OFFLINE SIGNATURE VERIFICATION

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Outline

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- ➢Literature review
- ➢Methodology
- ➢Experiments
- ➢Interface application
- ➢Conclusion & Further work

Claud Baker

Introduction

- Biometrics

  Automated individual identification related to human behavioral and physiological characteristics [1]

- Authorization form

  Still commonly used in bank system and law contracts

- Online and Offline

  Online signature records movement and shape (Dynamic)

- Genuine and Forgeries

  Three kind of forgeries: Random, Simple and Skilled Forgeries [9]

Problem statement

1. Offline signature dataset limitation
   - Most of research use private dataset
   - MCYT[67], GPDS[68], SigComp2011[69],CEDAR
   - Forgeries created by simulation or skilled forgers (incomparable)
2. In reality, system may not have someone's forgeries
   - Still a challenge to recognize forgeries without forgeries in training dataset
3. High intra-class variability [9]
   - Variability exists among samples even they are all genuine (inconsistency)

Literature review

1. Feature Extraction
   - Geometric feature: height, image area, width, signature orientation
   - Directional feature: gradient from local area
   - Key point feature: Harris, SIFT, SURF(scale and rotation invariance)
   - Raw data (the value of pixel): Deep learning CNN
2. Classification approach
   - Hidden Markov Models(HMM)
   - Probabilistic neural networks (PNN)
   - Support Vector Machines (SVM)
   - Convolutional Neural Network (CNN) (Softmax classifier)

Methodology-Feature extraction

1. PCA
   - Dimension reduction
   - Reconstruct the image with weighted uncorrelated principal component
   - The weight matrix for images is

$$W = \boxed{(Y^T Y)^{-1}} Y^T Z$$

# of PCs	% of variance explained
40	52.49%
100	84.38%
140	94.53%

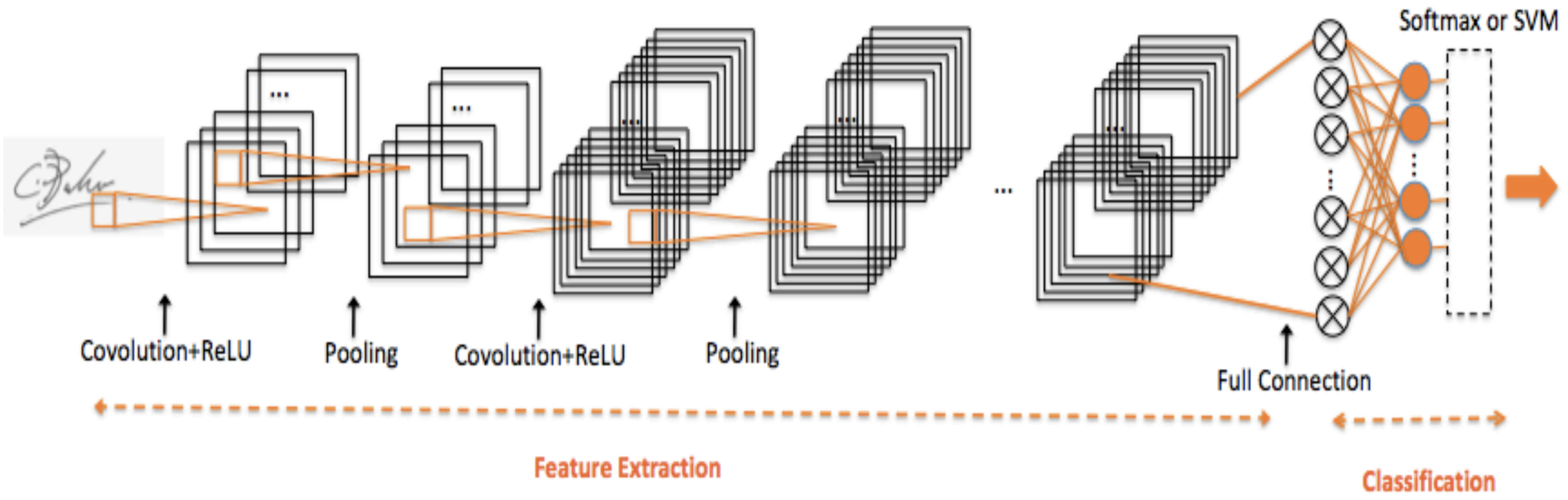
*Total number of PCs is 180

Test image

140PCs

Methodology-Feature extraction

2. Convolutional Neural Network (CNN)



Methodology-Feature extraction

- Forward Pass
  - Input Layer
  - Convolutional + ReLU Layer
  - Max Pooling Layer
  - Fully Connected Layer
  - Softmax function

$$u^l = W^l x^{l-1} + b^l \qquad x^l = f(u^l) = \max(0, u^l)$$

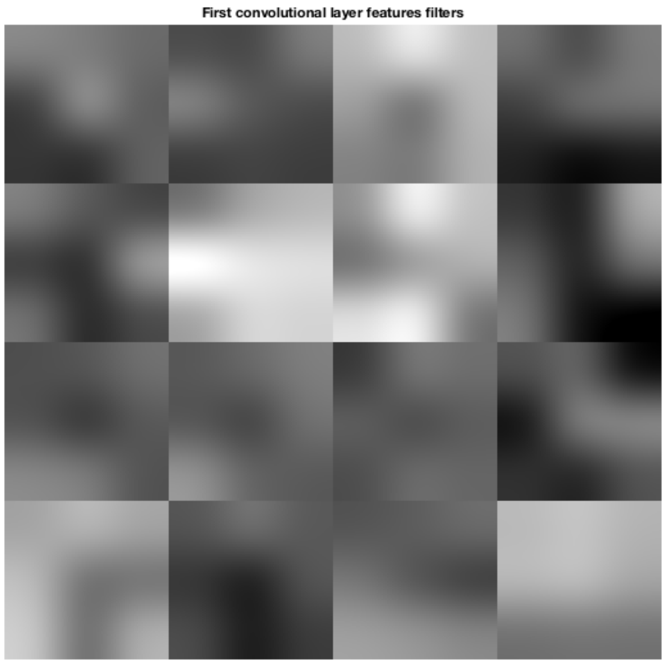
$$x_j^l = \beta_j^l \max(x_j^{l-1}) + b_j^l$$

$$f(x) = f(Wx + b)$$

$$p_j = \frac{e^{y_j}}{\sum_j e^{y_j}}$$

- Backward Pass
  - Backpropagation process
  - Update weights, multiplication bias and additive bias
  - Optimization method : stochastic gradient descent (SGD)

Methodology-Feature extraction



Convolutional layer feature filters

Output of Convolutional layer 1

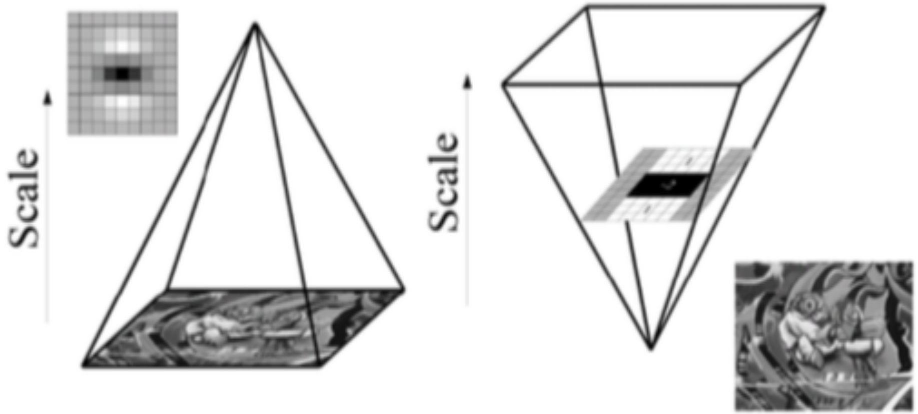
Methodology-Feature extraction

3. Bag of Words(BOW)
   - Feature detection approach : Speed up robust feature (SURF)
   - SURF make sure the feature is scale and rotation invariance

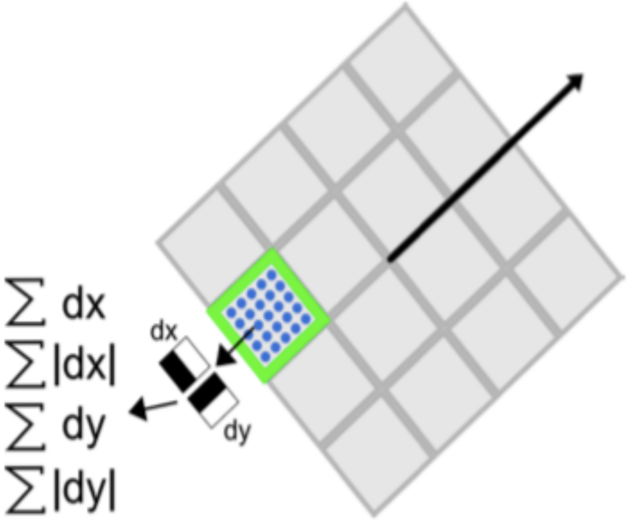
1) detect key points by calculating Hessian determinant (by using Box filter to calculate second order Gaussian derivative)
2) using filter pyramid to make sure the key point is scale-invariance
3) Using Haar wavelets as filter to determine the direction of keypoint
4) Using square window around key point to obtain the feature vector
5) K-Means clustering to reduce redundant features

Methodology-Feature extraction

3. Bag of Words(BOW)



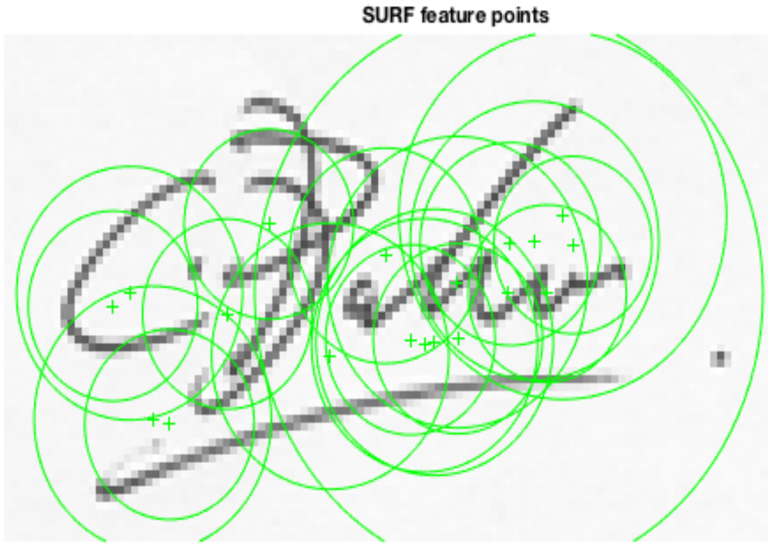
Filter Pyramid



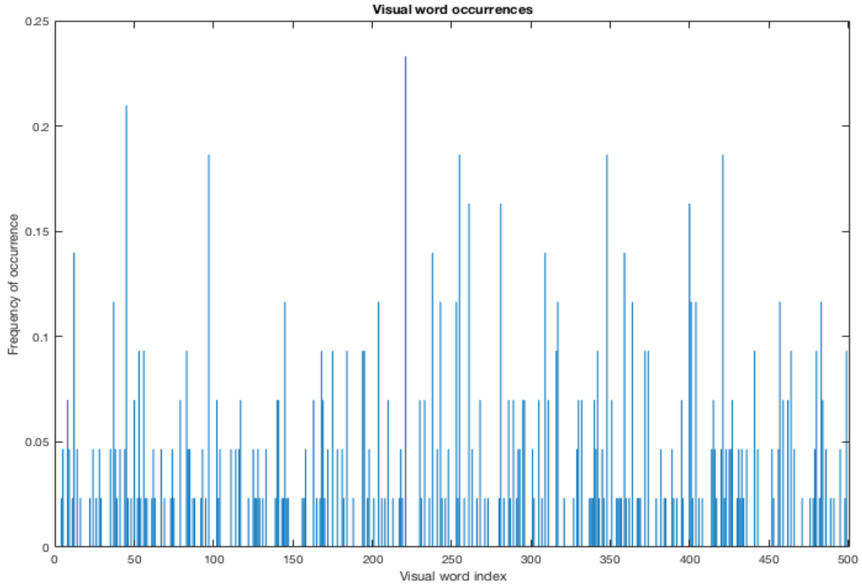
Feature vector

Methodology-Feature extraction

3. Bag of Words(BOW)



SURF Feature Points (19)



Histogram of Visual words

Methodology-Feature extraction

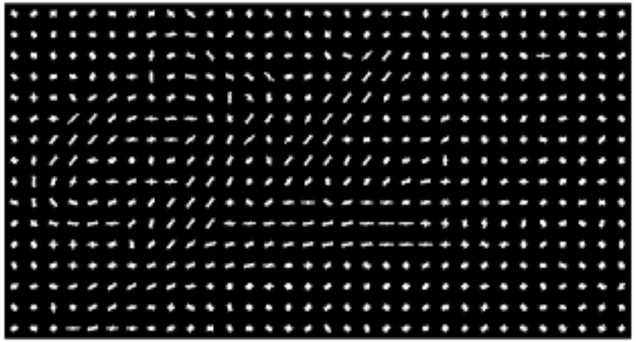
4. Histogram of Oriented Gradients (HOG)
   - Detect shape and edge orientation in local regions
   - invariance to small or local geometric changes
   - invariant to illumination change by block normalization
   - less computational complexity
   - only need calculate horizontal and vertical gradient

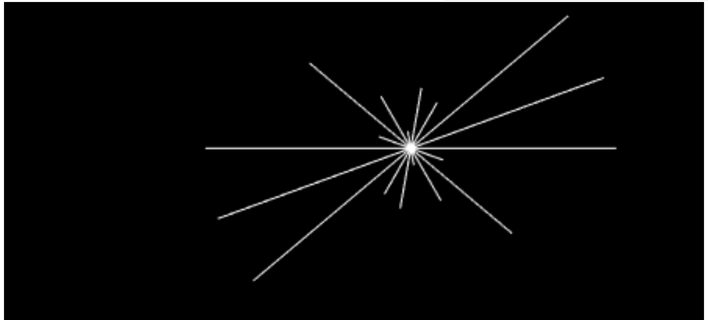
Methodology-Feature extraction

- Histogram of Oriented Gradients (HOG)

Test Image

HOG Visualization





Methodology-Classification approach

Classification Approach

1) Support Vector Machine
   - A “Kernel” method in machine learning
   - Transform training data into a higher dimension by kernel map
   - Belong to Maximum margin classifier
2) Softmax classifier
   - giving probabilities for each class, not like margin scores in SVM
3) Distance classifier
   - Euclidean distance classifier

Experiments

1. Data
   1) Collect signature in campus
      - (2583) signature from (123) students in University of Reading
   2) Public dataset -SigComp2011
      - Chinese signature (362) from 10 writers
      - Dutch signature (575) from 10 writers

2. Pre-processing
   - Cropping, Colour to Gray, Noise Reduction, Binarization, Resizing

Experiments

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- Table 1 Result on the SigReading2018 dataset

Approach	#Ref	Training Dataset	Testing Dataset	Average Accuracy
PCA+ Distance classifier	123	1845	738	1.13%
PCA+SVM	123	1845	738	5.56%
CNN+Softmax classifier	123	1845	738	75.52%
CNN+SVM	123	1845	738	74.98%
BOW+SVM	123	1845	738	91.47%
HOG+SVM	123	1845	738	89.80%

Experiments

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Table 2 Result on the SigComp2011 (Dutch) dataset

Approach	#Ref	Training Dataset	Testing Dataset	Average Accuracy
PCA+ Distance classifier	10	253	109	65.14%
PCA+SVM	10	253	109	66.36%
CNN+Softmax classifier	10	253	109	71.25%
CNN+SVM	10	253	109	72.48%
BOW+SVM	10	253	109	79.53%
HOG+SVM	10	253	109	84.10%

Experiments

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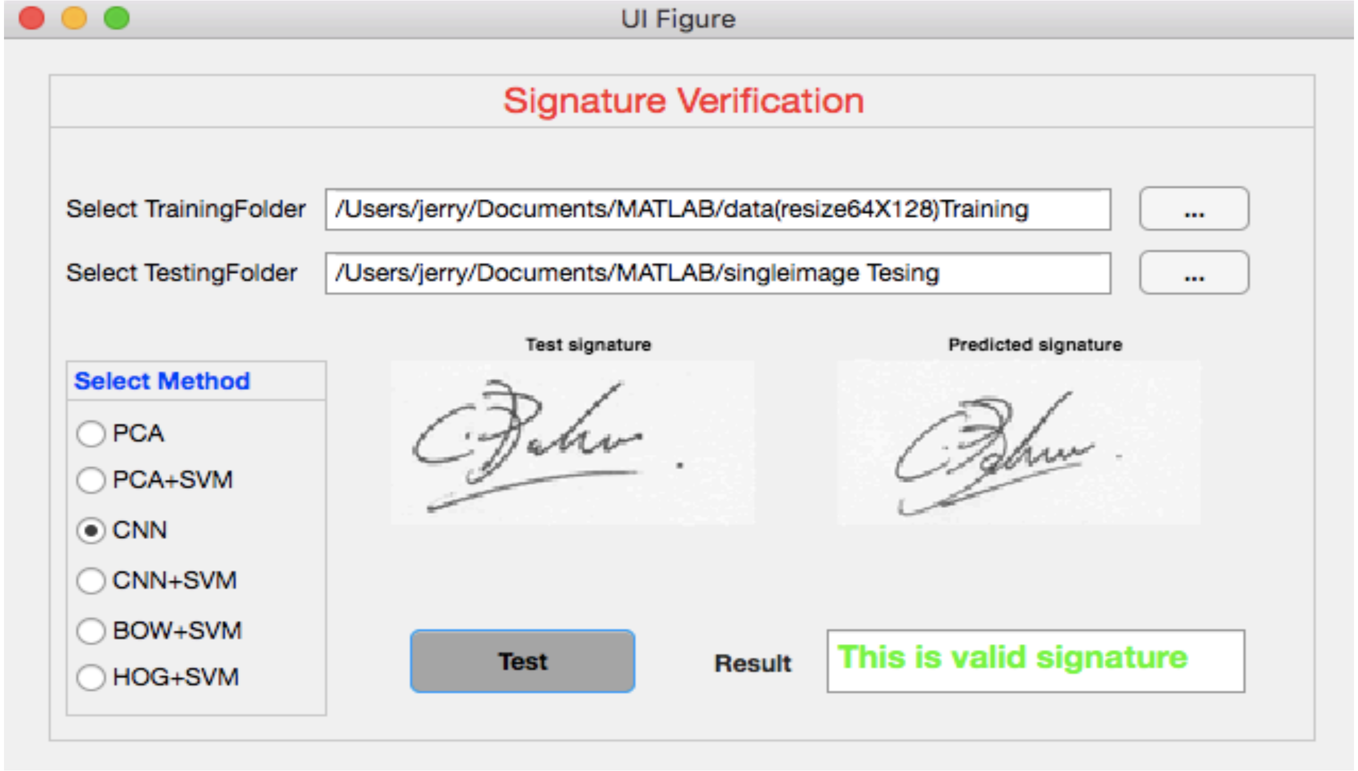
Table 3 Result on the SigComp2011 (Chinese) dataset

Approach	#Ref	Training Dataset	Testing Dataset	Average Accuracy
PCA+ Distance classifier	10	403	172	59.30%
PCA+SVM	10	403	172	68.99%
CNN+Softmax classifier	10	403	172	80.04%
CNN+SVM	10	403	172	82.36%
BOW+SVM	10	403	172	69.11%
HOG+SVM	10	403	172	88.95%

Interface application



Conclusion and Further work

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- Conclusion
  - Experiment on larger dataset may achieve better results
  - PCA may not be an efficient way to extract offline signature features
  - BOW and HOG perform better than CNN in genuine only system
  - HOG perform better than BOW and CNN in genuine and forgery system
  - The SVM and Softmax classifier have similar results
  - CNN, SURF and HOG can be consider as ‘convolution’ methods

Conclusion and Further work

- Further work
  - Investigate the factors that affect the accuracy of different approaches
  - Optimize the models by adjusting the parameter setting
  - The accuracy may depend on which dataset is used, so should attempt other dataset
  - Due to the limitation of CPU computer, GPU computer is more efficient choice for image process
  - All models are trained as writer-Independent system. It may test each writer’s signature with dependent model.
  - Evaluate the suitability of different approaches to the different tasks

Reference

- [1] Joseph N. Pato and Lynette I.Millett.Biometric Recognition: Challenge and Opportunities.2010
- [9] Luiz G. Hafemann, Robert Sabourin, Luiz SlOliveira, Offline Handwritten Signature Verification-Literature Review,IEEE(2017)
- [24] Lowe, David G. (1999)."Object recognition from local scale-invariant features" (PDF). Proceedings of the International Conference on Computer Vision. 2. pp. 1150–1157
- [33] Gabe Alvarez,Blue Sheffer,Morgan Bryant,Offline Signature Verification with Convolutional Neural Networks
- [65]Bay, H., A. Ess, T. Tuytelaars, and L. Van Gool. “SURF:Speeded Up Robust Features.” Computer Vision and Image Understanding (CVIU).Vol. 110, No. 3, pp. 346–359, 2008.

Questions

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Thank you !