COMPARISON EXPERIMENTAL RESEARCH ON THREE PRE-PROCESSING MODELS OF ONLINE HAND DRAWN DIAGRAM

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ABSTRACT

In this paper, we experiment the capabilities of three pre-processing models to eliminate the human-machine conversation signal noise produced by the movement of a pen when drawing a diagram sketch such as an electrical circuit diagram. Aiming at some sketch capturing problems, such as the different resolution of sampling device, different speed of the sketching tool, the different of writing style, the three models found on two sorts of normalization, that is equal distance normalization and unit-based normalization. On a dataset of 300 hand-drawn sketches and two different recognition algorithms, the proposed pre-processing models allow to locate most of the input track, especially, the unit-based models is able to be independent of different environments of sampling devices.

1. INTRODUCTION

Online hand drawn recognition is a representative species of multimedia human-machine conversation. It is the ability of a computer to receive and interpret intelligible handwritten input, which is an important portion of information processing, multimedia demonstration and Official Automation (OA). It involves the automatic conversion of text as it is written on a special digitizer or PDA, where a sensor picks up the pen-tip movements X(t),Y(t) as well as pen-up/pen-down switching. With the develop of Tablet PCs, digital pen and paper technologies, electronic whiteboards and other electric digitizers, pen interfaces are an actual convenient and welcome modality to input texts and sketches in a computer, playing an indispensable role of human-machine conversation.

While handwriting text recognition is already widely addressed as a research topic (e.g., [1]), much less effort has been devoted to hand-drawn sketch understanding. Hand-drawn sketch is a natural and direct way to express people's thought and meaning, and is of common use in many different fields. Diagram sketches are widely used in engineering and architecture fields. This is mainly due to the fact that a sketch is a convenient tool to catch enough ideal, so that the designers can focus more on the critical issues rather that on the intricate details (e.g. [2]). In this work, we propose to investigate the problem of automatic understanding of online sketches, and as an important processing step, we aim at analyzing the sketch raw input stream normalization which is the first step to implement a precise and suitable segmentation and recognition with different pattern matching algorithms.

In the current research, sketch recognition is classified into four directions (e.g. [3]), that is stroke-based, primitive-based, feature-based and composite-based recognitions. The stroke-based research directly applies the user hand drawn track. Rubin (e.g. [4]) presents typical trainable gesture recognition. Based on the linear discriminate classifier, it sorts the Gesture into 11 geometry features and 2 dynamic features, and thus, only a few train samples are demanded. But it requires users to finish one symbol in only one stroke. The second one is primitive-based research, which considers the graph as space combination of line, arc, circle, curve and other segment units, eliminating the limitation for user input mode and having a much more efficient recognition result. Segzin (e.g. [5,6]) and Calhoun (e.g. [7]) point out the basic template matching models. The third one is feature-based recognition, which extracting the sketch geometric feature to segmentation and recognition. Gross's Electronic Cocktail Napkin Project（ECNP）(e.g. [8]) is an typical model of multi-stroke recognition based on this kind. The last direction is composite-based recognition. The task is to solve the recognition of graph with complex figure structure. Some scientists (e.g. [8,9]) consider it to be a isomorphic problem of symbol and sub-symbol, so that it is able to translate into the three directions above.

Although different people may scribble the same symbol in different strokes numbers and orders, we are able to do segmentation by dint of the four unit symbol recognitions. However, we should first precisely pre-process the input raw stream before the sketch recognition. In this paper, we enumerate three kinds of pre-processing models and make a comparison with two typical recognition algorithms. The organization of the paper is as follows. Section 2 describes the pre-processing techniques for the raw sketches. Section 3 discusses the experiments and results, followed by the concluding remarks in the final section.

2. PRE-PROCESSING STAGE

Pre-processing stage is one key portion of hand drawn diagram recognition. After captured by a regular time intervals instrument, a raw input stream is generated, but it is not suitable for the unit composing recognition until being pre-processing. The target is to amend the raw signal to eliminate the diagram noise that is aroused by the input instrument limitation or the user writing style. Sampling the same coordinate value repeatedly, over-tracing are some typical phenomenon of this kind. However, the signal amendment should maintain the original diagram feature as far as possible, so that the writing thought is able to apprehend correctly.

2.1 Equal distance normalization model

Since there are many different kinds of symbols diagram in each sketch and each symbol has its own stroke connect relationship, the users have different speed and stress to each sketch and symbol. However, the sketch is captured by the regular time intervals instrument, which makes it possible to capture one point value more than one times. To eliminate the sort of diagram noise, the equal distance normalization model is rare necessary. A basic model is shown in Fig.1-c, with its function expression in eq.(1). In this model, all the captured data is normalized to a point stream with a fixed distance apart between each point. With this method, we have a common evaluation standard to one diagram sketch, and consequent is able to extract the writing feature and make the segmentation or recognition precisely.

$$\text{distance} = \frac{stroke - length}{no\#\_new - resample - \text{point}} \quad (1)$$

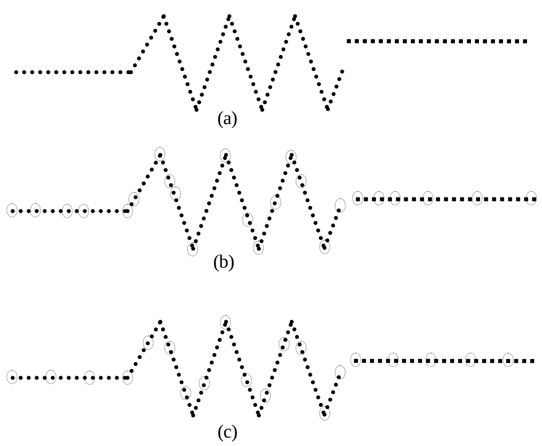


Figure 1 Basic equal distance normalization model. (a) shows the input track. (b) shows the raw sample stream which is generated by the regular time intervals instrument. (c) shows the point stream after the basic equal distance normalization algorithm.

Online hand drawn research and recognition is a process of studying human's writing habits. This basic equal distance normalization model is a very generic one, but it will delete some possible important signal point, leading to the non-ideal stroke segmentation. Therefore, Fig.2 shows an improved equal distance normalization model. In this model, the same raw input stream is adopted as Fig.1-b, but the new stream number is the same as the raw one, while that of the basic model is less than the raw one. Not only does it eliminate the hand drawn sketch noise, but also this model is able to recover the input track and reserve the turning-point as much as possible.

$$\text{distance} = \frac{stroke - length}{no\#\_original - stroke - \text{point}} \quad (2)$$

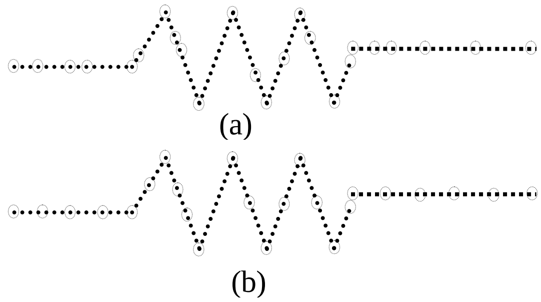


Figure 2 Improved equal distance normalization model. (a) is the raw sample stream which is generated by the regular time intervals instrument. The data is the same as Fig.1-b. (b) is the point stream with the improved equal distance normalization algorithm.

2.2 Unit-based normalized model

The velocity of the sketching tool can be very different in different places of the sketch or in sketches from different users (see Fig.3). In order to be independent with respect to the speed of the tool, but also of the size of the symbols, and the resolution of the sampling device, a unit-based normalized model is carried out.

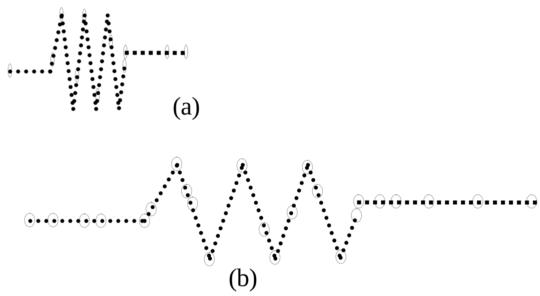


Figure 3 Symbol of different size symbol from different users which are captured by the same time intervals.

The unit-based normalized model consists in estimating a scaling parameter, which will be used to resample the sketch at a fixed spatial interval. However, straight lines and irregular segments are not processed in the same way. For long line segments, it is done with an idiographic equal distance based on the number of original points and on the line length. For arcs or lines with many turning-points in small distances, we will detect all the possible turning-point based on the symbol height variant and set the same number of points with an idiographic equal distance between two extremity turning-points.

Consequently, processed by this model, we expect to obtain approximately the same number of points for symbol features such as symbol height whatever their original size was, take the resistor of the electric circuit diagram for example (see

Fig.4). The scaling parameter is automatically computed from the histogram of the length of the small line-segments.

$$\text{distance} = \frac{Unit\,(High)}{4} \tag{3}$$

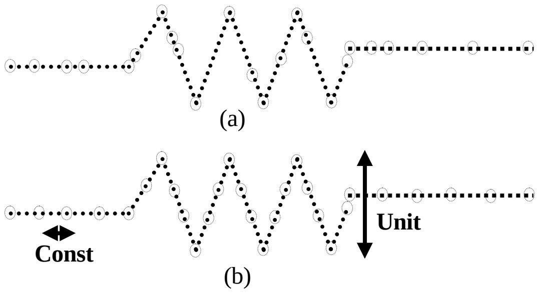


Figure 4 Unit normalized model. (a) shows the raw data. (b) shows the unit normalized model. For the long line segment, it is done with an idiographic equal distance based on the number of original points and the line distance in (a). For arcs or a line with many turning-points in short distance, all the possible turning-points are detected based on the symbol height variant and set the same number of point (we set 4 points in this symbol) with an idiographic equal distance between two neighbouring turning-points.

In Fig.4, the sketch normalized is classified into long line and short line (or arc) resample, instead of normalizing with the same fix distance everywhere, which can farthest avoid neglecting the inflexion or corner information.

3. SYSTEM EVALUATION

In our research, electric circuits have been considered as typical diagrams to test the proposed normalization models. We aim to extract all the connectors, which are supposed to be only straight line segments, and consequently to increase the level of understanding of the diagram sketch by providing a classification of the segments within connector or component classes. More details about the approach model description are in [10] and [11]. At the same time, Hidden Markov Model (HMM) and Support Vector Machine (SVM), which have been widely applied in the hand drawn diagram research, are the two algorithms introduced to segment and recognize the hand drawn sketches and make a comparison.

We asked 15 subjects to draw each a series of electric circuits. Samples are collected using our touch screen platform, so that drawing is done very freely, as on ordinary document. Each of them is asked to copy 20 diagrams and the information is stored as a series of 2D coordinates. As the samples are drawn on the paper, modification is not allowed. However, there are no constraint on the direction and the size. Fig.5 is an example of a collected electrical sketch. And table 1 shows the instruction of the recognition experience ground truth. Points of zone A and zone D show the connector and electric component extraction rate respectively. Points belong to zone B and C are miss-recognition points. Some connector points are recognized as components (zone B). Conversely, some points actually belonging to components are recognized as connector points (zone C).

Table 1 Recognition result instruction*

Ground truth \ Reco	Labeled Connector	Labeled Component
Connector	zone A	zone C
Component	zone B	zone D

*zone A = P (reco- Connector | label-Connector)

$$= \frac{num\!-\!recognized\!-\!connector}{num\!-\!labeled\!-\!connector} \times 100\%$$

(following zones are the same)

zone B = P(reco- Component | label-Connector)

zone C = P(reco-Connector | label-Component)

zone D = P(reco -Component | label-Component)

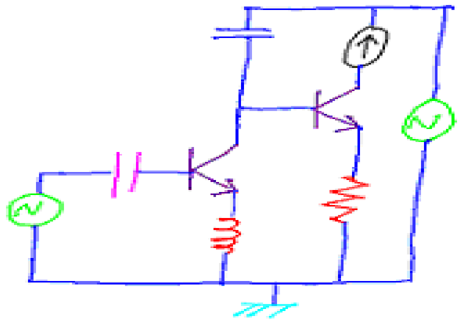
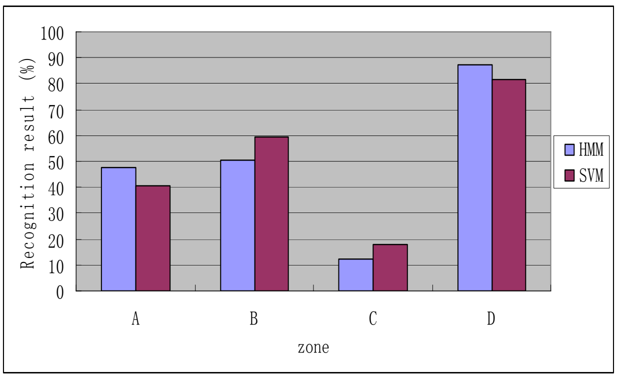


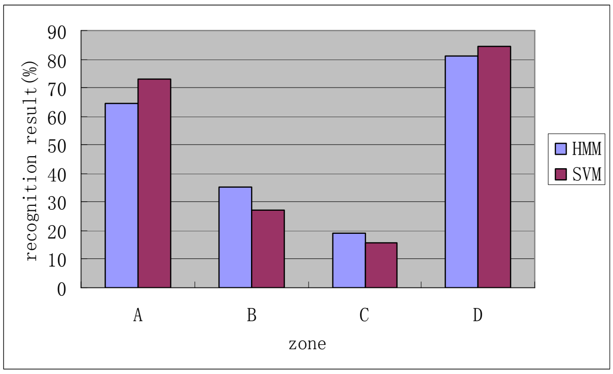
Figure 5 Online hand-drawn electric circuit diagram

Fig.6 presents the recognition results of the non-normalized model and the three normalization models processed by HMM and SVM separately. Fig.6-a shows the non-normalized model result. Fig.6-b shows the basic equal distance normalization model in Fig.1. Fig.6-c shows the improved equal distance normalization model in Fig.2. Fig.6-d shows the unit-based normalized model in Fig.4.

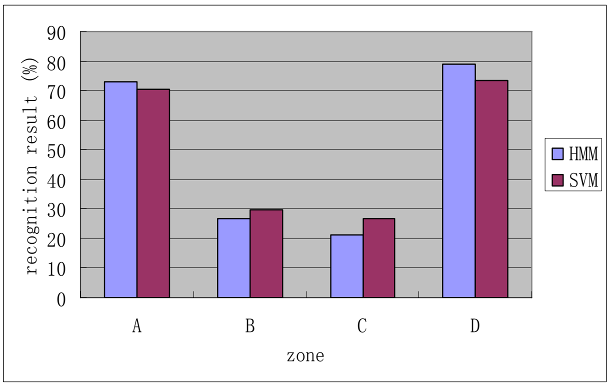
We also make a comparison on the electric circuit diagram connector extraction rate among the three normalization models (see Table 2).



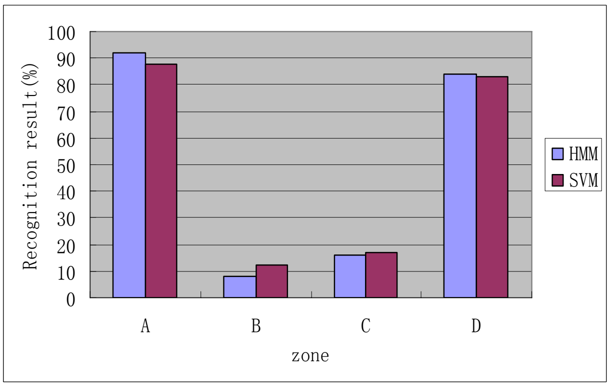
(a)



(b)



(c)



(d)

Figure 6. Recognition result of three different normalization models.

Table 2 connector extraction rate (zone A)

	Non normalized	Basic model	Improved model	Unit model
SVM	40.71%	75.24%	70.28%	87.65%
HMM	47.59%	64.57%	73.14%	91.91%

From table 2 it can be seen that, all the three resample models have obvious effect on the recognition with both HMM and SVM. That is to say, with the normalization technology is an appropriate and indispensable assistant for the sketch understanding correctly. All the three models have acquired a segmentation rate at least 70%, while the non-normalization model is only 40%. For the HMM algorithm, the sketches without normalized model receive only a result of 47.59%. Similarly, SVM is less, which also only receives a low recognition rate of 40.71%.

Compared the two equal distance models (see Fig.6-b and Fig.6-c), the segmentation result does not discrepance hugely. For the HMM algorithm (see the blue column), the connector extraction rate of improved model goes over 70%, while the basic one is under 70%. That is to say, the improved equal distance resample model has slightly higher efficiency than the basic model. However, the SVM algorithm (see the rose column) has an absolutely opposite result. It means that the basic model does favour of the SVM algorithm, nevertheless the improved one is suitable for the HMM algorithm. In despite of that, these two models have twin function, knew from the similar recognition results of Fig.6-b and Fig.6-c. The only difference of the required model is which kind of specific diagram. The rest zones follow the trend of the connector extraction rate.

The unit-based normalization model, both in HMM and SVM algorithm, has a higher efficiency than the others, observed from the results of Fig.6-d and Table 2. Concerning the connector extraction rate, with HMM recognition model, it is around 70% in model (b) and model (c), but it goes up more than 90% in model (d).At the same time, the SVM model has similar performance, which has an average of 87.65%. It means the model can locate and recover most of the real segment points. Therefore, among the three normalization models, the unit-based model is a better solution in the pre-processing stage, which is able to be independent with respect to the speed of the tool, but also the size of the symbol, and the resolution of the sampling device.

4. CONCLUSION

In this paper, we propose three pre-processing methods of online hand drawn diagram sketch that is an important species of multimedia human-machine conversation. With a view to the problems displaying in the course of online hand drawn, such as the different speed of the sketching tool, the different writing style, the different writing stress, the different resolution of sampling device, our methods adopt equal distance pre-processing, or unit-based pre-processing to eliminate the diagram noise, allowing the sketch to express the user track. Then, to make a comparison, two different algorithms are introduced to do stroke segmentation and recognition. The result shows that the pre-processing stage is an appropriate and indispensable assistant in the diagram understanding. Besides, all the three methods effectively eliminate the diagram noise, especially the unit-based model, which is independent of sampling device. This demonstrates that the research extension of multimedia human-machine conversation from handwritten character recognition to sketch understanding is a promising area of interest. In this domain, the more constraints can be integrated in the recognition topology, the more accurate the results would be.

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REFERENCES

[1] R. Plamondon, S.N. Srihari, "On-Line and Off-line Handwriting Recognition: A Comprehensive Survey", In *Proc. IEEE Transactions on PAMI, 2000*, Vol.22, No.1, pp.63-84.

[2] C. Calhoun, T.F. Stahovich, T. Kurtoglu and L.B.Kara, "Recognizing multi-stroke symbols". In *Proc. AAAI Spring Symposium on Sketch Understanding*, Palo Alto, USA, 2002, pp. 15-23.

[3] Sun Z., Feng G., Zhou R., "Techniques for sketch-based user interface：Review and research", *Journal of Computer-Aided Design & Computer Graphics*, 2005, 17(9):1889-1899 (in Chinese)

[4] Rubine D. "Specifying gestures by example". *Computer Graphics*,1991,21(4):329~337

[5] T.M. Sezgin, R. Davis. "Sketch recognition in interspersed drawings using time-based graphical models". *Computers & Graphics* 32 (2008) 500– 510

[6] T.M. Sezgin, R. Davis. "Sketch Interpretation Using Multiscale Models of Temporal Patterns". *Computer Graphics*, 2007 (Vol. 27, No. 1) pp. 28-37.

[7] Calhoun C, Stahovich TF and KurtogluT, etal. "Recognizing multi-stroke symbols", In *Proc. AAAI Spring Symposium on Sketch Understanding*, Palo Alto, California, 2002.15~23.

[8] Gross M D, "The electronic cocktail napkin：A computational environment for working with design diagrams", *Design Studies*, 1996，17(1）:53~69

[9] Sun ZX，Wang Q，Yin JF，et al. "Incremental online sketchy shape recognition with dynamic modelling and relevance feedback". In *Proc. International Conference on Machine Learning and Cybernetics*， Shanghai， 2004. 3787~3792.

[10] G. Feng, Christian. Viard-Gaudin, et al. "On-line hand-drawn electric circuit diagram recognition using 2D dynamic programming", *Pattern Recognition* (2009), doi: 10.1016/j.patcog. 2009.01.031

[11] Yingmin Zhang, Christian Viard-Gaudin, Liming Wu, "An online hand-drawn electric circuit diagram recognition system using Hidden Markov Models", In Proc. *International Symposium on Information Science and Engineering (ISISE2008),* Shanghai, Dec. 2008, Vol. 2, pp.143-148