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EFFICIENT DISTRIBUTED FACE RECOGNITION IN WIRELESS SENSOR NETWORK

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Abstract. *Face recognition enhances the security through wireless sensor network and it is a challenging task due to constraints involved in wireless sensor network. Image processing and image communication in wireless sensor network reduce the life time of network due to the heavy processing and communication. Face recognition system enhances the security and functionality using wireless sensor network and gains flexibility while integrated into wireless sensor network. This paper presents a collaborative face recognition system in wireless sensor network. The layered linear discriminant analysis is re-engineered to implement on wireless sensor network by efficiently allocating the network resources. Distributed face recognition not only helps to reduce the communication overload but it also increases the node life time by distributing the work load on the nodes. The simulation shows that the proposed technique provides significant gain in network life time.*

Keywords: Wireless sensor network, Distributed face recognition, LDA, Fusion, Subspace

1. Introduction.

Face recognition system enhances the security through wireless sensor network and it is a challenging task due to the lot of constraints involved in wireless sensor network and issues in face recognition. Wireless sensor networks are showing interest by both theoretical and practical problems for security applications during last decades and very helpful for contactless biometrics security applications. It becomes the most important technology and used in a wide range of security applications epically for espionage, target detection, habitat monitoring, military applications, etc. [1,2]. Normally, a wireless sensor node consists of low-power Digital Signal Processor, Micro-Electro Mechanical System, radio frequency circuit and small battery. Wireless sensors are characterized by several constraints, such as poor processing power, less reliability, short transmission range, low transmission data rates and very limited available battery power [3]. It provides a useful interface to real world with data acquisition and data processing capabilities. The sensor networks consist of multiple sensor nodes which are able to communicate with each other in order to perform the computation collaboratively to save the network life time. The time when the first node of the network becomes dead is the life time of sensor network. Although the computer is much faster and efficient in computation than human, in image processing, the human is much more efficient than computer due to high contextual knowledge and extra ordinary viewing devices such as eyes. On the other hand, constrained sensor node has not enough capability to process the image locally whereas image transmission is one of the most expensive tasks and it takes a lot of energy due to the communication overheads [5]. Hence, efficient distributed processing is required to overcome the issues in sensor networks. The use of wireless sensor network based applications are increasing due to data acquisition and its importance in security applications especially in the case of un-manned surveillance applications that work independently and send alert when finding suspicious in vision. The challenge in face recognition system in wireless sensor network environment requires considerable computation power, energy and bandwidth for processing and transmission [9]. The main objective in wireless sensor networks is to reduce the energy consumption while maintaining the accuracy. To overcome the energy and processing limitations of network, nodes collect the information from each other to perform the heavy task and exploit the energy by distributing the work load in sensor nodes [4].

2. **Related Work.** Face recognition is the branch of pattern recognition to imitate the human face recognition power to the machine. Face recognition applications have great demand for security applications, i.e., crimes and terrorism safety. Whereas face recognition involved several challenges, i.e., different types of variabilities of face under different environments that make it more difficult and less accurate. During the last few decades, computer scientists, neuroscientists and psychologists are working on face recognition algorithms. The psychologists and neuroscientists are modeling the visual perception for face recognition whereas the computer scientists are trying to develop methods based on the human brain modeling [6-8]. Face recognition includes face identification and face verification. Face identification shown in Figure 1 is the one to many match in which a huge database is matched with probe image. It is more challenging as compared with face verification. Face verification includes one to one match and has been implemented in mobile phones and personal login systems by FaceCode and OMRON, etc. [9]. The face identification is the contactless biometrics whereas face verification is partially contact biometrics. Face identification is the most popular biometrics used for security purposes due to its ease of end-user use, identification of an individual from distance. The contactless property of face identification makes it more suitable for espionage applications by using wireless sensor networks.

PCA and LDA based methods are the most powerful methods for dimensionality reduction and have been successfully applied in many complex classification problems such as face recognition and speech recognition [10]. LDA based methods perform better than PCA while LDA based methods are facing problems with SSS. The aim of LDA is to find the best representation of feature vector space. The conventional solution for small sample size problem and large data is the use of PCA into LDA. PCA is used for dimensionality reduction and LDA is performed on to the lower dimensional space obtained using PCA [11]. The use of LDA over PCA results in loss of significant discriminatory information. Direct linear discriminant analysis (D-LDA) is used to overcome this issue [12,13]. Fractional-step linear discriminant analysis (F-LDA) used weighting function by assigning the more weight to the relevant distance for dimensionality reduction to avoid misclassification [14]. Razzak et al. used layered discriminant analysis to overcome the issue of small sample set and large dataset [15]. Small dataset is extracted from large dataset using LDA instead of one single face. The further features templates are computed based on small new dataset. Finally, the probe image is projected to fine the best separablity criteria. Razzak et al. presented bio-inspired face recognition system. The face dataset is reduced in layered process by using the structural features and appearance based futures [16]. The dataset is reduced in layered manner to find the best separablity.

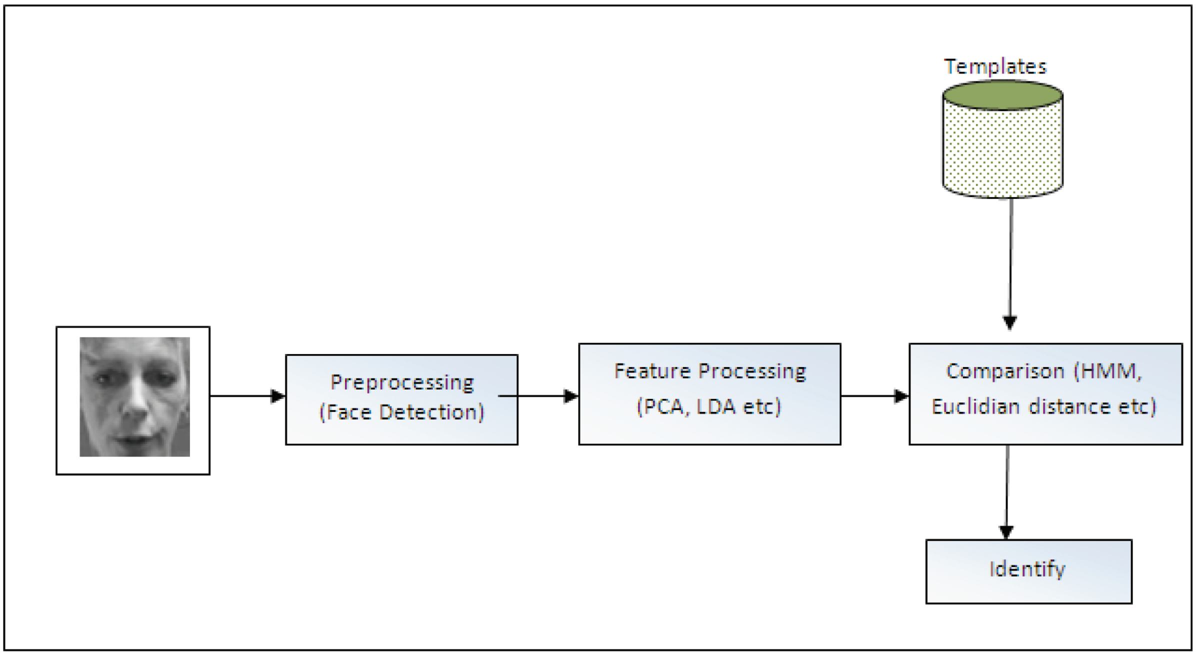

FIGURE 1. Normal face recognition process

Muraleedharan et al. presented wireless face recognition by swarm intelligence. The swarm intelligence is used to optimize the routing in ant system in distributed time varying network by maintaining required bit error for various channel conditions [17]. The contourlet or wavelet coefficients are transmitted for central processing. Yan et al. presented contourlet based image compression for wireless communication in face recognition systems [18]. Muraleedharan et al. presented face recognition for single or multi-hop ant based wireless sensor network using swarm intelligence [19]. They presented ant system for routing the wavelet or contourlet coefficients of faces to the sink node for processing. Yan et al. presented multistep static procedure to determine the confidence interval of features based on the Eigen decomposition of features and present a MIZM zone to present the interval [20]. Yan and Osadciw presented module based distributed wireless face recognition system [9]. They used five module (face and four sub modules) for face recognition and divided the wireless sensor networks into two groups, i.e., feature nodes and database nodes. The feature nodes calculate the features of probe image and transfer to the cluster node. The cluster node combines the features from all feature nodes and transfers them to the database nodes which compare with the templates stored and score is transferred to the sink node. Although the workload is divided into sensor nodes, but the communication overload between feature nodes itself and database nodes is still an issue. It is more pressure on feature nodes and database nodes. Razzak et al. presented distributed face recognition system by dividing the load on the nodes and reduce the processing by reducing the matching criteria for other modules based on one module [22]. Face recognition is classified into face identification and verification. Face verification is the one-to-one match and it is suitable for mobile phones, login systems, etc. Whereas face identification is one-to-many match, where a huge database is matched with probe face, shown in Figure 1 and it is pure contactless biometrics. Face identification is the most suitable biometrics for face recognition. The previous face recognition system in wireless sensor network is only for recognition whereas the training is performed separately and feature matrix is stored on the feature nodes. We preset efficient distributed wireless face recognition and discussed both training and recognition scenario by utilizing different algorithms. Instead of using one algorithm for training and recognition, we used two different methods for training and recognition. The net features of both methods are same, whereas both differentiate in computational complexity. We consider separate cluster head for each module, i.e., fore head, eye, lips and nose. Only the local cluster is responsible for internal module processing for both training and recognition, and we used the result of one module to reduce the matching dataset for other modes to find the best match and save the energy instead of projecting the feature space onto the whole dataset. The reset of the paper is organized as follows: Section 3 describes the proposed distributed wireless face recognition system; Section 4 presents the experimental results, performance evaluation and list of benefits of proposed technique; finally, conclusion is presented in Section 5.

3. **Distributed Wireless Face Recognition.** The use of wireless sensor network based applications is increasing due to data acquisition and its importance in security applications whereas a lot of issues are involved in it especially in case of image processing/recognition. Face recognition in wireless sensor network recognition is a challenging task due to the limitation of wireless sensor network. Human has extra ordinary viewing devices and brilliant brain whereas general face recognition has high processing and memory. Because wireless sensor network is energy, memory and processing power constrained network it is very difficult for doing pattern recognition tasks such as face recognition. Due to the physical structure of sensor network, the face images are affected by various factors such as pose, expression and illumination. The main objective of face recognition in wireless sensor networks is to reduce the energy consumption by maintaining the accuracy and efficiently allocating the resources in distributed environment. The limited battery, processing power of sensor nodes and various issues in image normalization makes image processing at node very difficult. The image communication takes lot of energy due to large dataset of image and overhead involved in communication, thus it is better to process the data either locally or in distributed environment in efficient way rather than transmitting to the destination for recognition. We present face recognition system in

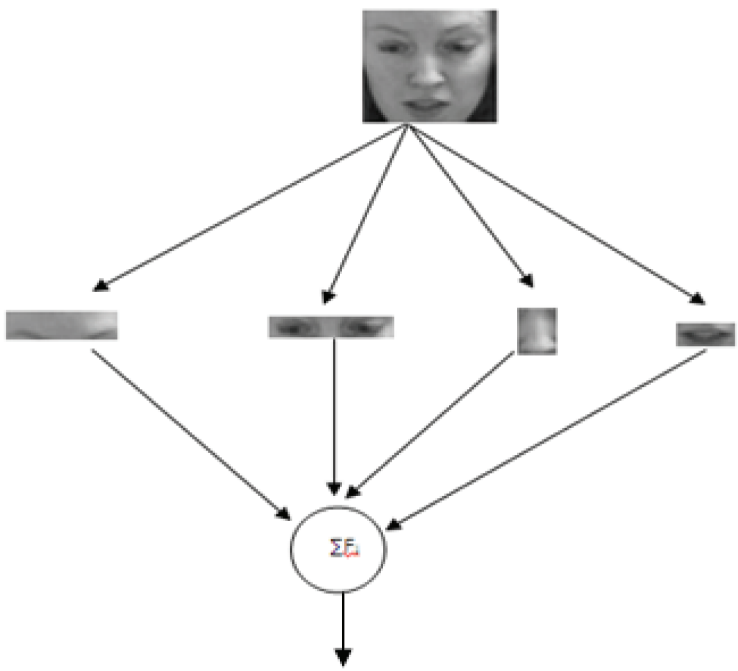

Figure 2. Module based face recognition

wireless sensor networks where training and recognition is performed in distributed environment using two different methods. The image is divided into four sub modules, i.e., forehead, eyes, nose and lips. Enrolment and identification of each sub modules is performed by separate cluster head. Each cluster head is responsible to process its sub module in distributed environment and each cluster head is responsible to communicate with sink cluster which perform the score level fusion.

The enrolment of faces is performed using linear discriminant analysis of principle component analysis and templates are stored in database nodes and the features and image templates of each sub module is stored on separate feature nodes and database nodes. For recognition, the probe modules of probe image are projected onto feature space to find the feature templates. These computed templates are compared with each templates stored in the database net to find the most similar identity. The feature nodes calculate the inner product of testing image with the feature stored on the feature nodes. The output of feature node form vector which is the template of the probe image.

Figures 3 and 4 show the proposed distributed wireless sensor face enrolment and recognition system respectively. The red shaded node is the destination node and camera equipped node is the source node. The blue shaded nodes are the database nodes and each database node in database net contains the feature set of corresponding sub part. The other nodes are used for processing to reduce the load on the database node. The feature and database nodes may be same shown in Figure 4.

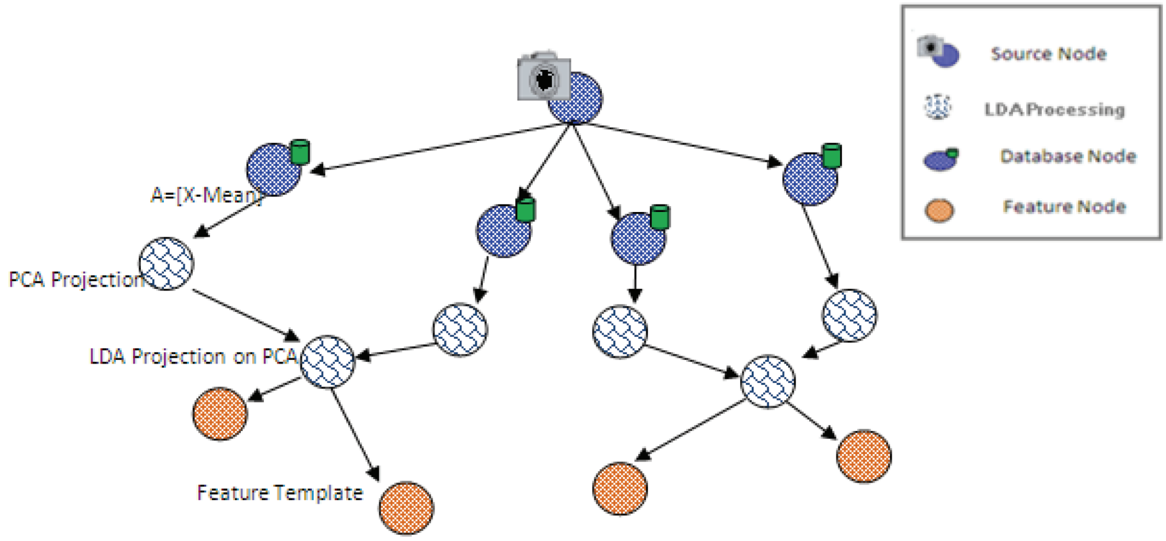

FIGURE 3. Conceptual diagram of WSN for distributed training for face recognition

3.1. **Enrolment phase.** The enrolment is performed using linear discriminant analysis of principle component analysis [23]. The linear discriminant analysis is applied to obtain linear classifier on principal component analysis and it reduces the within class variance. The input image X is mapped into the face subspace Y. This mapped subspace Y is further mapped into classification space Z. The input image matrix is reduced using PCA and linear discriminant analysis is applied on reduced feature set. The reduction of dimension using PCA for LDA needs $n(N-C)N$ multiplications.

$$y = \phi(x - m) \tag{1}$$

$$z = W_y^T y \tag{2}$$

$$z = W_x^T (x - m) \tag{3}$$

The computation of within class scatter matrix needs $N(N-C)^2$ multiplications. Whereas the computation of between classes scatter matrix needs $C(N-C)^2$ multiplications. Thus, the total number of multiplication is given as:

$$nN(N-C) + (N-C)^2(N+C) \tag{4}$$

$$n \ggg N \tag{5}$$

$$O(nN^2) \tag{6}$$

The training using LDA of PCA is less computational as compared with LDA using PCA. LDA using PCA, first compute the between and within class scatter matrix and then it uses PCA to reduce dimension. Thus, the computation of within class scatter matrix needs Nn^2 multiplications. Whereas the computation of between classes scatter matrix needs Cn^2 multiplications. Then, applying PCA projection on both scatter matrices which needs $n^2(N-C) + n(N-C)^2$ multiplications for each one thus the total number of multiplication is given as:

$$n^2(3N-C) + 2n(N-C)^2 \tag{7}$$

$$n \ggg N \tag{8}$$

$$O(n^2N) \tag{9}$$

$$\text{And } O(n^2N) \ggg O(nN^2) \tag{10}$$

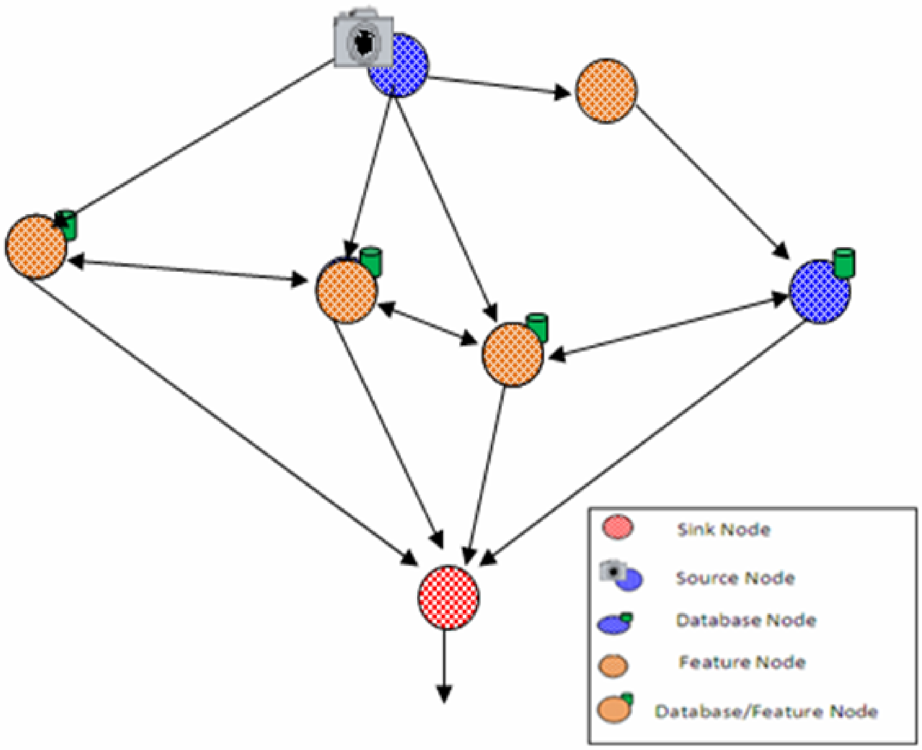

FIGURE 4. Conceptual diagram of WSN for distributed face recognition

3.2. **Recognition phase.** After subtracting the average of classes from the input image, the result is multiplied by the projection matrix so we need $n(C-1)$ multiplications and then we compare the result with each class projection.

The testing using LDA of PCA is much more complex because it needs to perform two projections. LDA of PCA requires $(N-C)(n+C-1)$ multiplications. Whereas LDA using PCA requires $n(C-1)$ multiplications. Thus, LDA of PCA is much more complex as compared to LDA using PCA.

The projection phase is performed by deriving the testing image template in distributed environment as shown in Figure 4. Based on the modules the features are stored on the feature nodes. The source node transfers the module to the feature nodes which calculate the templates. These templates are further transformed to the relative database module node in database nets. Each database node store few database samples, this depends upon the capacity of the node. The comparison is performed on the templates and similarity score is calculated between the stored templates and each probe modules template. The score result is further transformed to the cluster head or to other node to normalize it and to draw the final decision.

We used weighted score level fusion that utilized the scores of each modules to draw the final decision. The weighted fusion is performed on each module result where the weights are defined based on importance and uniqueness of sub module. We divided the face into four sub modules and each sub modules has its own matching score. The matching score is normalized and weighted score level fusion on sub modules result is performed.

All features node also act as dataset node except nose module which has separate database and feature node shown in Figure 4. The input face image is divide into four sub modules and transferred to the associated feature node in the feature net. The feature vector is stored on each feature node and inner product is carried out between incoming sub-module and respective stored features. Finally, the feature node transmits the probe image features to the database node. The database node of each sub-module collects the input from the respective feature node and perform inner product of stored templates and probe image to find the matching score with template of each class. The output matching score of each database node is transmitted to the sink node to draw the final decision. The fusion on the score results is performed on the next node, i.e., sink node or the node next to database node.

Figure 4 presents the reduced search methodology by selecting the few top results in the one sub-module for other three sub-modules in order to optimize the searching and minimized the energy consumption by reducing the communication between feature node and database node shown in Figure 5. In this case, the database node and feature node is the same for all other three modules except nose. As the nose is the most important part in face recognition, so we consider it to select the other small dataset from large dataset for each other sub modules. As energy consumption during communication is much more higher than computation due to the lot of overhead involved in communication thus it is better to reduce the communication overload between the nodes. This small list of selected classes is transformed to the other module nodes to avoid the communication overload during the communication between the feature node and database node. Moreover, the energy consumption can also be decreased by further reducing the list using other modules as shown in Figure 5. The output of nose module at database node is the list of selected classes from large dataset and is transformed to the forehead module. The forehead module performs the computation on the forehead and helps to reduce the list further. The

Figure 5. Sub modules extraction

list from forehead module further transfers to eye module database node and computation is performed on small list of identities. Finally, the eye module further reduces the list and transmits it to the lips database/feature node. Thus, in this way, the communication overhead is reduced by eliminating the communication between database node and feature node shown in Figure 5 and Equations (10) and (11) describe the reduction of dataset mathematically.

Suppose there are N clients and every client has k_i samples face images. The total number of sample is given by:

$$K = \sum_{i=1}^{N} k_i \tag{11}$$

The M is the selected number of classes using linear discriminant analysis based on nose using Equations (3) and (4).

$$Min[D] = | \text{ if } d_i < \theta \tag{12}$$

$$m_j = N_i(\underset{\theta}{Min}[D]) \tag{13}$$

$$\text{where } D = Euc\_dist\,[d_i, d_2, \ldots, d_N] \tag{14}$$

The above reduced dataset is further reduced by applying linear discriminant analysis on eyes. Suppose there are P client selected based on nose results.

$$K' = \sum_{i=1}^{P} k_i \tag{15}$$

Now again, the new adaptive dataset is reduced based on the results of eyes.

$$Min[D'] = | \text{ if } d_i < \theta \text{ where } d_i = 1, \ldots, P \tag{16}$$

$$m_j = N_i(\underset{\theta}{Min}[D']) \tag{17}$$

$$\text{where } D' = Euc\_dist\,[d'_i, d'_2, \ldots, d'_P] \tag{18}$$

Similarly, the dataset is further reduced by applying the forehead results. The step by step reduction in dataset is shown in Figure 5.

$$R \ll Q \ll P \ll N \tag{19}$$

$$\text{where } R \subseteq N \tag{20}$$

4. **Simulation Results and Discussions.** We performed the simulation on BANCA face database which consist of 40 classes and each class contain 10 samples with frontal pose and presented three cases. For both recognition and training, the face image is divided into four sub modules eye, nose, forehead and lips shown in Figure 2. The feature net and database net is divided into four sub parts and each sub part has its own cluster head to avoid the communication for one cluster and each cluster runs independently. In case-I, each sub module is recognized separately and it has separate four independent cluster in both feature and database node layer. In this case, the feature net compute the feature template of incoming face image which is transmitted to the database net. The database node compare with each class template stored on database node for each class. It takes lot of energy during the transmission of feature templates from the feature node to the database node. To overcome the communication overhead between feature net and database net, the feature net and database net are combined for eye, forehead and lips. Moreover, the computation on these three sub cluster is dependent on each other and nose cluster. This reduces the communication overhead and increase the life

time of sensor network. Figures 6 and 7 describe the recognition rate of case-I, case-II-A and case-II-B.

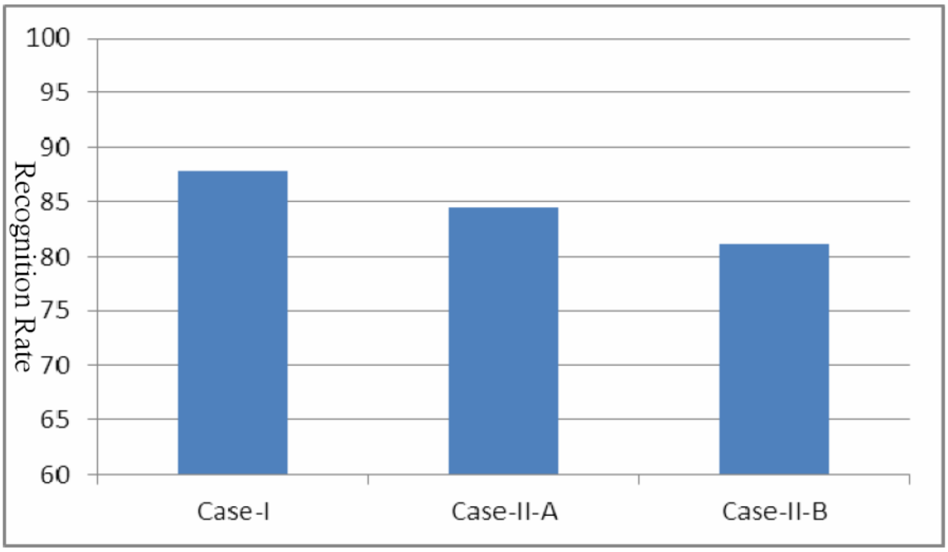

FIGURE 6. Performance comparison on BANCA database

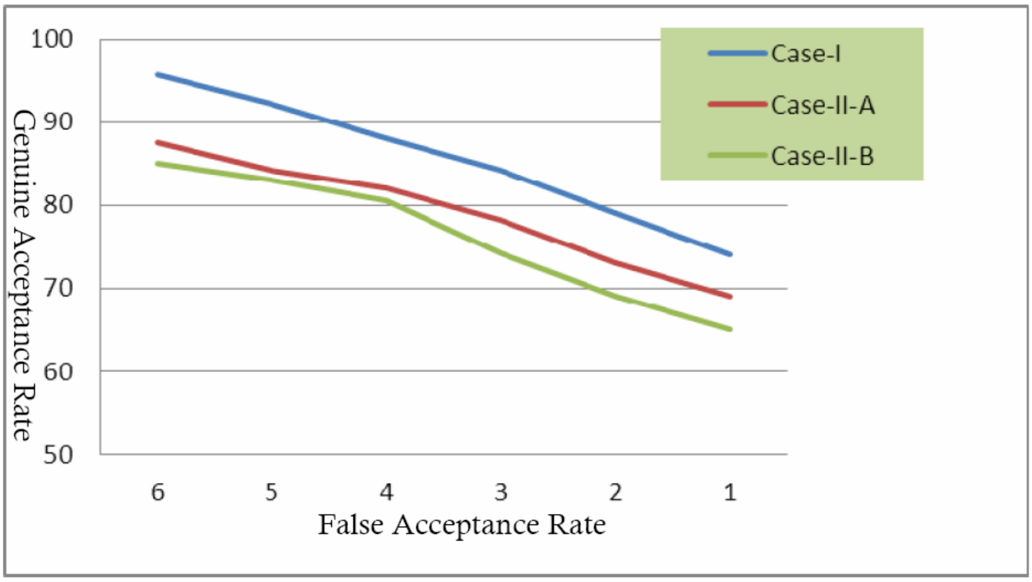

FIGURE 7. FAR and recognition rate

The score values are normalized and finally we performed weighted score level fusion on four sub-module using the following weighted formulas for case-I and case-II.

$$F_{Case\text{-}I} = 0.4S_i^N + 0.25S_i^L + 0.2S_i^E + 0.15S_i^{FH} \tag{21}$$

$$F_{Case\text{-}II} = 0.20S_i^N + 0.30S_i^L + 0.30S_i^L + 0.20S_i^L \tag{22}$$

where $i = R$ and R is the least number of classes selected in final module.

The second performance parameter is the network life time. It is the time when the network starts working until the time when the first node in the sensor networks fails due to insufficient level of energy. We used the transceiver energy dissipation modal [21] for

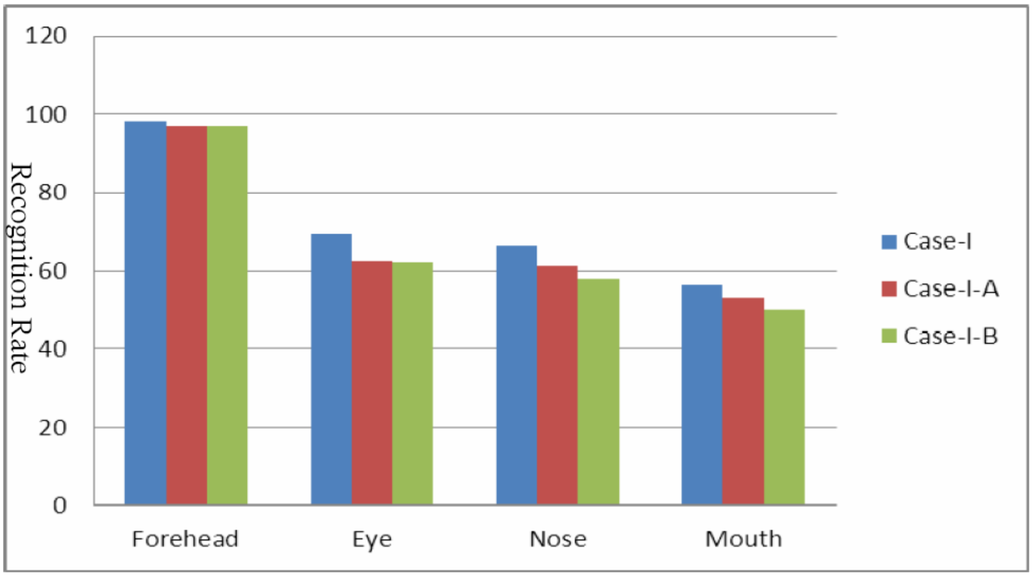

FIGURE 8. Recognition of sub module on BANCA database

energy performance measurement. The energy consumption in the reception of per bit E_r is defined as

$$E_r = \varepsilon_e \tag{23}$$

The energy consumed in transmission E_t of per bit is defined as

$$E_t = \varepsilon_e + \varepsilon_a d^a \tag{24}$$

where ε_a is the energy consumed by per bit per m^2, and d is the distance between wireless sender and receiver node. The energy consumed to calculate the feature template for each module is given as

$$E_{Nose} = \zeta_n \tag{25}$$
$$E_{Lips} = \zeta_l \tag{26}$$
$$E_{Eye} = \zeta_e \tag{27}$$
$$E_{Forehead} = \zeta_f \tag{28}$$

And similarly, the energy dissipated to match feature template with one class is given as

$$E_{match} = \zeta_m \tag{29}$$

The energy consumption in case-II-A and case-II-B on eye feature/database node is given as

$$E_{Case\text{-}II\text{-}A(eye)} = N \times \zeta_m + E_{Eye} \tag{30}$$
$$E_{Case\text{-}II\text{-}B(eye)} = R \times \zeta_m + E_{Eye} \tag{31}$$

Whereas R is the number of selected small dataset and N is the number of classes trained shown in Equation (11). Thus, by using Equation (10), we can conclude that

$$E_{Case\text{-}II\text{-}B(eye)} \ll E_{Case\text{-}II\text{-}A(eye)} \tag{32}$$

5. **Conclusion.** This paper presents a distributed face recognition system in wireless sensor network. We used two different methods LDA over PCA and LDA using PCA for training and recognition respectively. Linear discriminant analysis is re-engineered to implement on wireless sensor network. First, instead of considering one cluster head in feature nodes group and database nodes group, we consider four cluster head for each

module in both feature and database net. The local cluster is responsible for internal module processing. Secondly, instead of projecting the feature space onto the whole dataset, we used the result of one module to the other modes to find the best match and save the energy. Although it increases the computation overload on feature/database node while on the other hand communication load between the feature node to source node and database node to sink node is reduced. The simulation shows significant improvement in the life time of sensor network.

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