Off-line Signature Verification

Professor Michael Blumenstein

- Head of School
  School of Information and Communication Technology
  Griffith University

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Griffith University

- Griffith ranks in the **top five percent of universities worldwide**, according to the 2012 Academic Rankings of World Universities (ARWU)
- Griffith also features in the world university rankings of the best universities under the age of 50, **the QS Top 50 under 50** and the **Times Higher Education 100 under 50**

Outline

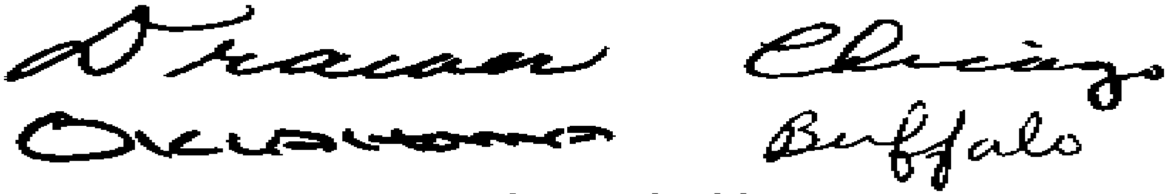
- Handwriting Recognition and applications
- Data processing and recovery of temporal information
- Features
- Neural Networks and Support Vector Machines
- Multi-Script Signature Identification & Verification
- Experiments

Automated Pattern Recognition

- The fields of Pattern Recognition and Computer Vision have incorporated aspects of such areas as:
  – Artificial Intelligence (Machine learning)
  – Digital Image and Video processing

Handwriting Recognition

Off-line – no temporal information



Sample Handwriting

- Applications include:
  - Bank cheque processing
  - Postal address recognition
  - Form processing
  - Automated exam assessment
  - Creating digital databases

Automated Handwriting Recognition

Preprocessing

Retrieve the boundary or skeleton of words or character images

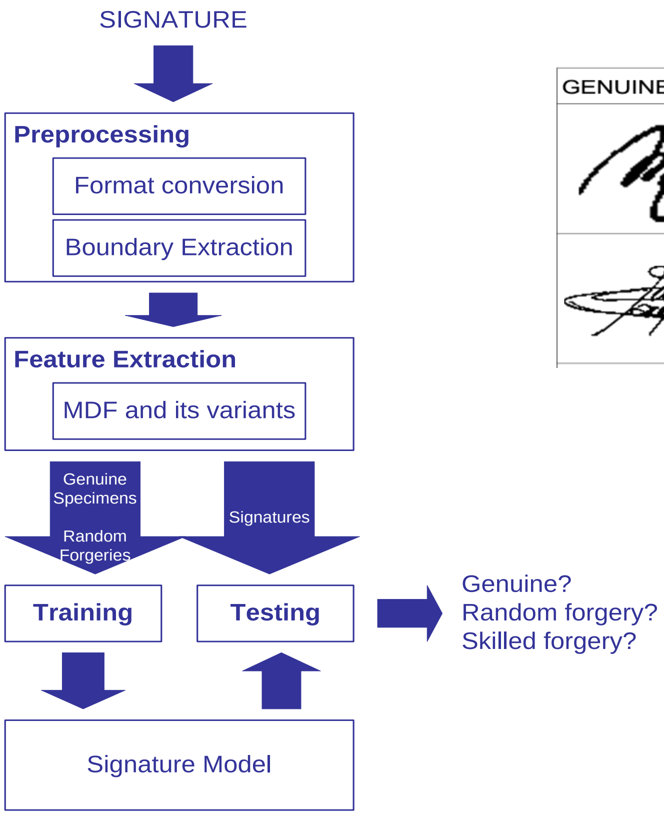
Extract salient features

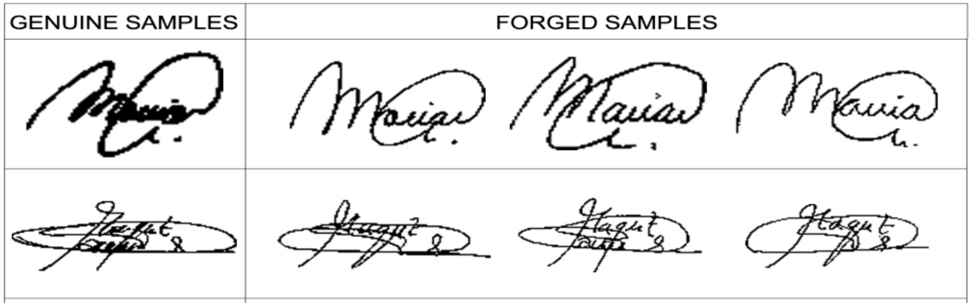
Classifier training and testing

Signature Verification

- The need to verify an identity occurs in many situations:
  - Contract, cheque and receipt analysis
    - Fraud detection
  - Personnel identification

Automated Off-line Signature Verification System





- Signature database

Data pre-processing

- Thresholding
- Noise removal
- Broken stroke restoration
- Boundary extraction
- Trajectory recovery

Recovery of Temporal Information

- Applications of trajectory recovery
  - Time ordering information
  - Segmentation: words, characters, strokes
  - Handwriting recognition
  - Signature verification

Recovery of Temporal Information (cont.)

Occluded start point

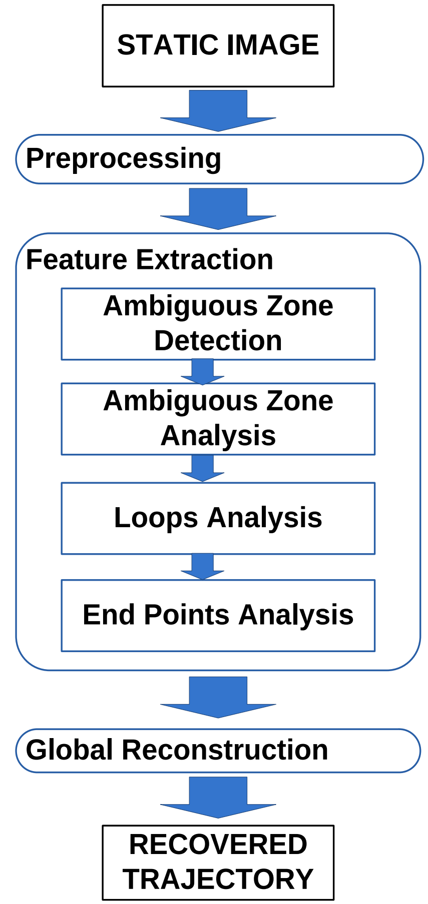
Double traced

Hidden loop

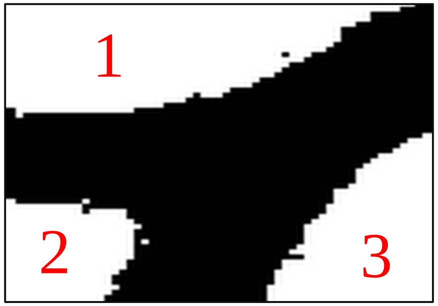
False loop

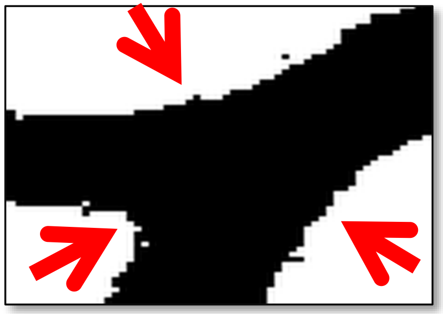
Hidden end point

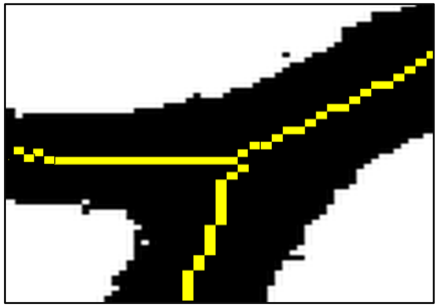
(Nguyen and Blumenstein, 2010)



Recovery of Temporal Information (cont.)







Swipe window
(Abuhaiba et al., 1995)

Curvature based
(Plamondon & Privitera, 1999)

Skeleton structure
(Kato et al., 2000)

Ambiguous zone detection techniques

Recovery of Temporal Information (cont.)

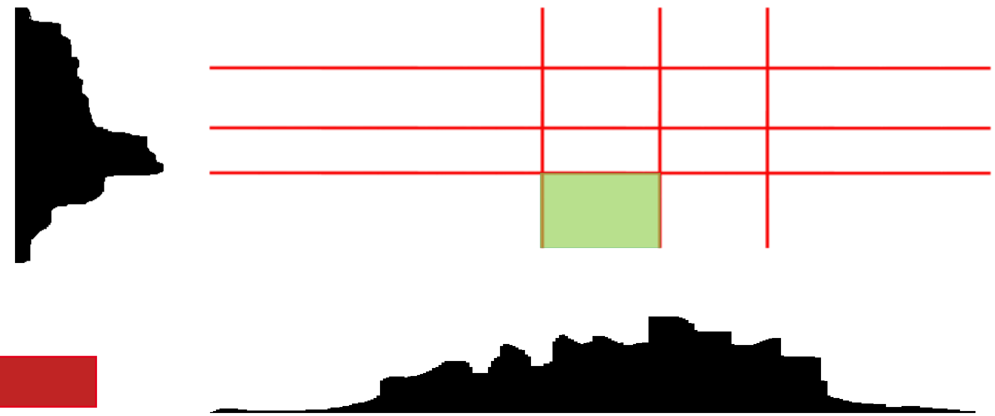
- Global reconstruction
  - Searching (Bunke et al., 1997)
  - Euler cycle (Kato et al., 2000)
  - Hamiltonian cycle (Jaeger, 1998)
  - Knowledge assisted (Rousseau et al., 2006)
  - Online data assisted (Nel et al., Qiao et al., 2007)

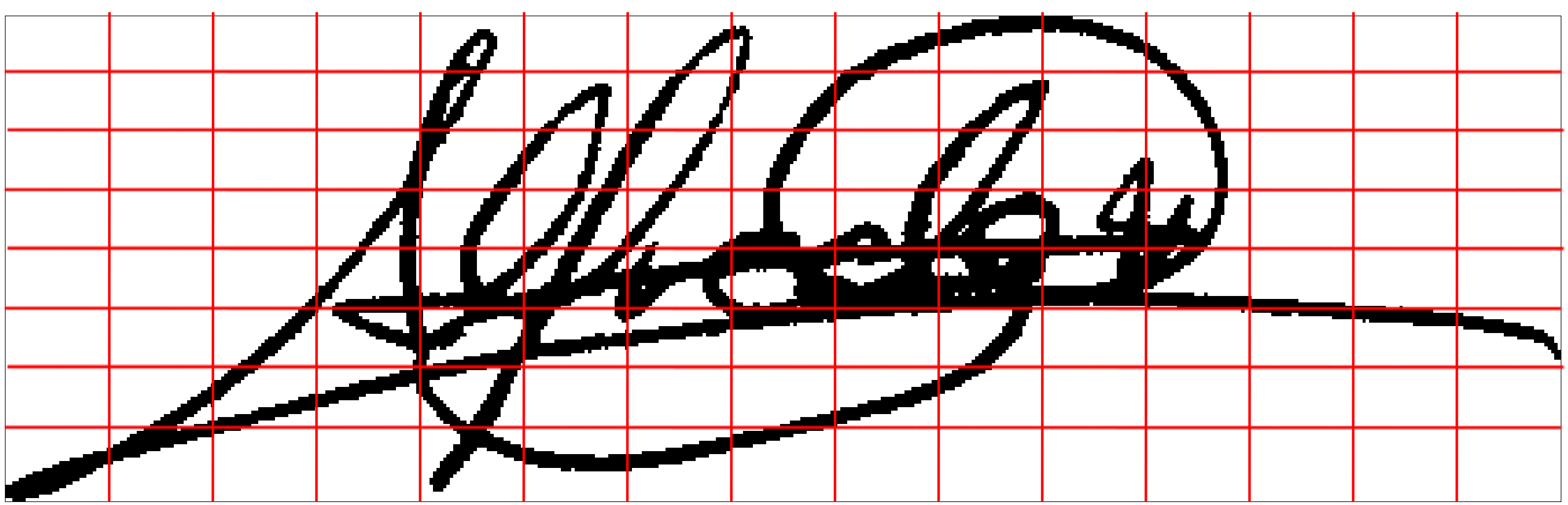
Feature Extraction

- Grid Based and Tree Based
- Rotation Invariant Features
- Global Features
- Feature Vector Dimension Reduction
- Feature Selection & Feature Combination

Feature Extraction – Grid Based and Tree Based

- Partitioning Strategy
  - Uniform size (Justino, 2005)
  - Adaptive size (Kalera, 2004)
  - Tree based (Jena, 2008)
- Element features
  - Global features





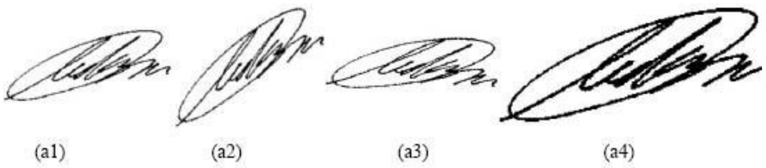
Feature Extraction – Rotation Invariant

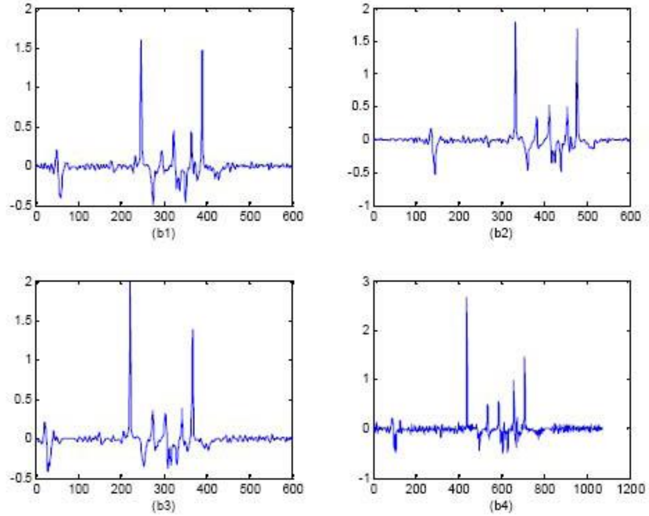
- Fixed Origin Features
  - A fixed point, which is rotation-invariant, is determined from the signature as the origin of an coordinate (e.g. Centre of Gravity)
  - Rotation-normalized
  - Features are extracted all around

(Jing, 2007)

Feature Extraction – Rotation Invariant (cont.)

- Curvature based
  - Dilated external boundary (Tai-ping, 2007)



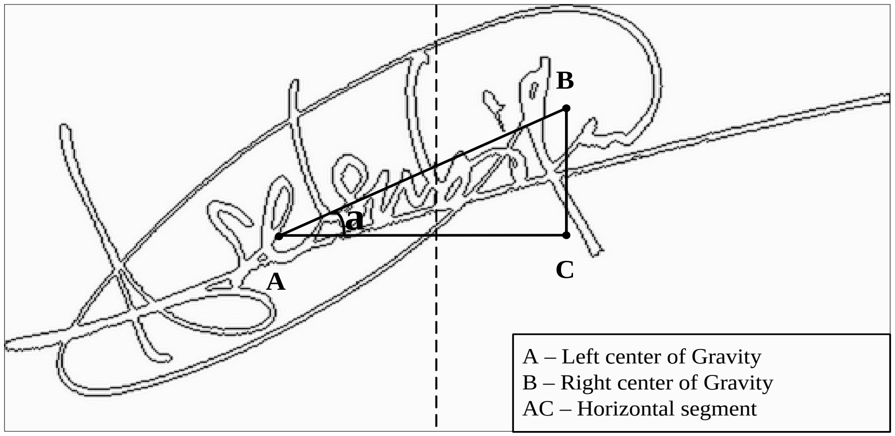


(Tai-ping, 2007)

Feature Extraction – Global

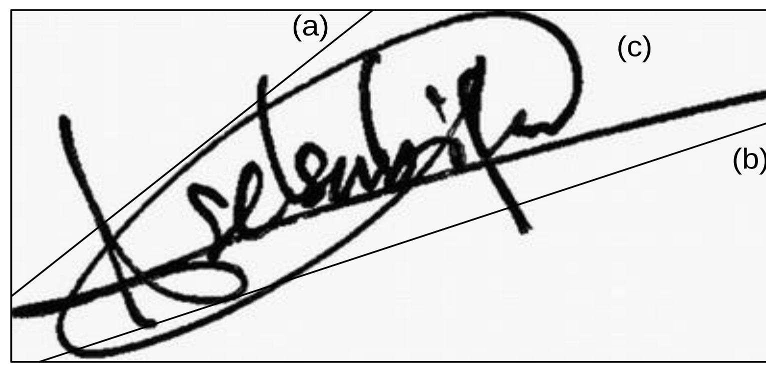
- Characteristics
  - Require less computation
  - More tolerant to variation and noise compared to local features
- Popular global features (Baltzakis, 2001)
  - Centre of Gravity
  - Height/width after width/height normalization
  - Image area
  - Pure width/height
  - Baseline shift
  - Vertical/horizontal centre of the signature
  - Aspect Ratio

Feature extraction examples



Centroid

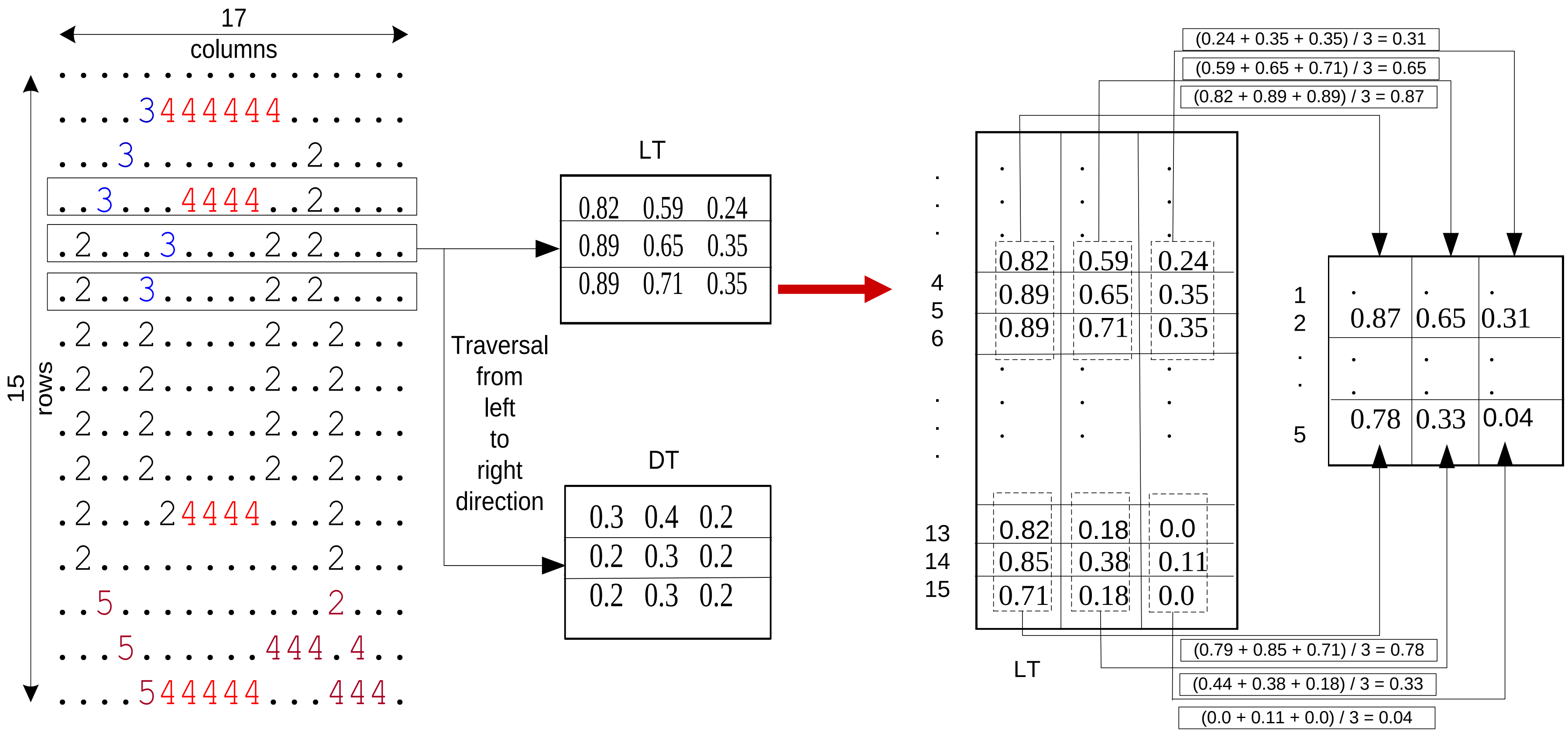
(Nguyen *et al.*, 2007)



(a) – Best fit line for the top
(b) – Best fit line for the bottom
(c) – The area of surface bounded by (a) and (b)

Best-fit

Feature extraction – Modified Direction Feature



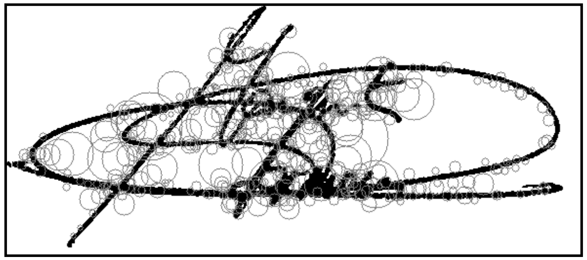
(Blumenstein *et al.*, 2004 & 2007)

Feature Extraction – Recent approaches

- In one of the techniques reported in Pal *et al.* (2012), an approach for signature verification using G-SURF was presented
- Two types of features were extracted for this off-line signature verification task:
  a) SURF
  b) G-SURF

Feature Extraction (cont.)

- SURF (Speeded Up Robust Feature) is a feature extraction approach, first presented by Bay *et al.* (2006)
- The SURF algorithm is composed of mainly two parts: firstly, key-point detection and secondly, key-point description.
- An example of key-points generated in one of our sample signature images is shown in the figure below:



Feature Extraction (cont.)

- **Gabor Features**
  - A two-dimensional Gabor filter in the spatial and frequency domain can be defined by the following formula:

$$G(x, y, \lambda, \theta, \psi, \sigma, \gamma) = \exp\{(x'^2 + \gamma^2 y'^2)/2\sigma^2\} \cos(2\pi x'/\lambda + \psi)$$

Where, $x' = x\cos\theta + y\sin\theta$

$y' = -x\sin\theta + y\cos\theta$

Feature Extraction (cont.)

- **G-SURF Feature Computation**
  - Here, 2500 (50x50) dimensional Gabor filter-based features are obtained from each key-point.
  - To get the final G-SURF feature, we concatenate the 2500-dimension Gabor filter response with the original SURF feature descriptor (128 dimension) of that key-point

Feature Extraction – Feature Dimension Reduction

- Feature vector of larger dimension
  - Higher computational cost
  - Not always returns better results
- Solutions
  - Local averaging
  - Principle Component Analysis (PCA)

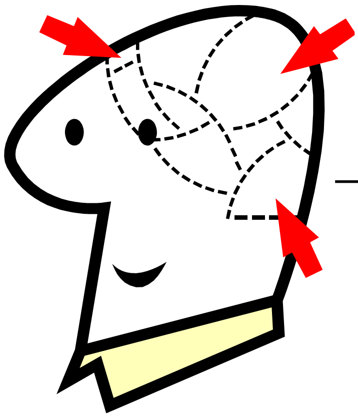
Feature Selection and Feature Combination

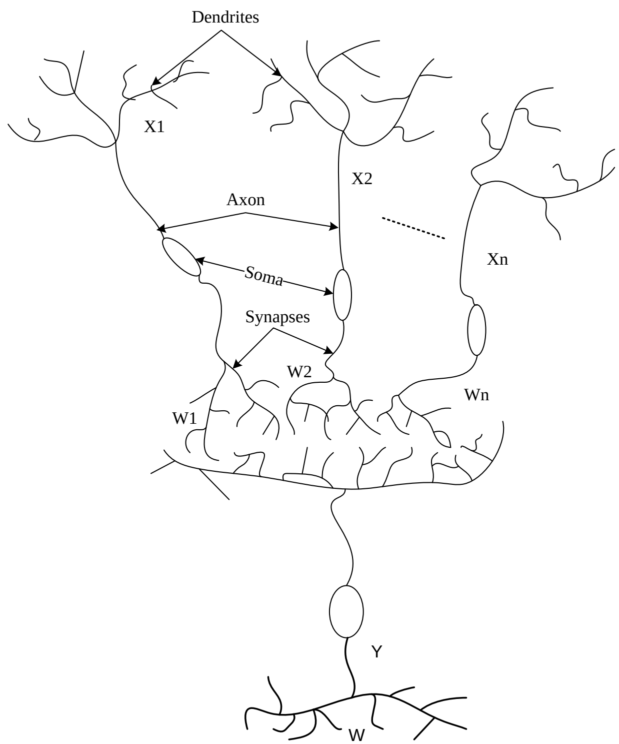
- Large number of feature extraction techniques
- The combination of several “Good” features not always returns higher accuracy
- Solutions
  - Exhaustive Search
  - Majority Voting
  - Genetic Algorithm (Leedham, 2005)

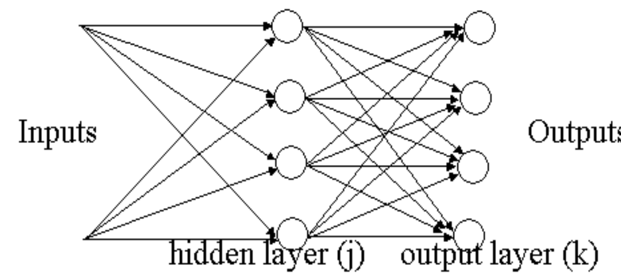
Computational Intelligence (1994)

- Artificial Neural Networks
- Evolutionary Systems
  – Genetic Algorithms
- Fuzzy Logic

Artificial Neural Networks (ANNs): Biological Inspiration



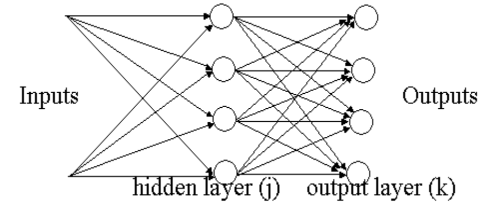




- Training (Learning) Algorithms
  - Supervised
  - Unsupervised

Backpropagation Algorithm

1986: Rumelhart, Hinton and Williams
1982: Parker and 1974: Werbos



- Step 1: Initialise weights
  - Initialise weights to small random values
- Step 2: Present input vector $x_1, \ldots, x_n$ and desired output vector $d_1, \ldots, d_n$
- Step 3: Calculate actual output (forward pass)

$$y = f\left(\sum_{i=1}^{n} w_i x_i\right)$$

- Step 4: Adjust weights (reverse pass)

$$w_{ij}(t+1) = w_{ij}(t) + \eta * \delta_j * y_i$$

where

η is a gain term or learning rate (0 - 1)

δ_j is an error term for node j

- **If node k is an output node, then:**

$$\delta_k = y_k * (1 - y_k) * (d_k - y_k)$$

- **If node j is an internal hidden node, then:**

$$\delta_j = y_j * (1 - y_j) * \sum_k \delta_k w_{jk}$$

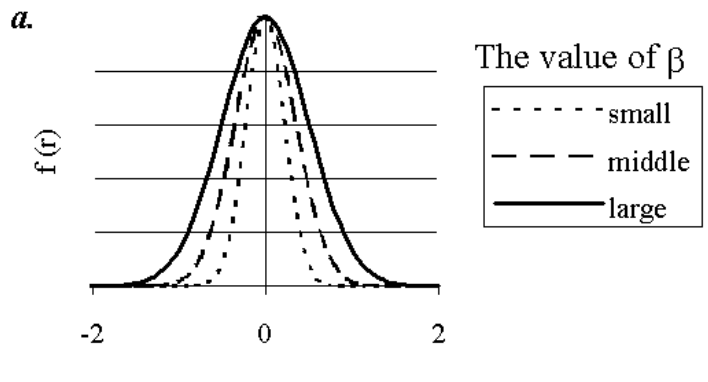
- Step 5: Repeat by going to Step 2

Radial Basis Functions (RBF)

- The general form of a radial basis function is

$$\Phi(r) = e^{-(\frac{r^2}{\beta})}$$

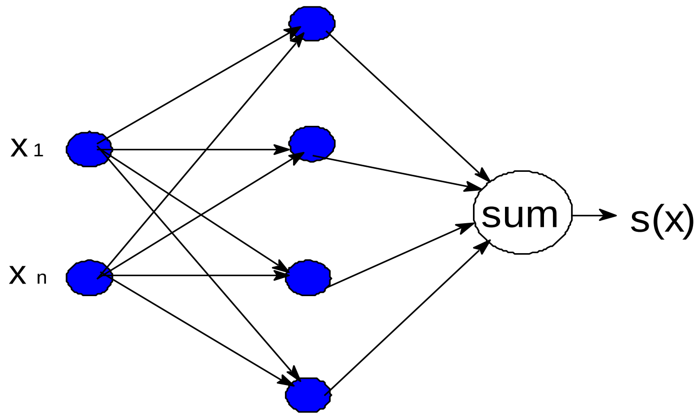
- where β is a parameter specifying the width of the basis function, often called the smooth factor or the receptive field. The shape of the function with three different sizes of β is shown opposite:



The Gaussian Basis Function

RBF (cont.)

- The structure of an RBF classifier with *n* inputs and one output is shown in the figure below:



RBF Neural Network

Support Vector Machines (SVMs)

- A relatively new statistical learning technique developed by Vapnik (1998)
- SVMs were designed for two class problems originally
- They look for the optimal hyper-planes which maximize the distance or margin between two classes
- These have been extended for multi-class problems

Recent experimental results on the GPDS-160 corpus

- When SVMs were employed in Nguyen *et al.* (2011), a 2D Gaussian Filter produced the lowest Average Error Rate (AER) of 13.93%
  - AER is average of the False Acceptance Rate (FAR) and False Rejection Rates (FRR)
- Comparison to other researches using the GPDS-160 corpus, the following experiments employed simple forgeries for training
  - Ferrer *et al.* (2005) – AER of 13.35%
  - Vargas *et al.* (2008) – AER of 12.33%

Accuracy obtained using G-SURF

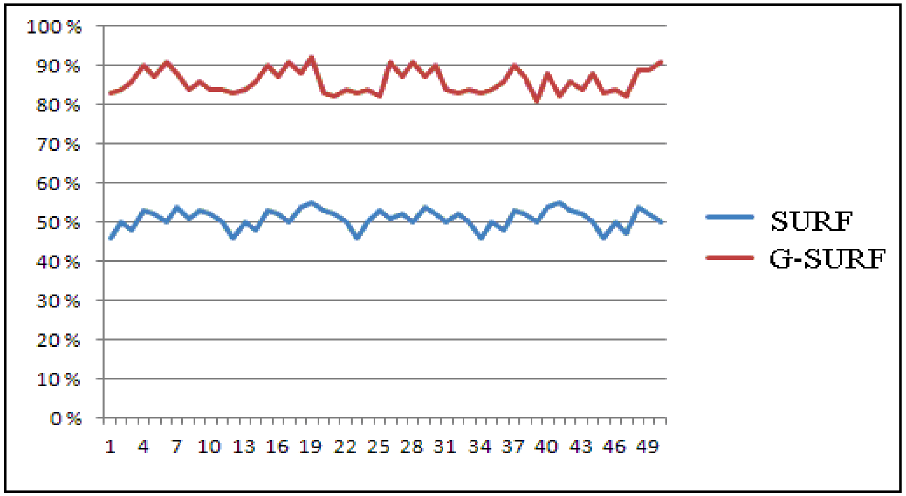
- When the SURF feature, G-SURF feature and SVM classifiers were employed, encouraging results were obtained (Pal *et al.*, 2012)
- Error rates of 23.25% (FRR) and 26.75% (FAR) were obtained as a result of experiments when the SURF features were employed
- Encouraging error rates of 2.35% (FRR) and 3.55% (FAR) were obtained as a result of experimentation using the G-SURF features

Accuracy obtained using G-SURF (cont.)

- Values of FRR and FAR using the SURF and G-SURF feature respectively are shown in the table and figure below:

Comparative results of SURF and G-SURF

Feature	FAR (%)	FRR (%)
SURF	23.25	26.75
G-SURF	2.35	3.55



Comparison of key-point classification using SURF and G-SURF

Multi-Script Off-line Signature Identification and Verification

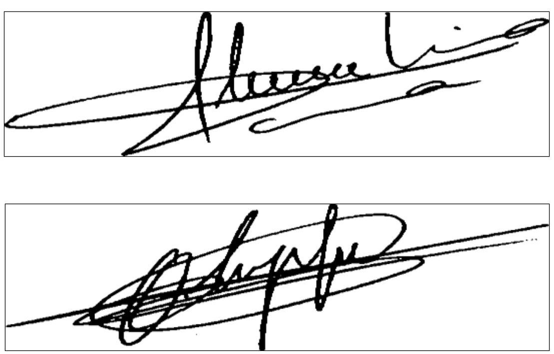
- Multi-script off-line signature verification is a new area of research in the signature verification field
- In the field of signature identification/verification, most of the published work has dealt with English signatures
- Some countries (e.g. India, Singapore) have more than one or two scripts that are not only used for handwriting but also for signing purposes

Multi-Script Off-line Signature Identification and Verification

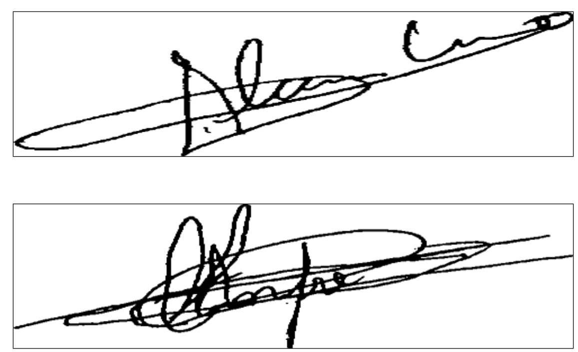
- A country having two or more scripts and languages is known as a multi-script and multi-lingual country
- In a multi-script and multi-lingual country, languages are not only used for writing/reading purposes but also applied for signing purposes
- In such an environment in India, the signatures of an individual with more than one language are essentially needed in official transactions (e.g. in a passport application form, an examination question paper, a money order form, bank account application form etc.)

Multi-Script Signature Database

- For one of our proposed multi-script signature verification systems, the signatures of English, Hindi and Bangla were considered
- Some English genuine signature samples with their corresponding forgeries are shown below



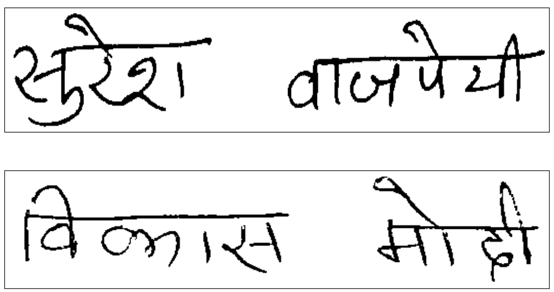
English (Genuine)



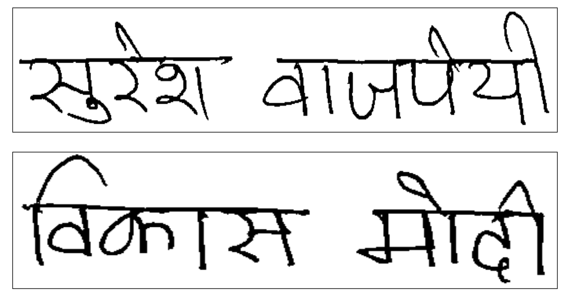
English (Forged)

Multi-Script Signature Database (cont.)

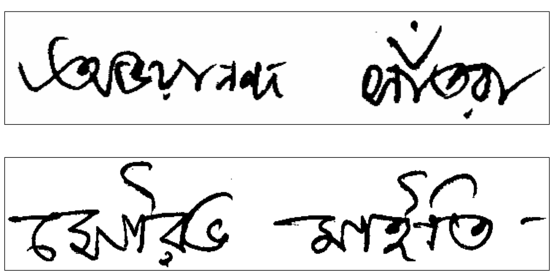
- Some Hindi and Bengali genuine signatures, with their corresponding forgeries, are shown below



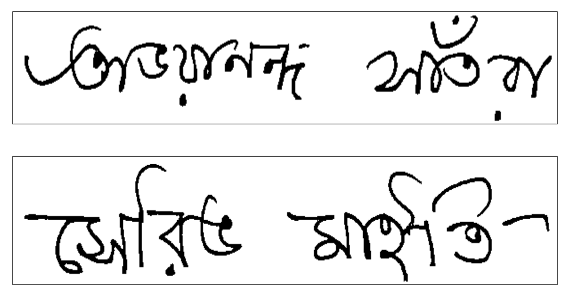
Hindi (Genuine)



Hindi (Forged)



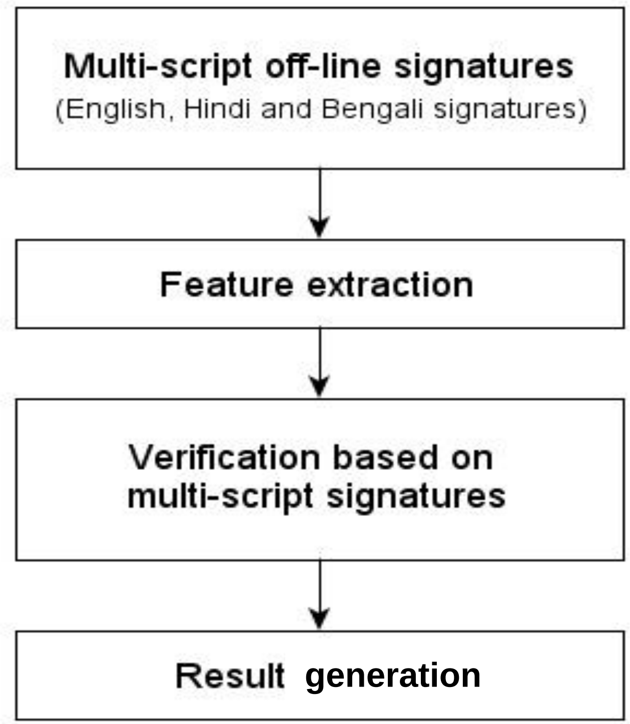
Bengali (Genuine)



Bengali (Forged)

Signature Verification without Signature Script Identification

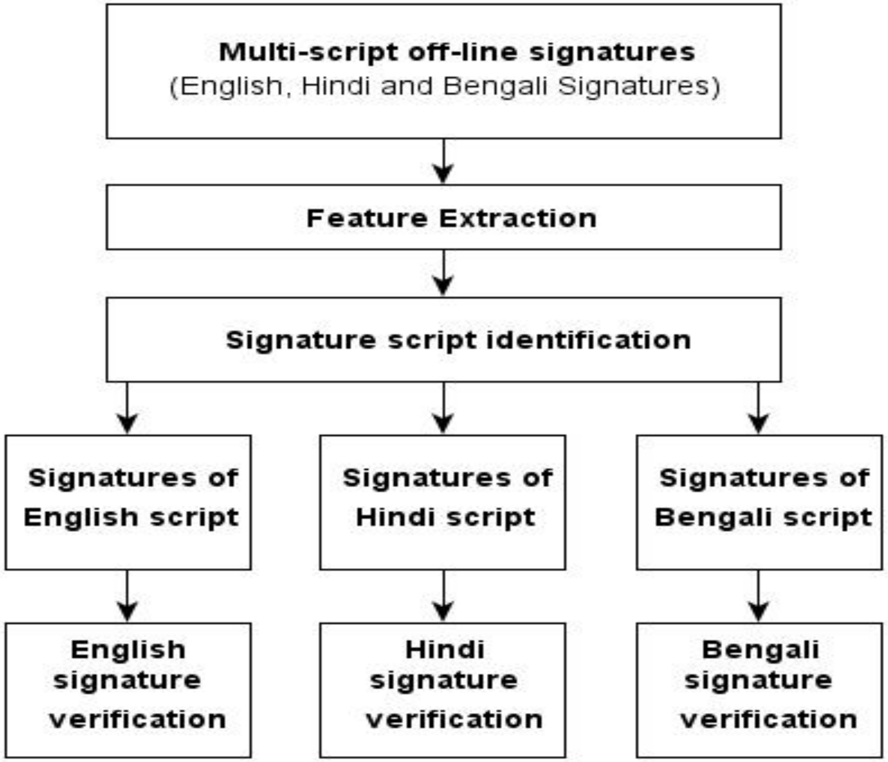
- As indicated, for multi-script off-line signature verification, the signatures of English, Hindi and Bengali have been considered
- Multi-script verification has been performed initially without signature script identification and this is illustrated in the adjacent figure



Multi-script signature verification without signature script identification

Signature Verification following Signature Script Identification

- In this multi-script signature verification example, signatures of English, Hindi and Bengali have again been considered.
- In this stage, verification has been performed following signature script identification



Multi-script signature verification after signature script identification

Feature extraction in Non-English Signature Verification

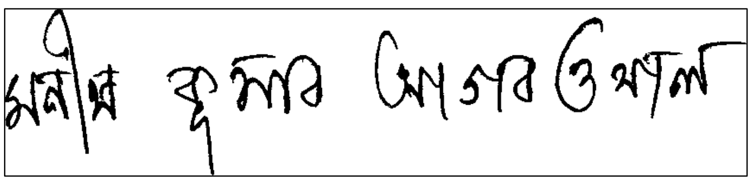
- Signature verification involving non-English signatures is a sparse area of research in the signature verification field
- In an approach proposed by Pal *et al.* (2013), a Non-English Signature verification technique considering Bangla signatures was presented
- Intersection/Junction/End Points were considered as features for verification

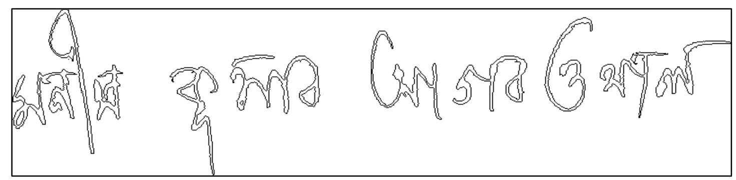
Feature extraction in Non-English Signature Verification (cont.)

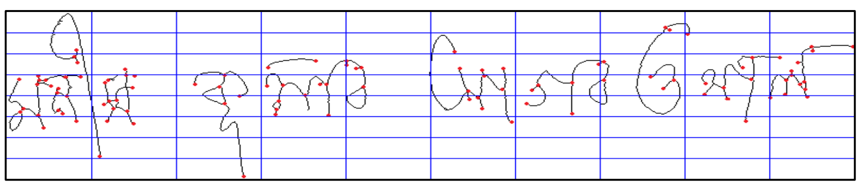
- An intersection point is defined as a pixel point, which has more than two neighboring pixels with 8-connectivity, while an endpoint has exactly one neighboring pixel
- Intersection features are extracted from the thinned signature image, which is first normalized into 200×800 pixels
- The thinned signature image is then divided into 20 blocks each of size 100×80 pixels
- For each block, the number of endpoints and intersection/junctions are found and counted separately

Accuracy obtained for Non-English Signature Verification (Bangla)

- Intersection points and endpoints of a Bangla signature image are shown in the figures below:





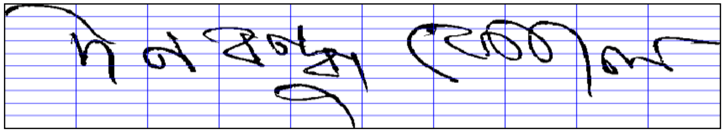


- An Average Error Rate (AER) of 15.57% was obtained

Feature extraction in Non-English Signature Identification (cont.)

- In another approach by Pal *et al.* (2011), a technique for a bi-script off-line signature identification system involving Bangla and English signatures was presented
- Under-sampled bitmap features were utilised
- To obtain the under-sampled bitmaps, each input image was divided into a number of non-overlapping blocks of similar size shown in the figures below
- The number of black pixels in each block was computed

Example of a normalized Bengali signature image



Non-overlapping window-map on the normalized signature image

Feature extraction in Non-English Signature Identification (cont.)

- The result of the pixel distribution obtained from the Figure in the last slide is shown in the following table:

367	9	0	0	0	0	0	0	0	0
1	93	14	75	30	159	285	325	0	0
70	133	186	338	119	169	347	260	46	196
15	372	268	404	326	97	259	262	232	192
0	313	304	280	430	109	118	212	413	138
0	110	123	5	333	64	104	0	269	48
0	30	0	135	173	54	44	0	80	0
0	0	0	86	284	2	0	0	31	0
0	0	0	0	91	0	0	0	0	0
0	0	0	0	64	0	0	0	0	0

Pixel distribution obtained from undersampled bitmaps using non-overlapping window-map of normalized image.

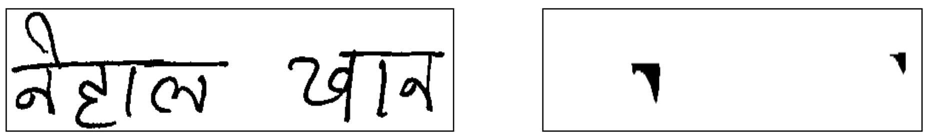
- An average accuracy of 99.41% was obtained in this experiment

Feature extraction in Non-English Signature Verification (cont.)

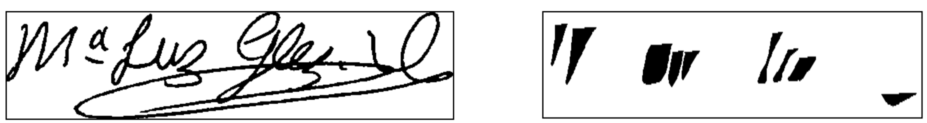
- Another multi-script signature verification approach was performed by Pal *et al.* (2013), which considered English and Hindi signatures
- Some local features were extracted for signature script identification (such as: water reservoir feature, aspect ratio (height/width) feature, loop feature etc.)
- Verification was conducted separately based on the identified script result

Feature extraction in Non-English Signature Verification (cont.)

- Two signatures of Hindi and English with their existing top water reservoirs are shown in Figures below.



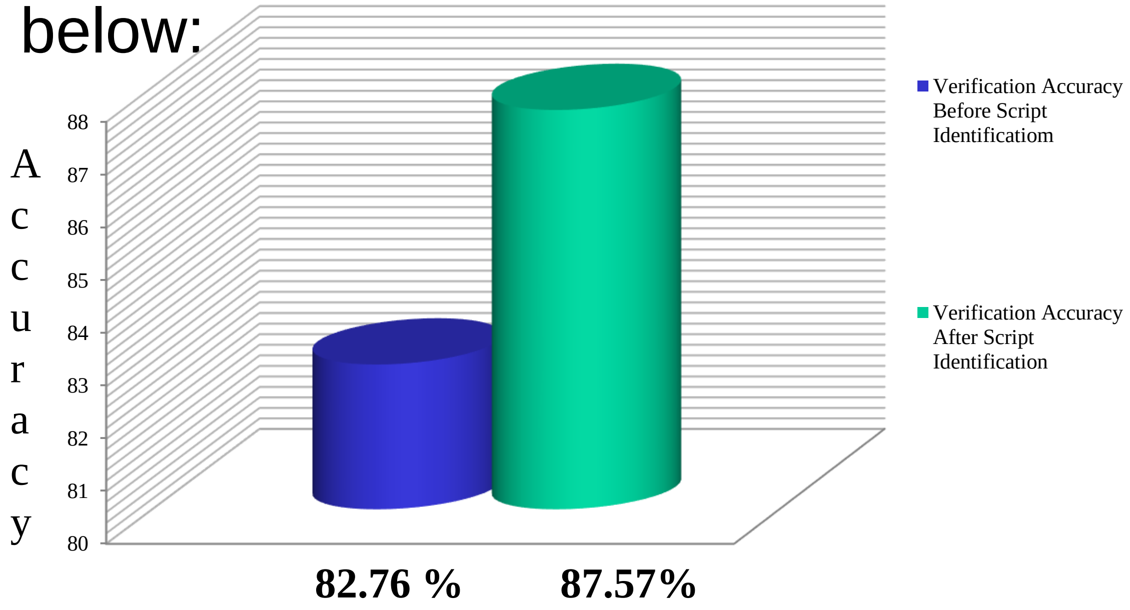
A Hindi sample and its top reservoirs



An English sample and its top reservoirs

Accuracy obtained for Non-English Signature Verification (Hindi)

- Verification accuracy after script identification was much higher than before script identification, as shown in the figure below:



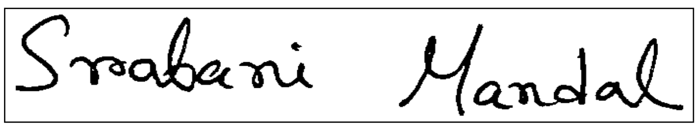
Representation of accuracy in two different phases of verification

Feature extraction in Non-English Signature Identification (Chinese)

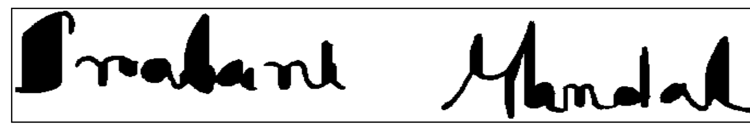
- In another report, a signature script identification technique was proposed by Pal. *et al.* (2012), considering English and Chinese signatures
- Background and foreground information was used to get the desired accuracy
- Two types of background information were considered
- For this experiment, it was necessary to create a custom database, which included English as well as Chinese signatures

Feature extraction in Non-English Signature Identification (cont.)

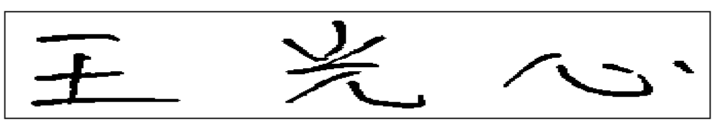
- The Background part of the English and Chinese signature images are shown in the following figures:



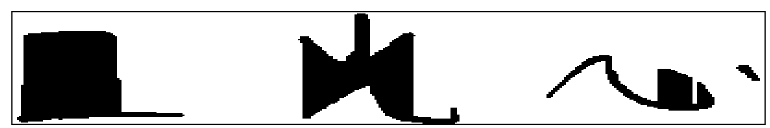
English signature sample (original)



The background part of English signature sample



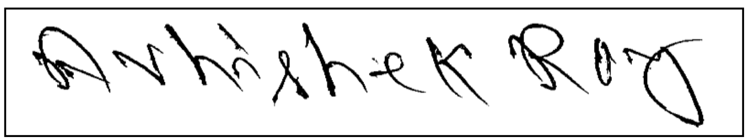
Chinese signature sample (original)



The background part of a Chinese signature sample

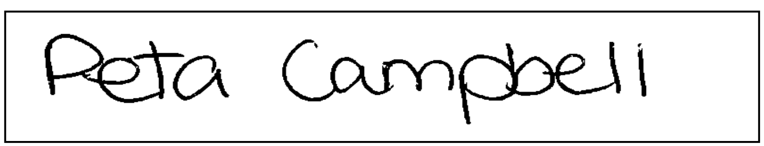
Feature extraction in Non-English Signature Identification (Chinese)

- Another technique was applied to extract different background parts of the signatures and these are illustrated in the following figures:



English signature sample(original)

The extended background part of an English sample



English signature sample(original)

The extended background part of an English sample

- The best result (97.70%) was obtained

Conclusions

- More research needed in the area of automated off-line signature verification to develop products, which are of use to practitioners
- Enhanced features, classifiers and combinations
- Clues from the area of forensic document examination
  - New methods for recovery of dynamic information from off-line images
- Emerging area: Multi-Script Signature Verification

Fin

Thank you.

Questions?