TRENDY REGULARIZED ROBUST CODING FOR FACE RECOGNITION

V. EZHILYA
1 HOD, Department Of ECE, VSA GROUP OF INSTITUTIONS, Salem, TamilNadu, INDIA
1 ezhilyavenkat@gmail.com

ABSTRACT
In present, automatic face recognition of people is a challenging problem which has received much attention during the recent years due to its many applications in different fields. Recently, sparse representation has been attracting a lot of attention due to its great success in image processing. In SRC, all training samples without disguise are used to compose an over-complete dictionary, and the testing sample with disguise is represented by the dictionary with a sparse coding coefficients plus an error. The coding residuals between the sample and each class of training samples are measured and the minimum of them is the identified class to which the sample belongs. It involve maximum likelihood estimation (MLE) process, which involves iteratively sparse representation based coding (ISRC), but it does not provide robust solution for face recognition and also require high computational cost. In this paper, we proposed an extensive experiments on representative face databases demonstrate that a novel Regularized Robust Coding (RRC) is much more effective and efficient methods in dealing with complicated variations such as face occlusion, corruption, lighting and expression changes, etc. with the help of maximum a posterior (MAP) principle which are using iteratively reweighted regularized robust coding (IR³C) algorithm.

Keywords: Face Recognition, ISRC, Maximum a posterior principle, Maximum likelihood estimation, Occlusions, Regularized Robust Coding, Sparse representation.

1. INTRODUCTION
In the last few decades, face recognition has attracted more and more attention in the field of computer vision and pattern recognition. As one of most successful applications in biometrics, face recognition can be applied in social robotics to fulfill the person identification task in a natural and non-contact way. A picture speaks more than words. In today’s world, images play an important role in real time operations. The field of image processing has grown vigorously in recent times. Digital image processing deals with manipulation and analysis of images by using computer algorithm, so as to improve pictorial information for better understanding and clarity. This area is characterized by the need for extensive experimental work to establish the viability of proposed solutions. Image processing involves the manipulation of images to extract information to emphasize or de-emphasize certain aspects of the information, contained in the image or perform image analysis to extract hidden information.

Recent advances in Precision Farming have resulted in significant improvements in agriculture by increasing crop production, with good quality and low operating cost. In this context, image processing is used for a number of application areas that include soil testing, good quality seed selection, identification of nutrient deficiencies, monitoring and controlling of stress, weeds and diseases, assessment of crop status and yield. In practice, face patterns are subject to changes in illumination, pose, facial expression, etc. Among them, face recognition with the real disguise is a very important and hard problem to be solved. Therefore, robust vision-based face recognition has been extensively studied by researchers from the area of computer vision, robotics, artificial intelligence, etc. Generally, face image is stretched into a high dimensional face vector, then feature extraction and dimensionality reduction algorithms can be applied in the face space, so that the high-dimensional face vector is transformed into a low-dimensional subspace. And in this face subspace classification and identification task can be implemented.

Recently, sparse representation is introduced from compressive sensing theory into the field of pattern recognition; the sparse representation-based classification (SRC) is a landmark algorithm for robust face recognition, which can deal with face occlusion, corruption and real disguise. The basic idea of SRC is to represent the query face image using a small number of atoms parsimoniously chosen out of an over-complete dictionary which consists of all training samples. The sparsity constraint of the coding coefficients is employed to insure that only a few samples from the same class of the query face have distinct nonzero values, whereas the coefficients of other samples are equal or close to zero. The sparsity of the coding coefficient can be directly measured by \( l_0 \)-norm, which counts the number of nonzero entries in a vector. However, the \( l_0 \)-norm minimization is an NP-hard problem; therefore the \( l_1 \)-norm minimization is widely employed instead of the above problem. It has been demonstrated that \( l_0 \)-norm and
1-

\[ ||\alpha|| \leq \sigma \] (3)

Where \( \sigma > 0 \) is a constant, \( y = [y_1; y_2; \ldots; y_n] \in \mathbb{R}^n \) is the signal to be coded, \( D = [d_1, d_2, \ldots, d_m] \in \mathbb{R}^{m \times n} \) is the dictionary with column vector \( d_i \) being its \( i \)-th atom, and \( \alpha \in \mathbb{R}^m \) is the vector of coding coefficients. In the problem of FR, the atom \( d_i \) can be simply set as the training face sample and hence the dictionary \( D \) can be the whole training dataset. If we have the prior that the coding residual \( \epsilon = y - D\alpha \) follows Gaussian distribution, the solution to Eq. (3) will be the MLE solution. If \( \epsilon \) follows Laplacian distribution, the \( l_1 \)-sparsity constrained MLE solution will be,

\[ \min_{\alpha} ||y - D\alpha||_2 \text{ s.t. } ||\alpha|| \leq \sigma \] (4)

The above Eq. (4) is essentially another expression of Eq. (2) because they have the same Lagrangian formulation: \( \min_{\alpha} [||y - D\alpha||_2 + \lambda||\alpha||_1] \). In practice, however, the Gaussian or Laplacian priors on \( \epsilon \) may be invalid, especially when the face image \( y \) is occluded, corrupted, etc. Inspired by the robust regression theory, in our previous work we proposed an MLE solution for robust face image representation. Rewrite \( D \) as \( D = [r_1; r_2; \ldots; r_n] \) where \( r_i \) is the \( i \)-th row of \( D \), and let \( \epsilon = y - D\alpha = [e_1; e_2; \ldots; e_n] \), where \( e_i = y_i - r_i^T\alpha \), \( i = 1, 2, \ldots, n \). Assume that \( e_1, e_2, \ldots, e_n \) are independent and identically distributed and the PDF of \( e_i \) is \( f_\epsilon(e_i) \), where 0 denotes the unknown parameter set that characterizes the distribution, the so-called RSC was formulated as the following \( l_1 \)-sparsity constrained MLE problem \( \{ \text{let } \phi(e) = -\ln f_\epsilon(e) \} \)

\[ \min_{\alpha} \sum_{i=1}^{n} p_0(y_i - r_i^T\alpha) \text{ s.t. } ||\alpha|| \leq \sigma \] (5)
Like SRC, the above RSC model assumes that the coding coefficients are sparse and uses $l_1$-norm to characterize the sparsity. However, the $l_1$-sparsity constraint makes the complexity of RSC high, and recently it has been indicated that the $l_1$-sparsity constraint on $\alpha$ is not the key for the success of SRC. In this project, we propose a more general model, namely RRC. The RRC can be much more efficient than RSC, while RSC is one specific instantiation of the RRC model. Let’s consider the face representation problem from a view-point of Bayesian estimation, more specifically, the MAP estimation. By coding the query image $y$ over a given $s$ dictionary $D$, the MAP estimation of the coding vector $\alpha$ is $\hat{\alpha} = \arg \max _{\alpha} p(y|\alpha)$. Using the Bayesian formula, we have

$$\hat{\alpha} = \arg \max _{\alpha} \{ \ln p(y|\alpha) + \ln p(\alpha) \}$$

(6)

Assuming that the elements $e_i$ of coding residual $r = y - Da = [e_1; e_2; \ldots; e_m]$ are i.i.d. with PDF $f_0(e)$, we have $p(y|\alpha) = \prod_{i=1}^{m} f_0(y_i - r_i, \alpha)$. Meanwhile, assume that the elements $a_{i,j} = 1, 2, \ldots, m$, of the coding vector $\alpha = [\alpha_1, \alpha_2, \ldots, \alpha_m]$ are i.i.d. with PDF $f_\alpha(a)$. There is $p(\alpha) = \prod_{i=1}^{m} f_\alpha(a_i)$. The MAP estimation of $\alpha$ in Eq.(6) is

$$\hat{\alpha} = \arg \min _{\alpha} \{ \sum_{i=1}^{m} p_0(y_i - r_i, \alpha) + \sum_{i=1}^{m} \rho_\alpha (a_i) \}$$

(7)

Letting $\rho_\alpha(e) = -\ln f_\alpha(e)$ and $\rho_\alpha(\alpha) = -\ln f_\alpha(\alpha)$, Eq.(7) is converted into

$$\hat{\alpha} = \arg \min _{\alpha} \{ \sum_{i=1}^{m} p_0(y_i - r_i, \alpha) + \sum_{i=1}^{m} \rho_\alpha (a_i) \}$$

(8)

We call the above model RRC because the fidelity term $\sum_{i=1}^{m} \rho_\alpha (a_i)$ will be very robust to outliers, while $\sum_{i=1}^{m} p_0(y_i - r_i, \alpha)$ is the regularization term depending on the prior probability $p(\alpha)$.

It can be seen that $\sum_{i=1}^{m} \rho_\alpha (a_i)$ becomes the $l_1$-norm sparse constraint when $a_i$ is Laplacian distributed, $p(\alpha) = \prod_{i=1}^{m} \exp (-|\alpha_i|/\sigma_\alpha)/2\pi \sigma_\alpha$. For the problem of classification, it is desired that only the representation coefficients associated with the dictionary atoms from the target class could have big absolute values. As we do not know beforehand which class the query image belongs to, a reasonable prior can be that only a small percent of representation coefficients have significant values. Therefore, we assume that the representation coefficient $\alpha_j$ follows GGD. There is

$$f_\alpha (\alpha_j) = \beta \exp \{-|\alpha_j|/\sigma_\alpha \alpha_j\}/(2\pi \sigma_\alpha \Gamma(1/\beta))$$

(9)

Where $\Gamma$ denotes the gamma function.

For the representation residual, it is difficult to predefine the distribution due to the diversity of image variations. In general, we assume that the unknown PDF $f_\theta(e)$ are symmetric, differentiable, and monotonic w.r.t $|e|$, respectively. So $\rho_\theta(e)$ has the following properties: (1) $\rho_\theta(0)$ is the global minimal of $\rho_\theta(e)$; (2) symmetry: $\rho_\theta(x) = \rho_\theta(-x)$; and (3) monotonicity: $\rho_\theta(x_1) > \rho_\theta(x_2)$ if $|x_1| > |x_2|$. Without loss of generality, we let $\rho_\theta(0) = 0$.

The proposed RRC model in Eq.(8) has close relations to robust estimation, which also aims to eliminate the effect of outliers. The robust estimation methods, e.g., Regression Diagnostics, $M$-estimator and Least Median of squares are widely used in parameter estimation and has various applications in computer vision, such as tracking, robust subspace learning and so on.

However, there are clear differences between the previous robust estimation methods and the proposed RRC. Most of previous robust estimation methods regard the whole pieces of samples but not the elements of a sample as inliers or outliers. Although the robust subspace learning method weights each pixel by the judgment of inlier or outlier, it aims to learn robust principle components but not to solve the regularized coding coefficients of a testing sample with outliers. Besides, the proposed RRC model is developed in order for classification tasks but not regression.

Two key issues in solving the RRC model are how to determine the distribution $p_0(\alpha)$ and $f_\theta(e)$, and how to minimize the energy functional. Simply tasking $f_\theta$ as Gaussian or Laplacian and taking $f_\theta$ as Laplacian, the RRC model will degenerate to the conventional sparse coding problem in Eq.(3) or Eq.(4). However, such preset distributions for $f_\theta$ have much bias and are not robust enough to outliers, and the Laplacian setting of $f_\theta$ makes the minimization inefficient. In this paper, we allow $f_\theta$ to have a more flexible shape, which is adaptive to the input query image $y$ so that the system is more robust to outliers. To this end, we transform the minimization of Eq.(8) into an iteratively reweighted regularized coding problem in order to obtain the approximated MAP solution of RRC effectively and efficiently.

2.2 RRC via Iteratively Reweighting

Let $F_\theta(e) = \sum_{i=1}^{m} \rho_\theta(e_i)$. The Taylor expansion of $F_\theta(e)$ in the neighborhood of $e_0$ is

$$\hat{F}_\theta(e) = F_\theta(e_0) + (e-e_0)^T F_\theta(e_0) + R_1(e)$$

(10)
When \( R(e) \) is the high order residual, and \( F_y(e) \) is the derivative of \( F_d(e) \). Denote by \( \rho_0 \) the derivative of \( \rho_0 \), and there is \( F_d(e_0) = [\rho_0(e_{0,1}); \rho_0(e_{0,2}); \ldots; \rho_0(e_{0,n})] \), where \( e_{0,i} \) is the \( i \)-th element of \( e_0 \). To make \( F_d(e) \) strictly convex for easier minimization, we approximate the residual term as \( R(e) = 0.5(c - e_0)^T W (c - e_0) \), where \( W \) is a diagonal matrix for that the elements in \( e \) are independent and there is no cross term of \( e \) and \( c \), for \( F_d(e) \).

Since \( F_d(e) \) reaches its minimal value (i.e., 0) at \( e = 0 \), we also require that its approximation \( \hat{F}_d(e) \) reaches the minimum at \( e = 0 \). Letting \( \hat{F}_d(0) = 0 \), we have the diagonal elements of \( W \) as:

\[
W_{ii} = \rho_0(e_{0,i})/\rho_0(e_{0,0}) \tag{11}
\]

According to the properties of \( \rho_0 \) we know that \( \rho_0(e_{0,i}) \) will have the same sign as \( e_{0,i} \). So \( W_{ii} \) is a non-negative scalar. Then \( F_d(e) \) can be written as:

\[
\hat{F}_d(e) = \frac{1}{2} \|W^{1/2} y - D \alpha\|^2 + b_0 \tag{12}
\]

Where \( b_0 = \sum_{i=1}^{n} 1/2 [\rho_0(e_{0,1})^2 \rho_0(e_{0,2})^2 \ldots] \) is a scalar constant determined by \( e_{0,i} \). Without considering the constant \( b_0 \), the RRC model in Eq.(8) could be approximate as:

\[
\hat{\alpha} = \arg \min_{a} \left\{ \frac{1}{2} \|W^{1/2} (y - Da)\|^2 + \sum_{i=1}^{n} \rho_0(a_i) \right\} \tag{13}
\]

Certainly, Eq.(13) is a local approximation of Eq.(8) but it makes the minimization of RRC feasible via iteratively reweighted \( l_2 \)-regularized coding, in which \( W \) is updated via Eq.(11). Now, the minimization of RRC is turned to how to calculate the diagonal weight matrix \( W \).

2.3 Weights \( W_{ii} \)

The element \( W_{ii} \), i.e., \( \rho_0(e_{ii}) \), is the weight assigned to pixel \( i \) of query image \( y \). Intuitively, in FR the outlier pixels should have small weights to reduce their effect on coding \( y \) over \( D \). Since the dictionary \( D \), composed of non-occluded/non-corrupted training face images, could well represent the facial parts, the outlier pixels will have rather big coding residuals. Thus, the pixel which has a big residual \( e_i \) should have a small weight. Such a principle can be observed from Eq.(11), where \( \omega_0(e_i) \) is inversely proportional to \( e_i \) and modulated by \( \rho_0(e_i) \).

Refer to Eq.(11), since \( \rho_0(e_i) \) is differentiable, symmetric, monotonic and has its minimum at origin, we can assume that \( \rho_0(e_i) \) is continuous and symmetric, while being inversely proportional to \( e_i \) but bounded. Without loss of generality, we let \( \rho_0(e_i) \approx [0, 1] \). With these considerations, one good choice of \( \rho_0(e_i) \) is the widely used logistic function

\[
\omega_0(e_i) = \exp(-\mu e_i^2 + \mu \delta) / (1 + \exp(-\mu e_i^2 + \mu \delta)) \tag{14}
\]

Where \( \mu \) and \( \delta \) are positive scalars. Parameter \( \mu \) controls the decreasing rate from 1 to 0, and \( \delta \) controls the location of demarcation point. Here the value of \( \mu \delta \) should be big enough to make \( \rho_0(0) \) close to 1. With Eq.(14), Eq.(11), and \( \rho_0 = 0 \), we could get

\[
\rho_0(e_i) = -2\mu (\ln(1 + \exp(-\mu e_i^2 + \mu \delta)) - \ln(1 + \exp(\mu \delta))) \tag{15}
\]

The PDF \( f_\alpha \) associated with \( \rho_0 \) in Eq.(15) is more flexible than the Gaussian and Laplacian functions to model the residual \( e \). It can have a longer tail to address the residuals yielded by outlier pixels such as corruptions and occlusions, and hence the coding vector \( \alpha \) will be robust to the outliers in \( y \). \( \omega_0(e_i) \) could also be set as other functions. However, as indicated by the proposed logistic weight function, the binary classifier derived via MAP estimation, which is suitable to distinguish inliers and outliers.

When \( \omega_0(e_i) \) is set as a constant such as \( \omega_0(e_i)=2 \), it corresponds to the \( l_2 \)-norm fidelity in Eq.(3); when set as \( \omega_0(e_i)=1/|e_i| \), it corresponds to the 11-norm fidelity in Eq.(4); when set as a Gaussian function \( \omega_0(e_i)=\exp(-e_i^2/2\sigma^2) \), it corresponds to the Gaussian kernel fidelity in FR. However, all these functions are not as robust as Eq.(14) to outliers, one can see that the \( l_2 \)-norm fidelity treats all pixels assigns higher weights to pixels with smaller residuals; however, the weight can be infinity when the residual approaches to zero, making the coding unstable.

Both our proposed weight function and the weight function of the Gaussian fidelity used in FR are bounded in \([0, 1]\), and they have an intersection point with weight value as 0.5. However, the proposed weight function prefers to assign larger weights to inliers and smaller weights to outliers; that is, it has higher capability to classify inliers and outliers.

There are also some candidates which could be adopted as the weight function of RRC. Like the Gaussian weight functions, these weight functions in M-estimation could also assign high weights to inliers and low weights to outliers. Nevertheless, the proposed RRC model is a general model which could utilize various weight functions, and in this paper we adopt the logistic weight function due to its advantage analyzed above.

The model in Eq.(4) is the case by letting \( \omega_0(e_i)=1/|e_i| \). Compared with the models in Eqs.(3) and (4), the proposed RRC model [Eq.(8) or Eq.(13)] is much more robust to outliers because it will adaptively assign small weights to them. Although the model in Eq.(4) also assigns small weights to outliers, its weight function \( \omega_0(e_i)=1/|e_i| \) is not bounded, making it less effective to distinguish between inliers and outliers.
2.4 Two Important Cases of RRC

The minimization of RRC model in Eq.(13) can be accomplished iteratively, while in each iteration W and α are updated alternatively. By fixing the weight matrix W, the RRC with CGD prior on representation and ρo(αj)=−ln(α) could be written as

\[ \hat{\alpha} = \arg \min_{\alpha} \left\{ \frac{1}{2} \| W^{1/2} (y - D\alpha) \|^2 + \sum_{j=1}^{n} (\lambda |\alpha_j|^2 + b_{\alpha_j}) \right\}\]

where \( \rho_o(\alpha_j) = \lambda |\alpha_j|^2 + b_{\alpha_j} \). When \( \beta = 1 \), CGD degenerates to the Laplacian distribution, and the RRC model becomes

\[ \min_{\alpha} \left\{ \frac{1}{2} \| W^{1/2} (y - D\alpha) \|^2 + \sum_{j=1}^{n} (\lambda |\alpha_j|^2 + b_{\alpha_j}) \right\}\]

where \( V \) is a diagonal matrix with \( V_{jj} = \frac{1}{\alpha_j^2} \). The value of \( \beta \) determines the types of regularization. If \( 0 < \beta \leq 1 \), then sparse regularization is applied; otherwise, non-sparse regularization is imposed on the representation coefficients. In particular, the proposed RRC model has two important cases with two specific values of \( \beta \).

When \( \beta = 2 \), GGD degenerates to the Gaussian distribution, and the RRC model becomes

\[ \min_{\alpha} \left\{ \frac{1}{2} \| W^{1/2} (y - D\alpha) \|^2 + \sum_{j=1}^{n} (\lambda |\alpha_j|^2 + b_{\alpha_j}) \right\}\]

In this case the RRC model is essentially an l2-regularized robust coding model. It can be easily derived that when W is given, the solution to Eq.(18) is

\[ \hat{\alpha} = (D^T WD + \lambda I)^{-1} D^T Wy. \]

When \( \beta = 1 \), CGD degenerates to the Laplacian distribution, and the RRC model becomes

\[ \min_{\alpha} \left\{ \frac{1}{2} \| W^{1/2} (y - D\alpha) \|^2 + \sum_{j=1}^{n} (\lambda |\alpha_j|^2 + b_{\alpha_j}) \right\}\]

3. IR3C ALGORITHM

3.1 INPUT:
Normalized query image y with unit l2-norm; dictionary D; \( \alpha^{(1)} \)

3.2 OUTPUT: \( \alpha \)

Start from \( t = 1 \):

1. Compute residual
   \( e^{(0)} = y - D\alpha^{(0)} \)
2. Estimation weight as
   \( \omega_j(e^{(0)}) = 1/1 + \exp(\mu e^{(0)2}) - \mu \delta \) Where \( \mu \) and \( \delta \) could be estimated in each iteration.
3. Weighted regularized robust coding:
   \[ \hat{\alpha} = \arg \min_{\alpha} \left\{ \frac{1}{2} \| W^{1/2} (y - D\alpha) \|^2 + \sum_{j=1}^{n} \rho_o(\alpha_j) \right\}\]
   where \( W^{1/2} \) is the estimated diagonal weight matrix with \( W^{1/2}_{jj} = \omega_j(e^{(t)}) \).
   \( \rho_o(\alpha_j) = \lambda |\alpha_j|^2 + b_{\alpha_j} \) and \( \beta = 2 \) or 1.
4. Update the sparse coding coefficients:
   If \( t = 1 \), \( \alpha^{(0)} = \alpha^{*} \);
   If \( t > 1 \), \( \alpha^{(t)} = \alpha^{(t-1)} - t \gamma \alpha^{(t-1)} \)
   where \( \gamma \) and \( t \) are chosen to be close to 1.
   \( \omega_j(e^{(t)}) \) can be searched from 1 to 0 by the standard line-search process.
5. Compute the reconstructed test sample: \( y_{rec}^{(t)} = \alpha^{(t)} \).
6. Go back to step 1 until the condition of convergence is met, or the maximal number of iterations is reached.

In this case the RRC model is essentially the RSC model in FR, where the sparse coding methods such as l1, l2, is used to solve Eq.(19) when W is given. In this project, we solve Eq.(19) via Eq.(17) by the iteratively re-weighting technique.

4. EXPERIMENTAL RESULTS

4.1 Pass the input image

Collect all the necessary images for the project and save it in the database.

Use entropyfilt to create a texture image. The function entropyfilt returns an array where each output pixel contains the entropy value of the 9-by-9 neighbourhood around the corresponding pixel in the input image I. Entropy is a statistical measure of randomness.

Threshold the rescaled image Eim to segment the textures. A threshold value of 0.8 is selected because it is roughly the intensity value of pixels along the boundary between the textures.
4.2 Segment the image based on region

Fig 4.1 Pass input image and feature extraction

Fig 4.2 Segmentation of input image
4.3 Find the intensity distribution

Fig.4.3 (a) Gradient Magnitude (Gradmag) (b) Watershed transform Of Gradient Magnitude (Lrgb)
Your first step is to maximize the intensity contrast in the image. You can do this using ADAPTHISTEQ, which performs contrast-limited adaptive histogram equalization. Rescale the image intensity using IMADJUST so that it fills the data type’s entire dynamic range.

4.4 Segment the image based on region(with and without intensity)

Granulometry estimates the intensity surface area distribution of snowflakes as a function of size. Granulometry likens image objects to stones whose sizes can be determined by sifting them through screens of increasing size and collecting what remains after each pass. Image objects are sifted by opening the image with a structuring element of increasing size and counting the remaining intensity surface area (summation of pixel values in the image) after each opening. Choose a counter limit so that the intensity surface area goes to zero as you increase the size of your structuring element. For display purposes, leave the first entry in the surface area array empty.

4.5 Comparison of Gaussian noise, speckle noise, and salt and pepper noise
Median filtering is a common image enhancement technique for removing salt and pepper noise. Because this filtering is less sensitive than linear techniques to extreme changes in pixel values, it can remove salt and pepper
noise without significantly reducing the sharpness of an image. In this topic, you use the Median Filter block to remove salt and pepper noise from an intensity image.

5. CONCLUSION
We have proposed a more general model for segmenting images with/without intensity inhomogeneities and with different types of noise. Our proposed level set energy function, which is dominated by the global Gaussian distribution and constrained by local neighbor properties, can overcome the artifacts from both the intensity inhomogeneity and image noise. A quantitative comparison on synthetic images and experimental results on real images showed that our model outperformed the LBF and LSII models designed specifically for segmenting the images with intensity in homogeneities. It was more robust and accurate than the CV model when segmenting the images without intensity in homogeneities.

6. REFERENCES

7. BIOGRAPHIES
V. Ezhilya received B.E degree in Electronics and Communication Engineering from Anna University, Chennai in 2010 and M.E in Power Electronics and Drives from Vinayaga Missions University. She is currently working as Head of the Department of Electronics and Communication Engineering in VSA Group of Institutions, affiliated to Anna University. Her major field of interest is Power Electronics, Digital Signal Processing, and Image Processing. She was also a recipient of the distinguished graduate student award from Vinayaga Missions University.