

A Portable Sketching Robot Based on Artificial Intelligence



Yunxiu Xu, Bingxia Shen*, Shan Luo, Mi Zhao and Xinghan Li

School of Information and Communication Engineering, Beijing Information Science & Technology University, Beijing, 100101, China

xuyunxiu@foxmail.com; shenbingxia@bistu.edu.cn*; LuoShan0713@163.com; 18811536982@163.com; Li_xinghan@foxmail.com

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Abstract. In recent years, sketching robot has entered an active period, the demand for sketching robot's creativity, technology, price, aesthetic and other requirements are also gradually increasing. In view of the present common sketching robots are typical of large size, high power consumption and high manufacturing cost, this project was designed and implemented a new type of portable sketching robot and a set of stick figure sketching recognition algorithm based on convolution neural network, able to convert hand drawn stick figure sketching into corresponding images which is more standard and can be drawn by the robot. It can also convert other different types of images into path points for robot sketching.

Keywords: convolution neural network (CNN), hand sketching quick correction system, parallelogram manipulator, portable sketching robot

1 Introduction

With the Internet wave sweeping the world in recent decades, information technology has penetrated into all aspects of human life. Human beings are increasingly calling for the new industrial revolution, among which "sketching robot" has attracted much attention. "Sketching robot" first appeared in the 1890s, it is made by Swiss watchmaker and his son in the 1770s [1]. In recent years, sketching robot has entered an active period, and its related news and concepts appear in the public.

In recent years, research has proposed to develop a robot arm mainly constructed for a disabled person who cannot write by himself [2], which is provided for the project using the robot arm. However, for the image to be drawn, it is obviously not enough to have only according to the speech. Based on this, we have studied the image drawing using the robotic arm. In this regard, in recent years, a semi-automatic robot pendulum system has been proposed, relying on the industrial seven-degree-of-freedom (7DoF) manipulator for control. This system creates visually pleasing and complex artistic strokes on a general surface without the need for explicit surface reconstruction and visual feedback [3]. This project has been improved in this experience. It is proposed to use a modified robotic arm to make a sketching robot. In addition, for writing applications, research has been proposed to teach children how to write and improve their writing and drawing skills. The method includes designing and implementing two DOF (DOF) robotic arms. The multi-segment Cartesian equation based on the adaptive neuro-fuzzy inference system (ANFIS) is used to perform the robot trajectory planning motion [4].

The last question is how to make robots perform motion tasks under certain conditions. After learning, the robot outlines the motion program obtained along the SOM network and is able to draw lines from any point in the 2D workspace. This method also allows the transfer of motor programs [5] throughout the workspace.

Nowadays, "sketching robot" is popular among people who are interested in writing and sketching. The common sketching robot usually has the problem of large size, high power consumption, and can only print the given picture. This project aims at the common problems of sketching robot in the market, and designs and realizes a new set of writing robot. The mechanical structure was redesigned to obtain a

* Corresponding Author

large sketching range with a small volume on the basis of the parallelogram mechanism, and there was an independent pen lifting mechanism. Convolutional neural network is used to design a software of identifying stick figure sketches, which can reduce the difficulty of sketching and improving the sketching efficiency.

2 System Architecture

The hardware part of the system is composed of motor, mechanical frame and pen clamping structure. The software is composed of a hand-drawn quick correction system, image to path points algorithm on the upper computer. Fig. 1 shows the basic structure of the system.

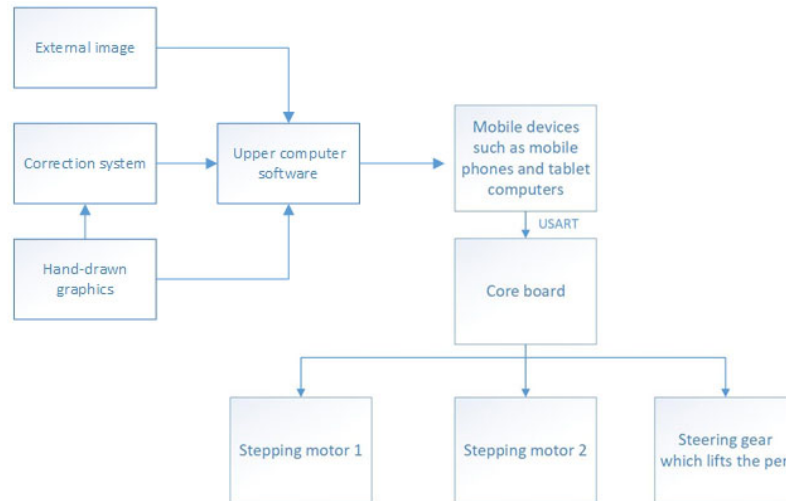


Fig. 1. Diagram of the robot system architecture

3 Mechanical Structure Designs

3.1 Arm's Coordinates-angle Conversion Algorithm

Among the feasible schemes, the most common type is the x-y based mechanical structure [6], in order to reach each point of the sketching surface, the occupied area of the machine should be greater than the area of the sketching surface. Common robot arm needs multi - axis and complex structure, these two mechanical structures needs to occupy a large volume.

This robot adopts the mechanical structure of double motors, and reach the corresponding point to complete the sketching task through continuous control of motor rotation of the specific angle. Since the path information of the drawn image is represented in the cartesian coordinate system, the robot needs an Angle that can be converted from the coordinates in the cartesian coordinate system to the angle of the mechanical arm controlled by two motors for the purpose of sketching. Fig. 2 and Fig. 3 shows how the robot arm moving.

In this conversion algorithm, L denotes the axis spacing length of the robot arm, in which the left arm must be on the left side of the right arm. Therefore, it is assumed that θ_2 denotes the larger Angle between the arm and the polar axis is relative to the polar axis, and θ_1 denotes the other.

Any sketch can be made up of points connected by straight lines, and a straight line can be made up of points as well. Therefore, it is necessary to design an algorithm that can convert the points of cartesian coordinate system into the angles of the robot arm's motor.

The following Fig. 4 describes the method of coordinating transformation.

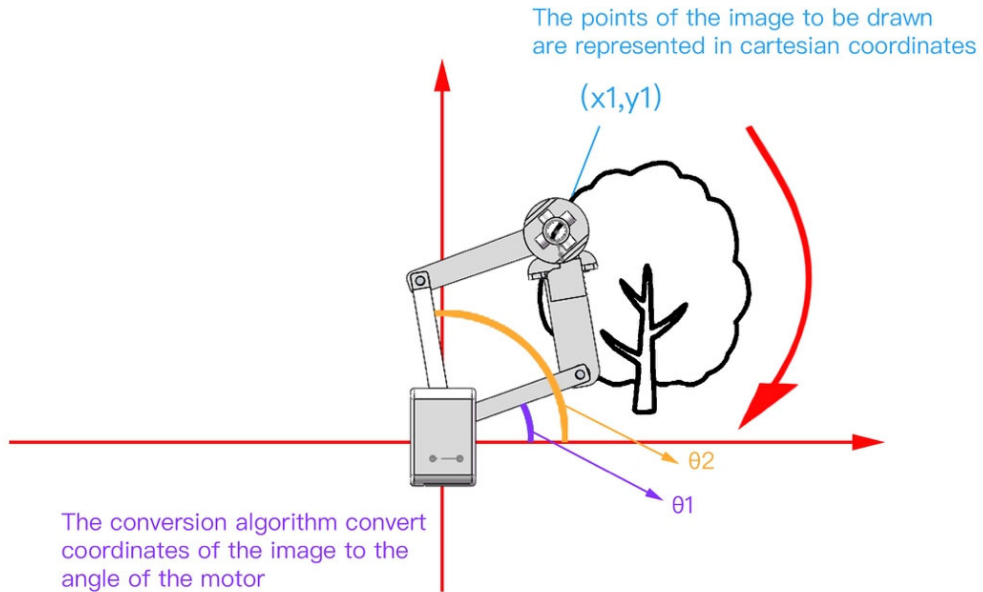


Fig. 2. Principle of the conversion algorithm

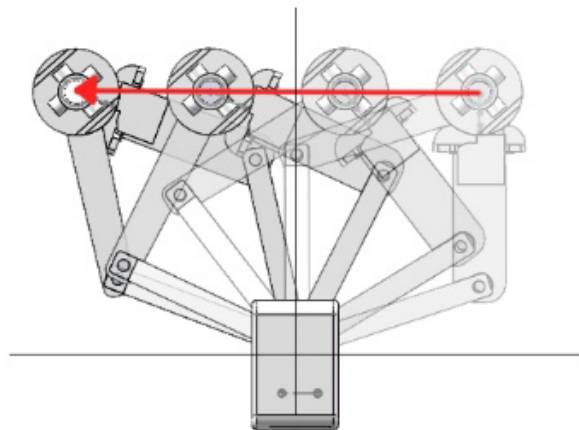


Fig. 3. Polar coordinates mechanical diagram

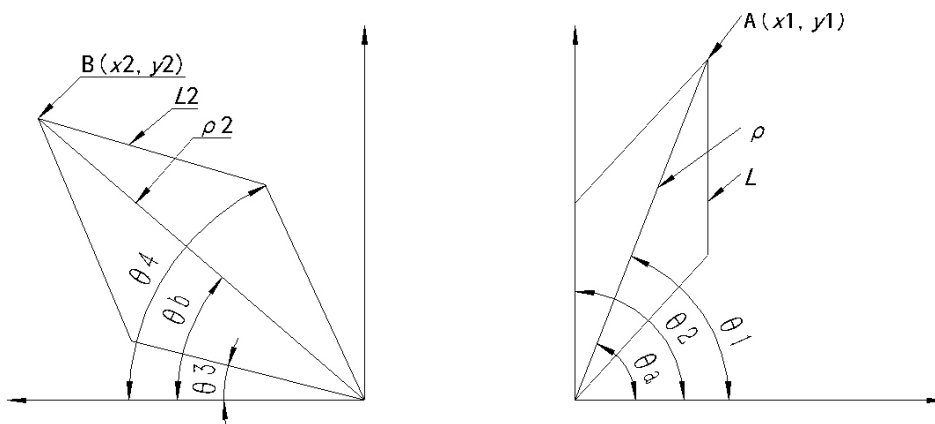


Fig. 4. Diagram of principle of conversion algorithm

Consider a moment the robot gets to the point $A(x, y)$ on the paper, in polar coordinates, that is $A(\rho, \theta)$.

So that

$$\rho = 2L \cos\left(\frac{\theta_2 - \theta_1}{2}\right) \quad (3.1.1)$$

it follows that:

$$\cos^{-1}\left(\frac{\rho}{2L}\right) = \frac{\theta_2 - \theta_1}{2} \quad (3.1.2)$$

Let $\theta = \frac{\theta_2 + \theta_1}{2}$, then

$$X = \rho \cos \theta \quad (3.1.3)$$

Substitution θ and simplify

$$\cos^{-1} \frac{x}{\rho} = \frac{\theta_2 + \theta_1}{2} \quad (3.1.4)$$

Combine (3.2), (3.4)

$$\begin{cases} \cos^{-1} \frac{\rho}{2L} = \frac{\theta_2 - \theta_1}{2} \\ \cos^{-1} \frac{\rho}{2L} = \frac{\theta_2 + \theta_1}{2} \end{cases} \quad (3.1.5)$$

Then obtain:

$$\begin{cases} \theta_1 = \cos^{-1} \frac{x}{\rho} - \cos^{-1} \frac{x}{2L} \\ \theta_2 = \cos^{-1} \frac{x}{\rho} + \cos^{-1} \frac{x}{2L} \end{cases} \quad (3.1.6)$$

After that, the robot can drive the motor to the corresponding angle to make it sketching on any position on paper.

3.2 Design of Main Mechanical Components

All the mechanical structures are made of SLA 3D printing technology, with has high accuracy and well material strength. The main parts of the robot are shown as Fig. 5, and the assembled robot is shown in Fig. 6.

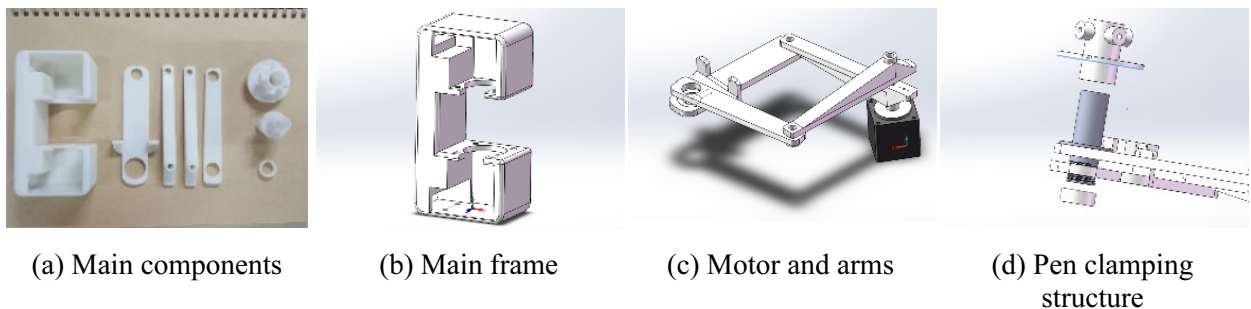


Fig. 5. The main parts of the robot

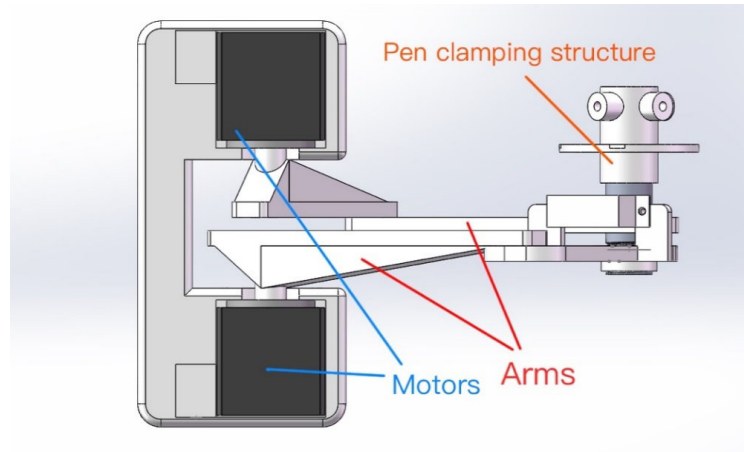


Fig. 6. Mechanical diagram of the robot

3.2.1 Main Frame

The main frame is used to accommodate two motors. Fig. 5(b) shows the main robot frame. In order to minimize the friction between the Stepper motor arms and avoid sketching problems caused by excessive space between the two arms, the accuracy has been adjusted to higher by adding washers and fixed screw. At the same time, the frame also has PCB mounting hole and motor wiring outlet which can be used to setup.

3.2.2 Robot Arm

As shown in Fig. 5(c), parallelogram structure is adopted to drive the robot arm. Most of the instability factors of the whole machine come from here, which have the most significant influence on the sketching effect. The arm is fixed with ball bearing and screw, they can reduce the friction to a very low level, to ensure well sketching effect.

3.2.3 Pen Clamping Structure

As shown in Fig. 5(d), due to the large length of the robot arm, it is far away from the main control board. In addition, the weight should be reduced as low as possible to avoid the structural problems. Therefore, micro servo is used to drive the pen structure. Micro servo is light in weight, simple in driving and large in torque. Fig. 7 shows the effect of lifting and dropping the pen.

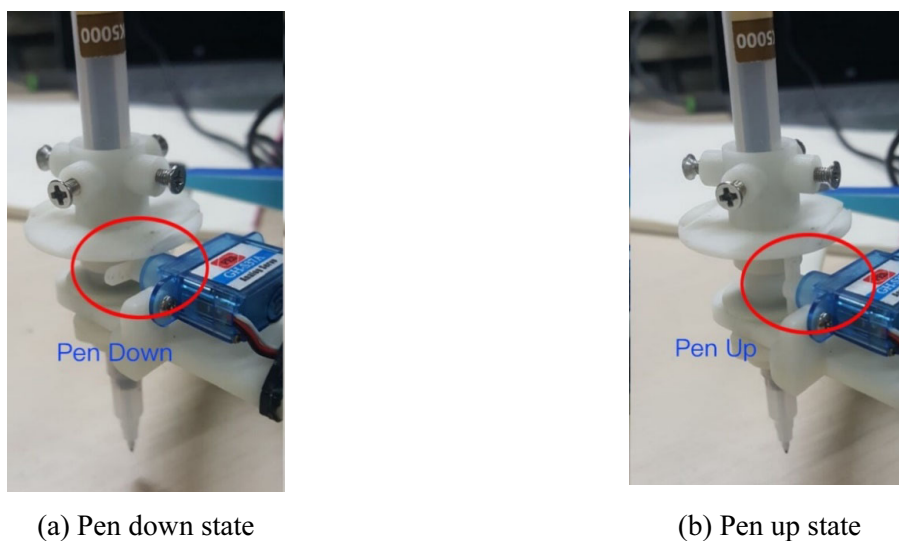


Fig. 7. The effect of lifting and dropping the pen

3.3 The Calculation of Sketching Range

One important question to consider is whether the range of the sketching can fetch the required position on paper. If the range of sketching is too small, the robot will have little practical value. The important parameter that determines the drawing range is the range of the motor can rotate. In order to obtain the rotation range of the robot arm, the maximum angle of collision of the arm and the body was calculated as 52.07° shown in Fig. 8.

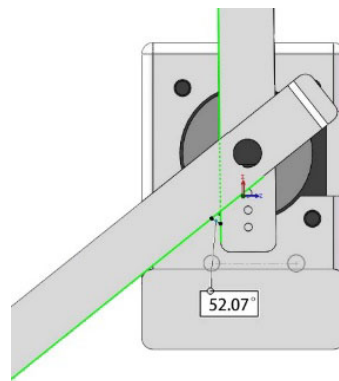


Fig. 8. Calculation results of the maximum Angle achievable by the arm (profile map)

In order to leave a surplus, we choose 45° for the 2 motors rotation Angle in the range of $-45^\circ \sim 225^\circ$. 4 robot arms of a length of 8CM was selected, and the coordinate transformation algorithm above was used for simulation to traverse all accessible points. The simulation results from these conditions are as follows. It can draw a semicircle with a radius of about 15CM. Up to 50% of a piece of standard A4 papers, can adapt certain sketching requirements. The diagram of sketching range is shown in Fig. 9.

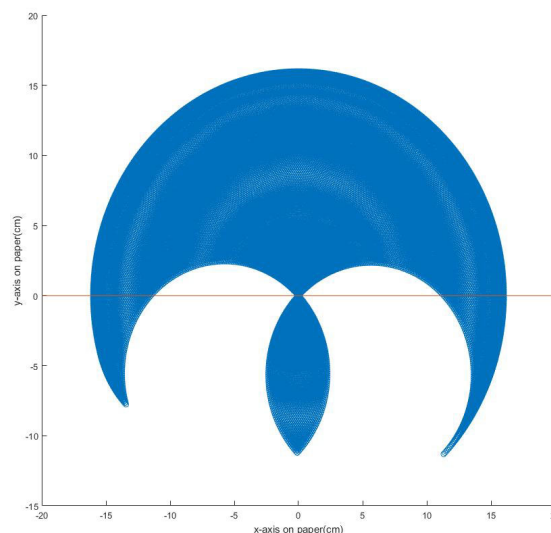


Fig. 9. The range of the robot that can be sketched (CM)

3.4 Motor Control Algorithm

After receiving the data from the upper computer, it is verified, converted and classified to obtain a set of coordinate data. Then, the coordinate transformation algorithm is used to calculate the target angles of the two motors required by the target coordinate, and then the step number of the stepper motor is converted into the target step number. After that, the resolution of the segmentation coefficient is calculated by taking the larger value of the total steps of the two motors. Enough segmentation is conducted for the straight-line segment between the current point and the target point to ensure that the number of rotation steps of each Stepper motor between each segmentation target is no more than two steps. Using the

DRV8825 [7] chip to drive the stepper motor, the stepper motor is always in the state of 32 subdivisions, i.e., the stepper Angle is 0.05625 degrees per pulse, which makes the sketching and calculation error in the system no more than 0.24mm. Then, the conversion algorithm is used again to calculate the number of steps required by the segmentation target. The driving motor passes through each segmentation target in turn, and records the number of steps taken by the actual driving motor. Finally, determine if there is any error caused by decimal error while computing. Floating variables calculation of the segmentation coefficient, and make up accordingly. Fig. 10 shows the working principle of the motor.

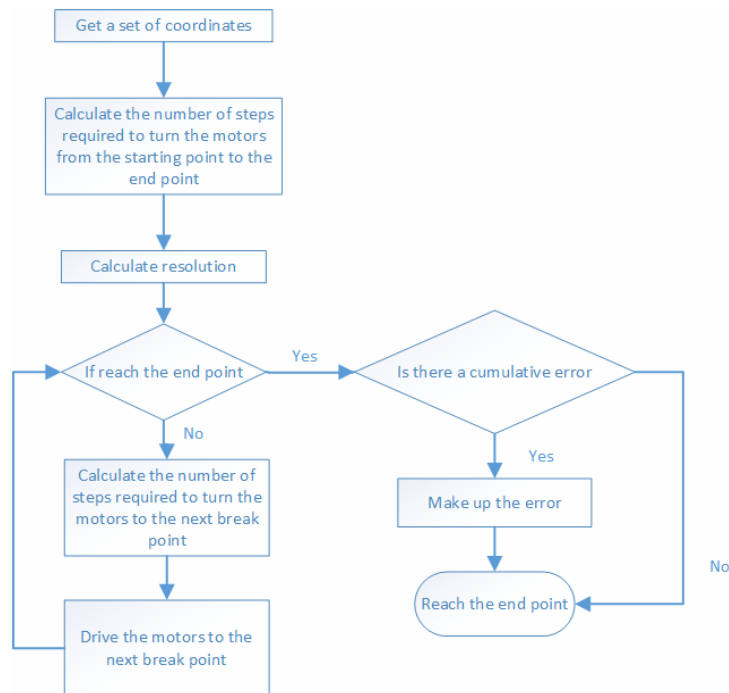


Fig. 10. Motor control algorithm flow chart

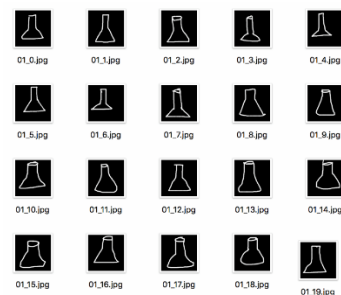
4 The Realization of Hand Sketching Quick Correction System

4.1 Fast Access to Data Set Extension and Preprocessing

This system studies stick figures and is used to quickly convert it to standard sketch in a short time. In conventional recognition machine learning algorithms, the acquisition of data sets is usually not an easy task, and the following parts will try to solve these problems. Some chemical instruments and some common items are selected for sample extension. First of all, hand-painted acquisition software is made, which can save and number the hand-sketching images in batch and shown in Fig. 11.



(a) Hand-drawn images



(b) A sample library of multiple sketching

Fig. 11.

It takes time to draw sketch in data set by hand, but the quantity is not simple to enough. Therefore, in order to increase the number of training samples, improve the accuracy of identification and reduce the workload, the sample sketches collected are randomly rotated and shifted. At the same time, in order to prevent the storage of these sketches too large, reduce the calculating time, and reduce the size of the pictures, the software extended each training sample into 100 different sketches, and then it will get 5000 sketches of each type shown in Fig. 12. Then reduce the size of image to 32x32. The sample still contains most of the information on the original line, so it is suitable for training.



Fig. 12. Extension of an image produces multiple results

4.2 Convolutional Neural Network Models

Convolutional neural network has been successfully applied in hand writing character recognition [8-9]. The convolutional neural network used in this project has improved the traditional LeNet-5 model. The diagram of the CNN is shown in Fig. 13. The type of output in the traditional LeNet-5 is 10, but this is obviously too small for common stick figure sketches. In this project, the stick figure sketching library contains 30 types of images, so we have made a small improvement on the typical LeNet-5.

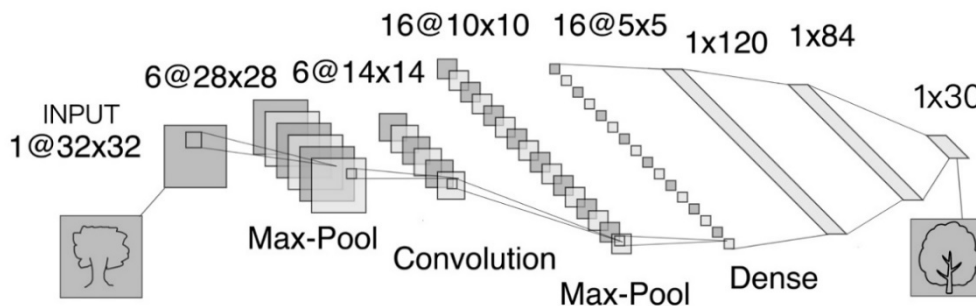


Fig. 13. Diagram of CNN

This network contains 7 layers entered a 32*32 pixel handwritten image. This network contains the following structures:

(1) Input layer. This layer uniformly converts the input image into a 28*28 pixel image to adapt to the input of neural network.

(2) Convolution layers [10]1: the first convolution operation is carried out on the image of the input layer with 6 5*5 convolution kernels, and 6 convolution feature graphs are obtained. We use the 5*5 convolution kernel, so we have $6*5*5+1=156$ parameters with a bias value.

(3) Pooling layer [11] 1: The first convolution is followed by pooling operation. The pooling is done by summing up the 2 by 2 cores of the previous layer multiplied by the weights and adding a bias parameter. There are $5*14*14*6=5880$ parameters.

(4) Convolutional layers 2: Conduct the second convolution after pooling to further extract features. It still using the 5*5 convolution kernel. Get 16 10*10 feature images.

(5) Pooling layer 2: Still use a 2*2 window to pool the results of the convolution of the previous layer to obtain 16 5*5 feature maps. There are $5*5*5*16=2000$ parameters.

(6) Convolutional layers 3: this is the last convolutional layer. Since the size of the 16 images input in this layer is 5*5, which is the same as the size of the convolution kernel, the size of the graph formed after convolution is 1*1. There are 120 convolution results. So, we have $(5*5*16+1) * 120=48120$

parameters.

(7) Full connection layer: There are 84 neural network nodes in this layer, corresponding to a binary image of 7×12 . The training parameters and the number of connections in this layer is $(120 + 1) \times 84 = 10164$. The activation functions sigmoid is used to output the function. The network structure of this layer is shown in the Fig. 14. The sigmoid function are shown as 4.2.1:

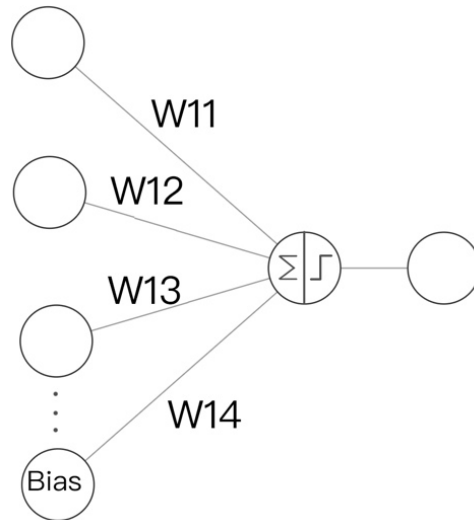


Fig. 14. Network structure of 7th layer

$$\text{sigmoid}(x) = \frac{1}{1 + e^{-x}} \quad (4.2.1)$$

8. Output layer, which is also a fully connected layer, has 40 nodes and is composed of radial basis function (RBF). Each neuron in the Output layer corresponds to a stick figure sketching category. The calculation method of output y of RBF unit is shown in equation 4.2.2:

$$y_i = \sum_j (x_j - w_{ij})^2 \quad (4.2.2)$$

LeNet-5 is a kind of neural network model that is very suitable for simple stick figure sketches. It can efficiently use the information on images, and involves fewer parameters and consumes fewer system resources. After the network structure is improved according to the number of stick figure sketches, it can adapt to the recognition requirements of this project.

4.3 Samples Training and Its Results

This model runs in TensorFlow AI framework and converges the model with gradient descent algorithm. The learning rate is 0.01, and the file name of the data set is the label of the file. In the training process, 90% of the pictures in the sample are taken as the training set, and 10% of the pictures are taken as the test set. The pictures in the sample are randomly input for learning. The batch size of learning $m = 90$, after training a batch of images, 10 pictures were tested, and the test results of these 10 pictures was recorded in the form of accuracy rate for effectiveness of statistical model.

After the training, the result is output in the diagram. In the early, the accuracy rate is about 8% to 14%. The accuracy of training has fluctuated, but the overall accuracy gradually increased, reaching about 95% in the later. The learning process is shown in Fig. 15 and the result is shown in Fig. 16.

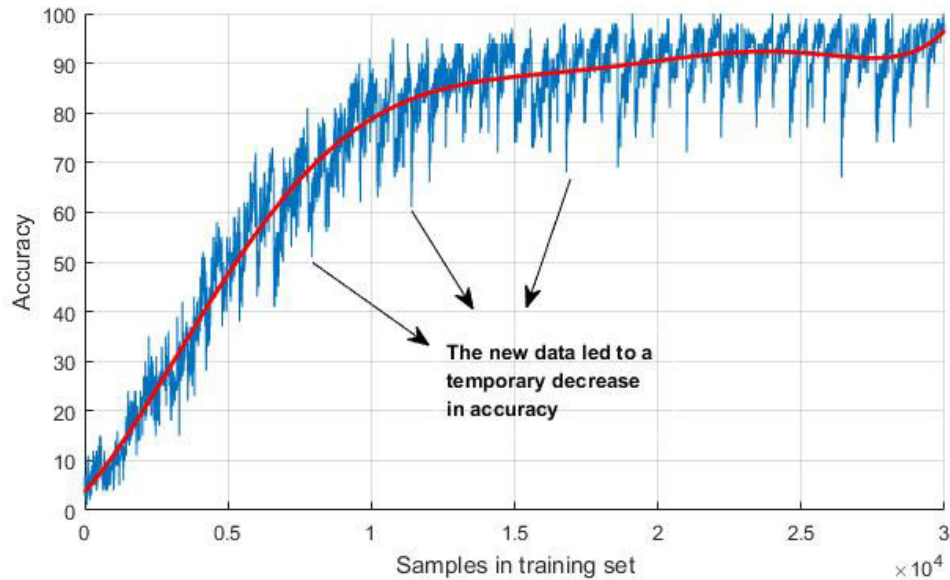


Fig. 15. The improvement of accuracy in training and its fitting curve



(a) Example of hand sketching quick correction system

(b) Results sketched by the robot

Fig. 16.

5 The Algorithm of Image to Path Point

5.1 Design of Image to Path Point Algorithm

The robot also needs to be able to draw a given image, not just the results of the correction system. Common images are in bitmap format and cannot be directly sketched by this robot, so we need to design an algorithm that can convert bitmap images into path points. This process is shown in Fig. 17.

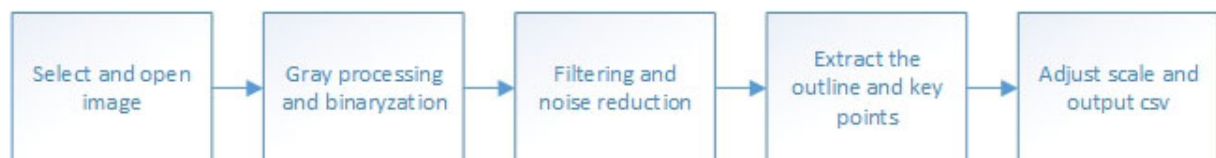


Fig. 17. The basic principle of image to path points algorithm

After the binarization of the image [12], the boundary tracking algorithm was used to obtain contour of the image, and a group of contours were obtained [13]. The robot connected these points with straight line then obtain the original image. This method is suitable for simple images without multi-layer contours like characters. This process is shown in Fig. 18.

**Crazy
Painter**

(a) Original image



(b) The original image and the extracted contour

**Crazy
Painter**

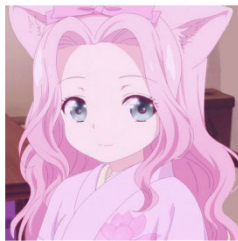
(c) Result of connecting the contour points with straight line



(d) The result of robot sketching

Fig. 18.

For the images with less obvious or more complex contour, we adopted the method of adding auxiliary white line in the images, and then binarized the images and extracted the contour to obtain the complex sketches drawn by the lines. The process is shown in Fig. 19. The closer the auxiliary lines are, the closer the result is to the original, but the longer of the sketching time.



(a) Original image



(b) Binary and add an auxiliary white line to the image



(c) Contour extraction of the image



(d) The results of robot sketching

Fig. 19.

5.2 Image Size Adaptive Algorithm

Since the input images are of different sizes, the image coordinates should be converted into the range of coordinates that can be reached by the robot before the extraction of the image coordinates. Firstly, we divide the coordinates into the left side of the picture and the right side of the picture. On the left side of the screen, the horizontal axis is negative and the rest is positive. Consider the robot arm's length $d = 8\text{CM}$, motor rotating Angle ranges from -45° to 225° , this program will map output point can be reached to all areas. Therefore, each time a new coordinate is converted, it is only necessary to judge whether the point belongs to the program, and then it can be judged whether the point is beyond the range of the sketching area, and the coordinate can be adjusted in proportion to the sketching area to the appropriate position. The formula of position adjustment is as follows:

$$\begin{cases} x_1 = (\sqrt{256 - x^2}) - \sqrt{16x - x^2} - \frac{(cing_x) \times 2x}{cing_y} \\ y_1 = \sqrt{256 - x^2} - 16x - x_1^2 \end{cases} \quad (4.2-1)$$

Where, x and y are the length or width of the image; x_{new} and y_{new} are the adaptive coordinate positions; $i[0]$ and $i[1]$ is the coordinate positions of the original image. Fig. 20 shows the result of this algorithm.

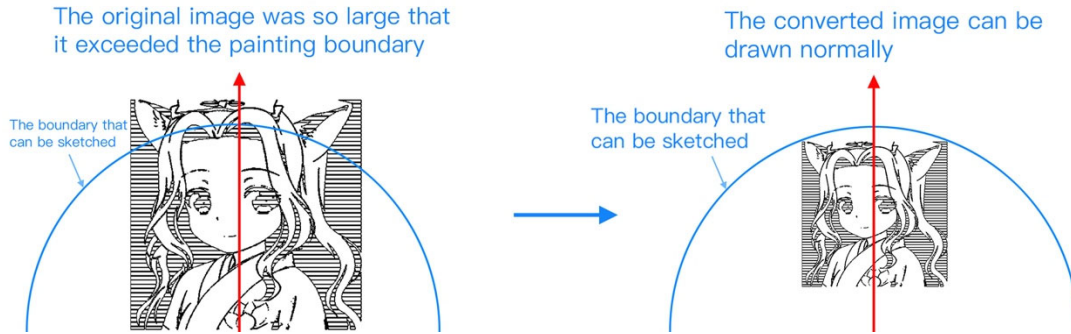


Fig. 20. Result of the image sizes adaptive algorithm

$$\begin{cases} x_{new} = 2x_1(i[0] - \frac{x}{2}) \\ y_{new} = y_1 \times i[1] \end{cases} \quad (4.2-2)$$

6 Conclusion

A portable tabletop sketching robot is designed by using the parallelogram mechanical structure which occupies a small volume, and adapted a set of images to path point algorithm. At the same time, the convolutional neural network is used to realize a sketching correction system. With this robot, people with low sketching foundation can draw beautiful images quickly. It is convenient for study and life and has the following advantages:

(1) the sketching robot using parallelogram structure, and improved the traditional sketching robot which has large volume, high power consumption, and high manufacturing costs, the sketching robot using this structure, make the volume, power consumption and cost is greatly reduced, at the same time, it still be able to keep large sketching area, improved the traditional sketching robot's largest problem.

(2) Designed a pen clamping structure integrated with the clamping structure on the robot arm, which makes sketching pen more flexible without occupying too much volume. This is one of the most difficult problems in volume reduction.

(3) A hand sketching correction system based on convolutional neural network is designed with LeNet-5 neural network, which occupies less system resources, is used to recognize hand-painted images in real time. After sketching, the hand-painted images can be immediately converted into corresponding images which are more standard and can be drawn by the robot.

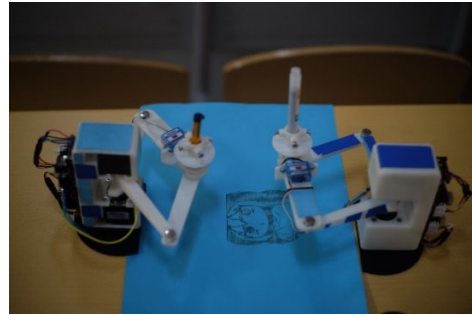
(4) An image-path conversion algorithm is proposed, which can process images with different complexity and convert them into paths that can be drawn by robots.

(5) For images of different sizes, adaption algorithm is carried out according to the sketching area, so that all of them can be normally drawn, and the problem of image beyond the sketching area is avoided.

The final product is shown in the Fig. 21. This sketching robot can be used for daily auxiliary sketching. It is a kind of small equipment with short production cycle and low manufacturing cost, which can meet different scenes. Equipment miniaturization is an effective way to develop science and technology, which can make more scientific and technological equipment convenient for production and daily life



(a) Interface of the upper computer



(b) the finished product

Fig. 21.

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