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# FUZZY LOGIC BASED ADAPTIVE RESONANCE THEORY-1 APPROACH FOR OFFLINE SIGNATURE VERIFICATION

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**Abstract.** This paper presents the use fuzzy logic with adaptive resonance theory-1 in signature verification. Fuzzy model is capable of stable learning of recognition categories in response to arbitrary sequences of binary input pattern. The work was carried out on two famous available signature corpuses i.e. MCYT (Online Spanish signatures database) and GPDS (Grupo de Procesado Digital de la se?al). Local binary patterns (LBP) and Gray Level Co-occurrence Matrices (GLCM) features were calculated for robust offline signature verification system. Training and verification was done using fuzzy adaptive resonance theory-1(FART-1). The system is trained and verified for different datasets to increase the accuracy of the classifier. The results thus obtained are robust than other existing techniques. The FAR and FRR for the system is 0.74% and 0.83% respectively.

**Key words.** Offline Signature Verification System, FART1 (Fuzzy Adaptive Resonance Theory), SVM Classifier (Support Vector Machine), LBP (Local Binary Patterns), GLCM (Gray Level Co-occurrence Matrices)

## 1 Introduction

The adaptive resonance theory (ART) has capability of learning in response to significant input patterns retaining stability during production of irrelevant patterns. Hence, the designed system can learn new information while keeping previous learned information. This is possible because of good feedback mechanism which ensures internal control mechanisms. This neural network stops learning when an appropriate pattern is developed and weight adaptation occurs. But, ART is an unsupervised learning algorithm. It can respond to any external signal or information. It estimates do not possess the statistical property of consistency.

A fuzzy adaptive resonance theory (ART) model is capable of rapid stable learning of recognition categories in response to arbitrary sequences of analog or binary input patterns [16]. When ART 1 neural network is combined with fuzzy logic, the resultant model becomes capable of learning binary input patterns and the resultant model does supervised learning. Fuzzy ART is a combination of basic features of ART systems and fuzzy operators. It is competent enough to match patterns between top-down bottom-up input and learned prototype vectors. The aim of pattern matching process is to reach to a considerable or to a autonomous parallel memory search. The significant state will focus attention and triggers stable prototype learning. In case of parallel memory search, the search can either ends by selecting an established category or it ends by selecting a previously untrained node. The category's prototype may be further improved to include new information in the input pattern. The selection of untrained node will lead to learning of a new category.

The fuzzy ART model developed herein generalizes ART-l to be capable of learning stable recognition categories in response to both analog and binary input patterns. When it follows supervised learning, ART-1 creates various stable recognition classes of best possible size. The classes are created by reducing the predictive error and increasing predictive generalization. Hence, this network gives optimum performance in image processing. The simple learning equations of this model help to learn within small number of iterations. The results of the implementation show that fuzzy ART model provides a robust technique for offline signature verification. Collectively, ART-1 and fuzzy provide efficient learning and training. It works on random vigilance values and finally helps to achieve the target range. However, our computer simulations show that the final vigilance will converge to the target range.

# 2 Methodology

This section describes the methodology behind the system development. The block diagram of offline signature verification based on fuzzy adaptive resonance theory 1(FART-1) is discussed in detail and is as shown in the Fig. 1. The process starts with data acquisition.

## 2.1 DATABASE

Experiments are performed on two offline signature databases. The offline MYCT database containing data of 50 persons. The GPDS database containing data from 960 individuals: 24 genuine signatures for each individual, plus 30 forgeries of his/her signature. Skilled forgeries are good imitations in the GPDS database. MYCT database consists of Spanish signatures.

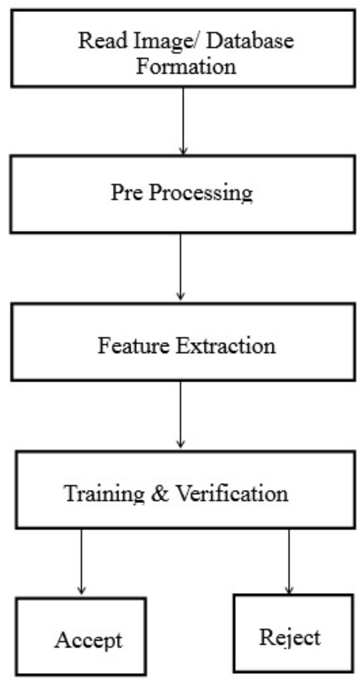
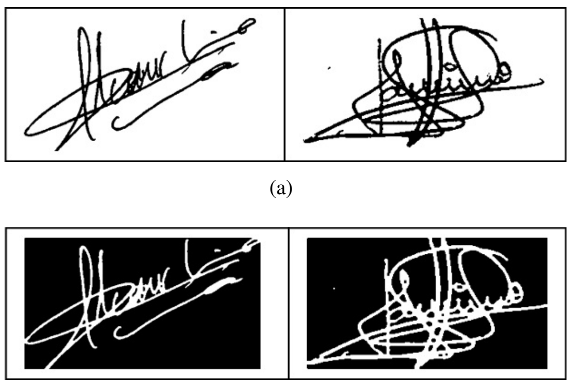



Fig. 1: Block Diagram for Fuzzy ART- 1

Total number of samples used for database are 1200.We have used this database because of following reasons: one, there is strong intra-class variation; and then signature are done in defined confined area which helps to extract region of interest accurately. Hence, this enables to test our system tolerance under different situations.

We have trained our system using four different datasets. Our main aim was to evaluate performance of our FART model.

First dataset consists of 200 genuine signature samples for training, 60 genuine signature samples and 40 forgery



(a)

(b)

Fig. 2: Genuine Signatures (a) Gray-level (b) Binary

(a) (b) (c)

Fig. 3: Pre-Processing Steps (a) Original Image, (b) Binarised Image (c) Thinned image

signature samples for testing. Dataset 2 consists of 400 genuine signature samples for training, 100 genuine signature samples and 100 forgery signature samples for testing. Dataset 3 consists of 600 genuine signature samples for training, 200 genuine signature samples and 100 forgery signature samples for testing. Dataset 4 consists of 800 genuine signature samples for training, 200 genuine signature samples and 200 forgery signature samples for testing. Fig. 2 shows genuine signatures.

## 2.2 SIGNATURE PRE-PROCESSING

Pre-processing is required to process the image for feature extraction. The scanned image contains spurious pixels (noise) which has to be removed to achieve accuracy in further processing steps. Noise is removed using median filter. Image is then converted to grayscale, which is then converted into binary by using OTSU's method. OTSU method assumes that image contains two classes of pixels i.e. foreground and background pixels, it then calculates the optimum threshold separating the two classes. Threshold value based on this method will be between 0 and 1. In next step, thinning is performed to get a smaller size thinned signature image. This process helps to perform feature extraction more efficiently. Fig. 3 shows the simulation of pre-processing steps.

## 2.3 FEATURE EXTRACTION

Feature extraction is essential to the success of a signature verification system. In an offline environment, the signatures are acquired from a medium, usually paper, and pre-processed before the feature extraction begins. Local binary pattern (LBP) is a powerful feature proposed to capture the texture in objects [17]. It is commonly used in object recognition with good success. Indeed, it was used previously in signature verification (Yasmine Serdouk et al. 2015) as well. Various forms of local binary patterns such as center symmetric LBP (CS-LBP), uniform LBP, local derivative patterns (LDerivP) were successfully used for offline signature verification (Miguel A. Ferrer et al. 2012).

The LBP tests the relation between pixel and its neighbors, encoding this relation into a binary code. Current pixel's intensities are compared with neighboring pixels. So, for instance, to encode relationship of center pixel with it $3 \times 3$ neighborhood, binary code is produced of length 8. This binary code (0 and 1s) is based on the relative intensities of the neighboring pixels. This is also termed as LBP operator and it produces 256 (28) different output values, corresponding to the 256 different binary patterns that can be formed by the eight pixels in the neighbor set.

The generalized LBP operator, given in Eq. (1), is derived on the basis of a circularly symmetric neighbor set of P members on a circle of radius R (S. Singh, A. Kaur 2014). Spatial resolution of the operator is determined by

R and angular space's quantization is controlled by parameter $P$.

$$LBP_{P,R}(J_C) = \sum_{P=0}^{7} s(i(J_P)_I(J_C)).2^P \tag{1}$$

where $s(I) = f(x) = \begin{cases} 1, & 1 \geq 0 \\ 0, & 1 < 0 \end{cases}$

In Eq. (1), the intensity values of the neighboring and center pixels are denoted by $I(JP)$ and $I(JC)$ respectively. Here, $P$ is the index of each pixel in neighborhood of center pixel, $C$.

When neighboring pixel has higher value (i.e. $I(J_P) - I(J_C) \geq 0$) then it is replaced by one and for lower value it is replaced with zero and weight (i.e. $2^P$) is assigned to each bit in circular neighborhood staring with upper left pixel. Fig. 4 shows computation performed by LBP operator. To count the number of occurrences of each binary code, a histogram is generated. Actually, the histogram of these binary codes contains information on the distribution of the edges, spots, and other local figures in an image. Fig. 4 shows how LBP divides the signature into grids. For each grid it generates a binary code. Each binary code is further represented in the form of histogram. Finally, all histograms are joined together and quantized into feature vector.

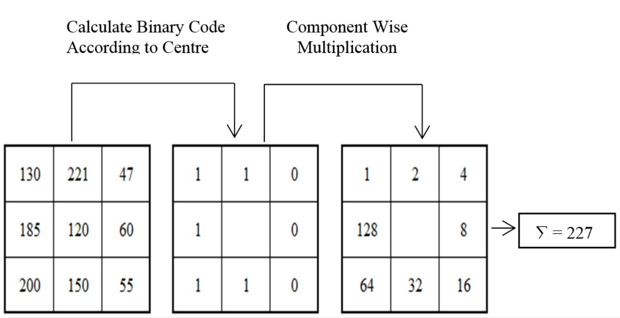



Fig. 4: LBP Pattern Extraction Algorithm

The best property of LBP is that it is stable during monotonic changes in gray scale and it can work on different sizes neighborhood. (T. Ojala et al. 2002). Gray-level spatial dependence matrix which is popularly known as grey-level co-occurrence matrix (GLCM) is a statistical method which examines texture of spatial connection of pixels. The GLCM functions prepare a matrix based on texture of an image. It calculates number of times each pair of pixels and pixels with specific relationship in an image. The number of grey levels i.e. intensity values in the image determines the size of the GLCM. The GLCM is a tabulation of how often different combinations of pixel gray levels could occur in an image. For offline signature verification system, preprocessed signature image is taken and is assigned to one of the set of texture classes. There are textural features such as spatial structure, orientation, roughness etc. GLCM provides a correlation of input image with desired output. We have created a GLCM using the gray comatrix function. In the signature image, gray comatrix function is dependent on the number of pixels in the strokes of signature instead of the size of image. A matrix $T(i, j|\Delta x, \Delta y), 0 \geq i \geq GL-1$, $0 \geq j \geq GL-1$ represents the GLCM of an image $I(x, y)$ where number of grey levels (GL) is equal to the number of rows and columns. The matrix element $T(i, j|\Delta x, \Delta y)$ is the relative frequency with which two pixels with gray levels $i$ and $j$ occurs separated by a pixel distance $\delta x, \Delta y$ (J.F. Vargas, M.A. Ferrer 2011). Further, we have used mean of all the four statistics: contrast, energy, homogeneity and correlation.

## 2.4 TRAINING AND TESTING THROUGH FART

To apply FART to signature verification system, the architecture is trained using vectors got from the feature extraction stage. This step starts with training through adaptive resonance theory neural network. Adaptive resonance theory 1 makes use of ordinary differential equations which leads to self-stability and convergence of its adaptive weights. ART1 is characterized by a system of ordinary differential equations with associated theorems proving its self-stabilization property and the convergence of its adaptive weights (Mohamad H. Hassoun 1995). Hence, its property to easily adapt to change in environment makes it suitable for training our feature vector.

Fuzzy ART is a supervised learning method used for data clustering purposes in data mining field. It is formed by incorporating fuzzy logic into ART modules [1]. The fuzzy ART network is a step forward network which reduces the architectural redundancy and computational overhead. Within a small number of training iterations, fuzzy logic model learns every single training pattern.

The fuzzy logic is applied on trained output obtained through ART 1. A fuzzy inference system (FIS) accepts trained output of ART1 which is in vector format. It uses fuzzy rules to map the input data vector into a scalar output.

#### 2.4.1 FUZZY ART ARCHITECTURE

Fig. 5 shows the architecture of FART architecture. Numbers of d features fed in the complement code are input vectors. All the input vector's complemented values are summed to double the size.

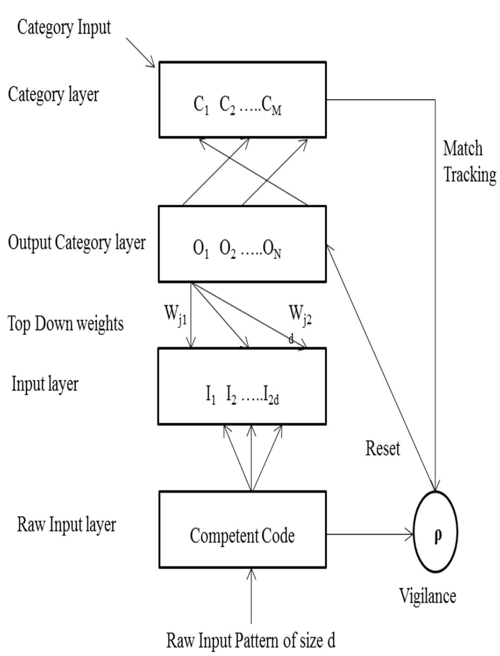



Fig. 5: Architecture of Fuzzy ART Network

In Fig. 5, Ia is the complement code input. Its size is 2d. The input layer takes all 2d inputs. Top down weights ($W_{ji}$) is the connection between output category nodes ($O_N$) input layer vectors. There are M category or classes in category layer mapfield. The network does learning for each one of the given input vectors. FART network is very subtle to the absolute sizes of the inputs and their instabilities; therefore, normalization of all the inputs into the same value range is essential.

The learning phase finds a match between output category class and input vector. For successful match, the current input vector is used to improve weight value of its matching category. This helps in incorporating more general characteristics for the current category. If current input vector do not matches category class, a new category is created through learning various related parameters. This whole process of refining weights is also referred as extended classification process. Generation of more categories during matching stage ensures that the similarity in input space is transferred for improved results. Fuzzy ART can use several categories to represent one class. This helps to capture the spectral variance in inputs and the related class, The inter-class and intra-class variability among classes is also categorized by Fuzzy ART.

### 2.5 DISCUSSION

The experiment is conducted using four different size databases. First dataset consists of 200 genuine signature samples for training, 60 genuine signature samples and 40 forgery signature samples for testing. Dataset 2 consists of 400 genuine signature samples for training, 100 genuine signature samples and 100 forgery signature samples for testing. Dataset 3 consists of 600 genuine signature samples for training, 200 genuine signature samples and 100 forgery signature samples for testing. Dataset 4 consists of 800 genuine signature samples for training, 200 genuine signature samples and 200 forgery signature sam-

Tab. 1: Results of FART based Offline Signature Verification System

| Dataset | Phase | Genuine Signature Samples | Forged Signature Samples | FAR% | FRR% |
|---|---|---|---|---|---|
| I | Training | 200 | | 0.435 | 0.536 |
| | Testing | 60 | 40 | | |
| II | Training | 400 | | 0.235 | 0.256 |
| | Testing | 100 | 100 | | |
| III | Training | 600 | | 0.154 | 0.201 |
| | Testing | 200 | 100 | | |
| IV | Training | 800 | | 0.74 | 0.83 |
| | Testing | 200 | 200 | | |

ples for testing.

The vigilance parameter is selected so that the number of categories to which the network settles is same as the number of classes in the training data. Signature verification using FART has shown vigilance parameter value of 0.75. The learning time taken by network is only 2 epochs. This shows that the network is very efficient in terms of time complexity. The training phase provides top-down weight matrices as its output. Further, the testing can be carried out using the matrix equivalent of the test input image. An offline signature verification system authenticates the signer based on two parameters: false acceptance rate (FAR) and false verification rate (FRR). Tab. 1 shows results with different datasets.

## 3 Conclusions

Experiments are conducted by increasing samples per person for training. Results show that there is no significant impact on values of FAR and FRR. The most important advantage of fuzzy system is that it adjusts uncertainty with input data. So, it can be used in testing signatures with intra personal variations. Our ART-1 when combined with capabilities of fuzzy logic leads to mixing power of supervised and unsupervised learning.

LBP and GLCM features are mostly used for texture analysis. The mixture of these features has a great ability to recognize forgeries and tolerate intrapersonal variations. After feature extraction we use FART classifier which gives us optimum performance with FAR and FRR values better as compared to other designed systems. The training time of designed signature verification system is negligible as the FART model provides learning in small number of iterations.

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