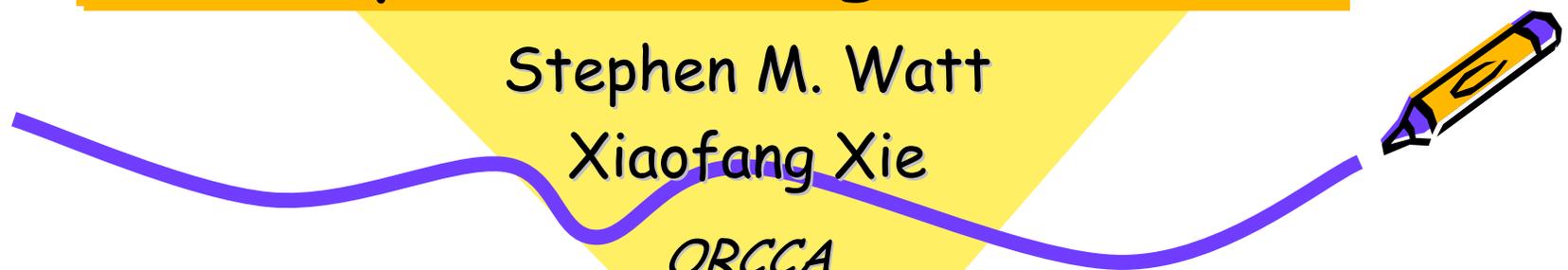


# Prototype Pruning by Feature Extraction for Mathematical Handwriting Symbol Recognition

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Xiaofang Xie

*ORCCA*



# Background & Motivation

Pattern Recognition



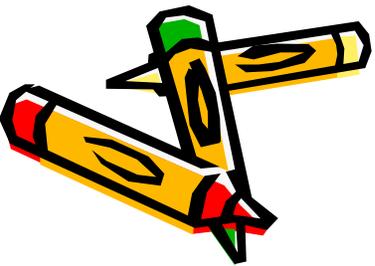
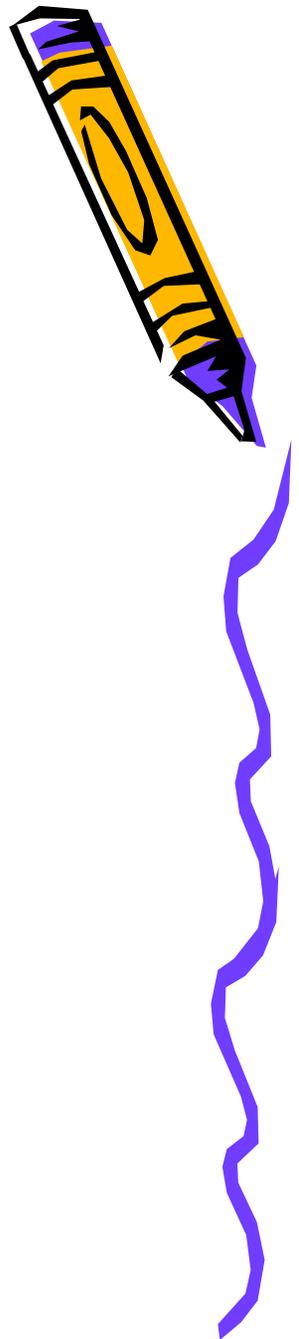
Optical Character Recognition



Handwriting Recognition



Mathematical Handwriting  
Recognition



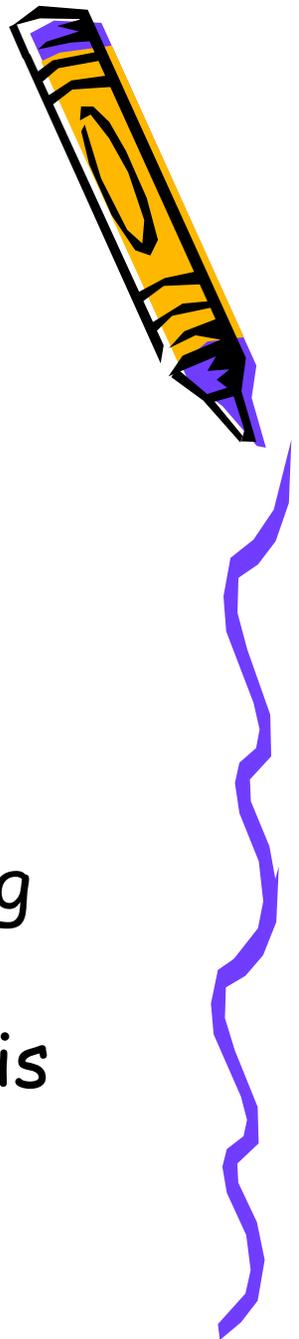
# Background & Motivation(Cont.)

- Why mathematical handwriting recognition?

Provide friendly interface for mathematics software.

Make mathematics editing and inputting much easier.

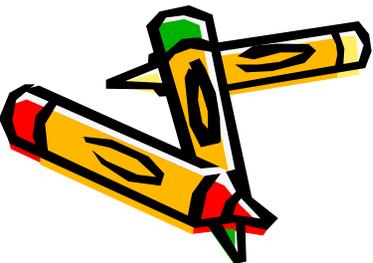
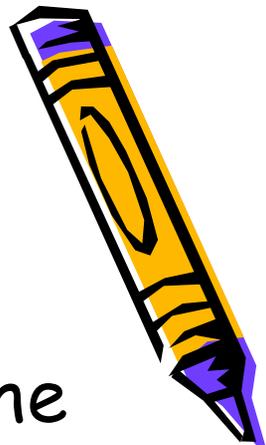
Mathematical Handwriting recognition is challenging.



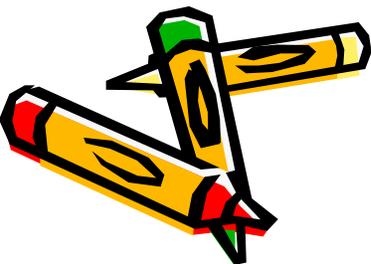
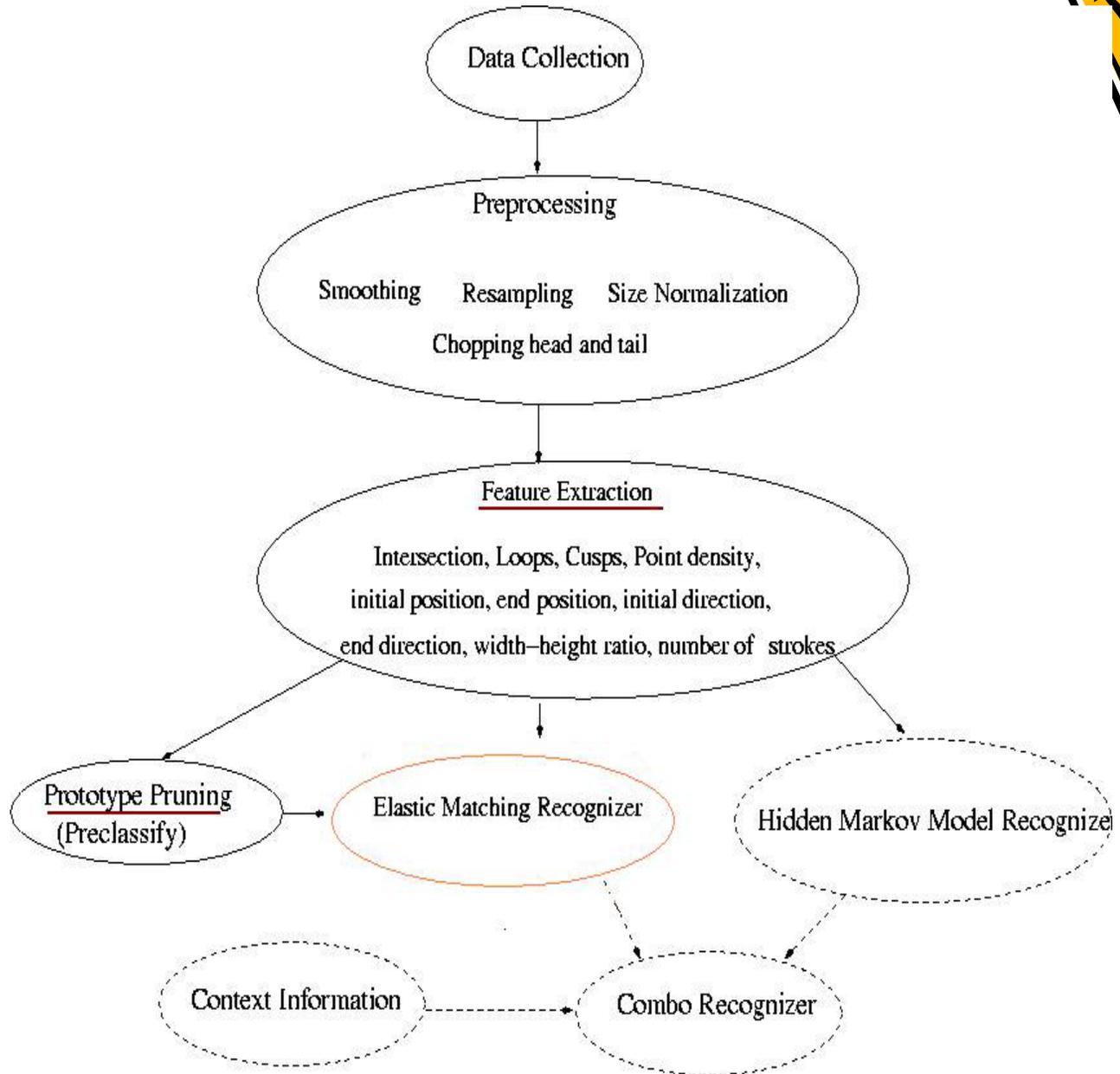
# Problems Statement

Mathematical handwriting differs from the other forms of handwriting.

- The set of possible input symbols is very extensive.
- No specific stroke order and stroke number.
- Spatial relation can use complex context-sensitive two dimensional rules.
- All of the above affect the recognition accuracy and speed.

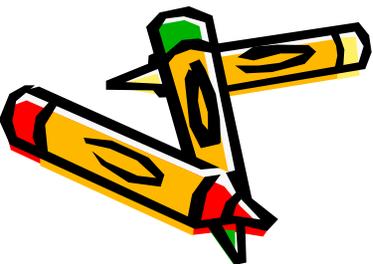
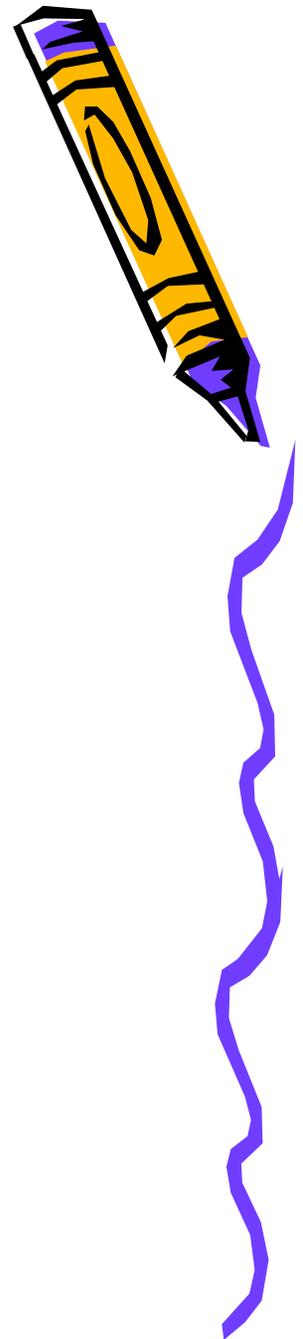


# The Architecture of the recognizer



# Data Collection

- IBM Cross Pad Data
- Tablet PC Data
- UniPen Data
- 240 symbols and a number of formulas.
- 227 symbols used in this presentation for comparison.



scl.csd.uwo.ca - default - SSH Secure Shell

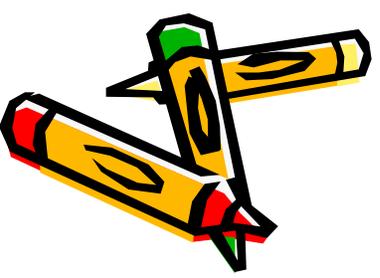
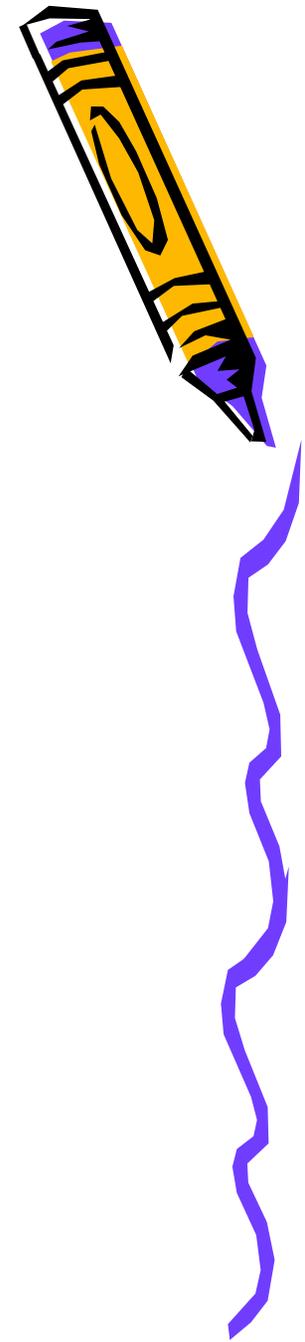
File Edit View Window Help

Quick Connect Profiles

```
Stroke TimeStart = "2003-05-05 14:50:15:8085248"
TimeStop = "2003-05-05 14:50:16:6897920"
1797 775 7 7
1797 775 1 14
1825 746 1 22
1825 746 1 30
1825 746 1 39
1841 720 1 48
1841 720 1 57
1841 720 1 65
1850 691 1 72
1850 691 1 79
1850 691 1 87
1848 661 1 91
1848 661 1 93
1848 661 1 93
1848 661 1 92
1829 635 1 92
1829 635 1 92
1829 635 1 91
1797 624 1 90
1797 624 1 89
1765 626 1 88
1765 626 1 88
1723 641 1 87
1723 641 1 86
1684 662 1 85
```

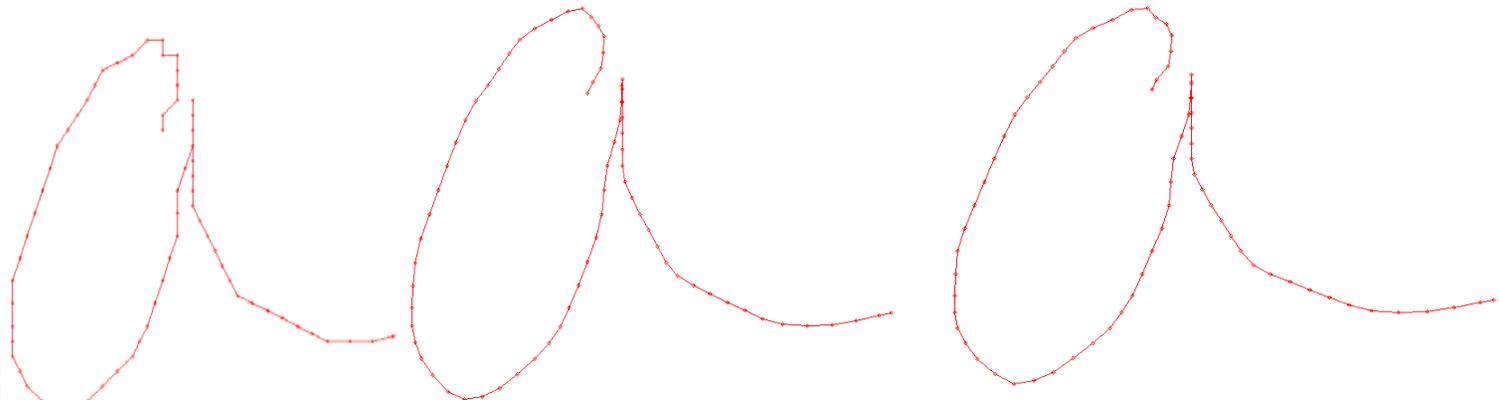
1,1 Top

Connected to scl.csd.uwo.ca SSH2 - aes128-cbc - hr



# Preprocessing

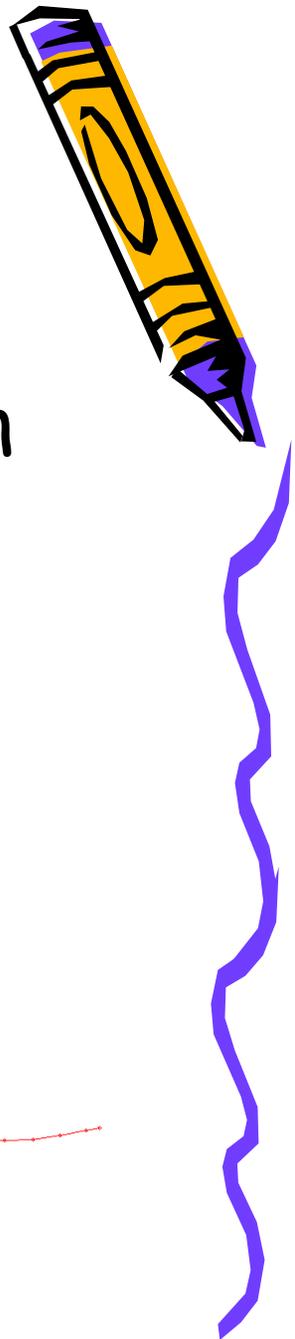
- Re-sampling to reduce computation and remove writing speed effect.
- Smoothing remove noise.
- Size normalization



Before Smoothing

Average Smoothing

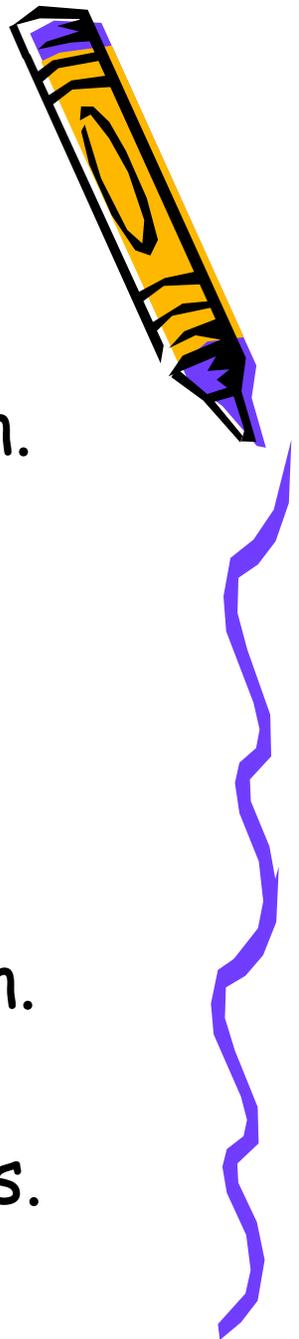
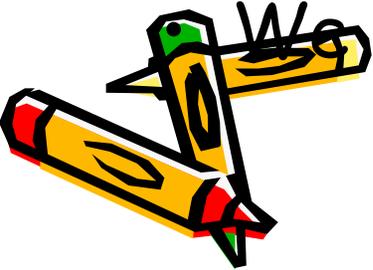
Gaussian Smoothing



# Feature Extraction

- It plays an important role in recognition.
- Features are defined as abstract characteristics which are unique to a symbol or a group of symbols.
- Features are often used for recognition.

We use features for pruning prototypes.



# Variance Analysis



- In order to identify proper features, we need to do handwriting variance analysis

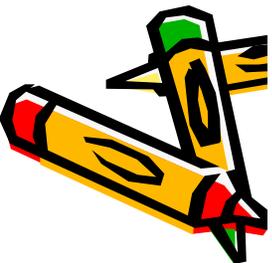
4 4 4 4 4 4

π π π π π π π π

H H H H H H H H

E E E E E

α α α α α α



# Feature Family

## Geometric Features

#loops

#intersections

#cusps

## Ink related features

#strokes

Point density

## Directional Features

Ini dir

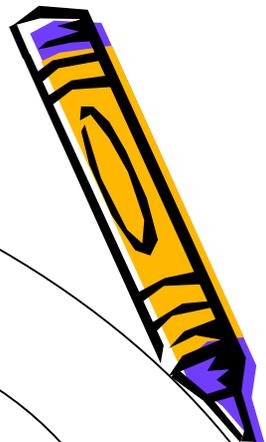
End dir

Ini-end dir

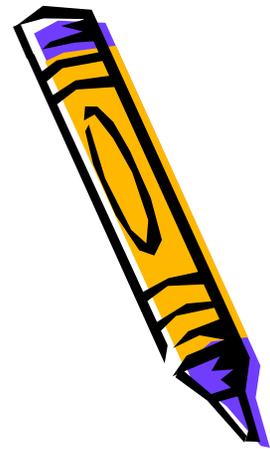
## Global Features

WHRatio

Ini and  
End pos

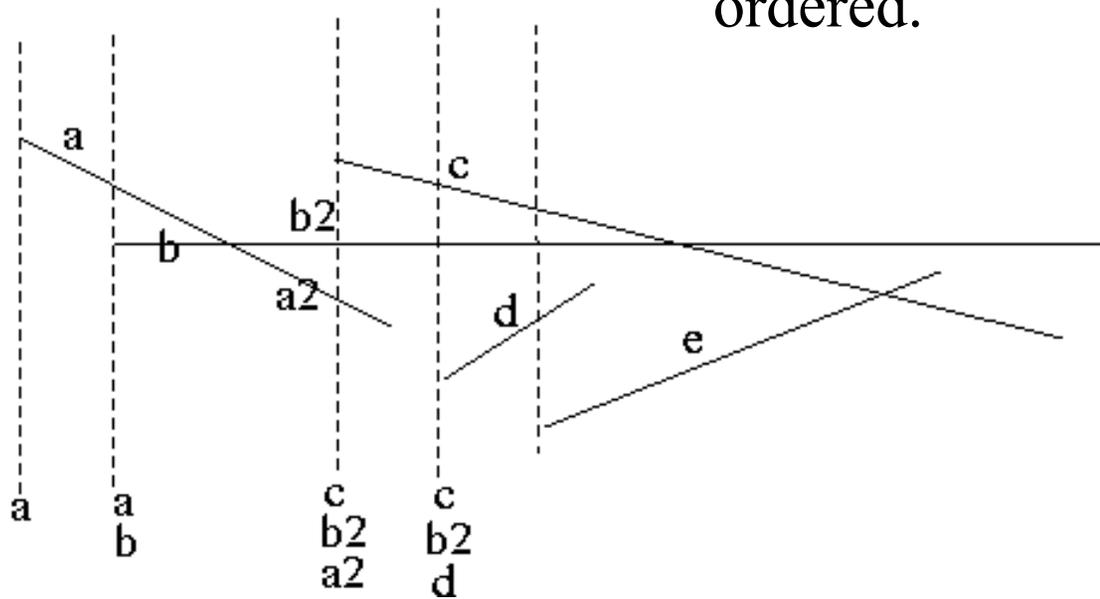


# Feature Extraction Algorithms

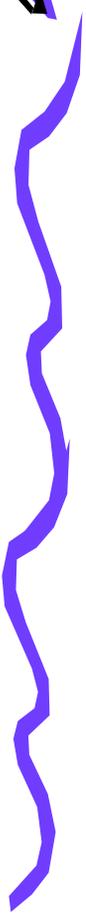
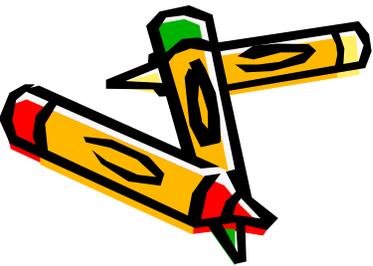


- Intersections:

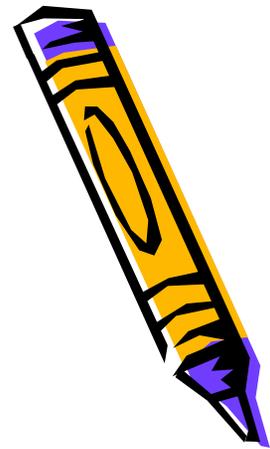
Line segments are ordered.



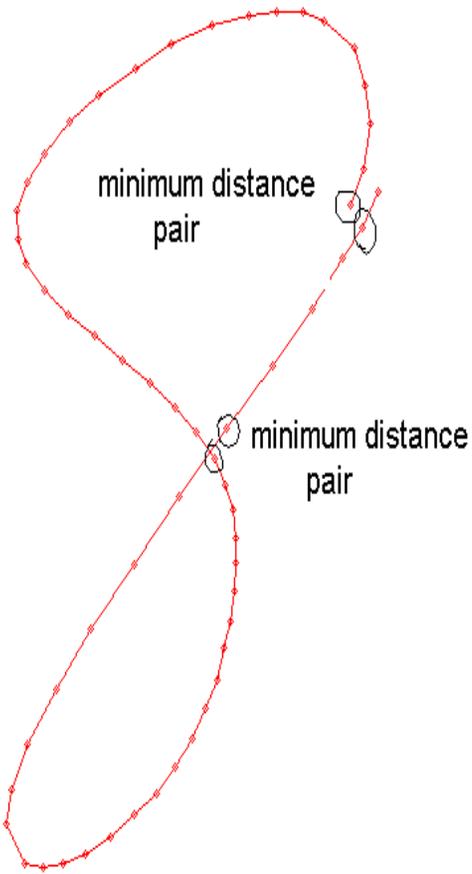
Modified Sweepline Algorithm



# Feature Extraction Algorithms(cont.)



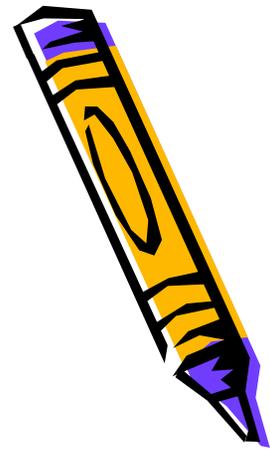
- Loops



Minimum distance pair: a pair of points which has the minimum non-local distance in a given area.

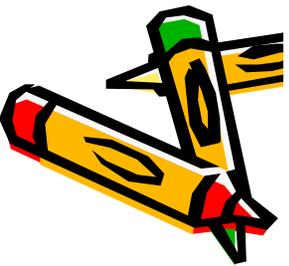
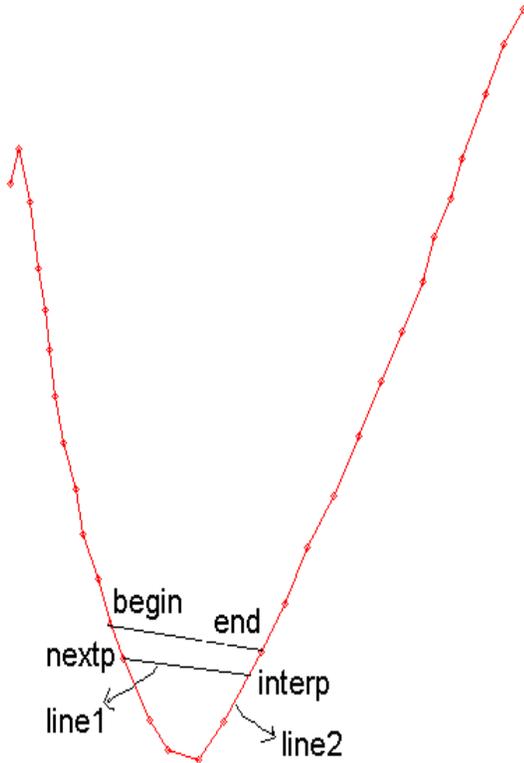


# Feature Extraction Algorithms(cont.)

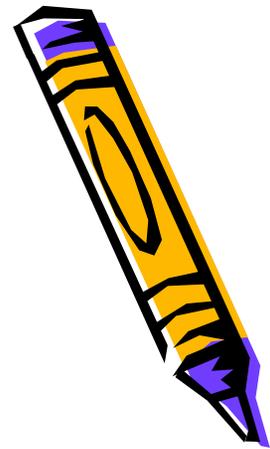


- loops

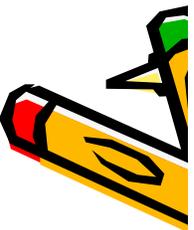
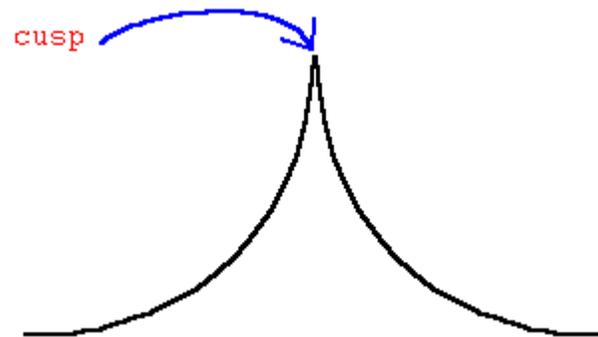
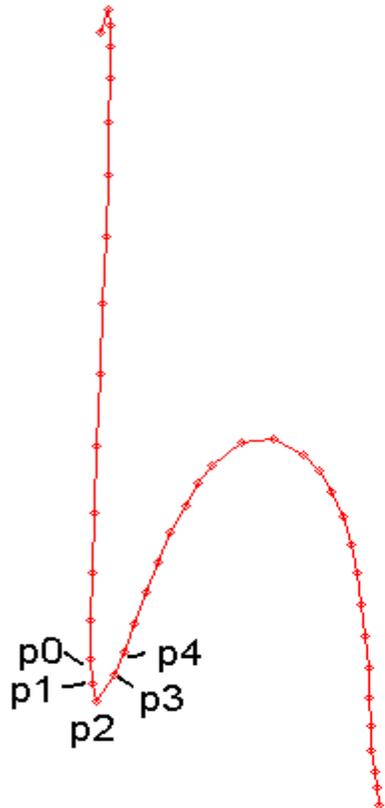
Use parallel line to filter the wrong loops



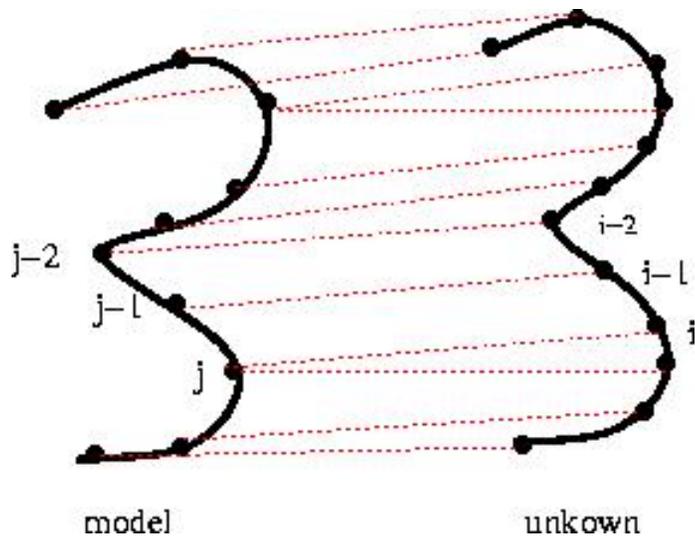
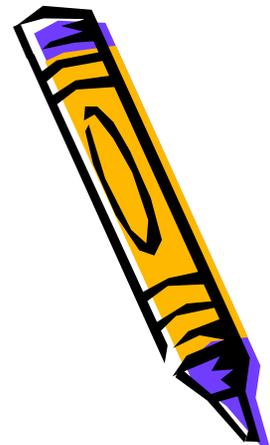
# Feature Extraction Algorithms(cont.)



- Cusps

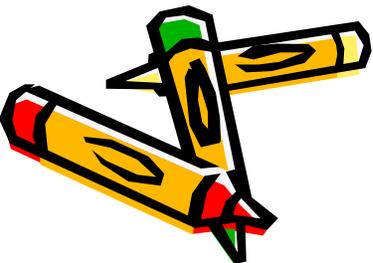


# Recognition



$$D(i, j) = \delta(i, j) + \begin{cases} \sum_{k=0}^{j-1} \delta(0, k) & \text{if } i = 0 \\ \sum_{k=0}^{i-1} \delta(k, 0) & \text{if } j = 0 \\ \min \begin{cases} D(i-1, j) \\ D(i-1, j-1) \end{cases} & \text{if } i > 0, j = 1 \\ \min \begin{cases} D(i-1, j-1) \\ D(i-1, j-2) \end{cases} & \text{if } i > 0, j > 1 \end{cases}$$

$$\delta(i, j) = (x_i - x_j)^2 + (y_i - y_j)^2 + C |\phi_i - \phi_j|$$



Elastic Matching

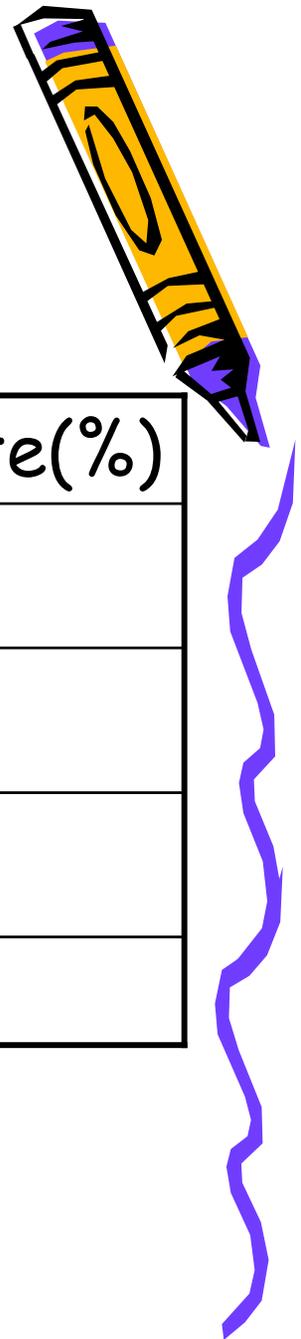


# Experimental Results

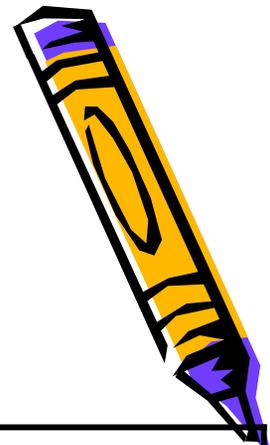
Experiment	#prototypes	Recog.Rate(%)
P1:T1,2,3,4	227	81.8
P1,2:T1,2,3,4	454	90.1
P1,2,3:T1,2,3,4	681	93.9
P1,2,3,4:T1,2,3,4	908	94.8



Results without Features



# Experimental Results(cont.)

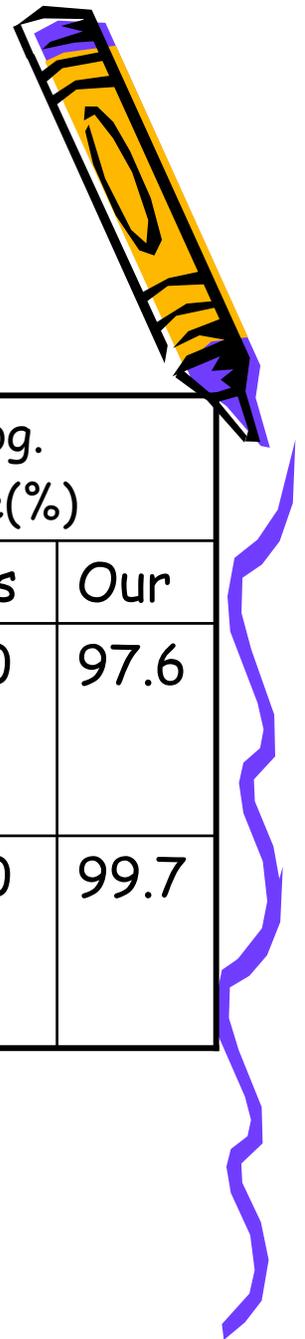


Experiment	#prototypes	Candidate prototypes	Percent. Pruned	Recog. Rate(%)
P1:T1,2,3,4	227	26	88.5	76.0
P1,2:T1,2,3,4	366	38	89.6	85.5
P1,2,3:T1,2,3,4	495	52	89.5	90.0
P1,2,3,4:T1,2,3,4	575	60	89.6	91.9

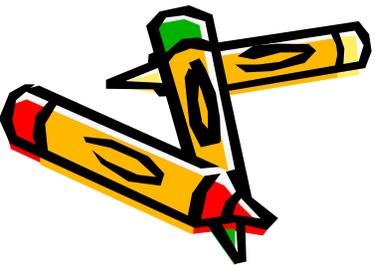


Results With Features

# Experimental Results(cont.)



experiment	#prototype		Candidate prototypes		Percentage Pruned		Recog. Rate(%)	
	J.K's	Our	J.K's	Our	J.K's	Our	J.K's	Our
P1-4:T1-4	121	169	47	24	61.5	85.8	99.0	97.6
P1-4:T1-4	122	288	92	288	N/A	N/A	99.0	99.7



Our vs. J.Kurtzberg's Results

# Conclusion

- We have made progress in handwritten mathematical symbol recognition area by using feature sets to prune the prototypes.
- We have attempted to identify these features, and analyzed thousands of handwriting samples.
- Our recognizer can recognize digits, English letters, Greek letters, most of the common mathematical operators and notations.
- Accuracy and speed are improved comparing with a recognizer in the literature.

