Circuit Sketch Recognition

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***Abstract*—Recognizing circuit sketch is very useful for electrical engineers. In this project, we use topology based segmentation method to segment circuit sketch, and classify each component using the Fourier descriptors as feature vector for Support Vector Machine. An accuracy rate of over 90% is achieved for each component.**

Keywords—Fourier Descriptor, SVM, topology based segmentation.

I. INTRODUCTION

It is a common practice for engineers to spend a considerable amount of time laying down initial concepts using pencil and paper. Typically, it requires additional time to transform the work into electronic media in the form of technical drawings. A sketch recognition program would save engineers much time redrawing these in technical software.

In our project, we want to achieve a trainable electronic sketched circuit recognizer that has fast response time, high accuracy and easy extensibility to new component.

Challenges in sketched symbol recognition lie in the different sketch styles of different users and various approaches have been made to solve this problem [1][2]. To achieve scale invariance, rotational invariance and tolerance of different drawing types, we used Fourier descriptor [3] of the boundaries of electronic component as feature vectors for SVM classification for recognizing the component. We also devised an efficient way of segmenting electronic circuits into individual components for recognition.

II. FEATURE EXTRACTION

Fourier Descriptors

Fourier transform is widely used for shape analysis. Their nice characteristics, such as simple derivation, simple normalization, and robustness to noise, have made them popular in a variety of applications. These descriptors represent the shape in frequency domain. Low frequency components contain information about the general features of the shape, and the higher frequency components contain finer details of the shape. Though different people may have different drawing habbits, the subset of the low frequency cofficients tend to be similar for the same electronic component. So although the number of coefficients generated from the Fourier transform is usually large, the dimensions of the Fourier descriptors used for shape recognition can be greatly reduced.

A shape signature is any 1-D function representing 2D areas or boundaries. In Fourier descriptor implementation, complex coordinates and central distance [4] are the most common shape signature used.

For complex coordinates signature, the Fourier descriptor is obtained through Fourier transform on a complex vector derived from the shape boundary coordinates. Suppose the boundary of a particular shape has K pixels numbered from 0 to K-1. The k-th pixel has position (x_k, y_k). The complex vector S is given by the difference of the boundary points from the centroid (x_c, y_c) of the shape

$$S(k) = x_k - x_c + i(y_k - y_c), \quad k = 0,1,\dots,K-1$$

where

$$x_c = \frac{1}{N}\sum_{k=0}^{K} x_k \;, y_c = \frac{1}{N}\sum_{k=0}^{K} y_k$$

The discrete Fourier transform of S is

$$a(u) = \frac{1}{k}\sum_{k=0}^{K-1} S(k)e^{-j2\pi uk/K} \;, u = 0,1,\dots,K-1$$

The complex coefficients $a(u)$ are called the Fourier descriptors.

By dividing the Fourier descriptors with the magnitude of the 1st Fourier descriptor, we achieve scale invariance , by only considering the magnitude of the Fourier descriptors, we achieve rotation invariance [5][6]. By applying normalization, the 0-th and 1st Fourier descriptors do not provide any information. Hence these are eliminated. Experimentally we choose number of coefficients of Fourier descriptor to be 16 and use 2^{nd} – 17^{th} Fourier descriptor as the feature vector in our SVM model.

Another common shape signature is the central distance, which is expressed by the distance of the boundary points from the centroid of the shape (x_c, y_c),

$$r_k = ([x(k) - x_c]^2 + [y(k) - y_c]^2)^{1/2}$$

We compared the accuracy of both shape signature in our experiment and found that complex coordinate is more accurate for our purpose.

III. CLASSIFICATION

Support Vector Machine is a supervised learning model widely used for classification and regression analysis. For two-class problem, SVM finds the optimal hyper-plane which maximizes the margin between the nearest samples of both classes, named support vectors. We used a linear kernel for SVM in our approach. And binary SVM is extended to our multiclass recognition problem using one-versus-rest approach. The SVM is trained with 55 training samples for each type of electronic component.

IV. Data Set and Training Process

To recognize battery and capacitor, we use a different mechanism than other components: amplifier, diode and resistor. For amplifier, diode and resistor, we draw 55 training images in different styles for each type of electronic component. For each training image, we binarize it using locally adaptive threshold, filter noise out by removing small regions. A minimum bounding box is then fitted to the component and the cropped image is resized to 100x100 pixels. For each training image, we then find the boundary points and extract the 2nd-17th Fourier coefficients and train multi-class SVM using the feature vector.

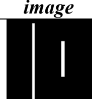
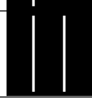
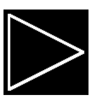
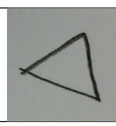
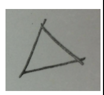
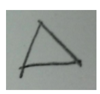
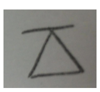
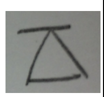
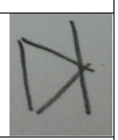
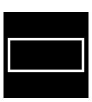
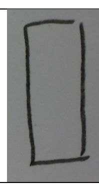
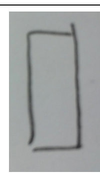
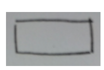
Components	**Database**			
	Standard image	***Sketch images***		
Battery		Different mechanism, N/A		
Capacitor		Different mechanism, N/A		
Amplifier				
Diode				
Resistor				

Figure 1: sample sheet of training images

V. Recognition Process

Our implementation primarily consists of four parts: Filter and binarize raw image; Segmentation of image to get each component; Classification for each component; Overlay Recognized component on the original images with proper orientation and size.

A. Image Filtering and Binarization

To recognize the different components from a sketch users draw, we first need to binarize the raw images using locally adaptive threshold method. Then we filter out small regions of noises.

After getting the binarized image, a crucial procedure would be to segment the image to get individual components.

B. Segmentation

To achieve high efficiency, instead of using a sliding window that may vary size in vertical and horizontal directions, we extract feature points based on the topology of the image and find boundingbox based on these feature points [7].

We classify each pixel in the skeleten of the circuit into four classes: end point, chain point, branch point and cross point which are determined by the following neighboring function:

Denote the eight neighboring pixels of the object pixels in a clockwise fashion as $n_0, n_1, \ldots, n_7$.

The neigboring function of the object pixel p is defined as

$$N(p) = \sum_{i=0}^{7} \Delta n_i \ ,$$

$$\text{where } \Delta n_i = \begin{cases} 1 & \text{img}(n_i) = 1 \text{ and } \text{img}(n_{i+1}) = 0 \\ 0 & \text{otherwise,} \end{cases}$$

and $n_8 = n_0$

If N(p)=1, then p is an end point;
If N(p)=2, then p is a chain point;
If N(p)>=3, then p is a branch point.

Chain point is just a connection point of a line, what we are interested in is end point and branch point. End point combined with other topology features are later used for deciding the orientation of the component and branchpoint is used for segmentation. We also need to remove spurious feature point generated by irregular sketches by merging feature point that are too near each other to one. After getting the set of valid branchpoints, we extract the two nearest branchpoint from the set each time and remove those from the branchpoint set. Each pair of branchpoints would determine one direction of the bounding box on the individual component. By comparing the horizontal and vertical values of the two branchpoints in each pair, we can determine the aligned direction of the component. Then we can search along the perpendicular direction till we find a region with all pixels to have the value of 0. Thus, we can find the minimum bounding box around the component, The bounding box would be enlarged several pixels on the aligned direction considering skewed sketches. This approach would be much faster than using a sliding window that may vary size in both perpendicular and horizontal directions.

C. Classification for each Component

After finding the bounding boxes for each component, for each component, we dilate the image and find how many connected regions it has. If it has two connected regions, then it is likely to be capacitor or battery, then based on the axis ratio of the axis of the two regions, we can classify it as capacitor or battery. Otherwise, we need to find boundaries of the component and extract the 2nd-17th fourier descriptors and perform SVM decision using the fourier descriptors. The classification process is summarized below.

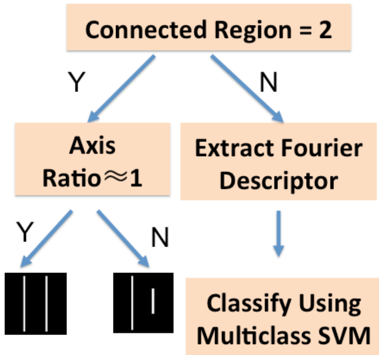


Figure 2:Classification Process

D. *Display on Original Image*

Finally, we need to correctly overlay the recognized component on the original image, though the horizontal and vertical direction can be determined by the alignment of branchpoint. For component such as battery and diode, we still need to decide whether we should flip the component by 180 degrees. We can divide the region containing to two halves and use topology features such as which region endpoints lie in or which region has more pixels with value 1 to determine whether we need to flip the component by 180 degree, then we can rotate the standard component and resize to overlay on the original sketch.

An sample run of the procedures is shown below.

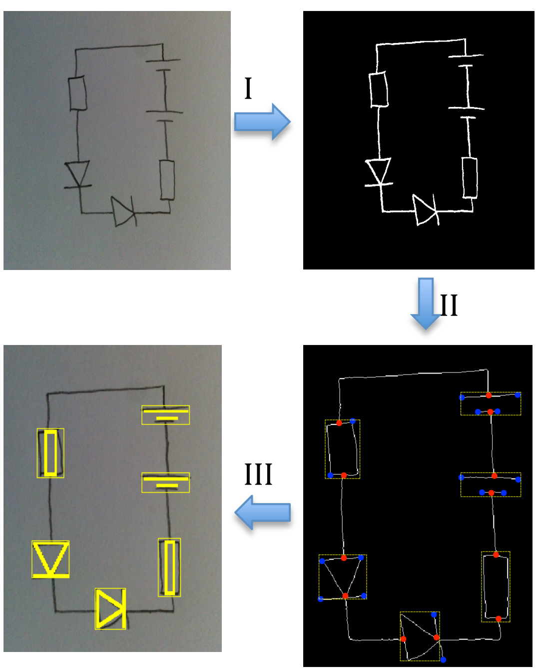


Figure 3: Recognition Procedures: (1) Binarization (2) Find feature points and corresponding bounding box for each component. (3) Classify each component using Fourier Descriptors as feature vector for SVM and overlay on original image.

VI. Experimental Result

For each of the component, we have 55 training images and 30 test images. The test images are drawn in different scales and orientations and in different style. By using low frequency subset of fourier descriptor of the complex coordinates of the pixels on the boundaries of the components as feature vectors for SVM, we achieved an accuracy of over 90%. And we found that our approach is fairly robust to change of scales, orientations and different styles of drawing. We also compared the accuracy of using complex coordinates shape signatures against the centroid distance signatures and find that complex coordinate is more accurate for our problem.

A. *Accuracy Dependence on Size of Traning Set*

Recognizing capacitor and battery uses a different approach and they achieve accuracy of 100%. What we disscuss here is the second group that are classified using SVM. For the second group, which consists of amplifier, diode and resistor, the accuracy for recognizing each component increases as our database for training images grows larger. When there are fifty-five training images, our correct rate for recognizing amplifier, diode and resistor are 93.33%, 93.33% and 96.67% respectively when testing the thirty test images individually. This gives us an estimation of how many training images we need for each component if we want to support more categories of component. The influence of traning size on recognition accuracy is shown as follows:

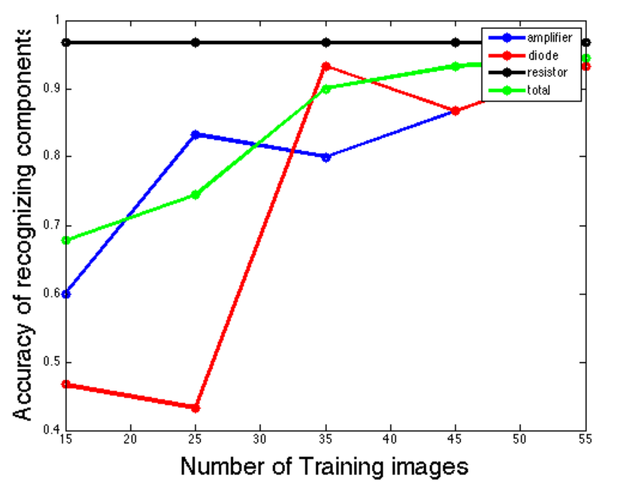


Figure 4: Accuracy Dependence on size of training set

B. *Comparison of Centroid Distance and Complex Coordinates*

The test result of using the centroid distance as shape signature is not as accurate as complex plane Fourier descriptor for detecting electronic components. The accuracy for amplifier, diode and resistor are all below 70% with training set size of 55 for each component. When using the complex plane Fourier descriptor we can achieve an average accuracy of 94.44% . The result for each component is shown in the following table:

TABLE I. ACCURACY COMPARISION

Centroid Distance Fourier Descriptor Accuracy(%)			Complex plane Fourier Descriptor Accuracy(%)		
amplifier	diode	resistor	amplifier	diode	resistor
70.00	60.00	56.67	93.33	93.33	96.67

C. Test on connected circuits

We tested on 6 hand-drawn connected circuits with a total of 26 components, and we correctly recognized 25 components. The one missing is due to when doing segmentation, we filtered out a branch point due to much noise near the branch point. The whole process (Including locally adaptive threshold, segmentation, and classification) would on average take 2 seconds to finish. This is much less time consuming than using a sliding window approach for segmentation. This is a balance between response time and accuracy. In a real-world application, if we have a small miss rate, we can ask the user to select a missed component to be recognized, and is in general a better approach than asking the user to wait a long time for an exhaustive search without feedback.

VII. CONCLUSION AND FUTURE WORK

We have developed a method to recognize components in a sketched electronic circuit effectively. We utilized topology based feature point for segmentation. We used Fourier descriptor of the complex coordinates of the boundary of the component as feature vector for SVM. We have demonstrated a high accuracy recognition rate with invariance to image rotation, scaling and modification. Our system is extensible to recognize more catogories of circuit component. We believe it is a promising approach to recognize hand-drawn sketches and produce standard circuit diagram. Future directions include (1)more training data for better SVM model and more types of component for recoginition. (2) Combine other features such as image moments as features for SVM. (3) Better and faster segmentation method. (4) Separate recognition of text and numerical values with electronic component.

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APPENDIX: CONTRIBUTIONS

Yuchi Liu
Implement preprocessing, Segmentation, Fourier descriptor extraction, SVM, displaying result.

Yao Xiao
Training image and test image generation. Accuracy Test.