

# Stroke based classification of handwritten digits



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## Introduction

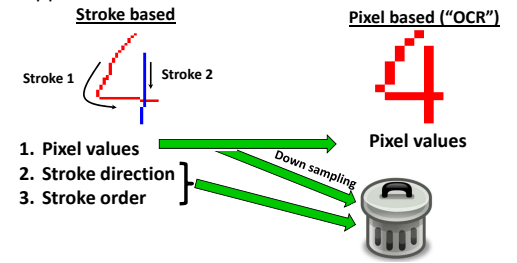
- Many modern devices have touch displays instead of keyboards
- Text input is tedious
- Drawing text is more natural than software keyboards



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## Stroke-based digit classification

- When digits are treated as images, information is discarded
- “OCR” problem more difficult than stroke-based approach



## Feature selection

- Stroke-based features should be:
  - Size invariant
  - Low-dimensional description
  - Accurate describe the shape and stroke direction
  - Smoothen over discrete pixel values
- Bezier-curve derivatives satisfy all of these properties

## Bezier curves

(Watt, A.H., 2005)

- Bezier curve defined as:

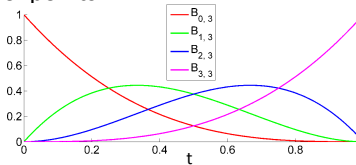
$$B(t) = \sum_{i=0}^n B_{i,n}(t) c_i$$

(unknown) Control points

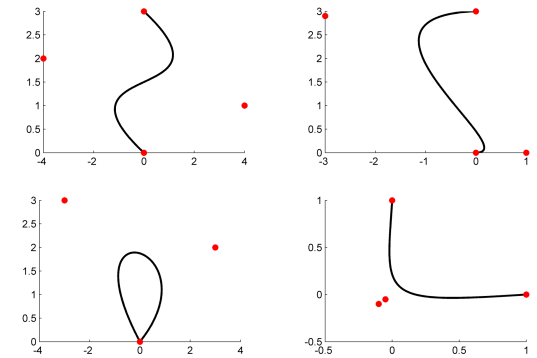
Bernstein basis functions:

$$B_{i,n}(t) = \binom{n}{i} t^i (1-t)^{n-i}$$

- Bernstein basis functions smoothens between control points



## Bezier curves: Examples



## Square loss fitting of a stroke

- The point list is defined as

$$\{(x_j, y_j)\}_{j=1}^N \quad t = \frac{j}{n} \quad \text{we fit} \quad \{(x_j, t_j)\}_{j=1}^N \quad (\text{Each dimension separately})$$

- Dimension-wise square-loss fit:

$$E = (x - \bar{c}_x^T M T) (x - \bar{c}_x^T M T)^T$$

$$= x x^T - 2 \bar{c}_x^T M T x^T + \bar{c}_x^T M T T^T M^T \bar{c}_x$$

$$\Rightarrow \bar{c}_x = (M T T^T M)^{-1} M T x^T \quad \bar{c} = \begin{bmatrix} \bar{c}_x \\ \bar{c}_y \end{bmatrix}$$

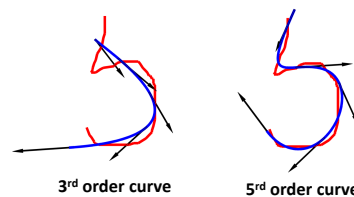
$$T = \begin{bmatrix} 1 & 1 & \dots & 1 \\ t_1 & t_2 & \dots & t_m \\ t_1^2 & t_2^2 & \dots & t_m^2 \\ \vdots & \vdots & \dots & \vdots \\ t_1^n & t_2^n & \dots & t_m^n \end{bmatrix} \quad M \text{ From Bernstein polynomial}$$

## Derivatives

- Derivative calculated as

$$\frac{\partial B(t)}{\partial t} = \sum_{i=0}^n \frac{\partial B_{i,n}(t)}{\partial t} c_i, \quad \frac{\partial B_{i,n}(t)}{\partial t} = n B_{i-1,n-1}(t) - n B_{i,n-1}(t)$$

- Example, '5'



- Derivatives are features

## Dataset

- 2250 multi-stroke ('4', '5', '=', '+', 'x') samples
- 4498 single-stroke ('1', '2', etc...) samples
- Dataset collected from only 6 users
  - May not be representative of all users
  - This perhaps explains the different performance in training and demonstration

## Selection of Features

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- Calculate the derivative at d points
- Compared the features using 5-nearest neighbour
- Cross-validation score on whole dataset

d	5	8	10	15
3 <sup>rd</sup> order Bezier	2.77%	2.65%	2.68%	2.71%
4 <sup>th</sup> order Bezier	2.68%	1.85%	2.11%	1.85%
5 <sup>th</sup> order Bezier	5.04%	3.46%	2.83%	2.73%

## Misclassification rate – single stroke characters

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Method	Misclassification rate
LSPC	1.98%
1-KNN	1.67%
3-KNN	1.64%
5-KNN	1.85%
9-KNN	1.99%
SVM, linear	1.47%
SVM, Polynomial p=2	1.08%
SVM, Polynomial p=3	0.98%
SVM, Polynomial p=4	0.84%
SVM, Gaussian	1.00%

## Discussion and conclusion

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- Bezier-curves fitted via least-squares and derivatives used as features
- Stroke-based approach yields excellent results
- SVM with 4<sup>th</sup> order polynomial gave highest accuracy:
  - 0.85% Misclassification rate
- Stroke-based approach simplifies tasks such as segmenting (**not discussed**)
- Lower practical performance perhaps due to **small dataset** (few samples, small amount of subjects)
  - Improve by enlarging dataset, and
  - Consider invariances (e.g. slight rotation)

## Questions?

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### Acknowledgements:

- Program written in Matlab, uses:
  - libSVM: <http://www.csie.ntu.edu.tw/~cjlin/libsvm/>
  - LSPC: <http://sugivama-www.cs.titech.ac.jp/~sugi/software/LSPC/>
- Thanks to the following people for entering data:
  - Duong Nguyen
  - Tomoya Sakai
  - Keisuke Nakata
  - Hyunha Nam

## References

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- Watt, Alan H., 3D Computer Graphics, Addison-Wesley, 2005

## Square loss fitting of a stroke (1)

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- Let  $B(t) = \begin{bmatrix} x(t) \\ y(t) \end{bmatrix}$   $c_i = \begin{bmatrix} c_i^x \\ c_i^y \end{bmatrix}$
- The curve can be expressed as
 
$$x(t) = \tilde{c}^x \mathbf{b}(t) \quad \tilde{c}^x = [c_0^x \ c_1^x \ \dots \ c_n^x]$$

$$\mathbf{b}(t) = [B_{0,n}(t) \ B_{1,n}(t) \ \dots \ B_{n,n}(t)]^T$$
- The point list is defined as
 
$$\{(x_i, y_i)\}_{j=1}^N \quad t = \frac{j}{n} \quad \text{we fit} \quad \{(x_i, t_i)\}_{j=1}^N \quad (\text{Each dimension separately})$$
- Output at different time-steps are  $\tilde{c}^x M T$ 

$$T = \begin{bmatrix} 1 & 1 & \dots & 1 \\ t_1 & t_2 & \dots & t_m \\ t_1^2 & t_2^2 & \dots & t_m^2 \\ \vdots & \vdots & \dots & \vdots \\ t_1^n & t_2^n & \dots & t_m^n \end{bmatrix} \quad M = \text{From Bernstein polynomial, e.g.} \quad M_3 = \begin{bmatrix} 1 & -3 & 3 & -1 \\ 0 & 3 & -6 & 3 \\ 0 & 0 & 3 & -3 \\ 0 & 0 & 0 & 1 \end{bmatrix}^T$$

## Square loss fitting of a stroke (2)

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- Square-loss fit:

$$E = (\mathbf{x} - \tilde{c}^x M T) (\mathbf{x} - \tilde{c}^x M T)^T$$

$$= \mathbf{x} \mathbf{x}^T - 2 \tilde{c}^x M T \mathbf{x}^T + \tilde{c}^x M T T^T M^T \tilde{c}^x$$

$$\Rightarrow \tilde{c}^x = (M T T^T M)^{-1} M T \mathbf{x}^T$$

- Same can be done for  $\mathbf{y}(t)$
- Regularize  $M T T^T M$  with  $\epsilon I$  for the case where the pixels are less than the control points