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HANDWRITTEN SIGNATURE VERIFICATIONS USING ADAPTIVE RESONANCE THEORY TYPE-2 (ART-2) NET

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Abstract— Authorizing hand-written signature has always been a challenge to prevent illegal transactions, especially when the forged and the original signatures are very 'similar-looking' in nature. In this paper, we aim to automate forged signature verification process, offline, using Adaptive Resonance Theory type-2 (ART-2), which has been implemented in 'C' language using both sequential and parallel programming. The said network has been trained with the original signature and tested with twelve very similar-looking but forged signatures. The mismatch threshold is set as 5%; however, it is set flexible as per the requirement from case-to-case. In order to obtain the desired result, the vigilance parameter (ρ) and the cluster size (m) has been tuned by carefully conducted parametric studies. The accuracy of the ART-2 net has been computed as almost 100% with ρ = 0.97 and m = 20.

Keywords- handwritten signature; automatic verification; ART-2; forged signatures

INTRODUCTION

Neural networks have been widely used in pattern recognition, especially where the patterns are complex due to close resemblance of 'original' and 'generated' patterns [1-4]. An important property of a neural network classifier is that, it learns the exemplary patterns (as inputs) by updating its nodal connectors' weights. The drawback of such type of learning is that, when new patterns are fed, the weights are updated and as a result, it loses the memory of older patterns and stores the impression of new patterns [5]. To handle this issue, Grossberg and Carpenter (1987) proposed the concept of Adaptive Resonance theory (ART) networks, where the networks retain the earlier learning, which is certainly advantageous over the conventional neural classifier [6].

ART is of two types i.e. type-1 and type-2. ART-1 takes binary input vector, whereas, ART-2 takes analog/continuous input vector and therefore more meritorious [7]. In our earlier work, ART-1 network has been considered for automatic verification of hand-written signature offline, with high level of accuracy (99.97%) [8]. In that paper, however, only two forged signatures were considered. In this paper, ART-2 has been considered for the offline verification of twelve very similar looking but forged handwritten signatures.

Handwritten signature is the principal biometric measure for personal identification. It is an important method for performing legal transactions. However, there are chances when signatures could be delicately copied, such that these apparently resemble originals and are difficult to be identified by the naked eyes. Hence, automating such a detection process could be of real advantage to us. However, it requires vast research prior its practical use. In this view, this paper is an attempt where ART-2 net has been used and implemented using both sequential and parallel programming techniques to note its detection accuracy and speed.

Automatic verification of handwritten signature is an age-old research topic. Available literatures show that several traditional and soft computing techniques have been used for accomplishing the said task. Due to space constraints, detail discussion of all the techniques are beyond the scope of this paper. Hence, some relevant studies have been shown, below.

Handwritten signature recognition using traditional techniques:

Author and year	Technique(s)	Avg. accuracy
Inglis and Witten, 1994[9]	Template matching	75%
Mizukami et al., (2002) [10]	Displacement extraction method	75%
Kholmatov and Yanikoglu, (2005) [11]	3-D vector and DWT	98.6%.
Shanker and Rajagopalan, (2007) [12]	modified and basic DWT	98% , 71%
Tian et al., 2007 [13]	DWT	86.04%.
Radhika et al., (2011) [14]	Zernike moments	98%

Handwritten signature recognition using soft computing techniques:

Author and year	Technique	Avg. accuracy
Hossain et al., 2003 [15]	HMM and BPNN hybrid	88.9%
Lv et al., 2005 [16]	SVM	95%
Aksoy and Mathkour, (2011) [17]	Rule-based inductive learning system	97%
Dash et al., (2012) [8]	ART-1	99.98%
Dash et al., (2012) [18]	AMN	92.3%

From these studies, it may be noted that ART has not been tested widely in this field, which leaves an opportunity to investigate ART-2, which is the motivation behind this work.

In the following section, we have described the methodology of ART-2 implementation using 'C' language using both the sequential and parallel programming.

METHODOLOGY

To accomplish the task, following steps have been taken:
Step-1: Acquisition of hand written signatures – *one* original and *twelve* forged (refer to Fig.1a and 1b) and computing the 'Similarity Index (SI)' pixel-wise using equation 1
Step-2: Feature extraction to obtain all the gray-scale values with equation 2
Step-3: Development of ART-2 net on 'C' language with (i) sequential and (ii) parallel programming
Step-4: Training the net with the 'original' signature, and finally
Step-5: Testing the net with the forged signatures and compute the error by estimating the percentage of mismatch (see equation 3).
The steps are discussed in detail in the following section.
Step-1: Acquisition of Handwritten signatures:
Figures 1a and 1b show the samples of hand-written original and one forged signature.

Figure 1a: Original signature

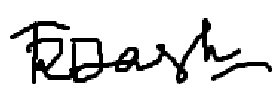

Figure 1b: One forged signature

The size of the signatures is 200×63 dpi with bit depth of 4 bit. Similarity Index (SI) is then computed between all forged signatures and the original signature using equation 1.

$$SI = \frac{1-D_p}{T_p} \times 100 \qquad (1)$$

The arrangements of pixels ('ON' and 'OFF') in the forged signatures are compared with that of the original signature, row and column-wise. The disparities are then computed. In equation 1, D_p is the number of 'dissimilar pixels' and T_p is the total number of pixels. The average SI computed for the forged signatures is around 51%.
Step-2: Feature extraction:
In this step, we have extracted the pixel values in RGB (Red-Green-Blue) format, which are then converted into gray scale values by using the following standard relation.

$$\text{Gray value} = 0.33 \times R + 0.56 \times G + 0.11 \times B \qquad (2)$$

Step-3 and 4: Development of ART-2 algorithm and its training:
As already mentioned, the ART-2 net has been developed on 'C' language. Figure 2 shows the schematic diagram of ART-2 structure. The implementation algorithm is as follows:

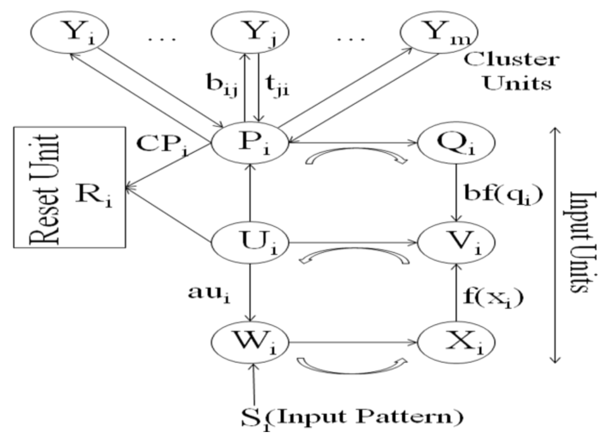

Figure-2: Structure of ART-2.

Step 0: Initialize the following parameters: $a, b, c, d, e, \alpha, \rho, \theta$. Also specify the number of epochs of training (*nep*) and number of learning iterations (*nit*).
Step 1: Perform *Step*s 2-12 (nep) times.
Step 2: Perform *Step*s 3-11 for each input vectors.
Step 3: Update F_1 unit activations:

$$U_i = 0;\ w_i = s_i;\ p_i = 0;\ q_i = 0;\ v_i = f(x_i);$$

$$x_i = \frac{S_i}{e + ||s||}$$

Update F1 unit activation again:

$$U_i = \frac{v_i}{e + ||v||};$$

$$w_i = s_i + aU_i;$$

$$P_i = U_i;$$

$$x_i = \frac{w_i}{e + ||w||}$$

$$q_i = \frac{p_i}{e + ||p||};$$

$$v_i = f(x_i) + bf(q_i).$$

Step 4: Calculate signals to F_2 units:

$$Yi = \sum_{i=1}^{n} b_{ij} p_i$$

Step 5: Perform *Step*s 6 and 7 when reset is true.
Step 6: Find F2 unit Y_J with largest signal (**J** is defined such that $Y_J \geq Y_j$, j=1 to m).
Step 7: check for reset:

$U_i = \frac{v_i}{e+||v||}$;

$P_i = U_i + dt_{ji}$;

$r_i = \frac{u_i + cp_i}{e+||u||+c||p||}$;

If $||\mathbf{r}|| < (\rho\text{-e})$, then y_J = -1 (inhibit J).

Reset is true; Perform *Step* 5.

If $||r|| \geq (\rho\text{-e})$, then $w_i = s + aU_i$;

$x_i = \frac{w_i}{e+||w||}$;

$q_i = \frac{p_i}{e+||p||}$;

$v_i = f(x_i) + bf(q_i)$.

Reset is false. Proceed to *Step* 8.

Step 8: Perform *Step*s 9-11 for specified number of learning iterations.

Step 9: Update the weights for winning unit **J:**

$t_{ji} = \alpha du_i \ + \{[1+ \alpha d(d-1)]\}t_{ji}$;

$b_{iJ} = \alpha du_i \ + \{[1+ \alpha d(d-1)]\}b_{iJ}$;

Step 10: Update F1 activations:

$U_i = \frac{v_i}{e+||v||}$;

$w_i = s_i + a\, U_i$;

$P_i = U_i + dt_{ji}$;

$x_i = \frac{w_i}{e+||w||}$;

$q_i = \frac{p_i}{e+||p||}$;

$v_i = f(x_i) + bf(q_i)$.

Step 11: check for the stopping condition of weight updation.

Step 12: Check for the stopping condition for the number of epochs

The *symbols* used in the above algorithm are:

n = number of components in input training vector;

m = maximum number of cluster units that can be formed;

$\boldsymbol{\rho}$ = vigilance parameter (set between 0 and 1);

s = binary input vector;

x = activation vector for F_1(b) layer;

$\boldsymbol{\alpha}$ = learning trials;

$\mathbf{b}_{ij}$ = bottom-up weights;

$\mathbf{t}_{ji}$ = top-down weights (Weights from Y_j of F_2 layer to X_i unit of F_1(b) layer);

$||\mathbf{x}||$ = norm of vector x and is defined the square root of the sum of the squares of the respective components of x_i (i=1 to n).

It is important to mention that both the sequential and parallel implementation is executed in Linux environment *(Ubuntu 10.04)*. It may be noted that, both 'sequential' and 'parallel' processing has been executed in a Intel dual core PC having 1 GB RAM and 2 GHz processor speed.

***Step*-5: Testing the performance of ART-2**

Each of the forged signatures is then passed through the trained ART-2 network and the number of matched b_{ij} is counted. Equation 3 expresses the mismatch percentage as follows,

$$mismatch = \left[1 - \frac{b^*_{ij}}{count}\right] \times 100 \qquad (3)$$

In this equation, '*count*' denotes the total number of bottom-up weights (b_{ij}) and 'b^*_{ij}' are the weights which are matched with the training cases. In this work, we have chosen 5% mismatch percentage to decide on whether a signature could be accepted or not, i.e. mismatches up to 5% are allowed else rejected. It is important to note that mismatch acts as a threshold and threshold setting must be situation specific and the choice of user /administrator [19].

RESULTS

The average similarity index (SI) between the original and forged signatures near 51%, which may have higher chance of matching, instead of rejecting the forged signatures. It is desired that even with slightest difference, the network must be able to differentiate those from the original signature based on its learning and assigned vigilance. The paper suggests that vigilance parameter (ρ) needs to be optimally set, which is the first challenge. In this work, optimum ρ has been set through a detail parametric study (see table-1 and 2). The second challenge is to assure that the network learns the exemplary patterns through several observations (number of clusters).

Table 3 shows how the cluster size (m) influences the accuracy and the computational times. In table 1, it may be seen that with forged signatures 11 and 12 the mismatch is <5% and therefore these are accepted as original. In case, the mismatch threshold is set <1%, the algorithm would be able to detect all forged signatures. Hence, we have made the algorithm very flexible to allow such modification, which depends on the situations. Table 2 shows that with ρ=0.97, the detection accuracy is almost 100% with minimum time in both sequential and parallel programming.

Table-1 Result obtained from ART-2 net with different values of vigilance parameter (ρ)

Test Cases (Original vs.)	**Vigilance Parameter (ρ)**					
	0.50	**0.63**	**0.78**	**0.89**	**0.97**	**0.99**
Original	0	0	0	0	0	0
Forged1	21	21	21	21	21	21
Forged2	20	20	20	20	20	20
Forged3	22	22	22	22	22	22
Forged4	19	19	19	19	19	19
Forged5	18	18	18	18	18	18
Forged6	17	17	17	17	17	17
Forged7	21	21	21	21	21	21
Forged8	21	21	21	21	21	21
Forged9	24	24	24	24	24	24
Forged10	21	21	21	21	21	21
Forged11	*1*	*1*	*1*	*1*	*1*	*1*
Forged12	*2*	*2*	*2*	*2*	*2*	*2*

Table-2 Accuracy rate at different vigilance parameter with corresponding computation time

ρ	Accuracy (%)	Computation Time (seconds)	
		Sequential	Parallel
0.50	96.01	1.96	1.02
0.63	97.09	2.12	1.16
0.78	97.61	2.002	1.29
0.89	98.97	2.30	1.56
0.97	99.9989	1.78	0.99
0.99	99.91	2.04	1.18

Fig.3 plots the 'ρ vs. accuracy' parametric study. As seen in table 2, for ρ = 0.97, the accuracies are 99.9989 in both the sequential and parallel programming, we have shown the plot for parallel processing.

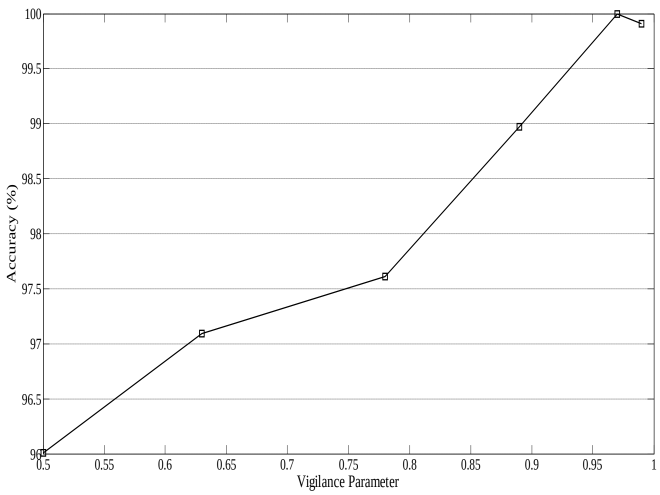

Figure-3: Parametric study with vigilance parameter and the detection accuracy.

Table-3 Improvement of accuracy with number of clustering units (m) in the F_2 layer

#m	Accuracy (%)	Computation Time (sec.)	
		Sequential	Parallel
2	97.66	0.53	0.33
3	97.66	0.59	0.32
5	97.66	0.77	0.41
7	97.75	0.76	0.62
8	98.001	1.09	0.63
10	98.78	1.21	0.79
12	99.35	1.69	1.08
14	99.72	2.23	1.8
15	99.92	2.33	2.13
20	99.9989	1.78	0.99
22	99.98	3	2.57
23	99.98	4.03	5.42
25	99.98	5.97	5.02
30	99.94	8.71	6.09

Table-3 shows that with 'ρ=0.97' and 'm' = 20, the detection accuracy is the highest. Fig. 4 plots the number of clusters (m) vs. the respective accuracy levels achieved.

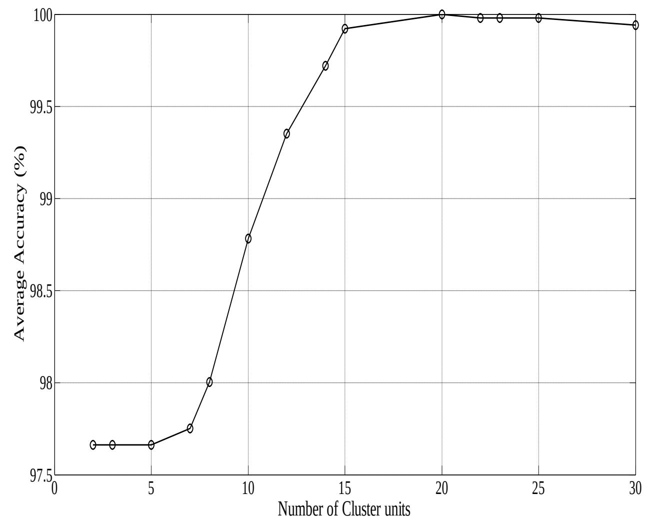

Figure-4: Parametric study with number of cluster units and the detection accuracy.

Therefore, we conclude that through parametric studies, our method gives more accurate result when compared with other techniques, described in section I.

CONCLUSIONS AND FUTURE WORK

An ART-2 type net has been developed in this work for automating the verification of very similar looking (SI ~51%) forged signatures, offline. It has been implemented with both sequential and parallel processing to achieve faster and accurate detection with a mismatch threshold of 5%. Through parametric studies the best 'ρ' and 'm' are obtained. The accuracy is found to be 99.98%.

It is important to mention that, in this study we have tested only twelve forged signatures, which is a small sized sample. This is certainly a limitation of this work. The net needs to be tested with many different types of original as well as forged signatures for obtaining a more authentic proof of its performance. We are currently working on it.

REFERENCES

[1] S. Chattopadhyay, P. Kaur, F.A. Rabhi, U.R. Acharya– "Neural Network Approaches to Grade Adult Depression", *Journal of Medical Systems* (2011), published online on 21/07/2011 DOI: 10.1007/s10916-011-9759-1

[2] S. Chattopadhyay, P. Kaur, F.A. Rabhi, U.R. Acharya – "An Automated System to Diagnose the Severity of Adult Depression". In the *proceedings* of *2nd International Conference on Emerging Applications of Information Technology (CSI* EAIT-2011), 19-20th February Kolkata India, (Editors - Jana D., and Pal P.), pp. 121-124. Publishers: IEEE Computer Society and Conference Publishing Services IEEE Xplore, Google Scholar, DOI: 10.1109/EAIT.2011.17.

[3] Chattopadhyay S., Pratihar D. K, De Sarkar S. C. –"Statistical Modelling of Psychoses Data". *Computer Methods and Programs in Biomedicine* (2010); 100(3): pp. 222-236.

[4] S. Chattopadhyay., D. K. Pratihar, S.C. De Sarkar - "Some Studies on Fuzzy clustering of psychosis data". *International Journal of Business Intelligence and Data Mining* (2007); 2(2): pp. 143-159.

[5] S.K. Ahmed, A.K. Ramasamy, A. Khairuddin, J. Omar. "Automatic online signature verification: A prototype using neural networks". TENCON 2009 pp. 1-4.

[6] G.A. Carpenter, S. Grossberg, "A self organizing neural network for supervised learning, recognition, and prediction. Can neural networks learn to recognize new objects without forgetting familiar ones?" IEEE Communication Magazine, 1992, pp. 38-49.

[7] S.N. Sivanandan, S.N. Deepa "Principle of Soft Computing (2nd Edition)" WILEY-INDIA, 2011. ISBN-978-81-265-2741-0, 2011.

[8] Dash T., Nayak T., Chattopadhyay S., "Offline Verification of Hand Written Signature Using Adaptive Resonance Theory Net (Type-1)," ICECT-2012, Vol-2, pp. 205-210, 2012.

[9] S. Inglis, I.H. Witten. "Compression-based Template Matching". Proc. IEEE Data Compression Conference. Los Alamitos, CA, pp. 106-115, 1994.

[10] Y. Mizukami, M. Yoshimura, H. Miike, I. Yoshimura. "An off-line signature verification system using an extracted displacement function". Pattern Recognition Letters. 23, 1569-1577, 2002.

[11] A. Kholmatov, B. Yanikoglu. "Identity authentication using improved online signature verification method". Pattern Recognition Letters. 26, 1400-2408, 2005.

[12] A.P. Shanker, A.N. Rajagopalan. "Off-line signature verification using DTW". Pattern Recognition Letters. 28, 1407-1414, 2007.

[13] W. Tian, Y. Qiao, Z. Ma. "A New Scheme for Off-line Signature Verification Using DWT and Fuzzy Net". ACIS Int. Conf. Software Engineering, Artificial Intelligence, Networking, and Parallel/Distributed Computing,. Vol.3, pp.30-35, 2007.

[14] K.R Radhika, M.K. Venkatesha, G.N. Sekhar. "An approach for online signature authentication using Zernike moments". Pattern Recognition Letters. 32, 749-760, 2011.

[15] A.K.M. A., Hossain, Md. G. Rahman, R.C. Debnath. "Comparative study of signature verification system using Supervised (BPNN) and Unsupervised (HMM) Models". ICCIT-2003, pp. 732-737, , 2003.

[16] H. Lv, W. Wang, C. Wang, Q. Zhuo. "Off-line Chinese signature verification based on support vector machines". Pattern Recognition letters. 26, 2390-2399, 2005.

[17] M.S.Aksoy, H. Mathkour. "Signature verification using rules 3-ext inductive learning system". Int. J. Physical Sciences. 6(18):4428-4434, 2011.

[18] Dash T., Nayak T., Chattopadhyay S., "Offline Hand Written Signature Verification Using Associative Memory Net ". Int. J. of Advanced Research in Computer Engineering & Technology. 1(4):370-374,2012.

[19] S. Chattopadhyay, S. Banerjee., F.A, Rabhi, U.R.Acharya " A Case-based Reasoning System for Complex Medical Diagnoses." Expert System :The Journal of Knowledge Engineering (2012); DOI:10.1111/j.1468-0394.2012.00618.x (in press).

