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Original Article

Adaptive Learning of Radial Basis Function Neural Networks Based on Traffic Sign Recognition using Principal Component Analysis

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Abstract - *Using the PCA and RBF neural networks developed in this study, it was possible to develop a practical method for recognising traffic signs. PCA has been used in traffic sign recognition algorithms for several years. It is among an autonomous driving system's most prevalent image representation techniques. The picture is not only reduced in dimensionality, but some of the fluctuations in the digital image and the image data are retained. It is true that when PCA was completed, the RBF neural netts' hidden node neurones were modelled using the training images' intra-class discrimination qualities in the hidden layer neurone. RBF neural networks benefit from this because it allows them to acquire a wide range of changes observed in the low-dimensional feature space, increasing their generalisation capabilities. The suggested approach is tested on different template traffic signs, with positive results. Results from the experiments demonstrate that the suggested technique has a promising recognition performance.*

Keywords - *PCA, RBF, Traffic sign recognition, Adaptive learning, Neural network.*

1. Introduction

Pattern recognition and computer vision researchers have long been interested in the recognition system [1]–[5], and they still are. It may be used for various purposes, including monitoring, issuing credit cards and passports, and providing security. Several methods have been proposed in the last few decades [6-12]. Traffic signs with less resolution and a significant computation time are used for traffic sign identification, which is a highly challenging task in artificial intelligence. Reduced picture data size reduces classification and recognition time. PCA [1] is a widely used approach for extracting features and data representation. As a result, not only does the image's dimensionality decrease, but it also keeps any variations within the image data set, resulting in an efficient description of a facial image. The PCA approach reduces many traffic images to a few eigenvectors, the significant elements of a basic set of traffic images.

The principal component analysis (PCA) approach was created in 1991 [1]. In linear discriminant analysis, the PCA technique is mainly used for dimension reduction (LDA), generating a novel Fisherface paradigm. Traffic sign recognition methods are more affected by variations in lighting, luminance, other environmental factors, and facial expressions than other approaches. This strategy, on the other hand, is more computationally costly than the PCA technique.

Traffic sign recognition utilizing PCA and RBF neural networks is discussed in this research, and we offer a new method for achieving this goal. It was decided to employ RBF neural networks because of their simple system and capacity to learn more quickly [8] and [9]. The principal component analysis (PCA) technique extracts traffic sign characteristics from the input space, reducing the input vector space's dimensionality. It was discovered that there are significant differences across photographs of the same object due to differences in stance, orientation, and other factors.

The structural information of traffic photos taken by the same individual should be considered throughout the classification process to get a high recognition rate. This has been accomplished through a clustering algorithm to discover sub-clusters that belong to each subject. The prototype of these sub-clusters will then be used to represent the RBF neural network's hidden node neurons, which are then utilized to represent the RBF neural network's hidden node neurons. Additionally, this method improves the system's generalization capabilities.

2. Related Work

Traffic sign recognition is a swiftly advancing research field that has attracted considerable attention from academia and business. Principal component analysis (PCA) and radial basis function neural networks (RBF) are well-known traffic recognition techniques. This literature review will discuss some traffic sign recognition studies that have employed PCA and RBF neural networks. The article "Eigenface for Recognition" was written by Matthew Turk and Alex Pentland [1]. This research presented the Eigenfaces approach, which first extracts the principle components of faces through principal component analysis (PCA) and then utilizes a neural network to classify the faces.

The Eigenfaces technique has gained widespread popularity and is the foundation for many other face recognition systems. The article "Face Recognition Using Kernel-Based PCA and SVM" was written by Li and Zhang. A kernel-based PCA method that is capable of handling nonlinear data was suggested in this study, and it was integrated using a support vector machine (SVM) for classification.

On several different face recognition datasets, the suggested technique obtained good accuracy. Written by Du et al., "Face Recognition Using RBF Neural Networks", The authors of this research proposed a facial recognition method based on RBF neural networks. The proposed method used an altered RBF network with a dynamic structure, and it obtained a high level of accuracy when applied to many face recognition datasets.[10, 11]

In research conducted by Lee et al., titled "Face Recognition Using Deep Learning-Based PCA and RBF Neural Networks" In this paper, the authors suggest a PCA approach that is based on deep learning and makes use of Convolutional Neural Networks (CNN) first to extract features before they apply PCA to achieve dimensionality reduction. After that, the reduced characteristics are input into the RBF neural network to be classified. On multiple face recognition datasets, the suggested technique attained accuracy that is considered to be state-of-the-art [12-14].

In this study, "Face Recognition Using Sparse Representation and RBF Neural Networks", the authors proposed a technique to face recognition that is based on sparse representations and makes use of RBF neural network models for categorization. The suggested method was demonstrated to be resilient to different lighting conditions, facial expressions, and occlusions, and it was able to attain a high level of accuracy on numerous face recognition datasets. PCA and RBF have been applied for most face recognition applications. However, minimal work has been done for traffic sign recognition applications. In this paper, PCA and RBF have been applied for traffic sign recognition. [15, 16]

3. Feature Extraction by Method of PCA

The method of PCA is used for extracting the features of a traffic sign from an image. Consider the following scenario: traffic photos T are among the set of learning, and for every image, Ai is a 2-dimensional array of intensity values with a size of m x n. In the case of a picture Ai, it is possible to convert it into a vector of Dim (Dim=mxn) pixels, where Ai = (ai(1), ai(2),..., ai(Dim)) pixels. A vector is formed by arranging the pixels in a row of an image in a straight line, one after another. The learning set of images T is defined as A = (A(1), A(2),..., A(T)), where A is the total number of images in the learning set. The covariance matrix is provided below:

$$\Gamma = (\tfrac{1}{T}) + \sum_{i=1}^{T}(A_i + \mathrm{A}')\,(A_i - A')T = \varphi + \varphi T) \qquad (1)$$

$\varphi = (\varphi_1, \varphi_2, \ldots \varphi_R)$ is a subset of R and $A' = 1/R\sum_{i=1}^{R}(Ai)$ corresponds to the average image of a training data set. The covariance matrix has a dimension of M x N, which stands for dimension by dimension. Both eigenvectors and eigenvalues of the covariance matrix are then determined from this matrix. Let $Q = (Q_1, Q_2, \ldots, Q_r)$ are eigenvectors that match the most significant eigenvalues of the largest eigenvalues. Every basis vector r is referred to as an Eigenvectors in this context. As a result, each of the pictures of traffic signs from the trained examples Ai is projected into the Eigen space in order to generate its corresponding Eigenvectors-based features Yi, which would be given as follows:

$$Yi = Q^T * Vi \quad \text{i=1,2,… R……} \qquad (2)$$

When the image of Vi is subtracted, Yi is the mean. The test images are translated into Eigenvectors and used in equation (2) to be recognized by the RBF neural networks. The inputs for classification are then supplied back into the RBF neural networks.

4. Methodologies for Designing RBF Neural Networks, as well as the Training Technique for these Networks

We utilized RBF neural networks to classify the traffic sign images because of their basic structure and ability to learn more quickly than different neural networks. The PCA approach, as mentioned in the preceding part, is used to extract features of images from all images [20].

The training technique for RBF neural networks has a significant effect on the performance of such networks. The training method for the RBF neural networks provided is detailed below.

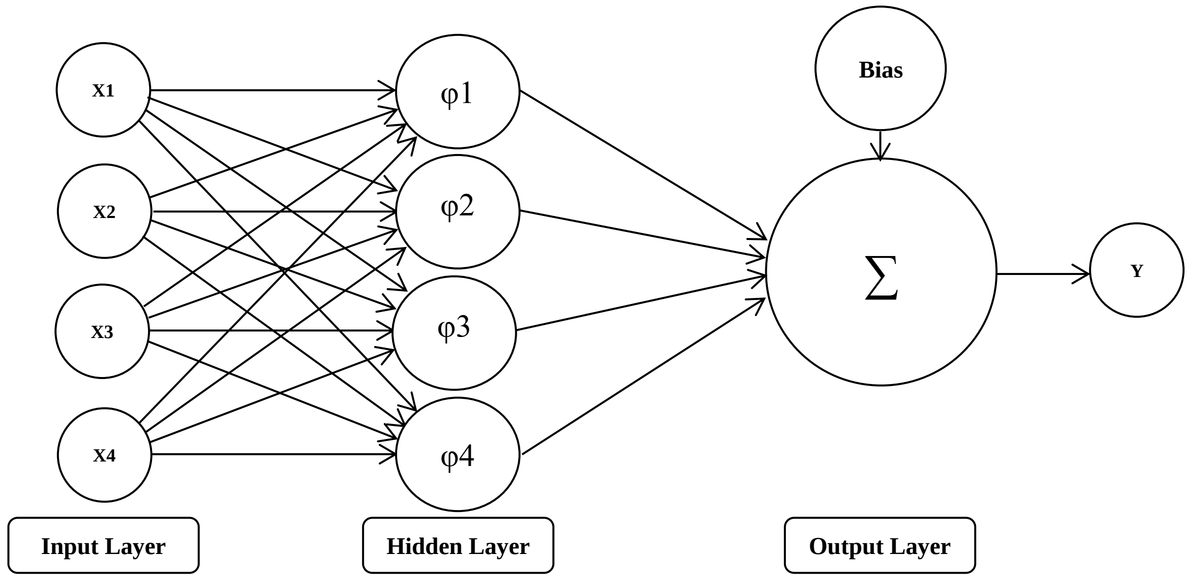

Fig. 1 RBF neural network structure with input, hidden and output layer

4.1. The RBF Neural Networks: Their Structure and Function

In the suggested method, classification is accomplished by a radial basis function neural network (RBF-NN), which has three layers. Figure 1 depicts the RBF structure with the output and hidden layers of neurons. When considered as a process, the purpose of an RBF-NN can be thought of as one that transfers an input pattern of dimensions' m from input data to a decision space of dimensions n. For this, the hidden layer uses a nonlinear function, while the output layer uses a linear function. Nonlinear functions, such as the Gaussian function, are commonly referred to as nonlinear functions, and they are defined as follows:

$$\Phi\text{q}(\text{Ap}) = \exp - \frac{||Ap - Xq||}{2\sigma\text{q\^{}2}}, \text{q} = 1,2,3 \ldots.\text{i: p} = 1,2,3 \ldots.\text{J} \quad (3)$$

In which X_q denotes the centre, and q denotes the width of the q th hidden neurons i & neuro J denote the overall number of neurons in the hidden layer and the overall number of patterns in the input. When the kth output neuron is activated, the signal will be produced by the corresponding linear function:

$$Ypk = \sum_{p=1}^{n} \emptyset q(\text{Ap})Wkp + SkWk; \quad k = 1,2,3 \ldots.i \quad (4)$$

In which wkp is said to be the link's weight connecting both hidden pth and qth layer neuron, Sk and wk are considered to be unit positive bias and weight of connecting link from the bias neuron to the kth layer of output, i is the number of actual classes in the problem at hand. The neuron is from the hidden layer neuron, respectively. The value of i, according to the findings of this study, is equal to the dataset's overall number of entities.

4.2. The Technique for Training RBF Neural Networks

The neural network of RBF is trained in two steps. The widths and centres of the Gaussians related to each of the neurons in the hidden layer are chosen in the first step. In the second step, hidden and output weights are estimated.

To achieve excellent generalization, the RBF-NN significantly relies on hidden-layer neuron selection. Because an RBF-NN gains information from all of these independently tuned neurons, which represent a subset of input space properties, Because the differences between traffic sign images, obtained by variable location, weather conditions, and other characteristics, are exceptionally high, it is fair to discover sub-clusters from each traffic sign's input images. This approach facilitates gathering structural data from the input images enclosed by the training sample with greater accuracy—the model of sub-clustered neurons using the RBF-hidden NN's layered neurons. To achieve the strategy above, clustering the training images related to every separate element. The process for clustering is described as follows:

1) Assume the train set comprises N images of traffic signs. We must identify K (K N) sub-clusters from the picture region spanning the training samples N.
2) At first, all of the training images are divided into N groups. Replace the value of k with N.
3) To calculate d(i, j), apply the following equation: The I and j clusters are represented by the letters Ci and Cj. The Euclidean norm is ||||.
4) Use the following formula to get the two closest clusters, Ci and Cj: Armin d(i, j) is the sum of the margins for each number 1, 2,..., N.
5) For example, you may divide the two closest ones by k-1 to come up with another cluster.

6) Keep repeating steps 3–5 until k equals K.
7) repeat steps 1–6 for each element as in training examples.

The breadth of the related Gaussian functions (basis functions) must be determined after the activation of hidden layer neurons. By overlapping sub-spaces, the layer neurons of RBF-hidden NNs gain knowledge about the feature space. The widths of two Gaussian functions determine how much they overlap. The output of the RBF neuron is insufficient for the inputs anticipated if there is insufficient overlap.

As a result, the RBF generalizability of NNs is dubious. However, if the overlap is excessive, further interactions with other classes will occur, and RBF neurons may generate a substantial amount of output in response to input from other classes. As a result, RBF-generalization NNs are also hampered. As a result, the breadth must be forecasted to minimise overlapping between classes and maximise the RBF-generalization of NN's capacity. We calculated the width as follows to meet the parameters above:

1) First, figure out how far apart the mean cluster is from the members of an individual class k cluster.
2) You may determine the width by multiplying dmax's width by kA's largest departure from the mean. This is done using the following formula for the covariance factor (0.5 1.0).
3) Calculate the distances between mean clusters to get the dmin nearest class distance.
4) Consider a k B min k B = xd (8) overlapping factor for class k, where (0.5 1.5) regulates overlapping across various classes.
5) At last, the following are the Gaussian functions widths of the kth class: max (,) = k max (,) = k max (,) = k (9). The values for and were intended to optimize RBFNN performance.

After several trial runs, we found =0.75 and =1.25 in our experiments. We use the LMS technique to estimate link weights between hidden and output layers. [17, 18].

5. Experimental Result

The proposed method's performance was examined on the traffic sign picture database. How many correct identifications did the method make in a single experiment? That is how you figure out the rate. Accordingly, Ravg is defined as the method's average recognition rate.

$$\text{Ravg} = \sum_{i=1}^{r} r^i \,/\, \text{s} \;.\text{rtot} \tag{5}$$

Wherein s is the number of tests. The number of correct recognitions in the ith run is, that is, the total number of road traffic sign photos tested in each run. As a result, Eavg (average error rate) can be calculated as 100-Ravg.

5.1. Experiment with the Database of Traffic Sign Images

The traffic sign picture database has 48 images in PNG format with dimensions of 360x270 pixels. The photos are divided into three classes, each corresponding to a distinct traffic sign template (pedestrian crossing, compulsory for bikes, intersection). Figure 2 shows examples of traffic images. The experiments were conducted using random database partitioning.

5.1.1. Randomly Partitioning the Database

Five random photos are necessary for the bike database to be used for training, while the remaining traffic signs are used as a test set in this experimental technique. This results in two sets of 48 traffic signs: one for training and one for testing the RBF-NN model. Table 1 shows the parameters of RBF consisting of mean position value, spreads value and output weights [19]. It is worth noting that the training and validation photos do not overlap. As a result, ten (q=10) specific training and testing sets were produced. Figure 3 shows the eigenvectors of one of the ten training datasets corresponding to the ten most significant eigenvalues.

In the clustering method described in the 3.2 sub-section, three sub-clusters are identified from five photos of a traffic sign in these trials. As a result, the RBF-NN employs neurons of the hidden layer. In ten experimental runs, the average recognition rate by altering the principal components (PCs) number is presented in Figure 5. When 1, 2, and 3 PCs are employed, the best recognition accuracy rate (94.05%) is reached.

Table 1. Parameters of RBF

Mean Position Value			Spreadness Value	Output Layer Weight
1.0627	26.4323	3.1423	14.1397	-0.3248
-10.0963	-12.3190	7.2116	17.7578	0.5903
8.1644	-6.1118	1.3461	22.3530	0.6543
1.4559	26.8237	2.8624	14.6489	0.6459
-7.1221	25.4415	-0.1310	16.8387	0.6536
-26.7551	6.3401	-2.2671	13.4484	-0.8416
-25.8298	8.0006	-3.0436	16.1968	0.8910
16.1369	1.4118	-4.7831	15.6293	0.3357
-27.0123	-7.9400	-0.0878	14.5207	0.5588
-25.9092	7.9703	-3.0269	15.4652	0.5671

Fig. 2 Sample traffic sign images from the traffic sign image database

Fig. 3 Eigenvectors from 1-10 training sets with the ten largest eigenvalues

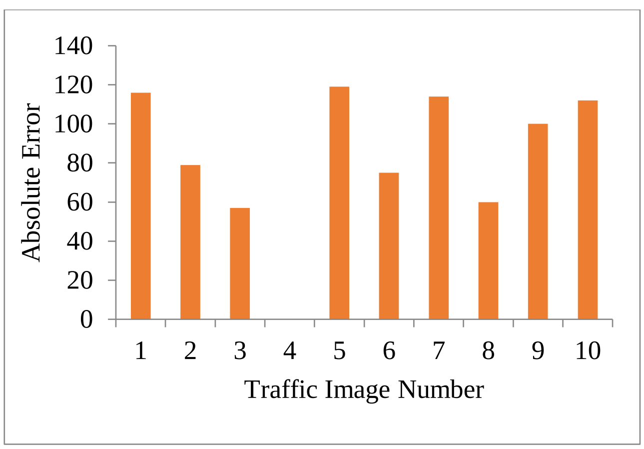

Fig. 4 Test traffic sign as image #4

We averaged the recognition rates from these experiments to determine how well this new method works. Notably, no training or test sets overlap in any given experimental run. When we tried the RBF-NN method in this experiment, three PCs were used, and we changed how many hidden layer neurons it had. A training set's eigenvectors are depicted in Figure 3.

According to Figure 6, as the number of iterations rises, the RBF-output NN's MSE converges. On the graph, the average of ten experimental tests is presented.

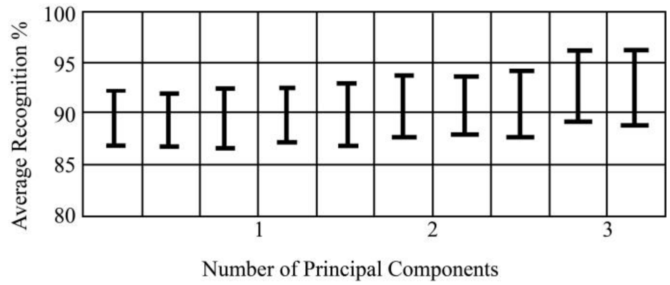

Fig. 5 Recognition rate vs principal components. The upper and lower extrema of the error bars represent the maximum and minimum values, respectively.

Figure 4 depicts the suggested technique's recognition of traffic sign image 4, with the absolute error being zero for traffic sign image 4.

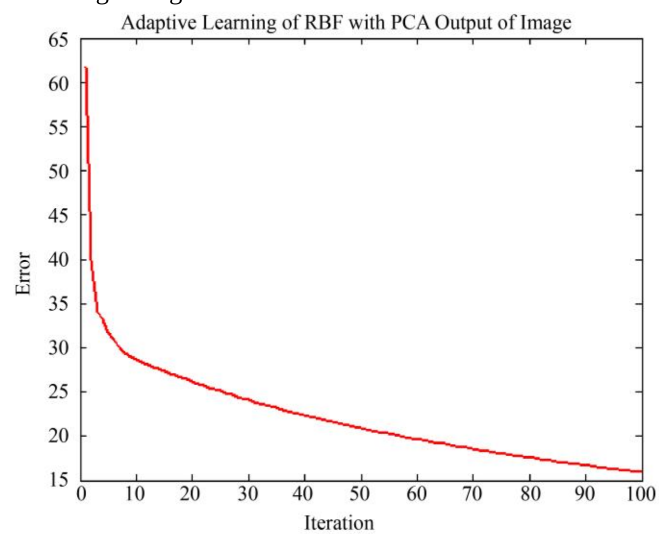

Fig. 6 Learning error in adaptive RBF for a traffic sign image

To get a successful average recognition accuracy of 94.10 per cent, we used the number of neurons in the hidden layer and three PCs. The minimum and maximum recognition rates over ten testing cycles are 95.90%. The recognition rate of our proposed method is improved compared to the PCA provided in [21].

6. Conclusion

This article uses PCA and RBF neural networks to recognize traffic signs. The PCA approach is used to extract features from the training images. This method decreases the dimension of the actual traffic sign images while still retaining certain discriminating elements from the training images. After completing the PCA, the structural information relating to each individual is obtained using lower-dimensional training images using principal component analysis. The RBF-NN hidden neurons are modelled using the structural information obtained from the RBF architecture. The proposed solution has been tested on the TSR image databases, and the results look promising. The effectiveness of the proposed method is presented.

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