Cross-People Mobile-Phone based Airwriting Character Recognition

Yunzhe Li, Hui Zheng, **He Zhu**, Haojun Ai, Xiaowei Dong

{liyunzhe, zhenghui_cs, zhuhe_cs, aihj, xwdong}@whu.edu.cn

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Supposing

When you are walking, suddenly come up with a wonderful idea. Would you like to ...

- Go back to the office, find the draft paper and pen and write it down?
- Turn on the phone, enter the password, find the notepad from many APPs, and finally type and record?
- Pick up the phone and write directly in the air?

Airwriting can make the third approach a reality!

Airwriting

- Airwriting refers to writing letters with hand or finger movements in a free space.
- Airwriting is especially useful for user interfaces that do not allow the user to type on a keyboard or write on a trackpad or touchscreen, or for text input for smart system control, among many applications.

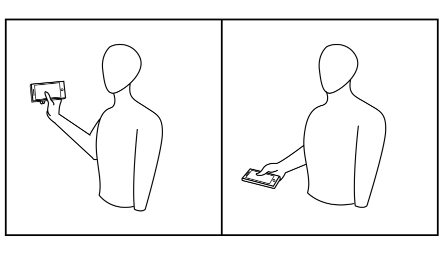

Figure: Airwriting

Challenges in Mobile-Phone based Airwriting

The machine learning method is very effective to solve the Airwriting problem, but there are still several challenges:

- Non-IID: Due to different people's habits and equipment, the data of different people do not obey the same distribution -> Fine-tuning from the base model
- Small Sample: Because there are many possible situations, the data needs to be collected by the user personally, and the user will be tired after collecting it for a period of time, it is difficult to obtain the data -> Transfer Learning

Data preprocessing

- Define the square of acceleration as the energy
- Segmentation based on writing energy: changes in energy are more sensitive at the beginning and end of writing numbers

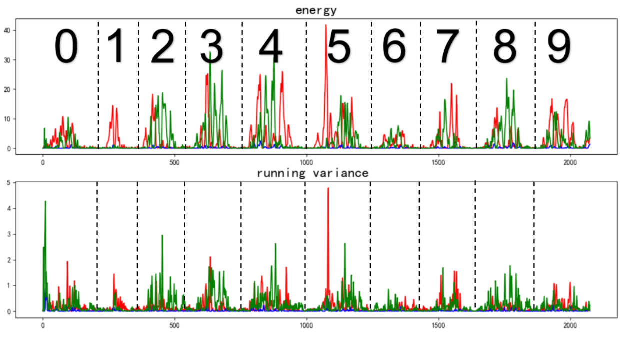

Figure: Energy of acceleration

Network

- CNNs are able to learn local higher-level features from spatial data
- RNNs are specialized for sequential modeling
- AdaBNs can be used for knowledge transfer

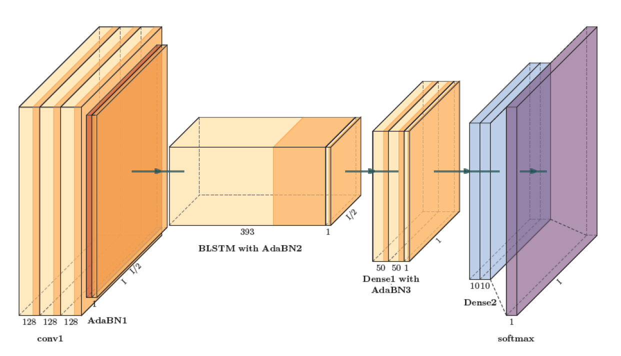

Figure: CNN-BLSTM-AdaBN

AdaBN

- Perform batch normalization for training domain and test domain
- Domain specific normalization mitigates the domain shift issue

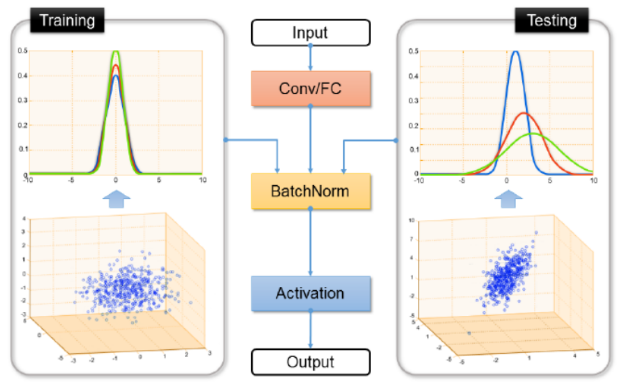

Figure: AdnBN

Base Model

- Training using more than 20000 pieces of data
- Achieve more than 99% accuracy

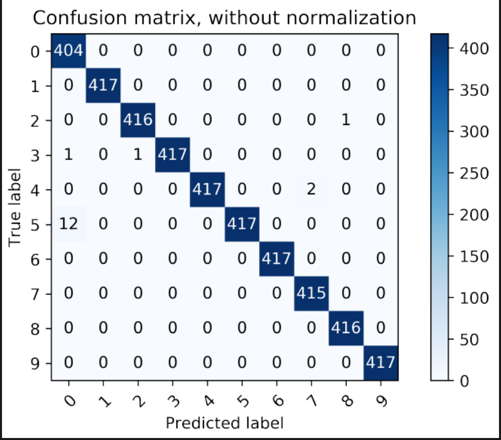

Figure: Confusion matrix of base model

Migrate to small datasets

- The size of the target data set is only 0.003% of the base model training set
- Our method is able to improve the performance of the model by 10% on average

Table: Performance

Target	Base Model	Transfer	Increase
2	96.35%	99.14%	2.79%
3	97.64%	99.23%	1.59%
4	68.33%	83.33%	15%
5	49.67%	68.67%	19%
6	52.67%	61.02%	8.35%
7	67%	75.92%	8.92%
8	62.33%	83.33%	21%
9	68%	75.45%	7.45%
10	75.59%	81.2%	5.61%

Conclusion

- We build an Airwriting recognition system on mobile phone.
- Using enough data for training, our model can achieve an accuracy of over 99%.
- When the new scene training set is only 0.003% of the base model, we can increase the performance of the base model in the corresponding scene by an average of 10%.