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ORIGINAL ARTICLE

Facial emotion recognition system for autistic children: a feasible study based on FPGA implementation

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Abstract Children with autism spectrum disorder have difficulty in understanding the emotional and mental states from the facial expressions of the people they interact. The inability to understand other people's emotions will hinder their interpersonal communication. Though many facial emotion recognition algorithms have been proposed in the literature, they are mainly intended for processing by a personal computer, which limits their usability in on-the-move applications where portability is desired. The portability of the system will ensure ease of use and real-time emotion recognition and that will aid for immediate feedback while communicating with caretakers. Principal component analysis (PCA) has been identified as the least complex feature extraction algorithm to be implemented in hardware. In this paper, we present a detailed study of the implementation of serial and parallel implementation of PCA in order to identify the most feasible method for realization of a portable emotion detector for autistic children. The proposed emotion recognizer architectures are implemented on Virtex 7 XC7VX330T FFG1761-3 FPGA. We achieved 82.3 % detection accuracy for a word length of 8 bits.

Keywords Facial emotion recognition · Real-time and portability · FPGA implementation

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1 Introduction

Recognizing and responding to facial emotions is a key feature of interpersonal communication and a significant modulator of social behavior. In typical children, recognition of emotional facial expressions is an early developing social skill. Failure of these fundamental early emotion recognition skills would have profound consequences for a child's social development, cutting the child off from learning about other people's feelings and responses [19].

People, especially children, diagnosed with diseases such as autism, Alzheimer's disease and/or Parkinson's disease often lack or have impairments in some set of representation abilities such that they have difficulties operating in our highly complex social environment [5, 9]. Children suffering from pervasive developmental disorders (PDD), such as Asperger's disorder [9], concentrate more on component parts rather than the wholesome features [5]. As a result, they have difficulties in tasks such as envisioning another's state of mind in social behavior or imaging future states to plan a task [6]. Such difficulties in empathy underlie their social communication difficulties that form a core of the diagnosis. Emotion expression is an essential part of human interaction. Emotions are universal means of communication which can be expressed nonverbally without any language constraints. They are recognized through facial expressions, voice tones, speech and physiological signals. The speech signals provide the context for the expressed emotions but cannot be used as a universal indicator for recognizing them as they are dependent on the language content. The physiological signals such as blood pressure, body temperature and force feedback are relatively more accurate and universal indicators of emotions, but they require user-aware and intrusive methods for collecting the data.

Researchers have applied various techniques to develop the interaction between humans and computers through the use of facial emotion detection. Mainly two types of approaches to extracting facial features are reported: geometry-based methods and appearance-based methods. In geometric feature extraction system, the shape and location of various face components are considered, and they require accurate and reliable facial feature detection, which is difficult to achieve in real-time applications. In contrast, in the appearance-based methods, image filters are applied to extract the appearance change in the face image. Principal component analysis (PCA) [18], linear discriminant analysis (LDA) and Gabor wavelet analysis [11, 24] have been applied to either the whole-face or specific face regions to extract the facial appearance. Local binary patterns (LBP) have been successfully applied as a local feature extraction method in facial expression recognition [14].

In [8], for the recognition of human facial expressions, a scheme using the backpropagation neural algorithms is designed. This scheme is capable of recognizing six common facial expressions depicting happiness, sadness, fear, anger, surprise and disgust. A fuzzy relational approach to human emotion recognition from facial expressions and its control was proposed in [3]. This scheme segments and localizes the individual frames into regions of interest. Selected facial features such as eye opening, mouth opening and the length of eyebrow constriction are extracted from the localized regions, fuzzified and mapped onto an emotion space by employing Mamdani-type relational models. In [4], an intelligent robot was implemented, which achieved 92 % accuracy rate for emotion recognition. They used the PCA and the Haar wavelet transform for extracting facial features, while the nonlinear support vector machine (SVM) and Euclidean distance technique have been used for the classification of emotions. Another work [22] studied the importance of emotions on color information concerning facial expressions. The result of this assessment demonstrated that adding dynamic color to the facial expression synthesis is an effective way to express emotions in virtual facial images [22]. Researchers have tried to improve the performance by using the 3D geometric information for feature extraction [17]. They have used the 3D Gabor library to extract a 3D visual facial feature vector. The power of this technique is that it is based on the color and density information of the face with 3D geometric information; whereas the normal approach is based on either the 3D geometric information or the color and density information. Additionally, the improved kernel canonical correlation analysis (IKCCA) algorithm has been used for the classification of the human emotions in this research [17].

All the above-mentioned methods are used for extracting facial features from images or videos. Other techniques used in emotion detection as assistive technologies are based on interactive voice response (IVR) [21], by brain activity using electroencephalograph (EEG) [2, 10] signals and also by monitoring various other physiological signals [7, 12]. In [2], EEG signals are used to classify the emotions as humans could control their facial expressions and vocal intonations. The system analyzes EEG signals and classifies them into five classes on two emotional dimensions, valence and arousal. This system is trained with a data set with EEG signals by measuring EEG signals from people that were emotionally stimulated by pictures. Classification accuracies of 71–81 % were achieved when using only the extreme values on both dimensions. But these methods are user-aware and intrusive for collecting the data. Use of this technique for assisting an autistic child will be difficult as the child needs to get the EEG information of the person interacting with him, which is not practical in daily life scenarios. Moreover, EEG recording devices are quite bulky and costly and have limited portability. Hence, in this paper, we primarily focus on non-intrusive modes of emotion recognition, to read other people's minds from nonverbal communication channels such as the facial expressions. In order to assist people who are unable to recognize facial emotions during their face-to-face communication, a real-time portable emotion detector as an assistive technology is required.

Overall, there are several techniques that have been used for the recognition of human emotions such as discrete cosine transform (DCT), fast Fourier transform (FFT), singular value decomposition (SVD), SVM, IVR and EEG. All these were implemented in software on personal computer (PC), and if they are to be used by an autistic child on the move for his daily activities, portability and power efficiency becomes the biggest concern. While numerous techniques have been proposed to detect human emotions based on facial expressions, there have been only a few researches [13, 20] on the potential of implementing the emotion recognition system on a compact, portable hardware platform. In [20], PCA architecture was implemented using Jacobi's method for a parallel and fast implementation. But due to the parallel implementation of eigenvalues and eigenvectors, the implementation in [20] has high area and power consumption. A neural network-based emotion recognizer is implemented in [13], which gives a classification accuracy of 70 %. But the work in [13] does not provide details on the FPGA implementation, its area and power. Please note that the accuracy (70 %) is low. In this paper, we present a feasibility study on the realization of PCA-based hardware-efficient and low-power and high-speed portable emotion recognizers on an FPGA which can aid an autistic child for emotion recognition. PCA architecture is used for implementation in this work due to its lower complexity when compared to fuzzy logic and neural network-based methods.

Fig. 1 Basic emotion recognition procedure

2 Methods

The general block diagram of the emotion recognizer is shown in Fig. 1.

The preprocessing step is done to the input images to normalize them so as to reduce lighting effects. In the feature extraction step, the distinctive features that indicate the emotions of anger, sad, happy and neutral are extracted. The facial region alone is extracted in preprocessing step and is given to feature extraction PCA algorithm. The PCA is a mathematical procedure that transforms a number of correlated variables into a smaller number of uncorrelated variables called principle component. The main aim of the PCA is to minimize the dimensionality of data set and retains at the same time most of original variability in the data set. PCA aids to reduce a complex data set to a lower dimension with a minimum effort. The extracted features are classified with the help of classification algorithm, which calculates the mean Euclidean distances from the feature points.

The main component in PCA computation is the eigenvalue and eigenvector calculation. There are several methods to calculate eigenvalues and eigenvectors such as Jacobi's algorithm, singular value decomposition (SVD) and QR method [1, 23], which results in the generation of all the eigenvalues and eigenvectors parallely from the input covariance matrix. The Jacobi method as well as the QR method is used in the literature due to its simplicity and regularity for parallel implementation [20]. These methods calculate the full set of eigenvalues and eigenvectors of the input covariance matrix in one set of iterations, thus making these methods faster. But these methods require more power and area as they need to compute all the eigenvalues and eigenvectors. Methods such as power iteration, shift inverse method and Rayleigh's quotient iteration generate eigenvalues and eigenvectors serially with the largest eigenvalue, which accounts for as much of the variability in the data set to be the first. Using deflation method along with Rayleigh's quotient iteration, we can generate rest of the eigenvalues and eigenvectors that account for as much of the remaining variability as possible according to our need. The advantage of serial-based methods is its low-power implementation due to the reduced quantity to be measured by compromising the speed.

The key idea in this paper is to replace PC-based emotion recognition with a portable as well as real-time implementation of emotion recognition architecture. We have done an initial study of this work in two conference papers published earlier [15, 16]. In [15] we proposed an efficient Jacobi-based high-speed implementation, whereas in [16] we proposed power iteration-based low-power eigen implementation. From the above works, we understood that there should be a clear comparison between the most efficient serial and parallel implementation for better understanding of selecting the best method for developing an emotion recognizer for autistic children. In this work, we present a comparison of implementations between parallel and serial calculation of eigenvalues and eigenvectors to exploit the same to aid an autistic person. We have used Jacobi's implementation to be the best hardware-efficient parallel method, whereas Rayleigh's quotient method to be the best serial method for implementation according to the results that we have obtained in Sect. 3. As our target device is a portable resource constrained hardware implementation, our initial analysis is to investigate whether we could compromise on the full image size. We have also made a comparative study on the number of selective eigenvalues called as eigen range when compared to the full eigenvalue set for the required accuracy of emotion recognition.

2.1 Image size analysis

The algorithms [3, 4, 8, 11, 14, 18, 22] use full size of the images as all of them were not implemented on hardware. In hardware, using images of large sizes would require very large area and thus high power consumption. We have analyzed the effect of image size on the emotion detection accuracy. In this work, we have taken the Japanese Female Facial Expression (JAFFE) database [18] which contains 213 images of female facial expressions of 10 individuals. Each image has a resolution of 256×256 pixels. The head is almost in frontal pose. The numbers of images corresponding to each of the seven categories of expressions (neutral, happiness, sadness, surprise, anger, disgust and fear) are provided in the database. For this analysis, we have taken 210 images from the image set. They are tested by using 10×10 cross-validation method: while 21 images of one set are tested, the rest of the nine sets become the training image set. This is done in ten folds, and we have plotted the average detection accuracy graph as in Fig. 2. Figure 2 shows that the deterioration in emotion detection accuracy is negligibly small even when the image size is reduced from 256×256 to 32×32. However, the accuracy reduces by 15 % when the size further reduces to 16×16. Hence, we can conclude that there is no performance deterioration if we try to reduce the image size from 256×256 to 32×32 for this training set.

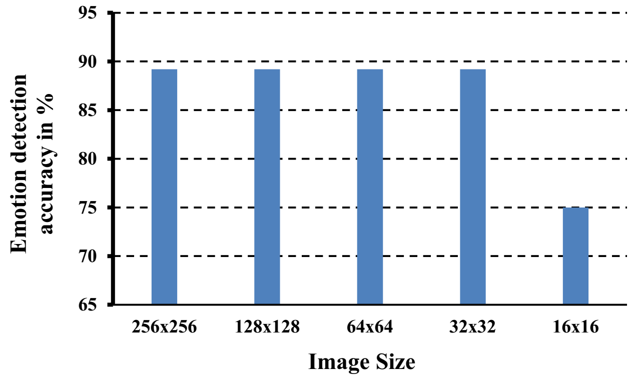

Fig. 2 Emotion detection accuracy versus image size

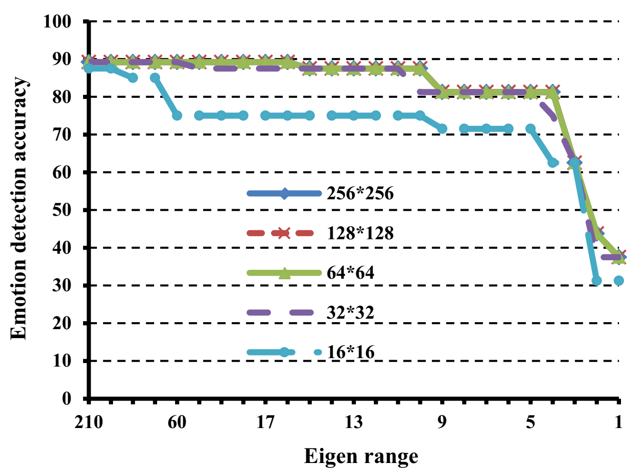

Fig. 3 Emotion detection accuracy versus eigen range

2.2 Eigen range analysis

We also evaluated the detection accuracy corresponding to the eigen range. Eigen range is that eigenvalue up to which the original variability is present. From Fig. 3, we can note that the accuracy remains constant at 89.2 % even when the eigen range is reduced from 210 to 16 for 64 × 64 images. Then, it slightly degrades to 87.5 % till eigen range of 11. We can also notice that for 32 × 32 images the accuracy is 87.5 % for eigen range up to 11. It is obvious that if we overly try to reduce the image size and eigen range, the detection accuracy decreases as shown in Fig. 3.

Hence, in our method, we analyze and find out through simulations the minimum image size and eigen range for which the accuracy remains within the acceptable range. We can note that by reducing the image sizes to 32 × 32, a reasonable accuracy of 87.5 % can be maintained with an eigen range of 11. So the choice of choosing the image size and eigen range is according to the time to respond, detection accuracy and power dissipated.

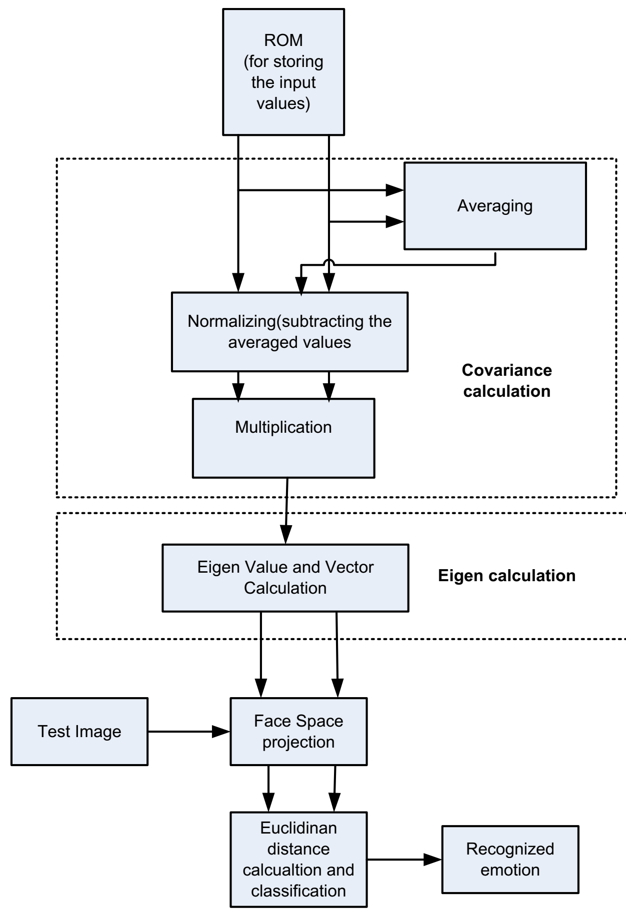

Fig. 4 Hardware implementation diagram of emotion recognizer

2.3 General steps of the emotion recognition procedure

The proposed PCA-based hardware implementation architecture of the portable emotion recognizer is shown in Fig. 4. The steps are explained below.

Step 1: We have taken two images each corresponding to five different emotions (neutral, happiness, sadness, surprise and anger) of three different people from the JAFFE facial expression database. We took only fewer emotions and fewer people in order to meet the hardware resource constraints. Even in the case of an autistic child, the caretakers will be few when compared to an open problem of emotion recognition.

Step 2: We analyzed the image size for this particular training set. According to the simulation analysis, we found out that 16 × 16 pixels can be used without compromising the accuracy to meet the hardware resource constraints, as a larger size image will take a longer time to process and will consume more area and power. In order to aid autistic children in their daily activities, portability and time to respond are very important and hence high power consumption will make the design impractical. The images undergo normalization and skin detection algorithm using C++ to extract the face from the background.

Step 3: The preprocessed images are stored in the ROM as shown in Fig. 4 and is represented as matrix A. The mean of the training images is calculated as $\hat{A}$ such that

$$\hat{A} = \frac{1}{q}\sum_{i=1}^{q} A_i \tag{1}$$

where q is the number of training images. In order to highlight the feature vectors, the input images are subtracted from $\hat{A}$ as

$$\tilde{A}_i = A_i - \hat{A} \quad \text{where } A_i = \left[A_1, A_2, \ldots, A_q\right] \tag{2}$$

Step 4: The feature extraction using PCA requires the calculation of covariance matrix of the preprocessed training images to find the eigenvalues and eigenvectors. Let the covariance matrix for the training data be represented as

$$C = \sum_{i=1}^{q} \tilde{A}_i.\tilde{A}_i' = \frac{1}{q}\sum_{i=1}^{q} (A_i - \hat{A})(A_i - \hat{A})' \tag{3}$$

In order to make the implementation area efficient, we calculate only the diagonal and upper triangular matrix of C by exploiting the symmetry property of the covariance matrix.

Step 5: Eigenvalues and eigenvectors of the covariance matrix are calculated using both Jacobi's iteration and Rayleigh's quotient iteration to analyze which among the methodology will suit accurate and hardware-efficient emotion recognizer for autistic patients. The Jacobi method is explained in Sect. 2.4, and the Rayleigh quotient method is explained in Sect. 2.5.

Step 6: The mean subtracted images are projected to this eigenvector space and also the test image. The Euclidean distance between the expression under test and the mean neutral expressions is calculated. Square root in Euclidean distance is calculated by CORDIC. The test images are also projected to the same eigenvector space, and the Euclidean distances are calculated as done for the training images.

Step 7: The Euclidean distances of the test images are compared with the training data set distances for the classification of the test images.

2.4 The Jacobi method—parallel implementation

The Jacobi iteration allows the users to calculate the eigenvalues and eigenvectors of the covariance matrix simultaneously. It starts from the bilinear form and a given symmetric covariance matrix C and looks for an orthogonal matrix U such that

$$U'CU = \text{E, yields a diagonal matrix } E. \tag{4}$$

The Jacobi method exploits (4) to generate matrices by applying a sequence of the orthogonal rotations to the left and right sides of the target matrix.

For 2 × 2 matrices, the $U = \begin{bmatrix} \cos\alpha & \sin\alpha \\ -\sin\alpha & \cos\alpha \end{bmatrix}$ allows a direct computation:

$$\begin{bmatrix} \cos\alpha & -\sin\alpha \\ \sin\alpha & \cos\alpha \end{bmatrix}\begin{bmatrix} C_{ii} & C_{ij} \\ C_{ji} & C_{jj} \end{bmatrix}\begin{bmatrix} \cos\alpha & \sin\alpha \\ -\sin\alpha & \cos\alpha \end{bmatrix} = \begin{bmatrix} e_1 & 0 \\ 0 & e_2 \end{bmatrix}$$

Matrix multiplication yields two identical off-diagonal elements in the resulting matrix, which should become zero:

$$(C_{ii}\cos\alpha\sin\alpha) - \left(C_{ji}\sin^2\alpha\right) + \left(C_{ij}\cos^2\alpha\right) - \left(C_{jj}\cos\alpha\sin\alpha\right) = 0$$

As $C_{ij} = C_{ji}$, $\cos\alpha \sin\alpha = 1/2 \sin(2\alpha)$ and $\cos^2\alpha - \sin^2\alpha = \cos(2\alpha)$, we can simplify the above equation as

$$1/2\left(C_{ii} - C_{jj}\right)(\sin 2\alpha) + \left(C_{ij}\cos 2\alpha\right) = 0$$

i.e., $\tan 2\alpha = \frac{2C_{ij}}{C_{jj} - C_{ii}}$,

$$\alpha = 1/2\tan^{-1}\left(\frac{2C_{ij}}{C_{jj} - C_{ii}}\right) \tag{5}$$

This solution can be extended to matrices with larger dimensions in the following manner: Start with U = Identity matrix.

1. Determine the off-diagonal element C_{ij} that is largest in absolute value and compute the rotation angle α from C_{ij} and the corresponding diagonal elements using Eq. (5).
2. Construct a matrix V that is identical to the unit matrix, except for $V_{ii} = V_{jj} = \cos\alpha$, $V_{ji} = \sin\alpha$ and $V_{ij} = -\sin\alpha$.
3. Then, compute the matrix products $C'' = U'CU$ and $U'' = UV$; C''_{ij} becomes zero by this operation, and the other elements in rows and columns i and j are changed.
4. If the largest absolute value of the off-diagonal elements C_{ij} is larger than a threshold, repeat the process from step no. 2 with C'' instead of C and U'' instead of U. Upon convergence, C'' contains the eigenvalues and U'' the eigenvectors.

The sin, cosine (angle rotations) and arctan were implemented using CORDIC using Xilinx CoreGen. The block "angle calculation" as shown in Fig. 5 calculates the angle α from the input vector.

This block uses CORDIC to calculate the ARCTAN value. The resultant angle is passed to the block indicated as "matrix calculation." The intermediate values are stored and are used for subsequent iteration for obtaining the eigenvalues and eigenvectors.

2.5 Rayleigh quotient iteration—serial implementation

Rayleigh's quotient iteration generates eigenvalues and eigenvectors serially, with the largest eigenvalue, which

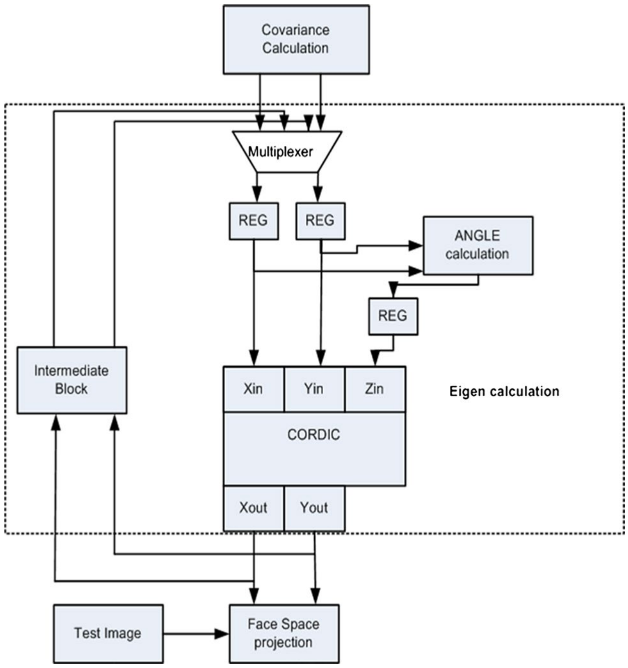

Fig. 5 Hardware implementation diagram of Jacobi's eigen calculation

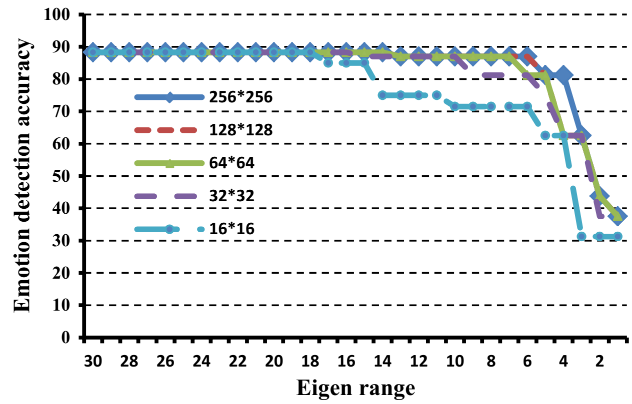

Fig. 6 Detection accuracy versus eigen range for the implementation set

accounts for as much of the variability in the data set to be the first. Using deflation method along with Rayleigh's quotient iteration, we can generate rest of the eigenvalues and eigenvectors that account for as much of the remaining variability as possible.

Here, we not only restrict our image size according to the simulation analysis to 16 × 16 pixels but also limit the eigen range to 18 when compared to the full eigen range as indicated in Fig. 6. In order to find the eigenvectors and eigenvalues within the pre-calculated eigen range, we use Rayleigh's quotient iteration method to calculate the largest and the most representative eigenvalue and eigenvector. Using deflation method, we further calculate the rest of the most significant eigenvalues and eigenvectors within the eigen range. The proposed Rayleigh quotient iteration hardware implementation of the portable emotion recognizer is shown in Fig. 7. The steps are explained below.

The eigen range is calculated initially as shown in Fig. 6 and set to a value P, let λ be the eigenvalue and X be the eigenvector, and the algorithm iteratively calculates till the error ε is within the specified range arbitrarily set for this implementation as 1 %. Setting the error range to a larger value will enhance the speed of the algorithm but the accuracy decreases. Initial guess of eigenvalue is required for Rayleigh's quotient iteration.

It can be obtained either using general power iteration or using $\lambda[i] = X[i]*AX[i]/X[i]*X[i]$, where λ is the eigenvalue, A is the Covance matrix and X[i] is the identity column vector which is used as the initial guess for eigenvectors. Using the initial guess of the eigenvalue and eigenvector, we continuously iterate for all the eigen range specified using the deflation method as shown in Fig. 7. In order to find the eigenvector $X[i + 1]$, we have to perform inverse operation. There are many methods to implement inverse operations such as Gram–Schmidt orthogonormalization, Givens rotations (GR), householder reflections, Jacobi's iteration, and Gauss–Seidel elimination. We have used Gauss–Seidel elimination for the inverse operation due to its simplicity.

3 Results

In this section, we carry out the architecture exploration for an efficient implementation using Xilinx ISE 13.2 (Verilog). The target system is Virtex 7 XC7VX330T FFG1761-3 FPGA. The designs are implemented with word length of 8 bits to provide comparison. The most area and power consuming operation in the emotion recognition is the feature extraction or the PCA. In this paper, we have compared two hardware-efficient implementations. Jacobi's iteration which is the parallel implementation is made hardware efficient by calculating only the diagonal and upper triangular matrix by exploiting the symmetry property of the covariance matrix. For Rayleigh's quotient method, we have calculated only the eigenvalues and eigenvectors within the eigen range. This serial method has a key advantage of fast settling of iterations which makes the emotion detection process fast. We have compared the PCA of the two proposed emotion detectors along with the implementation available in [20], for the same word length of 8 bits.

Table 1 shows a detailed comparison of serial and parallel implementations of PCA architecture, its advantages

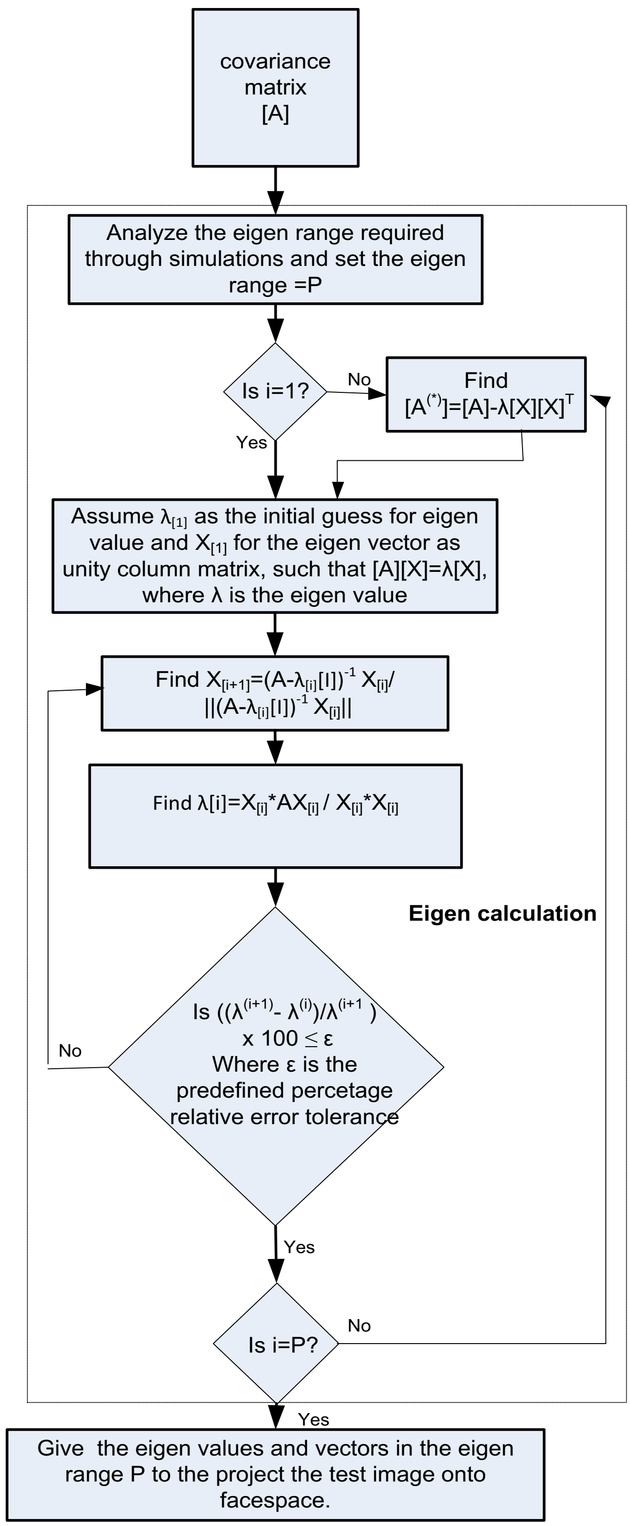

Fig. 7 Flow diagram of Rayleigh's quotient iterative method with deflation

and disadvantages. We can note that while comparing the serial-based implementations, power iteration-based method [16] gives 28.6 % lesser area and 20.5 % lesser

Table 1 Area, power and delay comparison of the proposed PCA method architectures

Area (slices)	Power (mW)	Total delay (s)
Serial PCA—Rayleigh's quotient iteration		
29,263	7.8	52.9
Serial PCA—Power iteration [16]		
20,892	6.2	85.3
Parallel PCA—Jacobi's iteration [15]		
78,458	18.3	25.1
Method in [20]—parallel PCA		
97,566	22.7	25.1

power when compared to Rayleigh's quotient-based iterative method. But power iterative-based method needs 38 % more delay than the Rayleigh quotient method. Power iterative method also fails when the principal eigenvalue is not distinctive from the rest of the eigenvalues. This drawback of power iterative method also introduces very long delay when the eigenvalues are closer together. Hence, a better serial implementation is the proposed Rayleigh quotient method. The parallel Jacobi implementation in [15] has 19.6 % lesser area and 19.3 % lesser power while maintaining the same delay by exploiting the symmetric property of the covariance matrix, when compared to [20]. A choice of best emotion detector implementation will purely depend on the desired specifications on speed, resource utilization and power. The proposed Rayleigh quotient method can achieve the same accuracy with 62.5 % lesser area and 57.7 % lesser power with delay increment of 52 % when compared to the parallel Jacobi method [15]. Hence, the optimal choice of low-power emotion detection method will be Rayleigh's method and the fastest emotion detection method to be Jacobi's method.

Using the proposed Rayleigh quotient serial method as well as the Jacobi parallel implementation, we achieved a classification accuracy of 82.3 % for a word length of 8 bits. Here, it can be noted that we have taken only two images each corresponding to five different emotions (neutral, happiness, sadness, surprise and anger) of three different people from the JAFFE facial expression database. Thus, a total of 30 images were taken for validation. For performing a 10 × 10 validation, a random set of three images is used for testing, while the rest is used for training. This is done in ten folds, and the average accuracy reported is given in the confusion matrix as given in Table 2.

4 Discussions

In this work, we have developed hardware-based emotion recognition for aiding autistic children in understanding

Table 2 Confusion matrix

Predicted emotion	Detected emotion						
	Neutral	Happiness	Sadness	Surprise	Anger	Disgust	Fear
Neutral	91.2 %	3.3 %	0	3.5 %	2 %	0	0
Happiness	9.4 %	83.1 %	0	7.5 %	0	0	0
Sadness	15.2 %	0	78.1 %	0	0	6.7 %	0
Surprise	7.2 %	9.5 %	0	80.5 %	0	0	2.8 %
Anger	0	0	4.7 %	3.2 %	82.8 %	9.3 %	0
Disgust	10.4 %	0	9.3 %	0	0	79.3 %	0
Fear	4.9 %	0	0	6.5 %	0	7.5 %	81.1 %
Overall accuracy	82.3 %						

the emotions of their caretakers. We have achieved 82.3 % classification accuracy for the proposed work. In comparison with the literature available on hardware-based emotion recognition, an FPGA-based neural network is implemented for emotion recognition [13] and its reported classification accuracy is 70 %. The accuracy of the proposed FPGA implementation outperforms [13].

We can note that the key objective of the hardware-based approach is to make the system power efficient, portable and faster to have a real-time feedback. This will allow the user to detect their caretaker's emotion as fast as possible. In PC-based approach, the portability becomes the bottle neck. The classification accuracy in a PC-based method can be made better by incorporating highly complex iterative algorithms, and the decision time for recognizing emotions will slower. The PC-based implementation of Jacobi's iteration using MATLAB as the tool (PCA and Euclidean distance for calculation) resulted in 89.2 % classification accuracy as reported earlier in Sect. 2.1. The increase in emotion detection accuracy is due to a large training set of 210 images from JAFFE, and all of them were 256 × 256 pixels with full eigen range.

An implementation of that full set in hardware will require 38 % increased area and 59 % increased delay when compared to the proposed approach. We can note that the reduction in accuracy for the proposed FPGA implementation compared to software implementation is due to the limited bit precision and the rounding off/truncation procedure in hardware.

The work in [7] reports emotion recognition using physiological signals such as electrocardiogram, skin temperature variation and electrodermal activity. Classification ratios were 78.4 and 61.8 % and were reported for 50 subjects, for the recognition of three and four categories, respectively. Our method is able to beat this method in terms of accuracy. The PC-based method proposed in [24], which is based on facial movement analysis, shows 92.92 % accuracy when tested on Set 1 containing 180 images from JAFFE database showing six emotions (except neutral). In this method, they have taken the features of facial element as well as muscle movements. The higher accuracy of this method is due to the complex 3D Gabor filtering and SVM classification after obtaining salient features using patches via AdaBoost. Even though this method has higher classification accuracy than the proposed method, it has restricted portability due to the fact that it is a PC-based approach. Due to the complexity of the algorithm in [24], a hardware realization of the same is difficult.

5 Conclusions

In this paper, we have proposed portable hardware-efficient emotion recognizer architecture for enhancing the quality of life of autistic children. In this paper, we provide a comparison between serial and parallel method of principal component analysis method in order to understand which among them will be the best method for realization of a portable emotion detector for autistic children. The proposed emotion recognizer architecture is implemented on Virtex 7 XC7VX330T FFG1761-3 FPGA. We were able to achieve 82.3 % detection accuracy for a word length of 8 bits.

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