

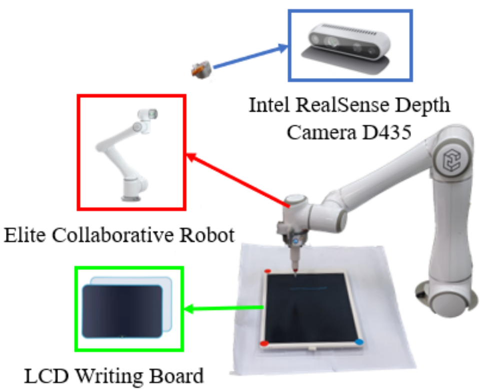
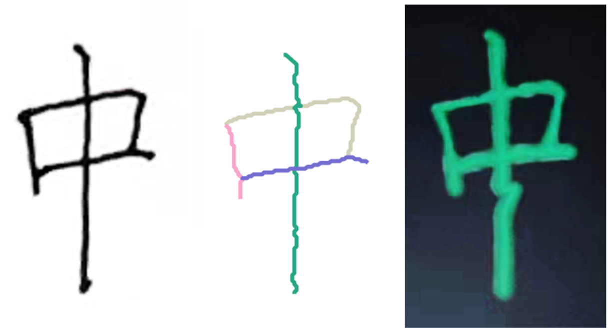


Fig. 11. The setup of experimental platform.

the trajectory point according to the translation and rotation matrices. Finally the manipulator moves to the new trajectory point. The steps of real-time detection, generalization and tracking are repeated until the writing is complete. As the trajectory is modelled before the robot writes, when the writing environment changes, the robot only needs to calculate new trajectory points based on the trajectory model and the writing environment, meeting the computational speed requirements for online generalization.

The Chinese character ”zhong” used for demonstration is shown in Fig. 13(a). The result of the extraction of strokes for the Chinese character ”zhong” is shown in Fig. 13(b). The Chinese character ”zhong” written by the robot is shown in Fig. 13(c). Fig. 13(c) shows that the robot is able to write each stroke in the correct position despite human intervention. As shown in Fig. 14, while the robot is writing the red dotted part of the Chinese character ”zhong”, the human continuously rotates the writing board at random speed and direction with the pen tip as the centre of rotation. The robot is able to adjust its trajectory in real time and write down strokes without distortion. While the robot is writing the blue dotted part of the Chinese character ”zhong”, the human randomly moves the writing board. After the font is deformed due to the relative displacement of the nib and writing board, the robot smoothly returns to the exact position and continues writing the stroke. Therefore, the robot is able to adjust its trajectory in time to write down the Chinese characters accurately, even with human intervention, with great adaptive capabilities.



(a) (b) (c)

Fig. 13. Experimental results: (a) the character of demonstration by human; (b) the reproducing character by learned writing skills.

V. Conclusion

In order to extract the strokes of Chinese characters, this paper first designs the rules of updating the direction vector and the search rules based on the direction vector to find the basic strokes, and then designs the connection scheme of the basic strokes to extract the strokes of Chinese characters. Aiming at the problem that traditional DMPs can not effectively generalize the trajectory to rotation objects, this paper integrates the rotation matrix into the formula of traditional DMPs. Finally, according to the Chinese character stroke extraction algorithm and frame independent DMPs, a robot writing Chinese character system is designed, where the robot can write Chinese character when the writing board is constantly moving. Experimental results demonstrated the adaptive capacity of the proposed framework.

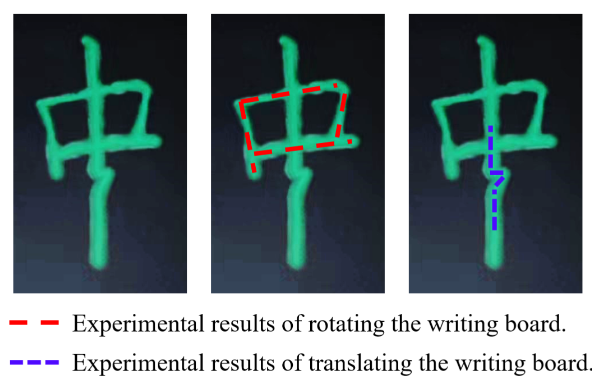


Fig. 14. Experimental results of rotating and translating the writing board.

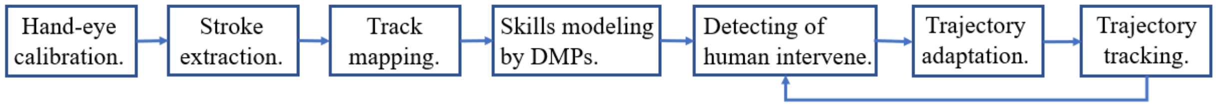


Fig. 12. The experimental scheme of the proposed framework.

However, due to the limitations of the camera's field of view, this method is difficult to adapt to situations where the writing tablet is flipped. In future work, we will use a multi-camera combination to solve the problem.

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