Hand-Drawn Diagram Correction Using Machine Learning

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Abstract: This paper introduces a real-time correction technique for hand-drawn diagrams on tablets, leveraging machine learning to mitigate inaccuracies caused by hand tremors. A novel fusion of classification and regression models is proposed; initially, the classification model discerns the geometric shape being drawn, aiding the regression model in making precise corrective predictions during the drawing process. Additionally, a unique Mean Angle of Vector (MAV) loss function is introduced to minimize angle changes in vectors formed by consecutive points, thereby reducing hand tremors especially in straight line segments. The MAV function not only facilitates real-time corrections but also preserves the drawing fluidity, enhancing user satisfaction. Experimental results highlight improved correction accuracy, particularly when employing classification alongside regression. However, the MAV function may round off sharp corners, indicating areas for further refinement. This work paves the way for more intuitive and user-friendly digital sketching and diagramming applications.

1 INTRODUCTION

Hand-drawn diagrams on tablet devices are recognized as intuitive and convenient. However, a greater susceptibility to shakes is observed compared to traditional paper-based drawing. As a result, various handshake correction methods have been developed. One notable method that has been employed is the moving average process. In this method, the output point is computed from the moving average of the preceding and subsequent n steps for the input point at time t. Advanced methods, wherein the filter size n is adjusted based on the path's curvature, have also been introduced (Kawase et al., 2012). Predictions can be made using past coordinate data by these methods, but the prediction of specific shapes remains a challenge.

Moreover, in applications designed for the correction of hand-drawn figures, the shape is typically classified after being drawn, and corrections are then applied. This approach ensures that geometric figures are drawn without imperfections such as shakes or blurs. However, pauses in prediction are often introduced, leading to a less fluid drawing experience.

In the realm of hand-drawn diagram correction, most existing methods have been centered around bitmap images. The novelty of this research lies in leveraging vector data for real-time correction, a facet that has not been extensively explored before. This vector-based approach is anticipated to offer better accuracy and efficiency in correcting hand-drawn diagrams on digital mediums.

In response to the challenges aforementioned, it was recognized that online hand-drawn figures can be treated as time series data. A proposal has been made to utilize machine learning for real-time regressive path predictions, allowing corrections to be made during the drawing process. This research further aims to enhance correction accuracy by introducing concurrent classification prediction. This allows the regression prediction model to adapt based on the type of figure drawn.

2 RELATED WORK

Up to now, numerous applications of machine learning to hand-drawn data, often utilizing datasets like MNIST, have been reported. Distinct from these studies that rely on bitmap images, the present research is characterized by its emphasis on vector images for correction.

When attention is given to the correction of hand-drawn figures and time series prediction, several pertinent studies can be identified.

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2.1 Sketch-RNN

Sketch-RNN, a model based on a recurrent neural network, was developed by (Ha and Eck, 2017). This model captures the movement of the pen as time series data and is capable of generating new sketches accordingly. The concept behind Sketch-RNN has been extended in the current research to address real-time figure correction. While the Sketch-RNN methodology employs both Long Short-Term Memory (LSTM)(Hochreiter and Schmidhuber, 1997) and Variational Autoencoder (VAE) for time series prediction, only the LSTM, deemed essential for time series prediction, is utilized in this study.

2.2 Multivariate Time Series Transformer

Conversely, a novel framework for multivariate time series representation learning, based on the transformer encoder architecture, was proposed by (Zerveas et al., 2021) in their study titled "A Transformer-based Framework for Multivariate Time Series Representation Learning". This framework incorporates an unsupervised pre-training scheme and has been shown to offer significant performance advantages for supervised learning by leveraging existing data samples. In the present research, time series data of two variables, x and y coordinates, is employed, aligning perfectly with the aforementioned framework and task. Although it has not been adopted in this iteration, the framework holds potential value for the current study.

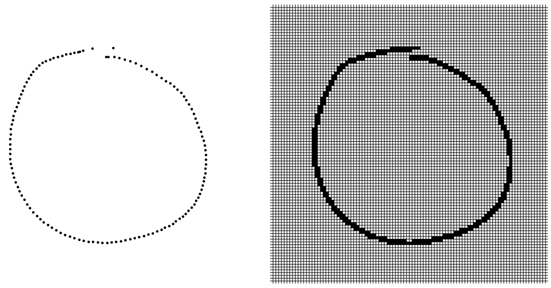
3 THEORY

3.1 Online Patterns and Offline Patterns

Hand-drawn figure patterns can be categorized into online patterns and offline patterns (Zhu and Nakagawa, 2012). Online patterns, as depicted in Figure 1a, are comprised of time series pen point coordinate data, referred to here as paths. Conversely, offline patterns, shown in Figure 1b, are made up of pixel value data from a single image. In this study, we utilize data from hand-drawn figures consisting of online patterns.

3.2 Normalization

Variability in size due to feature values may cause larger features to disproportionately influence the result, independent of their weights. The figures in this study also demonstrate size variations, with each time's coordinates (or vectors) used as the feature values. Consequently, merely shifting the same figure (changing its position) might impact the computational outcome.



(a) Online Pattern. (b) Offline Pattern.

Figure 1: Examples of online and offline patterns.

For offline patterns, normalization can be achieved by dividing each pixel value by its maximum. However, this approach does not suit the online patterns utilized here. It neither addresses the issue of different figure positions nor prevents changes in the aspect ratio. Therefore, we employ normalization using a bounding box. This box, illustrated in Figure 2, represents the smallest square enclosing the figure. Paths are shifted so that the figure box's top-left corner aligns with the origin, and all points are normalized to lie between 0 and 1 by dividing by the box's length l.

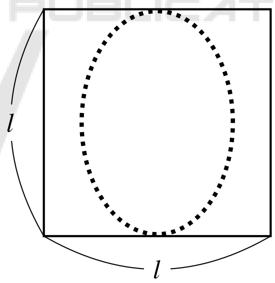


Figure 2: A Example of Bounding Box.

3.3 Correction Method

Correction of hand-drawn paths involves predicting these paths using a machine learning model. This model comprises two components: a classification model and a regression model. The correction process unfolds as follows:

1. The classification model predicts what type of figure the online pattern of the hand-drawn figure is.
2. The path of the hand-drawn figure is passed to the regression prediction model suitable for the type predicted by the classification model.

3. The regression prediction model predicts the corrected path from the path of the hand-drawn figure.
4. Repeat steps 1 to 3.

The models' input and output images are portrayed in Figure 3.

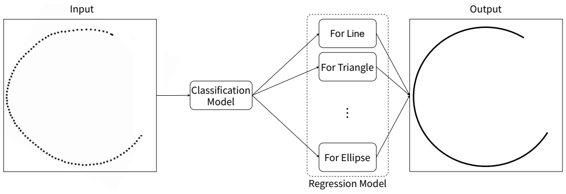


Figure 3: Classification and regression model.

To enable real-time predictions during writing, the machine learning model must receive inputs of consistent array lengths. This necessitates data shaping into x, y coordinates with an array length of 512, meaning the model accepts inputs in the format 512×2. Linear interpolation is employed during the data shaping phase. Training utilizes data from five figure types: straight line, triangle, square, circle, and ellipse.

3.4 Loss Function

In previous studies (Yoshida and Kobayashi, 2022), the Mean Square Error (MSE) was used as the loss function given by

$$\mathrm{MSE} = \frac{1}{n}\frac{1}{length}\sum_{i=1}^{n}\sum_{t=0}^{length}\left(p_{t+i}^{\text{prediction}} - p_{t+i}^{\text{teacher}}\right)^2. \tag{1}$$

This is to bring the handwritten path closer to the teacher path at each time. In contrast, this study introduces a new loss function. Until now, there has been no quantitative evaluation indicator for the standing. Therefore, it was decided to incorporate the change in the angle of the vector at each time into the loss function. This loss is named Mean Angle of Vector (MAV) in this study, and is represented by

$$\mathrm{MAV} = \gamma \cdot \frac{1}{n}\sum_{i=1}^{n}\cos^{-1}(\mathrm{COS}) \tag{2}$$

$$\mathrm{COS} = \frac{1}{length - 2\times n\_steps} \times \sum_{t=n\_steps}^{length-n\_steps} \frac{(p_{t+n\_steps} - p_t)\cdot(p_t - p_{t-n\_steps})}{|p_{t+n\_steps} - p_t||p_t - p_{t-n\_steps}|}. \tag{3}$$

MAV takes the difference of the vectors of the points before and after n_steps, and calculates their angles based on the inner product. In other words, it is equivalent to finding θ as shown in Figure 4. By applying MAV only to prediction, it minimizes the change in the angle at each point and suppresses hand shaking. γ is the weight of MAV, and it was set to 0.001 in the loss during training. MAV is an indicator of shaking, and MAV is also used as metrics, but in that case, γ is set to 1. Also, n_steps was set to 5.

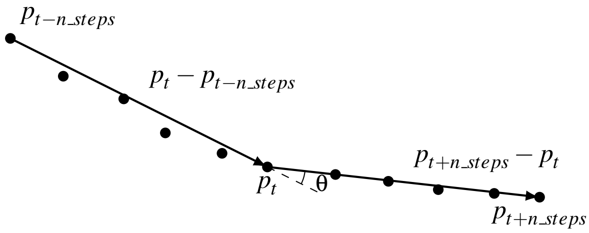


Figure 4: The angle of the vector at each time.

The final loss is the sum of MAV and MSE, represented by Eq. (4).

$$\mathrm{Loss} = \mathrm{MSE} + \mathrm{MAV} \tag{4}$$

4 EXPERIMENT

4.1 Classification Model

First, we conducted experiments with the classification model alone. We predicted the type of data after 10% of the path array length (for data of length 100, this is from time 10 onwards). The accuracy of this model was about 33%.

Predictions were then made for data after 50% of the path array length, and the accuracy achieved was about 60%.

Predictions made after 80% of the path array length yielded an accuracy of about 76%.

Additionally, we made predictions using only the final path, which refers to the completed figure. The accuracy for this approach was about 97.2%. The detailed breakdown can be seen in Table 1. It's evident that the accuracy of the classification model increases as it approaches the end of the drawing.

Table 1: Classification results.

OUT / IN	line	tri-angle	rect-angle	circle	ellipse
line	929	0	1	0	0
triangle	0	972	2	0	2
rectangle	0	1	918	0	4
circle	0	0	2	909	25
ellipse	0	0	3	121	787

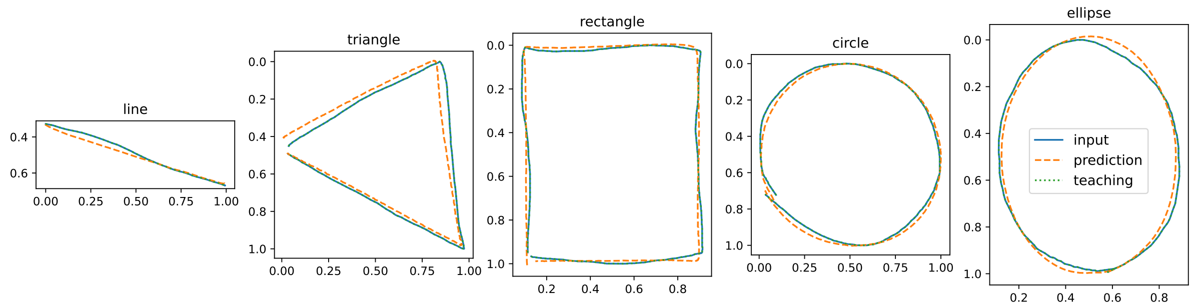
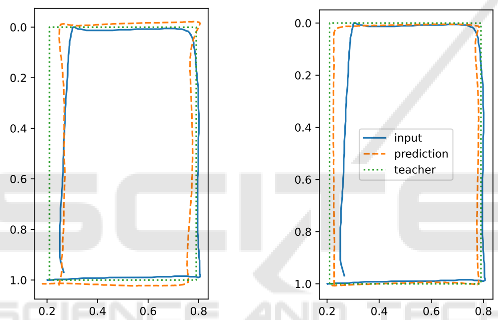


Figure 5: Results of combining classification and regression models.

4.2 Combined Use of Classification and Regression Models

The results from combining the classification and regression models are presented in Figure 5.

Comparisons of results with and without classification can be viewed in Figure 6.



(a) Without classification. (b) With classification.

Figure 6: Comparison of results with and without classification.

4.3 Loss Using MAV

The results using the loss with MAV are depicted in Figure 7. These were obtained exclusively with the regression model, without the inclusion of the classification model.

The following figure, Figure 8, compares the correction results obtained using MAV and those using MSE only.

A zoomed-in version focusing on the straight line from Figure 8(i) is presented in Figure 9.

Similarly, a zoomed-in version focusing on the corner from Figure 8(ii) is presented in Figure 10.

Lastly, Table 2 presents the MAV and MSE values when validation data is fed into each respective model. The "Base Model" here represents a model without classification prediction and without training using MAV.

Table 2: Classification results.

Model type		MSE	MAV [rad]
Base Model		1.2310e-04	0.2852
Model with MAV		9.5786e-05	0.1490
With classify	line	1.6718e-04	0.6486
	triangle	3.2093e-04	0.2167
	rectangle	1.0126e-04	0.2381
	circle	4.0689e-04	0.1630
	ellipse	2.9909e-04	0.3540

5 DISCUSSION

Also, in the task of classification only, the accuracy increased as it approached the end of the drawing. This is thought to be because the figure is accurately formed as the drawing progresses, which enabled accurate classification. However, in the prediction while drawing, it is necessary to increase the accuracy from the beginning of the drawing, and this low accuracy at the beginning of the drawing will become a bottleneck.

Looking at Figure 6, it can be seen that a closer correction result to the teacher path is obtained when classification is performed than when it is not performed. This confirmed that the correction accuracy improved by performing classification. However, for each regression prediction model, there is a tendency for overfitting, and it is believed that generality has been lost.

Next, looking at the results using the loss function with MAV, it is not significantly improved as seen in Figure 8. However, looking at Figures 9 and 10, it can be seen that the hand tremor is reduced in each. However, looking at Figure 10, it can be seen that the corners are rounded when using MAV. This is thought to be because the corners are rounded by suppressing the change in angle at each time. In other words, this method is thought to have a similar effect to the moving average method.

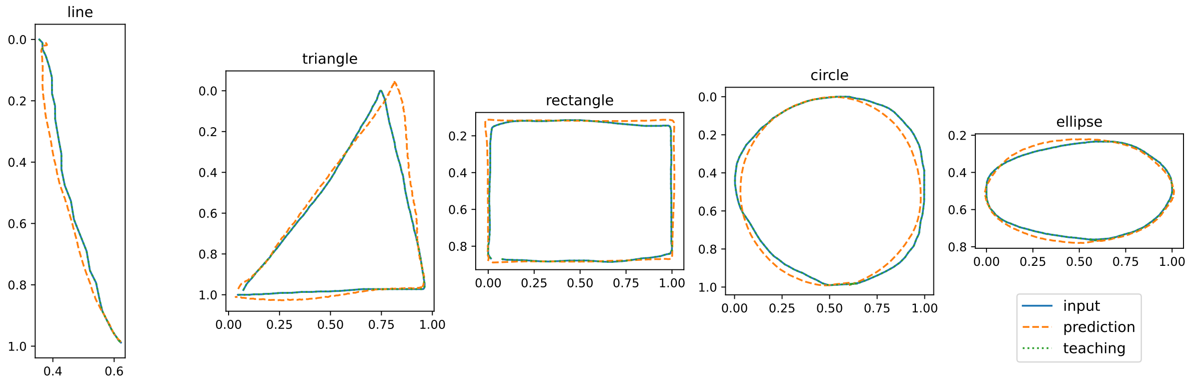
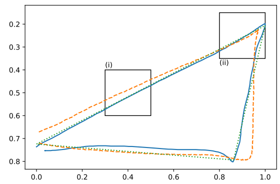
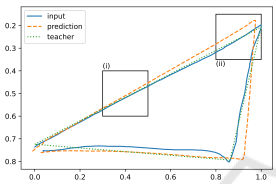


Figure 7: Results using loss with MAV.

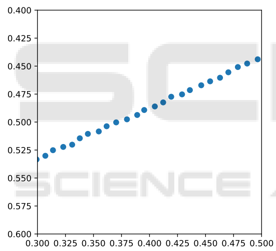


(a) MSE only.

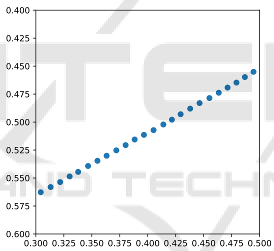


(b) With MAV.

Figure 8: Comparison of results using MAV and MSE only.

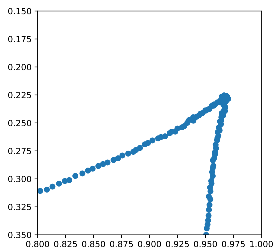


(a) MSE only.

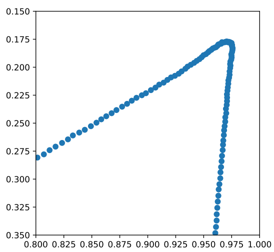


(b) With MAV.

Figure 9: Comparison of results using MAV and MSE only (zoomed in on the straight line, only prediction).



(a) MSE only.



(b) With MAV.

Figure 10: Comparison of results using MAV and MSE only (zoomed in on the corner, only prediction).

For shapes other than straight lines, it is not always good for MAV to be 0, so this method is thought to have room for improvement. For example, designing a loss function to bring the distribution of MAV closer to a normal distribution using the Kullback–Leibler divergence may result in better results.

Looking at Table 2, it can be seen that when the loss function using MAV is used, the value of MAV decreases significantly. This result is consistent with the result in Figure 8. However, in the case of the model using classification, the value of MAV fluctuates greatly. These need to be verified in the future.

6 CONCLUSION

In this study, we introduced a method that combines classification prediction with traditional regression prediction. While we observed an improvement in accuracy over the conventional approach, the classification model's accuracy remained suboptimal. Furthermore, the large model size resulted in longer correction times, posing potential challenges for applications on mobile devices. Addressing these issues is an area of ongoing consideration.

We also proposed a loss function using MAV. While MAV proved effective in reducing hand tremors for straight-line segments, it introduced issues like rounding at the corners. Nevertheless, as MAV has not undergone quantitative evaluation to date, we still regard it as a promising metric for assessing hand tremors.

Looking ahead, we are exploring the adoption of the Transformer architecture, which has gained prominence in recent natural language processing endeavors, to enhance our classification model's accuracy and reduce its size. The recursive models, such as LSTM and RNN, employed in this study are adept at handling time series data. However, they suffer from information loss as input sequences grow. In contrast, the Transformer's performance is not dictated by input length, allowing it to maintain data fidelity over extensive sequences. This trait suggests that employing Transformers can optimize predictions with fewer parameters, leading to a more streamlined model. Future work will focus on leveraging the Transformer, as discussed in (Zerveas et al., 2021), to elevate our classification model's accuracy and decrease its overall footprint.

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