

Overview

Comparing different density feature methods for recognition of math symbols written on a tablet.

Dataset- CROHME 2014[1]. Training- 85782 symbols. 101 symbol classes.

Classifier- Random Forest: 200 trees, Max depth 18, Max features 50, GINI criterion with 5 fold cross validation.

Methods

Counting- Count the number of symbol points in a bin and normalize the count histogram.

Parzen- Fix a 2D Gaussian at each symbol point, use the intensity of the function at sample point.

Inverse distance- Weight the bin corner by the inverse of the distance to a symbol point.

Shape Context

Encapsulate the symbol in concentric circles of varying radii and dividing those circles with an angle.

2D Histograms

Bound the symbol in a box and divide the box into NxN square bins

Results

Shape Context Parameters: 1,2,..7 circles x 2,4,..., 22 angles

2D Histograms Parameters: 2x2, 3x3,..., 11x11 grids

Parzen σ : 0.05,0.1,0.15...,0.5,0.6,0.7,...,1.0

Table 1: Rec. Rate observed using approximately same number of features

Method	Rec. Rate	Configuration
2D Point Histograms[4]	86.233%	9x9 grids
Shape Context		
Counting	82.695%	4 circles with 20 angles
Parzen (σ factor = 0.15)	86.534%	
Inverse distance	86.61%	
2D Point Histograms		
Counting	82.827%	9x9 grids
Parzen (σ factor = 0.15)	86.754%	
Inverse distance	86.009%	

Table 2: Rec. Rate by combining the densities

Methods used	Rec. Rate
Shape Context (Inverse) & 2D Point Histograms (Parzen)	87.507%
Davila et al[4]	92.629%

Table 3: Top confused symbols with top errors counts

Symbols	Classification Output	No. of Errors
Shape Context (Inverse) & 2D Point Histograms (Parzen)		
1	(:26,):16, /:9, :8, ,:7	112
x	a:18, *:6, n:6, y:5, 2:5	72
z	2:32, y:9, x:7, t:4, +:3	68

Combining the two densities gives a better classification accuracy. But the improvement in errors counts for top confused symbols is marginal.

For example, symbol '1' was confused 146 times using shape context and 117 times using 2D histograms and 112 times using the combined densities.

Conclusion

For shape contexts, inverse distance performs better. For 2D grids, parzen estimations performs better. Combining shape contexts and 2D grids was beneficial.

References

- [1] H. Mouchère, R. Zanibbi, U. Garain, C. Viard-Gaudin, "Advancing the State-of-the-Art for Handwritten Math Recognition: The CROHME Competitions, 2011-2014", Int'l Journal on Document Analysis and Recognition, 2016.
- [2] S. Belongie, J. Malik, and J. Puzicha, "Shape matching and object recognition using shape contexts", TPAMI, 2002.
- [3] L. Hu, R. Zanibbi, "Line-of-Sight Stroke Graphs and Parzen Shape Context Features for Handwritten Math Formula Representation and Symbol Segmentation", Proc. Int'l Conf. Frontiers in Handwriting Recognition, 2016.
- [4] K. Davila, S. Ludi, and R. Zanibbi, "Using Off-line Features and Synthetic Data for On-Line Handwritten Math Symbol Recognition", Proc. Int'l Conf. Frontiers in Handwriting Recognition, 2014.

