

Compact Representation and Recognition for Handwritten Mathematical Characters

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What this talk is about

- The main problem:
In handwriting recognition, the human and the computer take turns thinking and sitting idle. Small devices therefore challenged by MHR.
- We ask:
Can the computer do useful work while the user is writing and thereby get the answer faster after the user stops writing?
- We show:
The answer is “Yes”!

Outline

- Mathematical handwriting recognition
- Representing curve traces using truncated orthogonal series
- A complexity model for on-line computation
- An on-line algorithm to compute series coefficients

Math Handwriting Recognition

- Considered natural and desirable by many
- Different than natural language recog:
 - 2-D layout is similar to a combination of writing and drawing.
 - No fixed dictionary.
 - Many more similar few-stroke characters.



Usual Character Recog Methods

- Smooth and then re-sample data
- Match against N models, *OR...*
- Identify “features”, such as
 - Coordinate values of sample points, Number of loops, cusps, Writing direction at selected points, Center of mass, *etc*

Use a classification method, such as

- Nearest neighbour, Subspace projection, Cluster analysis, Support Vector Machines
- Rank choices by consulting dictionary

Difficulties

- Many characters in mathematics means comparison against all models slow.
- Determining features from points
 - Requires many *ad hoc* parameters.
 - Replaces measured points with interpolations
 - It is not clear how many points to keep, and most work depends on number of points

Series Representation

Reference Char and Watt [ICDAR 2007]

- **Main idea:** represent x and y coordinate curves as truncated series.
- **Advantages:**
 - *Compact* – few coefficients needed
 - *Geometric* – the truncation order is a property of the character set, not the device
 - *Algebraic* – desired properties of curves can be computed algebraically
 - *Numerically stable*

Series Representation – Details

- Functional inner product:

$$\langle f, g \rangle = \int_a^b f(t)g(t)w(t)dt$$

- Given a, b, w , the basis functions can be obtained from monomials by Gram Schmidt orthogonalization and can write:

$$f(t) = \sum_{i=0}^{\infty} c_i b_i(t), \quad c_i \in \mathbb{R}, b_i \in B$$

Series Representation – Details

- Coefficients may be obtained by:

$$c_i = \langle f, b_i \rangle / \langle b_i, b_i \rangle, \quad i \in \mathbb{N}_0$$

- Choosing weight fn $w(t) = 1/\sqrt{1-t^2}$ gives Chebyshev polynomial basis.

$$T_n(t) = \cos(n \arccos t)$$

- Series may be truncated, leaving a residual error that decreases with order.

Advantages of Series Rep.

- The representation is compact
- Device and scale invariance
- Other features can be computed
- Degree determined intuitively
(# cusps and turns)

Disadvantages of Series Rep.

- All the work to compute the series coefficients must be done after the series is written [non-linearity of $w(t)$].
- Many other recognition techniques share this problem.
- Can we somehow be more efficient by computing the series coefficients as the data is collected?

An On-Line Complexity Model

- Input is a sequence of N values received at a uniform rate.
- Characterize an algorithm by
 - $T_{\Delta}(n)$ no. operations as n -th input is seen
 - $T_F(n)$ no. operations after last input is seen
- Write on-line time complexity as
$$\text{OL}_n [T_{\Delta}(n), T_F(n)]$$
- E.g., linear insertion requires time
$$\text{OL}_n [O(n), 0]$$

On-Line Complexity Model (2)

- An algorithm that takes on-line time

$$OL_n[T_\Delta(n), T_F(n)]$$

takes total time

$$\sum_{i=0}^N T_\Delta(i) + T_F(N)$$

- That is, a factor of N can come for free.

On-Line Algorithm for Series Coeffs

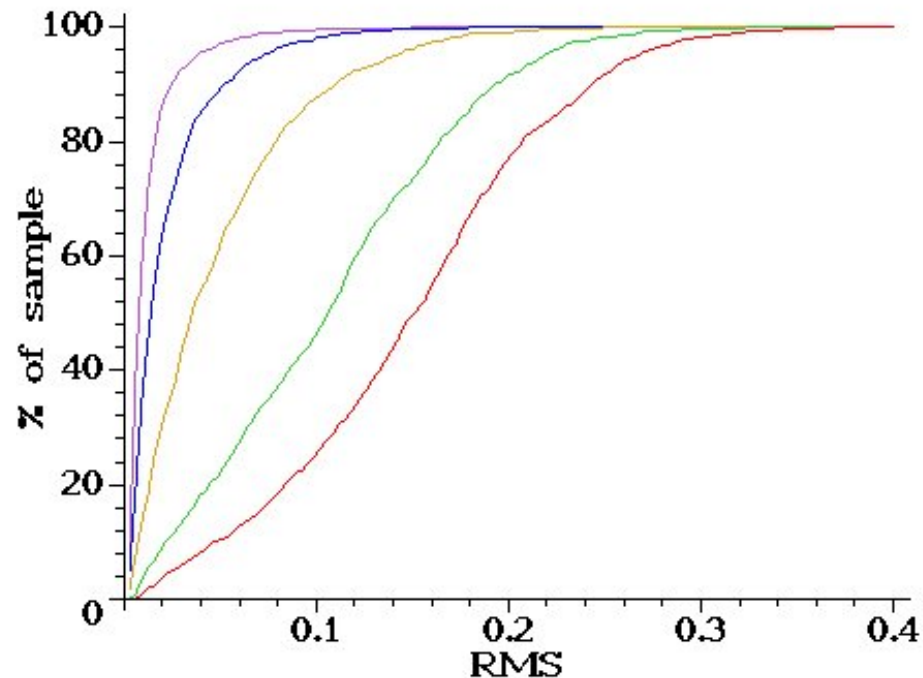
- If we choose a series whose weight function is linear, then the series coefficients can be computed on line.
- The series coefficients are linear combinations of the moments, which can be computed by numerical integration as the points are received.
- This is the **Hausdorff moment problem** (1921) and has been shown to be unstable by Talenti (1987).
- It is just fine, however, for the orders we need.

On-line Series Coeffs – Outline

- Use Legendre polynomials P_i as basis on the interval $[-1,1]$, with weight function 1.
- Collect numerical values for $f(\lambda)$ on $[0, L]$.
 L is not known until the pen is lifted.
- As the numerical values are collected, compute the moments $\int \lambda^i f(\lambda) d\lambda$.
- After last point, compute series coeffs for f with domain and range scaled to $[-1,1]$. These will be linear combinations of the moments.

Quality of Legendre Series

- Legendre series give the same order of RMS error as the Chebyshev series representation, but can be computed on-line.



On-line Series Coeffs – Details

$$\hat{f}(\tau) = f((\tau + 1)L/2) = \sum_{n=0}^{\infty} \hat{\alpha}_n P_n(\tau)$$

$$\hat{\alpha}_n = \left(n + \frac{1}{2}\right) \int_{-1}^1 \hat{f}(\tau) P_n(\tau) d\tau$$

$$= \frac{2n + 1}{L} \int_0^L f(\lambda) P_n(2\lambda/L - 1) d\lambda$$

$$= \frac{2n + 1}{L} \sum_{i=0}^n [t^i] P_n(2t - 1) \int_0^L f(\lambda) (\lambda/L)^i d\lambda$$

$$= \frac{2n + 1}{L} \sum_{i=0}^n \frac{[t^i] P_n(2t - 1)}{L^i} \mu_i(f, L).$$

$$\hat{\alpha}_n = (-1)^n \frac{2n + 1}{L} \sum_{i=0}^n \left(\frac{-1}{L}\right)^i \binom{n}{i} \binom{n + i}{i} \mu_i(f, L)$$

On-line Series Coeffs – Details

- A specialized numerical integration scheme is required for the moments.

$$\int_0^L \lambda^n f(\lambda) d\lambda \approx$$
$$\sum_{i=1}^{L-1} \frac{i^{n+1}}{n+1} \times \frac{f(i-1) - f(i+1)}{2} +$$
$$\frac{L^{n+1}}{n+1} \times \frac{f(L-1) + f(L)}{2}.$$

On-line Series Coeffs – Details

- The range of f can be scaled to any desired range $[a, b]$

$$\begin{aligned}\hat{f}(\tau) &= \frac{b - a}{f_{\max} - f_{\min}} \hat{f}(\tau) + \frac{a f_{\max} - b f_{\min}}{f_{\max} - f_{\min}} \\ &= \sum_{i=0}^{\infty} \hat{\alpha}_i P_i(\tau),\end{aligned}$$

Complexity

- The on-line time complexity to compute coefficients for a Legendre series truncated to degree d is then

$$T_{\Delta} = 2(d + 2)$$

$$T_F = \frac{3}{2}d^2 + \frac{11}{2}d + 10.$$

- That is, the time at pen up is *constant* with respect to the number of points.

Practical Cost

- The construction of the series coefficients at the end is the real time limiting operation.
- This should take on the order of 200 to 500 machine instructions for a series of order 10 to 15.

Comparison with Models:

Distance between curves

- Some classification methods compute the distance between the input curve and models.
E.g. Elastic matching, which takes time quadratic in the number of sample points.
- With orthogonal series representation, we have a much less expensive comparison:

$$\rho^2(C, \bar{C}) = \int_0^1 \left[x\left(\frac{t}{N}\right) - \bar{x}\left(\frac{t}{N}\right) \right]^2 + \left[y\left(\frac{t}{N}\right) - \bar{y}\left(\frac{t}{N}\right) \right]^2 dt$$
$$\approx \sum_{i=0}^d [c_i^x - c_i^{\bar{x}}]^2 + [c_i^y - c_i^{\bar{y}}]^2$$

- Linear in d . About 60-100 machine instructions!

Conclusions

- It is possible to compute series representation of characters quickly and compactly.
- This representation is compact, high-fidelity, device independent, numerically robust and allows algebraic treatment of the curves.
- The work to compute this rep. at pen-up is minimal, on the order of a few hundred machine instructions.
- Likewise, the cost to compute the distance between two curves is on the order of 100 machine instructions.
- The computations are straightforward and are suitable for hardware implementation.

References

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