International Journal of Technical Innovation in Modern Engineering & Science (IJTIMES)
Impact Factor: 5.22 (SJIF-2017), e-ISSN: 2455-2585
Volume 5, Issue 06, June-2019

Face Recognition using Gabor features and Adaptive resonance theory (ART)

[1]R.G. Dabhade

[1]*Research Scholar, Dr. Dr. Babasaheb Ambedkar Marathwada University, Aurangabad*

Abstract*— *In this proposed contribution, we derive Gabor features of the face images both while training and testing experiments. Later we use a ARTMAP for classification that merges two somewhat customized ART-1 or ART-2 units into a supervised learning structure wherein the 1st unit accepts the input data (training set of images) and the 2nd unit acquires the accurate output data (image labels), after that are used to create the lowest possible adjustment of the vigilance parameter in the 1st unit so as to make the accurate classification. Our results of experiments show that performance comparable with the computationally intensive evolutionary methods could be achieved in much less time.

Keywords*— *Face Recognition, Gabor features, ARTMAP, Adaptive Resonance Theory

I. INTRODUCTION

Among various biometrics, face recognition has attracted a lot of attention because it has several advantages over other biometric technique. Research in automated face recognition has been conducted since past few decades. Even though many face analysis and face modelling techniques have proposed significantly in the last decade, however, the reliability of face recognition systems still poses a great challenge to the scientific community. Face recognition (FR) has been extensively studied, due to both scientific fundamental challenges and current and potential applications where human identification is needed. FR systems have the benefits of their non intrusiveness, low cost of equipments and no user agreement requirements when doing acquisition, among the most important ones. Nevertheless, despite the progress made in last few decades and the different solutions proposed, FR performance is not yet satisfactory when more demanding conditions are required (different viewpoints, blocked effects, illumination changes, strong lighting states, etc). With this motivation in view face recognition system employing Gabor filter for feature extraction and ARTMAP [1] for classification is presented in this paper. Prospective to adjust fresh patterns indefinitely, capability to maintain earlier learned knowledge and because of its exclusive solution to a stability-plasticity problem motivates the use of ARTMAP as classifier. The dilemma of extended training period and without forgetting the previous learnt data incremental learning is also overcome by using ARTMAP.

II. FEATURE EXTRACTION USING GABOR FILTER

The characteristics of a Gabor filters, particularly for orientation and frequency representations, can be equivalent to like human visual system and these are predominantly suitable for texture representation and discrimination. With Gabor filter features, straightly extracted from gray level images, are extensively and successfully utilized to diverse pattern recognition tasks [2,3,4]. Within a spatial domain, the 2-dimentional Gabor filter is the Gaussian kernel function that is modulated with a sinusoidal plane wave, which may be represented as follows:

$$\boldsymbol{\Psi_{\omega,\theta}(x,y) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{y' + y'^2{}'}{2\sigma}\right)\exp(j\omega x')} \qquad \mathbf{(2.1)}$$

$$\boldsymbol{x' = x\cos\theta + y\sin\theta,\quad y' = -x\sin\theta + y\cos\theta}$$

Here (x, y) represents pixel position within a spatial domain, (ω) represents central angular frequency of a sinusoidal plane wave, (θ) represents anti-clockwise rotation of a Gaussian function, and (σ) is the sharpness of a Gaussian function along the directions (x) and (y) . Generally set (σ) *is set to* $(\sigma \approx \pi / \omega)$ which defines the relationships between σ and ω. A Gabor filters having the diverse frequencies and orientations that forms a Gabor filter bank, has been utilized to derive most expressive important features of face images. A Gabor filter bank with 5 frequencies and 8 orientations is utilized in most applications [8]. Fig. 2.1 represents the real parts of Gabor filter bank employing five dissimilar scales and eight dissimilar orientations, depicted in equation below:

$$\boldsymbol{\omega_m = \frac{\pi}{2}\,\mathrm{X}\,\sqrt{2^{-(m-1)}}\;,\theta_n = \frac{\pi}{8}\,(n-1)} \qquad \mathbf{(2.2)}$$

Where (m = 1, 2… 5) and (n = 1, 2… 8)

For extracting Gabor features the given input greyimage $I(x, y)$ is convolved with a Gabor filter $\Psi\omega,\ \theta(x, y)$ that obtains Gabor features depiction as:

$$\boldsymbol{G_{m,n}\,(x,y) = I(x,y) * \psi_{\omega_m,\theta_n}\,(x,y)} \qquad \mathbf{(2.3)}$$

In the above expression, $G_{m,n}\ (x,y)$ is the complex convolution that can be decomposed into real and imaginary (even or odd) parts by with:

$$\boldsymbol{E_{m,n}\ (x,y) = \ Re[G_{m,n}\ (x,y)] \quad and \quad O_{m,n}\ (x,y) = Im[G_{m,n}\ (x,y)]} \qquad (\mathbf{2.4})$$

Depending upon these outputs, the phase ($\phi_{m,n}\ (x,y)$) and magnitude responses ($A_{m,n}\ (x,y)$) both are derived, i.e.:

$$\boldsymbol{A_{m,n}\ (x,y) \ = \ \sqrt{E^2{}_{m,n}\ (x,y) + \ O^2{}_{m,n}\ (x,y)}}$$

$$\boldsymbol{\phi_{m,n}\ (x,y) = \frac{\mathbf{arctan}\left(\ O_{m,n}\ (x,y)\right)}{E_{m,n}\ (x,y)}} \qquad (\mathbf{2.5})$$

An example of the magnitude information from a Gabor face representation resulting from a testing face image is shown in Fig. 2.2.

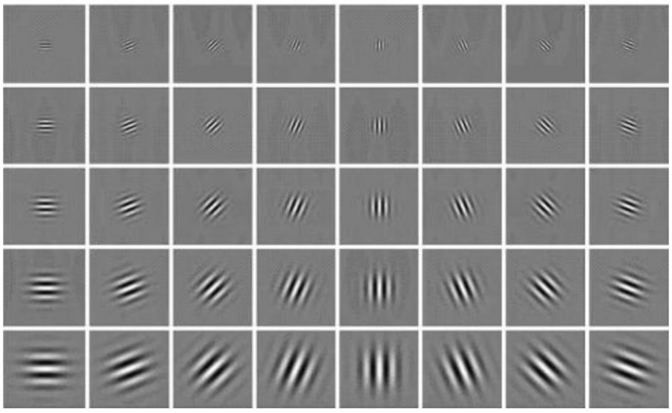

Figure 2.1: Real parts of a Gabor filter with 5 x 8 scales and orientations.

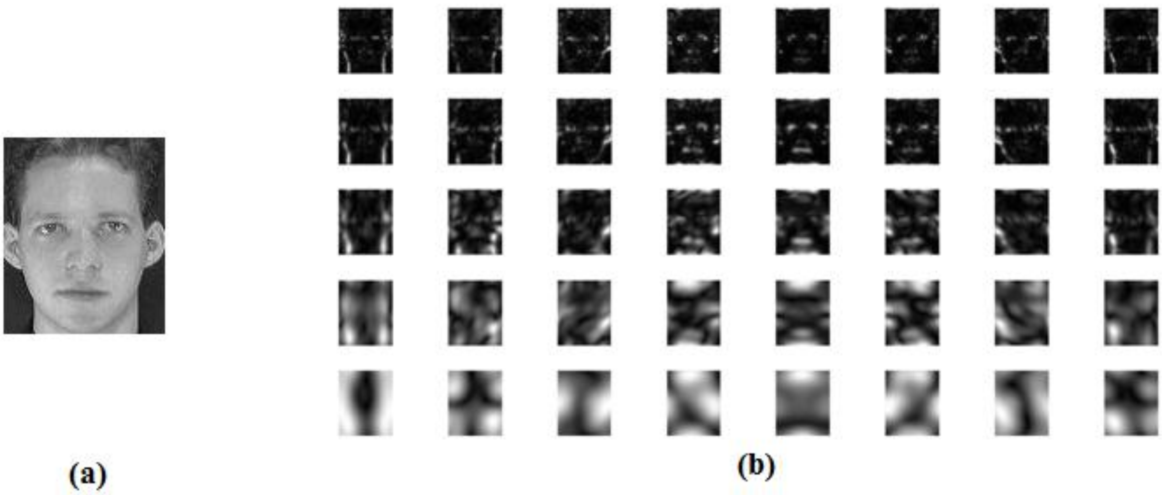

Figure 2.2: An example of the Gabor magnitude output: a sample image from ORL database (a) and the magnitude output of the filtering operation with the entire Gabor filter bank of 40 Gabor filters (b).

III. ADAPTIVE RESONANCE THEORY

Adaptive resonance theory (ART) is a hypothesis created by Stephen Grossberg and Gail Carpenter after thoroughly researching on information processing by the human brain [1,5] . The human brain has the unique ability as a primitive function to group objects and concepts and to think abstractly to perform clustering. ART is widely used for pattern recognition, clustering and prediction. The plasticity stability problem has been solved using Adaptive resonance theory. The Adaptive resonance theory1 (ART1) was generalized to accommodate both digital as well as analog data. Resonance pertains to the resonant of neural network in which a category prototype is matched to an input vector. ART matching tries to achieve this resonant state, which permits learning. This is analogous to concept drift, in which the statistical properties of a target variable change over time in unpredictable ways [6]. In unsupervised ART nets, input patterns may be applied several times and in any order. Each time a pattern is applied, an appropriate cluster unit is chosen and related cluster weights are adjusted to let the cluster unit learn the pattern. In such nets, choosing a cluster is based on the relative similarity of an input pattern to the weight vector for a cluster unit, rather than the absolute difference between the vectors (that is used in SOM nets). As in most cases of clustering nets, the weights on a cluster unit may be considered to be an exemplar (or code vector) for the patterns placed on that cluster [7]. ART nets are designed to allow the user to control the degree of similarity of patterns placed on the same cluster. This can be done by tuning the vigilance parameter in such nets. In ART nets, the number of clusters is not required to be determined previously, so the vigilance parameter can be used to determine the proper number of clusters in order to decrease the probability of merging different types of clusters into the same cluster. Moreover, ART nets have two other main characteristics, stability and plasticity. Stability means a pattern not oscillating among different cluster units at different stages of training, and plasticity means the ability of net to learn a new pattern equally well at all stages of learning.

3.1 ART1

It is a type of ART, which is designed to cluster binary vectors [1,9]. Bidirectional connections exist between the input layer and the output layer. ART1 is an unsupervised learning model specially designed for recognizing binary patterns. It typically consists of an intentional subsystem, an orienting subsystem as shown in Fig. 1, a vigilance parameter and a reset module. The vigilance parameter has considerable influence on the system. High vigilance produces higher detailed memories such as fine categories etc, while lower vigilance results in more general memories. The ART1 attentional subsystem has two competitive networks, comparison field layer F1 and the recognition field layer F2, two control gains, Gain1 and Gain2 and two short-term memory (STM) stages F1 and F2. Long-term memory (LTM) traces between F1 and F2 multiply the signal in these pathways.

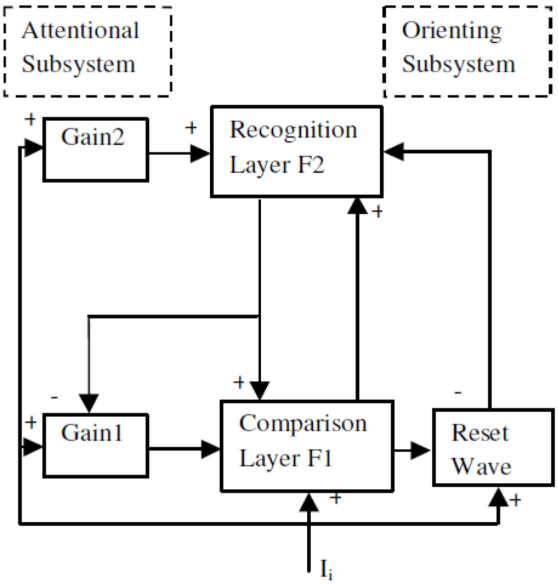

Figure 3.1.1: Structure of ART1

Two layers are included in the attentional subsystem, connected via bottom-up and top-down adaptive weights [fig.3.1.1]. Their interactions are controlled by the orienting subsystem through a vigilance parameter.

Depending on the similarity between the top down weight and the input vector, the cluster unit is allowed to learn a pattern or not. This is done at the reset unit, based on the signals it receives from the input and interface portion of the F1 later. If the cluster unit is not allowed to learn, it becomes inhibited and a new cluster unit is selected for learning. It dictates the three possible states for F2 layer neurons; they are namely active, inactive and inhibited. The difference between the inactive and inhibited is that for both the cases activation state of F2 unit is zero. In its inactive state, the F2 neurons are available in next competition during the presentation of current input vector which is not possible when the F2 layer is inhibited.

3.2 ART2

ART2 is similar to ART1, can learn and recognize arbitrary sequences of analog input patterns. ART2 is designed to perform for continuous-valued input vectors the same type of tasks as ART1 does for binary-valued input vectors [7]. The capability of recognizing analog patterns is significant enhancement to the system. A typical ART2 architecture is illustrated in Figure 3.2.1. The F1 layer consists of six types of units (W, X, U, V, P, and Q units). There are n units of each of these types, where n is the dimension of an input vector.

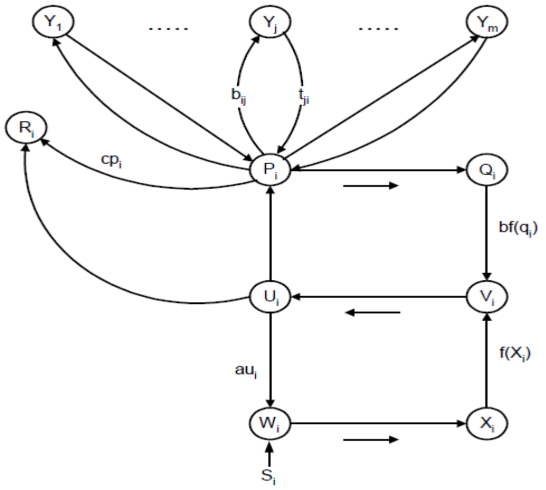

Figure 3.2.1: ART-2 Basic Configuration

The differences between ART2 and ART1 are :

- The modifications needed to accommodate patterns with continuous- valued components.
- The F1 field of RT2 is more complex because continuous-valued input vectors may be arbitrarily close together. The F1 layer is split into several sunlayers.
- The F1 field in ART2 includes a combination of normalization and noise suppression, in addition to the comparison of the bottom-up and top- down signals needed for the reset mechanism.
- The orienting subsystem also to accommodate real-valued data.

The main advantages of ART2 are:

- Rapid learning and adapt ability to a non-stable environment.
- Stability and plasticity.
- Unsupervised learning of preferences behavior that the target does not know at initial step.
- Deciding the number of clusters exactly and automatically.
- The learning laws of ART2 are simple though the network is complicated The learning laws of ART2 are simple though the network is complicated

3.3 ARTMAP

ARTMAP also known as Predictive ART [1] is a supervised neural network that comprises of two unsupervised ART modules, ARTa (ART1) and ARTb (ART2), and an inter-ART module called a map-field (Figure 3.3.1). An ART module has three layers of nodes: input layer F_0, comparison layer F_1, and recognition layer F_2. The F_2 layer is connected through weighted associative links to an L node map field F_{ab} , where L is the number of classes in the output space. One of the main reasons for the successful classification of nonstationary data sequences by ARTMAP is its ability to recalibrate the vigilance parameter based on predictive success.

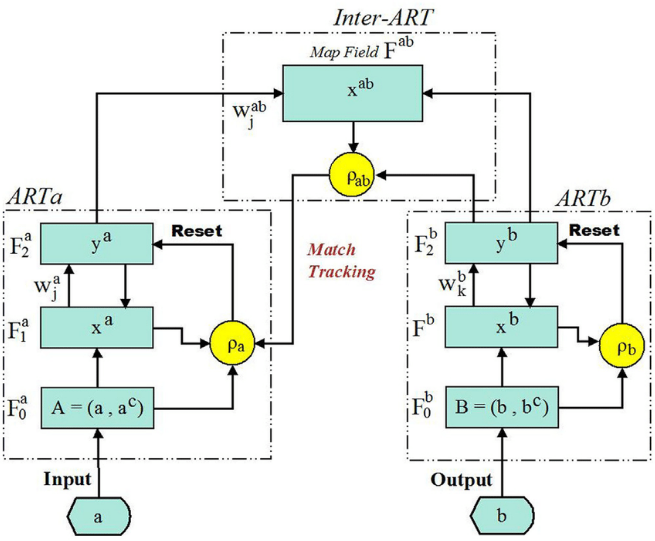

Figure 3.3.1: ARTMAP Architecture Basic Configuration

Inter-ART module incorporates a Map Field which manages the learning of an associative map from ART_a recognition categories to ART_b recognition categories. This map does not directly associate exemplars a and b, but rather associates the compressed and symbolic representations of families of exemplars a and b. The Map Field also controls match tracking of the ART_a vigilance parameter. A mismatch at the Map Field between the ART_a category activated by an input a and the ART_b category activated by the input b increases ART_a vigilance by some minimum amount needed for the system to search for and, if necessary, learn a new ART_a category whose prediction matches the ART_b category.

IV. PROPOSED ALGORITHM

The initial input vectors have the form: a = (a_1, . . . , a_n) ∈ $[0, 1]^n$ which are derived using Gabor filters. A data pre-processing technique called *complement coding* is performed in the two fuzzy art module by the F_o^a (and F_o^b respectively) layer in order to avoid proliferation of nodes. Each input vector a produces the normalized vector A = (a, 1 − a) whose L1 norm is constant: |A| = n.
Let M_a be the number of nodes in F_1^a and N_a be the number of nodes in F_2^b. Due to the preprocessing step, M_a = 2n. W^a is the weight vector between F_1^a and w_j^{ab}. Each F_2^a node represents a class of inputs grouped together, denoted as a “category”. Each F_2^a category has its own set of adaptive weights stored in the form of a vector w_j^a , j= 1,….., N_a whose geometrical interpretation is a hyper-rectangle inside the unit box. For a classification problem, the class index is the same as the category number in F_2^b , thus ART_b can be simply substitute an N_b–dimensional vector. The Mapfield module allows fuzzy artmap to perform heteroassociative tasks, establishing many-to-one links between various categories from ART_a and ART_b, respectively. The number of nodes in Mapfield is equal to the number of nodes in F_2^b . Each node j from F_2^a is linked to every node from F_2^b via a weight vector w_j^{ab} . The learning algorithm is sketched below

$$T_j\,(A) = \frac{\left|A \wedge \;\; w_j^a\right|}{\propto_a + \; w_j^a} \quad , j = 1, \dots \dots N_a \qquad (4.1)$$

Let J be the node with the highest value computed as in eq. (6.5.1). If the resonance condition from eq. (6.5.2) is not fulfilled, then the J^{th} node is inhibited such that it will not participate to further competitions for this pattern and a new search for a resonant category is performed. This might lead to creation of a new category in ART_a.

$$\rho\,(A, \;\; w_j^a) = \frac{|A \wedge \;\; w_j^a\,|}{|A|} \quad \geq \rho_{\,a} \qquad (4.2)$$

A similar process occurs in ART_b and let K be the winning node from ART_b. The F_2^b output vector is set to:

$$y_k^b = \begin{cases} 1, & k = k \\ \quad if & ---- \\ 0, & otherwise \end{cases} \qquad k = 1, \dots \dots N_b \qquad (4.3)$$

An output vector X^{ab} is formed in Mapfield: $X^{ab} = y^b \wedge \;\; w_j^{ab}$. A Mapfield vigilance test controls the match between the predicted vector X^{ab} and the target vector y^b :

$$\frac{|X^{ab}|}{|y^b|} \geq \rho_{ab} \qquad (4.4)$$

Where ρ_{ab} ∈ [0, 1] is a Mapfield vigilance parameter. If the test from eq. (6.5.4) is not passed, then a sequence of steps called match tracking is initiated (the vigilance parameter ρ_a is increased and a new resonant category will be sought for ART_a); else the learning take place in ART_a, ART_b and Mapfield:

$$w_j^{a(new)} \;\; = \beta_a\left(A \wedge w_j^{a(old)} \;\right) + \;\; \left(1 - \beta_a\right) \beta_a\, w_j^{a(old)} \qquad (4.5)$$

V. EXPERIMENTAL RESULTS

Following graphs shows the results obtained for four standard publically available face databases (ORL, YaleB, IFD and AR) with the ARTMAP method.

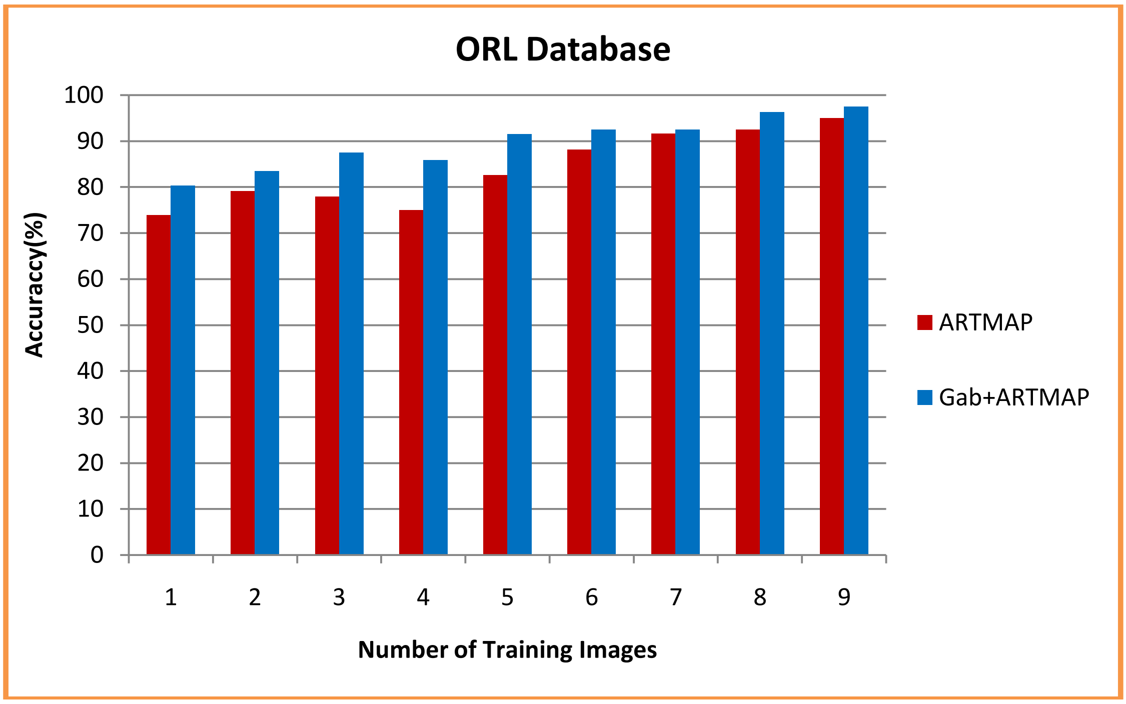

Figure 5.1: Accuracy (%) s for ORL Face Database

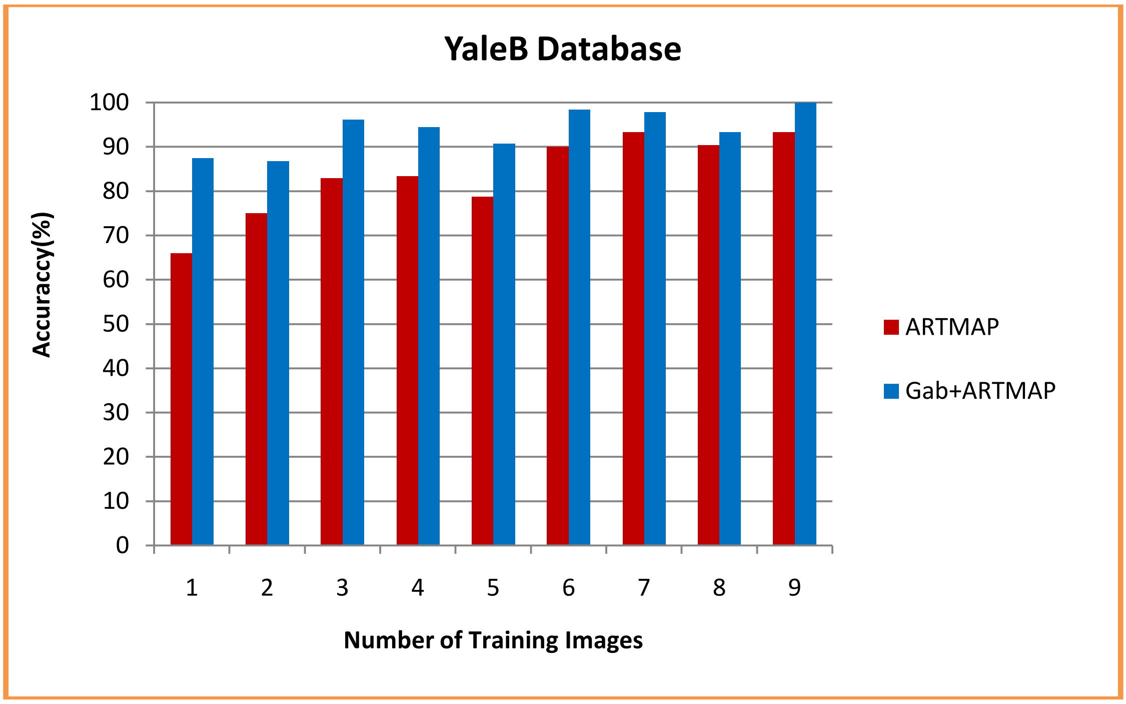

Figure 5.2: Accuracy (%) for YaleB Face Database

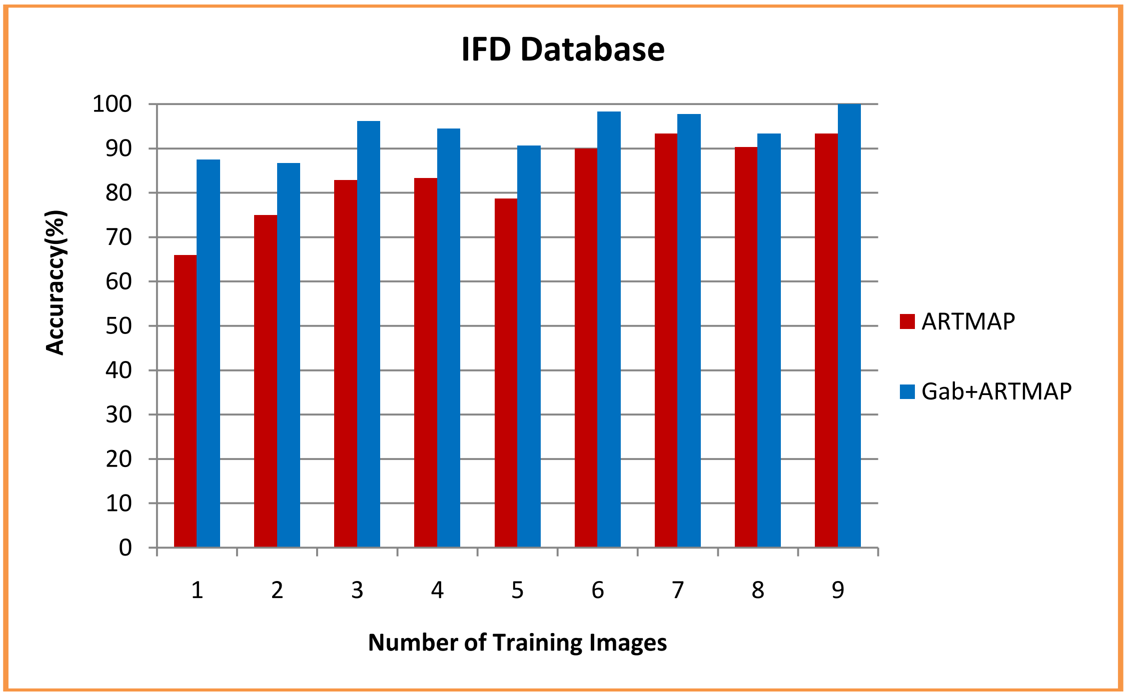

Figure 5.3: Accuracy (%) for IFD Face Database

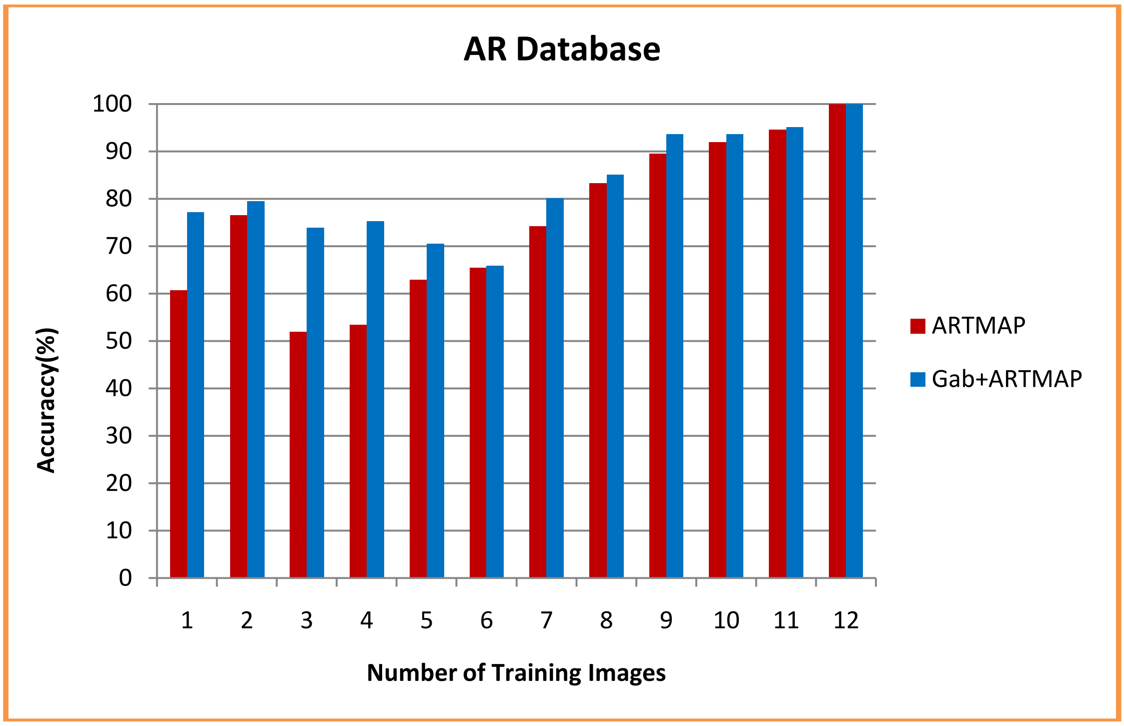

Figure 5.4: Accuracy (%) for AR Face Database

VI. CONCLUSION:

The performance of the ARTMAP algorithm is tested for four different databases with different types of variations viz. Expressions, illumination, pose and occlusion. The result of the proposed technique has better overall recognition rates. For ORL face database (fig.5.1) at lower number of training images (3 & 4 training images) improvement in accuracy is around 9 to 10% using Gabor features as compared to only ARTMAP. For YaleB face database (fig.5.2) at lower number of training images (2 to 6 training images) improvement in accuracy is between 12% to 21% using Gabor features as compared to ARTMAP alone. For IFD face database (fig.5.3) at lower number of training images (1 and 2 training images) improvement in accuracy is around 10% to 11%. For AR face database (fig.5.4) with partially occluded face images the maximum improvement in accuracy is around 21% at lower number of training images (3 and 4 training images). The proposed method is thus capable to handle different variations in face images such as expressions, pose, illumination and occlusion.

REFERENCES:

[1]. G. A. Carpenter, S. Grossberg and John H. Reynolds, "ARTMAP: Supervised Real-Time Learning and Classification of Nonstationary Data by a Self-Organizing Neural Network", Pergamon Press Neural Networks, vol. 4, pp. 565 - 588, 1991.
[2]. C. Ren, D. Dai, X. Li, and Zhao-Rong Lai, "Band-Reweighed Gabor Kernel Embedding for Face Image Representation and Recognition", IEEE Transactions on Image Processing, vol. 23, no. 2, 2014.
[3]. J. K. Kamarainen, V. Kyrki, and H. Kalviainen, "Invariance Properties of Gabor Filter based Features - Overview and Applications," IEEE Transactions on Image Processing, vol. 15, no. 5, pp. 1088 - 1099, 2006.
[4]. C. Liu and Harry Wechsler, "Gabor Feature Based Classification using the Enhanced Fisher Linear Discriminant Model for Face Recognition", IEEE Transactions on Image Processing, vol. 11, no. 4, pp. 467 - 476, 2002.
[5]. T. Dash and Tanistha Nayak, "Offline Verification of Hand Written Signature using Adaptive Resonance Theory Net", International Journal of Signal Processing Systems, vol. 1, no. 1, 2013.
[6]. N. Lu , G. Zhang , J. Lu , "Concept drift detection via competence models", Artif. Intell. 209 (2014) pp. 11–28, 2014.
[7]. Ebin Deni Raj, L.D.Dhinesh Babu, " A fuzzy adaptive resonance theory inspired overlapping community detection method for online social networks", Knowledge-Based Systems 113 (2016), pp. 75–87,2016.
[8]. M. M. Kasar, D. Bhattacharyya and Tai-Hoon Kim, "Face Recognition using Neural Network: A Review", International Journal of Security and its Applications, vol. 10, no. 3, pp. 81-100, 2016.
[9]. N. C. Kavuri and Madhusree Kundu , "ART1 Network: Application in Wine Classification", International Journal of Chemical Engineering and Applications, Vol. 2 , No. 3 , June 2011.
[10]. V. Struc and Nikola Pavesic, "The Complete Gabor-Fisher Classifier for Robust Face Recognition", Hindawi Publishing Corporation EURASIP Journal on Advances in Signal Processing, DOI:10.1155/2010/847680, 2010.
[11]. V. Jain and A. Mukherjee, "The Indian Face Database", http://vis-www.cs.umass.edu/vidit/IndianFaceDatabase, 2002.
[12]. "The Database of Faces," AT&T Laboratories Cambridge, 2002. Available:http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html.
[13]. A. Georghiades, "Yale face database." Center for computational Vision and Control at Yale University, http://cvc.cs.yale.edu/cvc/projects/yalefaces/ yalefaces. Html, 2002.
[14]. A. M. Martinez, "The AR face database", CVC Technical Report,24, http://www2.ece.ohio-state.edu/~aleix/ARdatabase.html , 1998.