

# **Comparison of Offline Signature Verification Systems with Support Vector Machines and Neural Network Classifiers Using Geometrical and Statistical Features**

Padmajadevi. G<sup>1</sup>, Dr. Aprameya K.S<sup>2</sup>

Associate Professor, Department of Electronics and Communications Engineering, Malnad College of Engineering, Hassan, India<sup>1</sup>

Research Guide, Department of Electrical and Electronics Engineering, University B.D.T College of Engineering, Davanagere, India<sup>2</sup>

**ABSTRACT:** Signature has been a distinguishing biometric feature for human verification for long time. Even today, the signature of a person is used for human identification because each individual has distinct signature and every signature has its own physiology or behavioural characteristics. So, the human signature is used for identification of person in various authentication work like bank cheques, contract letters etc. The signature identification is a hot topic of research from decade and still lot of research happening in this field. The signature identification can be done either off-line or on-line. The off-line signature verification schemes work on pattern features present in signature images and on-line signature verification schemes work on dynamics acquired during the process of signature. Here in this paper, we used the geometrical and statistical features of images for offline signature verification. The proposed offline signature verification has been tested on 2004\_MCYTDB\_OffLineSignSubCorpus dataset through support vector machine (SVM) and neural network (NN) training and classification. The experimentation done on standard data set show that, the results obtained from SVM and NN are competent to other offline signature verification techniques and SVM results for verification are ahead compared to results of NN.

**KEYWORDS:** Offline Signature Verification, Support Vector Machine, Neural Network, Geometrical Feature, Statistical Feature.

## **I. INTRODUCTION**

Offline signature verification (OffSV) is not only area of research in image processing and pattern recognition but also it is widely used for human identification in finance, access control, contractual matters and security.

There are two types signature verification methods namely On-line signature verification (OnSV) [1][2] method and OffSV method. In OnSV signature image is captured and analysed in real time as the person is signing it. To capture the signature in real time OnSV [1] approach uses a touch screen monitor and an electronic tablet to take dynamic information for verification purpose and extract information about a signature and records the motion of the stylus sensor at the time of signature is produced and includes location, velocity, acceleration and pressure on pen. In OffSV method optical scanner is used to digitize handwriting data written on paper deals with a 2-D image of the signature. Here stable dynamic characteristics are absent because of the non-repetitive nature of variation of the signatures, due to age, illness, geographic location and perhaps to some extent the emotional state of the person accentuating the problem. Thus the OffSV method is complex. The researchers in above techniques use neural network (NN) [3][4][5], hidden markov model (HMM) [6]–[9], support vector machine (SVM) [10]–[13], discrete cosine transform (DCT) [13][14], global features [16]–[18], stroke [19][20] based approach in verifying signatures.

# International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor & UGC Approved Journal)

Website: [www.ijirset.com](http://www.ijirset.com)

Vol. 6, Issue 8, August 2017

In our current research emphasis is on producing reduced robust feature set using geometric and statistical features present in signature image. The algorithm for developing geometric and statistical features is shown in figure 2 and 3 respectively. The generated features are trained using SVM and NN with different number of signature each time and the verification statics are shown in table 3 and 4 respectively. The designed algorithm works much faster because of small number of feature set.

This remaining part of this paper is ordered as: The segment 2 discusses the in depth literature survey, segment 3 illuminate proposed architecture with algorithms geometric\_feature, statistical\_feature methods feature extraction. The obtained features for signature set and their error metric statistics measured in FAR, FRR, AER & OER are discussed in segment 4 finally the paper is summarized in segment 5.

## II. LITERATURE SURVEY

Universally accepted traditional authentication mechanism is signature verification and it is significant evidence in economical sector of any individual and on his behalf. The most crucial aspect in signature analysis is the psychological impact of signer on signature style, even then signatures are extensively acknowledged biometric for official means to verify an individual identity in economic/administrative sector. The research in signature analysis is primarily divided into OnSV and OffSV.

The VahabIranmanesh et. al. [3] in OnSV used signature coordinate point and pen pressure features with back propagation NN for verification. Shiwanisthapaket et. al. [5] in OffSV used global features, mask, texture normalized feature vector to the NN. H.S. Yoon et. al. [8] in OnSV used polar coordinate system with robust feature set with angle variation and used HMM to match test signature with reference signature. K N Pushpalatha et. al. [9] applied HMM in OffSV with two level contourlet transform to obtain feature vector later textural features are calculated and concatenated with coefficients of contourlet transform to form the final feature vector. Fauziyah s. et. al. [13]. developed OnSV using SVM for characterizing pen-strokes consisting X Y coordinates and stored in the signature database. Kruthi C et. al. [10] applied SVM on OffSV using features such as centroid, centre of gravity, number of loops, vertical and horizontal and normalized area in a database. Saeid Rashid et. al. [15] used DCT in OnSV by using features like position, pressure and angle of pen. The most crucial component of signature analysis is extracting features from signature, Vu Nguyen et. al. [18] combined global feature energy with horizontal and vertical projection of distance in between key stroke in signature image, and the height-width of the signature for generating feature set. Ramachandra A C et. al. [16] extracted features based on ratio of height to width, maximum horizontal histogram and maximum vertical histogram horizontal center and vertical center of the signature, end points of the signature, signature area.

The various researchers in OnSV and OffSV used different strategies and different feature set for verifying query signature. But still research is in progress in further reducing error metric in verifying/recognizing signature image. This paper focus on developing fusion on geometric and statistical features present in offline signature image with reduced error rate.

## III. PROPOSED ARCHITECTURE

OffSV is primarily a pattern recognition problem that accepts query signature as input. Then the query signature is compared against signature set of pre existing trained dataset of a particular individual for verification of genuine of an individual. The proposed architecture for OffSV constitute four major phases, i.e. acquiring signature, preprocessing of acquired signature, extracting features from preprocessed signature and matching of extracted features to prove genuine. For matching purpose SVM and NN are used in proposed experimentation.

# International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor & UGC Approved Journal)

Website: [www.ijirset.com](http://www.ijirset.com)

Vol. 6, Issue 8, August 2017

## 3.1 NOTATIONS

The following table 1 describes the notations used in this paper.

Table 1: Used Notations

Notation	Description
OffSV	Offline signature verification
OnLV	On-line signature verification
GFE	Geometrical Feature Extraction
SFE	Stastical Feature Extraction
GLCMs	Gray Level Co-occurrence Matrices
Cr	Correlation
Hm	Homogeneity
Me	Mean
Sd	Standard_Deviation
En	Entropy
Rms	RootMeanSquare Level
Va	Variance
Sm	Smoothness
Ku	Kurtosis
Sk	Skewness
FAR	False Acceptance Rate
FRR	False Recognition Rate
AER	Average Error Rate
OER	Overall Error Rate

## 3.2 ACQUIRING SIGNATURE

The signature image for experimentation is taken from dataset 2004\_MCYTDB\_OffLineSignSubCorpus. The experimented dataset contains samples of 75 individual signature set. Where in each individual signature set contains 15 genuine and 15 forgery signatures. The sample signatures shown in figure 1 are of group 0002, where in the

## International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor & UGC Approved Journal)

Website: [www.ijirset.com](http://www.ijirset.com)

Vol. 6, Issue 8, August 2017

signatures 0002v00, 0002v03, 0002v02, 0002v01 are genuine and 0003\_0002f00, 0003\_0002f01, 0003\_0002f02, 0003\_0002f03 are forgery signatures.



Fig. 1: Signature Image from group 0002.

### 3.3 PREPROCESSING OF SIGNATURES

The signature set images shown in figure 1 are cropped to extract only signature portion leaving beyond boundary elements. The cropped signatures are preprocessed to convert to binary representation. The resultant signature group is shown in figure 2.

## International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor & UGC Approved Journal)

Website: [www.ijirset.com](http://www.ijirset.com)

Vol. 6, Issue 8, August 2017



Fig. 2: Binary equivalent of figure 1 signature images

The binary signature images shown in figure2 are converted into pixel point images and shown in figure3. The pixel map signature images are the down sampled binary signature images of figure 2, which are down sampled with a factor of 2 in along both row and column.

## International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor & UGC Approved Journal)

Website: [www.ijirset.com](http://www.ijirset.com)

Vol. 6, Issue 8, August 2017



Fig. 3: Pixel points in signature image

### 3.4 EXTRACTING FEATURES FROM PREPROCESSED SIGNATURE

The most important phase in OffSV is extracting features from preprocessed signature. Different researchers applied several strategies to extract the features. Extracted features of queried signature image in this phase are the input of recognition/classification phase. The recognition/classification step compares features of queried signature against trained dataset of that individual to prove genuineness. In this paper the feature extraction is divided into geometrical feature extraction (GFE) and statistical feature extraction (SFE).

# International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor & UGC Approved Journal)

Website: [www.ijirset.com](http://www.ijirset.com)

Vol. 6, Issue 8, August 2017

### 3.4.1 GEOMETRICAL FEATURE EXTRACTION (GFE)

The proposed algorithm for GFE is shown in fig. 4

```

Algorithm Geometric_Feature( )
//Input: Signature image
//output: 32 geometric features consisting of 16 distance features & 16 angle features
begin
    Step 1: Calculate the centroid(c) for pixel points in signature image
    Step 2: Divide pixel points in signature image into four partition centered at c.
    Step 3: Extract 4 pixels from each partition totaling 16 pixels using following criteria
        First partition      Second partition      Third partition      Fourth partition
        d1=(xmin,y)          d5=(xmin,y)          d9=(xmin,y)          d13=(xmin,y)
        d2=(xmax,y)          d6=(xmax,y)          d10=(xmax,y)         d14=(xmax,y)
        d3=(x,ymin)          d7=(x,ymin)          d11=(x,ymin)         d15=(x,ymin)
        d4=(x,ymax)          d8=(x,ymax)          d12=(x,ymax)         d16=(x,ymax)
    Step 4: Find Euclidian distance of d1 to d16 with centroid and take them as first 16 geometric features named Dist1-Dist16.
    Step 5: Find angle of d1 to d16 with centroid C and take them as next 16 geometric features named Ang1-Ang-16.
endGeometric_Feature
    
```

Fig.4:Algorithm Geometric\_Feature

### 3.4.2 STASTICAL FEATURE EXTRACTION (SFE)

The proposed algorithm for SFE works directly on input signature image and gives 10stasticalfeatures of signature image. The proposed algorithm for SFE is shown in fig. 5

```

Algorithm Stastical_Feature( )
//Input: Signature RGB color image
//output: 10 stastical features.
begin
    Step1: Preprocessing
        Convert RGB signature to gray image
    Step 2: Find top left and bottom right for fixing boundary for signature.
    Step 3: Create the Gray Level Co-occurrence Matrices (GLCMs)for signature image
    Step 4: Derive Statistics from GLCM& Signature image
        1. Correlation(Cr)          2. Root-Mean-Square Level(Rms)
        3. Homogeneity(Hm)         4. Variance(Va)
        5. Mean(Me)                6. Smoothness(Sm)
        7. Standard_Deviation(Sd)  8. Kurtosis(Ku)
        9. Entropy(En)             10. Skewness(Sk)
endStatistical_Feature
    
```

Fig. 5:Algorithm Statistical\_Feature

## IV. RESULTS AND DISCUSSION

The proposed algorithms shown in figure4 and 5 are experimented on 2004\_MCYTDB\_OffLineSignSubCorpus dataset. Each group in dataset contains 15 genuine signatures and 15 forgery signatures. The experimentation o above dataset conducted in 2 stages, in the first stage the experimentation done with 4 genuine signature and 4 forgery signatures used for training in SVM and NN for each group and tested against all 30 signatures of that group. The table 2 shows feature values extracted for signature group 0002 of above dataset using algorithms Geometric\_Feature and Statistical \_Feature shown in figure4 and 5 respectively.

# International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor & UGC Approved Journal)

Website: [www.ijirset.com](http://www.ijirset.com)

Vol. 6, Issue 8, August 2017

Table 2: Feature values extracted for signature group 0002 for 4 Authentic & 4 Forgery signatures

Features	Genuine Signatures				Forgery Signatures			
	0002v00	0002v01	0002v02	0002v03	0003_0002f00	0003_0002f01	0003_0002f02	0003_0002f03
Dist1	185.61	221.38	175.07	221.11	242.69	135.06	289.82	237.70
Dist2	4.12	6.08	1.41	19.02	69.01	14.04	41.01	44.01
Dist3	151.00	188.02	281.51	344.03	291.25	299.28	334.90	305.08
Dist4	4.12	7.07	1.41	9.06	63.01	32.02	26.02	102.00
Dist5	157.00	189.00	255.00	342.00	259.00	260.00	304.00	241.00
Dist6	167.87	186.46	226.77	178.28	314.23	285.08	242.92	326.22
Dist7	301.94	313.44	310.65	342.00	346.60	336.81	320.26	341.79
Dist8	134.00	28.02	62.01	43.01	57.01	71.01	42.01	47.01
Dist9	180.85	186.1	234.1	155.71	212.2	146.16	130.87	191.44
Dist10	218.00	149.00	306.00	139.00	255.00	29.017	28.018	129.00
Dist11	48.01	43.01	91.01	86.01	103.01	136.00	89.01	116.00
Dist12	218.00	188.16	309.03	139.00	291.04	147.49	131.89	193.31
Dist13	43.01	33.02	2.24	1.41	29.02	3.16	128.32	1.41
Dist14	133.02	271.67	62.39	355.08	56.44	71.06	41.20	59.48
Dist15	47.01	19.03	2.24	1.41	51.01	4.12	36.01	1.41
Dist16	308.55	315.48	293.00	355.08	292.34	225.38	133.45	188.10
Ang1	-2.58	-2.33	-2.43	-2.18	-2.15	-3.11	-2.02	-2.24
Ang2	-1.82	-1.74	-2.36	-1.62	-1.59	-1.64	-1.60	-1.59
Ang3	-1.58	-1.59	-1.63	-1.59	-1.89	-1.78	-1.70	-2.01
Ang4	-1.82	-3.00	-2.36	-3.03	-3.13	-3.11	-3.10	-3.13
Ang5	-1.56	-1.57	-1.57	-1.57	-1.57	-1.57	-1.57	-1.57
Ang6	-0.38	-0.62	-1.09	-0.82	-1.18	-1.07	-1.17	-1.32
Ang7	-1.43	-1.48	-1.51	-1.57	-1.24	-1.29	-1.45	-1.34
Ang8	-0.01	-0.04	-0.02	-0.02	-0.02	-0.01	-0.02	-0.02
Ang9	1.75	1.93	2.11	2.25	2.21	2.85	2.47	2.43
Ang10	1.58	1.58	1.57	1.58	1.58	1.61	3.11	1.58
Ang11	1.59	3.12	3.13	3.13	3.13	3.13	3.13	3.13
Ang12	1.58	1.90	1.58	1.58	1.78	2.10	2.43	2.16
Ang13	1.55	1.54	1.11	0.79	1.54	1.25	1.50	0.79
Ang14	0.02	1.26	0.11	1.32	0.12	0.04	0.10	0.47
Ang15	0.02	0.05	0.46	0.79	0.02	0.25	0.03	0.79
Ang16	1.31	1.40	1.57	1.32	1.48	1.51	1.49	1.54
Cr	0.90	0.91	0.91	0.92	0.92	0.93	0.92	0.92
Hm	0.89	0.90	0.90	0.91	0.93	0.93	0.94	0.93
Me	227.72	227.52	228.18	228.05	229.94	230.46	232.56	229.79



## International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor & UGC Approved Journal)

Website: [www.ijirset.com](http://www.ijirset.com)

Vol. 6, Issue 8, August 2017

Sd	37.49	38.75	38.56	38.25	37.37	37.43	33.74	37.91
En	4.71	4.72	4.64	4.68	4.53	4.43	4.23	4.54
Rms	15.97	15.96	15.96	15.97	15.97	15.97	15.97	15.97
Va	1249.68	1379.79	1360.97	1337.10	1316.18	1295.58	1051.48	1307.84
Sm	1	1	1	1	1	1	1	1
Ku	16.02	15.12	15.94	15.26	16.25	16.49	21.63	15.66
Sk	-3.74	-3.62	-3.72	-3.63	-3.74	-3.78	-4.39	-3.68

The second stage experimentation done with extracted features of 8 genuine signature and 8 forgery signatures used for training in SVM and Neural Network for each group.

Once the training set is built with limited genuine and forgery signatures, all the signatures of group are tested against trained dataset through false acceptance rate (FAR) and false recognition rate (FRR). FAR gives measure of incorrect acceptance of forgery signature i.e. FAR is used as ratio of number of false acceptance by the total number of detection attempt. FRR gives measure of incorrect rejection of genuine signature i.e. FRR is used as ratio of number of false rejection by the total number of detection attempt. Average error rate (AER) of the group is the average of FAR and FRR of that group. Overall error rate (OER) is the average of average error rate of all groups.

The experimentation done on dataset with 4 Authentic & 4 Forgery signature in first stage and with 8 Authentic & 8 Forgery signature used for training and when all 30 signatures in that group are sent for verification using SVM classifier are tabulated in table 3. The experimental statistics reveal OER is decreased with increase in number of sample signature used in training in SVM training and classification.

Table 3: SVM Training and Classification

SVM	4 Authentic & 4 Forgery for training			8 Authentic & 8 Forgery for training			
Folder	FAR in %	FRR in %	AER in %	FAR in %	FRR in %	AER in %	
0002	26.67	0	13.33	26.67	0	13.33	
0005	13.33	13.33	13.33	6.67	6.67	6.67	
0008	53.33	6.67	30	33.33	6.67	20	
0010	40	6.67	23.33	33.33	0	16.67	
0013	46.67	0	23.33	26.67	6.67	16.67	
	OER in %			20.67	OER in %		14.67

The experimentation repeated on dataset with 4 Authentic & 4 Forgery signatures in first stage and with 8 Authentic & 8 Forgery signature used for training and when all 30 signatures in that group are sent for verification using NN classifier are tabulated in table 4. The experimental statistics reveal OER is decreased with increase in number of sample signature used in training in NN training and classification too.

Table 4: NN Training and Classification

NN	4 Authentic & 4 Forgery for training			8 Authentic & 8 Forgery for training			
Folder	FAR in %	FRR in %	AER in %	FAR in %	FRR in %	AER in %	
0002	26.67	0	13.33	26.67	0	13.33	
0005	40	20	30	6.67	53.33	30	
0008	40	13.33	26.67	26.67	6.67	16.67	
0010	40	6.67	23.33	33.33	0	16.67	
0013	40	0	20	33.33	20	26.67	
	OER in %			22.67	OER in %		20.67

# International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor & UGC Approved Journal)

Website: [www.ijirset.com](http://www.ijirset.com)

Vol. 6, Issue 8, August 2017

## V. CONCLUSION

Signature is a unique biometric characteristic for human identification and verification in all major areas of person identity like finance, access control, contractual matters and security. Digitalizing OffSV is challenging task because every signature has its own physiology or behavioural characteristics. In our research we focus on developing robust algorithm for extracting geometrical features and statistical features. The proposed algorithms are tested against 2004\_MCYTDB\_OffLineSignSubCorpus dataset using SVM and NN training and classifier. The analysis results obtained reveal OER is decreased with increase in number of sample signature used in training and obtained results are competent to other strategies discussed in literature.

## REFERENCES

- [1] Napa Sae-Bae and Nasir Memon, "Online Signature Verification on Mobile Devices," IEEE Transactions on Information Forensics and Security, Volume9, Issue6, pp. 933–947, June 2014.
- [2] Mohsen Fayyaz, Mohammad Hajizadeh Saffar, Mohammad Sabokrou, M. Hoseini and M. Fathy, "Online signature verification based on feature representation," *Artificial Intelligence and Signal Processing (AISP), 2015 The International Symposium on Artificial Intelligence and Signal Processing AISP*, pp. 211–216, 2015.
- [3] Vahab Iranmanesh, Sharifah Mumtazah Syed Ahmad, Wan Azizun Wan Adnan, Fahad Layth Malallah and Salman Yussof, "Online Signature Verification Using Neural Network and Pearson Correlation features," *Proceedings.Open Systems (ICOS), IEEE Conference on Open Systems (ICOS)*, pp. 18–21, 2013.
- [4] Othman o-khalifa, Md. Khorshed Alam and Aisha Hassan Abdalla, "An evaluation on offline signature verification using artificial neural network approach," *Proceedings.Computing, Electrical and Electronics Engineering, International Conference on Computing, Electrical and Electronic Engineering (ICCEEE)*, pp. 368–371, 2013.
- [5] Shiwani Sthapak, Minal Khopade and Chetana Kashid, "Artificial Neural Network Based Signature Recognition & Verification," *International Journal of Emerging Technology and Advanced Engineering*, vol. 3, no. 8, pp. 191–197, 2013.
- [6] J.G.A. Dolfig, E.H.L. Aarts and J.J.G.M. van Oosterhout, "On-line signature verification with hidden Markov models," *Proceedings. Fourteenth Int. Conf. Pattern Recognit. (Cat. No.98EX170)*, vol. 2, pp. 1309–1312, 1998.
- [7] Edson J. R. Justino, Flavio Bortolozzi and Robert Sabourin, "Off-line signature verification using HMM for Random, simple and skilled forgeries," *Proc. Int. Conf. Doc. Anal. Recognition, ICDAR*, pp. 1031–1034, 2001.
- [8] H.S. Yoon, J.Y. Lee and H.S. Yang, "An online signature verification system using hidden Markov model in polar space," *Proc. - Int. Work. Front. Handwrit. Recognition, IWFHR*, pp. 329–333, 2002.
- [9] K N Pushpalatha, Supreeth Prajwal S, A K Gautam and K B Shiva Kumar, "Offline signature verification based on contourlet transform and textural features using HMM," *Proc.International Conference on Recent Advances and Innovations in Engineering (ICRAIE-2014)*, pp. 1–6, 2014.
- [10] C. Kruthi and Deepika C. Shet, "Offline Signature Verification Using Support Vector Machine," *Proc.Fifth International Conference on Signal and Image Processing*, pp. 3–8, 2014.
- [11] Jaspreet Kour, M. Hanmandlu and A.Q Ansari, "Online signature verification using GA-SVM," *Proc. International Conference on Image Information Processing*, pp. 1–4, 2011.
- [12] Christian Gruber, Thiemo Gruber, Sebastian Krininger and Bernhard Sick, "Online signature verification with support vector machines based on LCSS kernel functions.," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), Volume: 40, Issue: 4*, pp. 1088–100, Aug. 2010.
- [13] S. Fauziyah, O. Azlina, B. Mardiana, A.M. Zahariah and Hazura Haroon, "Signature verification system using Support Vector Machine," *6th International Symposium on Mechatronics and its Applications*, pp. 1–4, 2009.
- [14] Yishu Liu, Zhihua Yang and Lihua Yang, "Online Signature Verification Based on DCT and Sparse Representation," *IEEE Transactions on Cybernetics, Volume: 45, Issue: 11*, pp. 1–14, Nov. 2015.
- [15] Saeid Rashidi, Ali Fallah and Farzad Towhidkhah, "Dynamic signature verification based on DCT of local features," *Proc. 18th Iranian Conference of Biomedical Engineering (ICBME)*, pp. 284–289, 2011.
- [16] C RamachandraA, Jyothi Srinivasa Rao, K B Raja, K R Venugopla and L M Patnaik, "Robust Offline Signature Verification Based On Global Features," *proc. IEEE International Advance Computing Conference*, pp. 6–7, 2009.
- [17] Muhammad Talal Ibrahim, Matthew Kyan and Ling Guan, "On-line signature verification using global features," *Canadian Conference on Electrical and Computer Engineering*, pp. 682–685, 2009.
- [18] Vu Nguyen, Michael Blumenstein and Graham Leedham, "Global features for the off-line signature verification problem," *Proc. 10th International Conference on Document Analysis and Recognition, ICDAR*, pp. 1300–1304, 2009.
- [19] Bence Kovari, Gergely Kiss and Istvan Albert, "Stroke matching for off-line signature verification based on bounding rectangles," *Proc. 23rd International Symposium on Computer and Information Sciences*, pp. 1–5, 2008.
- [20] Oleg Golubitsky and Stephen M. Watt, "Online recognition of multi-stroke symbols with orthogonal series," [Courtesy of <http://www.csd.uwo.ca/~watt/pub/reprints/2009-icdar-multistroke.pdf>]