On-line Signature Authentication

K.R.Radhika†, M.K.Venkatesha††, and G.N.Sekhar†

†B.M.S.College of Engineering, Bangalore, India
††R.N.S.Institute of Technology, Bangalore, India

Summary
Authentication systems which are covenant with a measurable behavioral trait are essential in on-line system. The flow of signature with respect to time is termed as on-line signature data. This paper deals with, authentication of an individual's on-line signature patterns using continuous dynamic programming [CDP]. Modern systems aim to move security from simple static passwords to more dynamic security measures to suit the comfort level of the user in mobile-commerce and web-commerce. Recognition of individual's signature is text dependent self-certification process with constant behavioral variation. CDP aid in recognition process with a concept of grouping items with similar characteristics together. Segmentation is possible for online data because signature is a ballistic motion which is learnt over a period of time.

Key words:
Continuous Dynamic Programming, Handwritten signature, Acceleration, Signature Authentication

1. Introduction

Secure communications for mortgage, passport, Internet commerce and mobile commerce are some of the applications areas which thrive on signature recognition for payments, logins via a tablet PC, crypto-biometrics and bio-hashing. New pattern recognition techniques that can mine and discover behavioral knowledge in large data sets are very much essential. When compared to fingerprint, face, iris and other recognition techniques, the signature is a ballistic movement, has some characteristics such as, it is user-friendly, non invasive, as a pattern it is stored in number of applications, it is ubiquitous, it can be changed on a compromise, it is not dependent on age [1] and it is well exposed to forensic environments. Challenging concept of signature authentication is that, it is strongly affected by user-dependencies as it varies from one signing instance to another in a known way. It is well known that no two genuine signatures of a person are precisely the same and some signature experts note that if two signatures written on paper were same, then they could be considered as forgery by tracing [2]. The structural features should be invariant to rotation, translation and scaling of the object sample [3]. In the process of acquisition, types of forgeries are to be analysed for proper training and testing of the authentication system [4, 5].

2. Continuous Dynamic Programming [CDP]

CDP aid in recognition process with a concept of grouping items with similar characteristics together. This procedure accumulates minimum local distances. Distances can be difference of any selected feature value between reference template and input sample. Trajectory optimization problems can be considered as continuous problems. The method developed by R.Oka [6, 7] is the verification method based on spotting that ignores the portions of data that lie outside the task domain generally contaminated by noise and discontinuities. The system registers user input which forms the reference patterns for verification. The dynamic features are combined so that the system becomes unbreakable at the time of verification. The system is proved to be more flexible for online training [8]. The dynamic programming scheme is employed to evaluate the similarity of different features by spotting the main features that are quite distinguishable in the image samples. With spotting, segmentation and recognition can be performed simultaneously [9]. The matching is obtained by piecewise parametric function [10]. The solution of a continuous decision problem by dynamic programming involves the determination of a whole family of external trajectories as we move from one point to an another [11].A novel dynamic Programming scheme that yields a continuous solution to the problem of finding an optimal path on a 2D plane using CDP yielded better matching contours than discrete dynamic programming [10, 12]. CDP is a nice tool to tackle problems of time warping and spotting for classification. Using CDP makes the new system more flexible for online training, as the model can be easily updated with the optimized sample, furthermore we can build personalized model with a few samples to improve the system performance [8]. 2DCDP characteristically allows transformation and is a quasi-optimal algorithm for row axis and column axis [13] which is combination of spotting recognition with a reference image for tracking a target and making a segmented image as a reference image for the next frame. Yuya Iwasa, explains 2DCDP algorithm for treating arbitrary shapes and multiple object references. 2DCDP

Manuscript received February 5, 2010.
Manuscript revised February 20, 2010.

performs spotting recognition for images and is extended to deal with multiple object images with arbitrary shapes and used for deformable object tracking. This method allows transformation and works in two steps. In the first step a nonlinear matching between the row patterns in the reference image and input image is performed. The result of the first step is integrated optimally in the column direction [13].

3. Generalised CDP algorithm which is extended for Signature samples

CDP accumulates minimum local distances. For a sample r(t) ($1 \le t \le S$) and another sample i(τ) ($1 \le \tau \le T$) v_a and v_b value arrays are generated, which are bounded with τ. The value of S and T is 8, which depicts 8 percentile components. $v_a = \{v_a(1), v_a(2), v_a(3), v_a(4), v_a(5), v_a(6), v_a(7), v_a(8)\}$ and $v_b = \{v_b(1), v_b(2), v_b(3), v_b(4), v_b(5), v_b(6), v_b(7), v_b(8)\}$. Dynamic programming method follows scan-line algorithm of the (t, τ) plane from line with t = 1 to the line with t = S. R(t,τ) contain minimum of accumulated distance. The weight will normalise the value of R(t, τ) to locus of '3T'. This is using the theorem that between the 2 fixed points A and B, circle of Appolonius is the locus of the point P such that | PA| = 3.|PB|, where |PA| means the distance from point P to point A.

For the cases of τ = -1 and τ = 0, the accumulation is defined by $R(t,-1) = R(t,0) = \infty$.

For t=1, $R(1,\tau)=3*d(1,\tau)$, where 'd' is local distance measure between r(t) and i(τ). $d = |v_a(1)–v_b(\tau)|$.

For t=2, $R(2,\tau)=\min \{R(1,\tau-2) +2.d(2,\tau-1) +d(2,\tau), R(1,\tau-1)+3.d(2,\tau), R(1,\tau)+3.d(2,\tau)\}$.

For t=3 to S,

$R(t,\tau) = \min \{R(t-1,\tau-2) + 2.d(t,\tau-1) + d(t,\tau), R(t-1,\tau-1) + 3.d(t,\tau), R(t-2,\tau-1) +3.d(t-1,\tau)+3.d(t,\tau)\}$.

Given the two value arrays v_a and v_b, the cdp-value can be found.

cdpvalue = min{R(1,8), R(2,8), R(3,8), R(4,8), R(5,8), R(6,8), R(7,8), R(8,8)}*(1/(3*T)).

3.1 Reference template or standard template selection

"P" is the number of training samples considered for reference template value array calculation. In this work the value of P is 10. P genuine samples are required for registration. The first P genuine signature samples of a person form training set [T-SET]. The first sample of T-SET is considered as standard template forming v_a array and all the samples in T-SET (including first sample) form P different v_b arrays.

The first row of P X P matrix is formed by the P cdpvalues with standard v_a array and P different v_b arrays. Similarly second sample of T-SET is considered as template forming v_a array and all the samples in T-SET(including second sample) form P different v_b arrays to form second row of P X P matrix. This is a leave-one-out method. Accumulated distance of P-1 samples with one selected sample as reference is found. This constitutes a row. Procedure is repeated for P-1 samples forming P X P matrix. For each row, average is found using Eq. (1). av = $\{av_{row1}, av_{row2}, av_{row3}, av_{row4}, av_{row5}, av_{row6}, av_{row7}, av_{row8}\}$.

min-avg-row = min(av)

i = row index of min-avg-row (1)

0	0.125	0.375	0.2917	0.125	0.25	0.1667	0	0.125	0
0.4167	0	0.625	0.125	0.125	0.5	0.2917	0.25	0.3333	0.25
0.125	0.25	0	0.5	0.375	0	0	0.25	0	0.125
0.5	0	0.5	0	0	0.375	0.375	0.125	0.25	0.125
0.375	0.125	0.375	0.375	0	0.25	0.1667	0	0.125	0
0.25	0	0.2917	0.25	0	0	0.2083	0.125	0.1667	0.125
0	0.125	0.2083	0.375	0.125	0.125	0	0	0.125	0
0.25	0	0.25	0.25	0	0.25	0.2083	0	0.125	0.125
0.125	0.125	0.2083	0.375	0.125	0	0.0417	0	0	0
0.25	0.0833	0.25	0.125	0.25	0.125	0.125	0.125	0	0

Fig. 1 Minimum average row selection

The reference value array $v_{a\text{-}person}$ for one person, whose P genuine samples are considered in T-SET is v_a array of i^{th} sample of P X P CDP value matrix of P training samples, as shown in Fig. 1. The minimum average row is selected. This provides reference template for the person to calculate $v_{a\text{-}person}$ array.

3.2 Threshold value calculation

The threshold value is average of P row averages multiplied by a constant Z. Z = 1, 2, 3 and 4. As it is average of P genuine samples of same person, the threshold calculated is writer dependent threshold for signature samples.

3.3 Analysis of direction changes with reference to acceleration values

For one percentile range, say [40% - 49%], set of acceleration values are generated. Let the set be represented by $A = \{a_1, a_2, a_3, a_4, \ldots, a_k\}$.

$$\forall a_i < a_{i+1}, D_i = -1$$

$$\forall a_i > a_{i+1}, D_i = +1$$

else $D_i = 0$ (2)

The direction sequence set D is generated as D = {1,-1,0,1,1,1,-1,…} using Eq. (2). The count of change over from '-1' to '+1' are counted as $c_{40\text{-}49}$. These are the acceleration values of local minima in 'A'. The set of 8 counts $[c_{10\text{-}19}, c_{20\text{-}29}, c_{30\text{-}39}, c_{40\text{-}49}, c_{50\text{-}59}, c_{60\text{-}69}, c_{70\text{-}79}, c_{80\text{-}89}]$ form the value array, $v_a = \{v_a(1), v_a(2), v_a(3), v_a(4), v_a(5), v_a(6), v_a(7), v_a(8)\}$ where $v_a(1) = c_{10\text{-}19}$, $v_a(2) = c_{20\text{-}29}$, $v_a(3) =$

$c_{30\text{-}39}$, $v_a(4) = c_{40\text{-}49}$, $v_a(5) = c_{50\text{-}59}$, $v_a(6) = c_{60\text{-}69}$, $v_a(7) = c_{70\text{-}79}$, $v_a(8) = c_{80\text{-}89}$.

The reference value array v_a for one person is calculated as minimum row average of P X P normalized accumulated distance matrix of P training samples. This is a leave-one-out method. Accumulated distance of P-1 samples with one selected sample as reference is found. This constitutes a row. Procedure is repeated for P-1 samples forming P X P matrix. The minimum average row is selected. This provides reference template for the person to calculate v_a. The threshold value is average of P matrix multiplied by a constant Z for values from 1 to 4.

4. Authentication Procedure for on-line signature

x-coordinate sequence (x), y-coordinate sequence (y), pressure coordinate sequence (z), pen azimuth coordinate sequence and pen inclination coordinate sequence are features considered [14]. These features form spherical co-ordinate system. Azimuth is the angle between the z axis and the radius vector connecting the origin and any point of interest. Inclination is the angle between the projection of the radius vector onto the x-y plane and the x-axis. z-axis is the pressure axis.

4.1 Analysis of velocity values

Velocity and acceleration are the two derived features considered. The velocity profile of the signature and the acceleration characteristics of the pen are unique characteristics of an individual's signature. Even if the forger takes great pain in remembering the styles and contours of the strokes, it is extremely unlikely that he/she would be able to match the velocity profile or any other dynamic characteristics of the original signature [15].The velocity value is calculated using Eq. (3).

$$\vec{v} = \hat{r}r' + \hat{\theta}r\theta' + \hat{\varphi}r\varphi'\sin\theta \qquad (3)$$

where

$$\hat{r} = \hat{x}\sin\theta\cos\varphi + \hat{y}\sin\theta\sin\varphi + \hat{z}\cos\theta,$$

$$\hat{\theta} = \hat{x}\cos\theta\cos\varphi + y\cos\theta\sin\varphi - \hat{z}\sin\theta,$$

$$\hat{\varphi} = -\hat{x}\sin\varphi + y\cos\varphi,$$

$$r = \sqrt{x^2 + y^2 + z^2}, \quad r' = \frac{dr}{dt}, \quad \theta' = \frac{d\theta}{dt}, \quad \varphi' = \frac{d\varphi}{dt}.$$

The r is radial distance of a point from origin. $\hat{x}$, $\hat{y}$, $\hat{z}$ are unit vectors. θ is azimuth angle and φ is angle of inclination. $\hat{r}$, $\hat{\theta}$ and $\hat{\varphi}$ are unit vectors in spherical co-ordinates. r', θ' and φ' are derivatives of spherical co-ordinates. The velocity values for each pixel of a signature pattern is calculated. The top 50 velocity values were considered in descending order. These values were plotted according to positional values. Velocity plots of top 50 values for two genuine samples and for a forged sample of one person were considered. The signing process can be in various lengths and sizes. By considering the positional concept, which specifies "what percentage of signature has what velocity value", we can acheive segmentation. It is analysed that, the velocity scatter plot look similar for two genuine samples. It is analysed that, the velocity scatter plot of forged samples does not match with velocity plots of two genuine samples. The similar analysis concept with the acceleration values provided more promising deviation scatter plots between genuine and forgery samples to achieve classification.

4.2 Analysis of acceleration values

The signature is a ballistic motion which is learnt over a period of time, which are rapid practiced motions without driven by feedback. This characteristic motion is the basis for segmentation. The acceleration values for each pixel of a signature pattern is calculated using Eq. (4) to form set A. The complete set of online co-ordinates are considered in unsorted way of one signature sample. The acceleration values are normalised with respect to positional values. It is observed that, irrespective of the length of signature, scatter of acceleration values form same shape pattern for genuine signatures.

$$a1 = \hat{r}(r'' - r\theta'^2 - r\varphi'^2\sin^2\theta)$$

$$a2 = \hat{\theta}\left(\frac{1}{r}\frac{d}{dt}(r^2\theta') - r\varphi'^2\sin\theta\cos\theta\right)$$

$$a3 = \hat{\varphi}\frac{1}{r\sin\theta}\frac{d}{dt}(r^2\varphi'\sin^2\theta)$$

$$\vec{a} = a1 + a2 + a3 \qquad (4)$$

where $r'' = \dfrac{dr'}{dt}$.

The acceleration plot with respect to positional values is shown in Fig. 2.

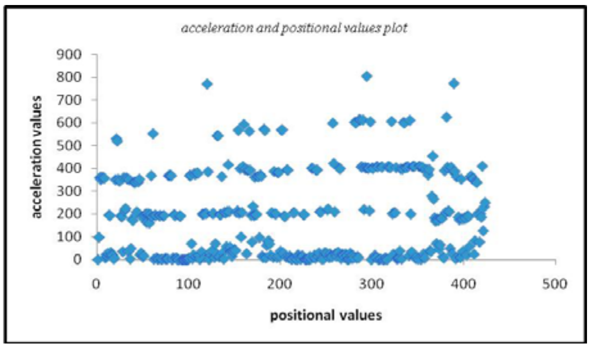

Fig. 2 Acceleration and positional values plot

p_{inorm} is calculated and the set $position_{norm}$ is formed for values of p_{inorm} upto the maximum range of 100. This is shown in Fig. 3.

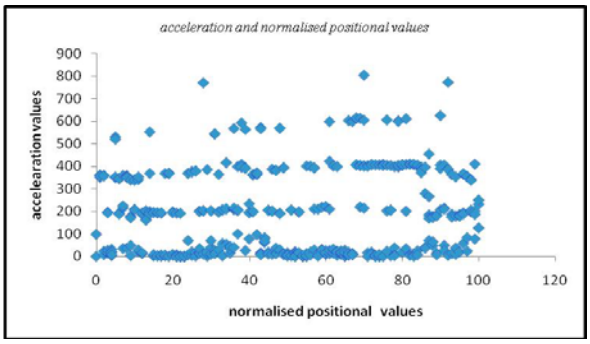

Fig. 3 Acceleration and normalised positional values plot

We achieve acceleration values in class intervals like 10-20, 20-30, 30-40 and so on. By normalisation, what percentage of signature has what acceleration value, is achieved. The signature sample can be now segmented to `m' equal parts with respect to acceleration values. In this paper we have considered m = 10. By considering only the initial parts of genuine training samples, it is observed that, the rate of change of acceleration values vary. The pressure of the writing device may change initially by same person due to emotional variation. The similar variation in acceleration values are observed in the ending stage of signing process. First and last parts are eliminated as they contain the settling down acceleration components. The plot of acceleration for each percentile, of a genuine sample matches the shape with another genuine sample, for each component respectively. It is observed that, there are variations in the values of the acceleration within genuine samples, in each percentile due to length of signing process but with fewer variations in shape of acceleration plot. Fig. 4 shows the shape similarity of acceleration plot between the two genuine samples of same person and Fig. 5 shows enormous variation in shape of acceleration plot when compared between a genuine and forged sample of same person.

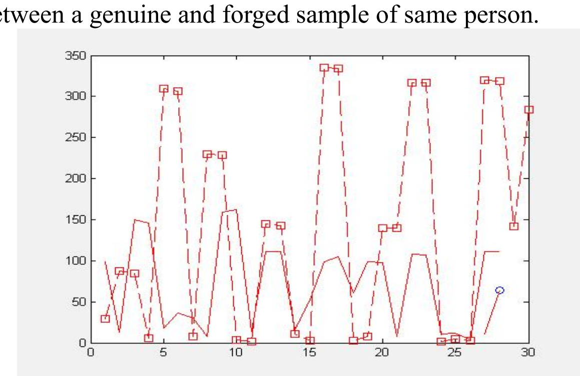

Fig. 4 Acceleration plot of two genuine signature samples in 40-50 percentile, depicts similarity in shape of plot.

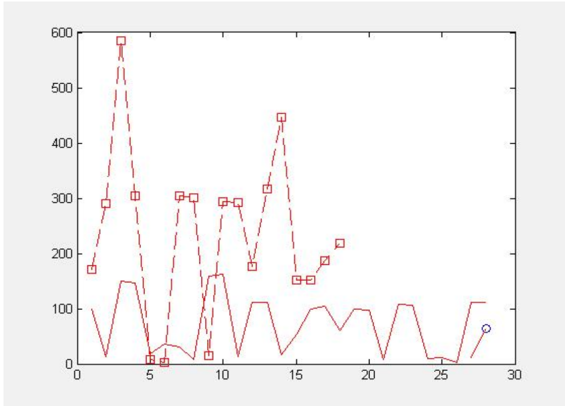

Fig. 5 Acceleration plot of a genuine sample and forged sample in 40-50 percentile, depicts dissimilarity in shape of plot.

For one percentile range, say [40% - 49%], set of acceleration values are generated. Let the set be represented by A = $\{a_1,a_2,a_3,a_4,\ldots a_k\}$. The direction sequence set D is generated given in equation (2). The v_a array is formed corresponding the count of change over in different percentiles. Here, P = 10 training genuine samples are considered for a person. Each training sample will generate a value array. The reference genuine sample in the set of P training samples should be selected for further testing given genuine or forged sample as discussed in section 3.1.

4.4 Classification procedure

CDP works on differences between $v_{a\text{-}person}$ and v_b value arrays in respective eight percentile parts of signature. The v_b array can be obtained from any input sample either testing samples or forged samples.The cummulative difference value is less between a reference sample and genuine sample. The cummulative difference value is more between a reference sample and forged sample.

Overall Algorithm

Repeat for N people(loop - a1)
Begin
Repeat for P genuine training samples(loop - a2)
Begin
Read the on-line signature data file;
Extract the on-line features
of signature(x ,y ,z ,azimuth ,inclination);
Calculate acceleration values A[n] and save normalised positions;
Form m parts or segments;
Find directional changes D[n] and elements of value array segment wise;
Estimate $v_{a\text{-}person}$ array and threshold by applying leave-one-out method on CDP

algorithm
End(loop - a2)
Repeat for remaining genuine testing samples and forged
samples(loop - a3)
Begin
Find CDP values and estimate acceptance and rejection performance for different values of Z
End(loop - a3)
End (loop - a1)

5. Experimental Results

100 x 25 x 2 signature samples were used from MCYT - 100 Signature Baseline Corpus,an online database. This database provides 25 genuine and 25 forged samples per person. 10 genuine samples formed T-SET. The remaining 15 genuine samples form testing set, to find false rejection rate [FRR]. The 25 forged samples where used to find false acceptance rate [FAR]. The minimum value of FAR of 3.07% and minimum value of FRR of 2.37% are obtained. The average value of FRR of 8.73%, 5.71%, 3.37%, 2.37% are obtained for Z = 1,2,3,4 respectively as shown by Fig. 6. The average value of FAR of 3.07%, 5.06%, 6.6%, 8.02% are obtained for Z = 1,2,3,4 respectively as shown by Fig. 7.

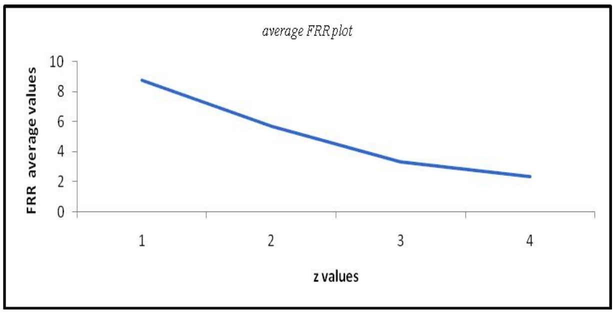

Fig. 6 Average FRR plot

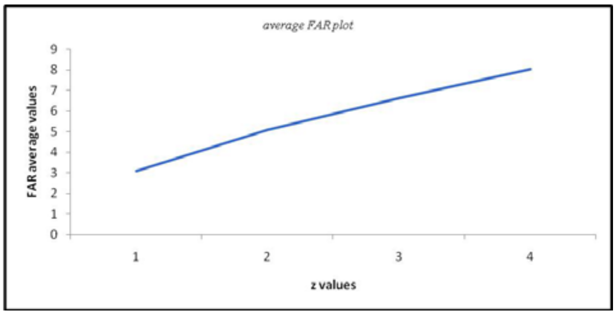

Fig. 7 Average FAR plot

6. Previous work done for on-line signature verification

Work proposed by Guru [16] used MCYT signature corpus with 8250 genuine and 8250 forged on-line signatures with all 100 features proposed by Nelson [17] achieved Equal Error Rate [ERR] of 5.35%.The work has tabulated FRR and FAR for the range of feature dependent threshold values. The work proposed by Julian [18] has verification performance results as 0.74% and 0.05% EER for skilled and random forgeries respectively with a posteriori user-dependent decision thresholds on a database of 145 subjects comprising 3625 client signatures, 3625 skilled forgeries and 41,760 random imposter attempts. Comparison with state-of-the-art using SVC (signature verification competition organized in 2004) evaluation set, the HMM system was ranked second for skilled forgeries and first for random forgeries. DTW based approach by Kholmatov was ranked first for skilled forgeries. The work done by Oscar [19] was on MCYT signatures database of 2500 genuine and 2500 skilled forgeries from 100 users with a performance of 8% EER for skilled forgeries of a subset of 26 features. The work done by Saeed Mozaffari achieved 83% recognition rate using MDRCLM on entropy and moment. This was tested on a database of 15 signature classes, each containing 10 unconstraint samples gathered by a hyper pen 1200u digitizer tablet. Each of the samples were normalized into 300 spatially uniform points. The work done by Moussa Djioua [20] used panel interface to display simulated signals of the test pattern and to compare with standard pattern simulated signals analytically and visually.

Previous work done for biometric verification under CDP

Until now CDP has been used for writer identification which is text-independent either charater based or figure-based [21, 22]. The work done by Kameya achieved more than 90% verification rates with experimental data comprising two genuine patterns by five individuals [22]. The work done by Kameya et al obtained 26.47% error rate using azimuth feature of a genuine data size of 29410 and 198750 forgery datasize.

7. Conclusion

The proposed system is carried on the kinematic value such as acceleration under CDP for on-line signature which is text dependent. This factor differentiates our method from others. The work can be extended to decreasing segmentation value of P from 10 to a lower value. By this number of training samples decrease to form reference v_a array. The moments at each percentile can be found for global optimization instead of considering only local minima. Zernike moments are suitable for multimodal biometric framework in both 2D and 3D domain. Authentication of an identity based system by providing the characteristics of acoustic emissions emmited during a signature scribble [23] can be worked on CDP algorithm where the velocity values corresponded to pitch values.

Acknowledgment

The authors would like to thank J.Ortega-Garcia for the provision of MCYT Signature database from Biometric Recognition Group, B-203, Universidad Autonoma de Madrid SPAIN [14].

References

[1] Richard Guest, "Age dependency in handwritten dynamic signature verification systems", J. Pattern Recognition Letters, Vol. 27, pp. 1098 - 1104, 2006.

[2] G..K.Gupta, R.C.Joyce, "Using position extrema points to capture shape in on-line hand written signature verification", J. Pattern Recognition, Vol. 40, pp. 2811 - 2817, 2007.

[3] George D. da C. Cavalcanti , Rodrigo C. Doria and Edson C. de B.C. Filho, "Feature selection for off-line recognition of different size signatures", 12th IEEE workshop on Neural Network for Signal Processing, Vol. 1, pp. 355 - 364, 2002.

[4] Vu Nguyen, Michael Blumenstein, Vallipuram Muthukkumarasamy, Graham Leedham, "Off-line signature verification using enhanced modified direction features in conjunction with neural classifiers and support vector machines", Int. Conf. of Pattern Recognition, Vol. 4, pp. 509 - 512 , 2006.

[5] Stephane Armand, Michael Blumenstein, Vallipuram Muthukkumarasamy, "Off-line signature verification based on the modified direction feature", IEEE Int. Conf. on Pattern Recognition , Vol 4 , pp. 509 - 512 , 2006.

[6] H.Kameya, S. Mori, R. Oka, "A segmentation-free biometric writer verification method based on continuous dynamic programming", J. Pattern Recognition Letters, Vol. 27, Issue 6, pp. 567 - 577, 2006.

[7] Hiroshi Kameya, Shunji Mori, R.Oka, "A method of writer verification without keyword registration using feature sequences extracted from on-line handwritten sentences", MVA2002 IAPR workshop, Vol 1, pp. 479 - 483, 2002.

[8] Haihong Zhang, Yan Guo, "Facial Expression Recognition using Continuous Dynamic Programming", IEEE ICCV Workshop on Recognition, Analysis, and Tracking of Faces and Gestures in Real-Time Systems, pp.163…., 2001.

[9] T. Nishimura, H. Kojima, Y.Itoh, A. Held, S. Nozaki, S. , and R. Oka, "Effect of Time-spatial Size of Motion Image for Localization by using the Spotting Method", 13th Int. Conf. on Pattern Recognition, pp. 191 - 195, 1996.

[10] Bruno Serra, Marc Berthod, "Subpixel contour matching using continuous dynamic programming", IEEE Computer. Society Conference", Computer Vision and Pattern Recognition, pp. 202 - 207, 1994.

[11] Singiresu S. Rao, "Engineering Optimization: Theory and Practice", Wiley-Interscience Publication, 1996.

[12] R. Oka, "Spotting Method for Classification of Real World Data", Computer Journal, Vol. 41, No. 8, pp. 559-565, 1998.

[13] Yuya Iwasa, Ryuichi Oka, "Spotting Recognition and Tracking of a Deformable Object in a Time-Varying Image Using Two-Dimensional Continuous Dynamic Programming", The Fourth Int. Conf. on Computer and Information Technology, pp. 33 - 38, 2004.

[14] J.Ortega-Garcia, Fierrez-Aguilar, et al, "MCYT Baseline Corpus: A Bimodal Biometric Database", IEEE Proc . Vision, Image and Signal Processing, Vol. 150, No. 6, pp. 395 - 401, 2003.

[15] G.V.Kiran, R. Srinivasa Rao Kunte, Sudhaker Samuel, "On-line signature verification system using probabilistic feature modeling", Int. Symposium on Signal Processing and its Applications, Vol. 1, pp. 355-358, 2001.

[16] D.S.Guru, H.N.Prakash, "Symbolic Representation of On-line signatures", Int. Conf. on Computational Intelligence and Multimedia Applications, Vol. 2, pp. 313 - 317, 2007.

[17] R.S Kashi, J Hu, N.L.Nelson, W.Turin, "On-line Handwritten signature verification using hidden Markov Model features", 4th Int Conf. on Document Analysis and Recognition, Vol. 1, pp. 253 - 257, 1997.

[18] Julian Fierrez, Javier Ortega-Garcia, Daniel Ramos, Joaquin -Rodriquez, "HMM-based on-line signature verification: Feature extraction and signature modeling", J. Pattern Recognition Letters, Vol. 28, No. 16, pp. 2325 - 2334, 2007.

[19] Oscar Migual-hurtado, Luis Mengibar-Pozo, Micheal G. Lorenz, Judith Liu - Jimene, "On-line signature verification by Dynamic Time Warping and Gaussian mixture models", 41st annual IEEE Int Carnahan Conf on Security Technology, pp. 23 - 29, 2007.

[20] Moussa Djioua, Christian O'Reilly and Rejean Plamondon, "An interactive trajectory synthesizer to study outlier patterns in handwriting recognition and signature verification", 18th Int Conf on Pattern Recognition, Vol. 1, pp. 1124 - 1127, 2006.

[21] Hiroshi Kameya, Shunji Mori, R.Oka, "A method of writer verification without keyword registration using feature sequences extracted from on-line handwritten sentences", MVA2002 IAPR Workshop, Vol. 1, pp. 479 - 483, 2002.

[22] Hiroshi Kameya, Shunji Mori, R.Oka, "Figure-Based writer verification by matching between an arbitrary part of registered sequence and an input sequence extracted from on-line handwritten figures", IEEE 7th Int. Conf. on Document Analysis and Recognition, Vol. 2, pp. 985 - 989, 2003.

[23] A.K. Jain, R.Bolle, S.Pankanthi, "BIOMETRICS: Personal Identification in Networked Society", Fourth edition, Kluwer Academic, United States of America, 2006.

Radhika K.R is working as a faculty, since 1995 in the department of Information Science and Engineering. She received her Master of Engineering degree in Computer Science in 2000. Presently she is working as Assistant Professor, in the Computer Science in 2000. She is presently working as Assistant Professor, in the department of Information Science and Engineering, B.M.S College of Engineering, Bangalore, Karnataka, India. She is currently, working on Online and Offline Biometric Behavioral Pattern Authentication System (BBPAS) using handwritten signature as a pattern. She is a member of IEEE and IEEE Computer Society.

Dr.M.K.Venkatesha is working as a faculty, since 1981, in the department of Electronics and Communication. He received his MSc Engineering degree in the year 1986 from the University of Manitoba, Canada on a fellowship. He received his PhD in Electronics and Communication in the year 1998 from the University of Mysore. He has received J C Bose Gold Medal and has 28 years of experience. Presently he is working as Principal of R.N.S. Institute of Technology, Bangalore, India. His interests are in the field of Digital Signal Processing and its Applications. He is also the author of multiple articles in journals and communications at conferences.

Dr.G.N.Sekhar is Professor and Head of the Department of Mathematics. He is working as a faculty since 1988. He received his PhD in Mathematics in the field of Fluid Mechanics in 1991. Presently he is working as the Vice-Principal, B.M.S.College of Engineering, Basavangudi, Bull Temple Road, Bangalore 560019, Karnataka, India. His interests are in the field of Fluid Mechanics, simulation and Mathematical Modeling. He is also the author of multiple articles in journals and communications at conferences.