Increased Efficiency of Face Recognition System using Wireless Sensor Network

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ABSTRACT

This research was inspired by the need of a flexible and cost effective biometric security system. The flexibility of the wireless sensor network makes it a natural choice for data transmission. Swarm intelligence (SI) is used to optimize routing in distributed time varying network. In this paper, SI maintains the required bit error rate (BER) for varied channel conditions while consuming minimal energy. A specific biometric, the face recognition system, is discussed as an example. Simulation shows that the wireless sensor network is efficient in energy consumption while keeping the transmission accuracy, and the wireless face recognition system is competitive to the traditional wired face recognition system in classification accuracy.

Keywords: Wireless Sensor Network, Face Recognition, Wavelets, Swarm Intelligence, Ant System.

1. INTRODUCTION

Unlike human intelligence based face recognition, the computerized face recognition using tiny inexpensive sensors with limited processing power and energy is a challenging task. 3D faces are usually represented by 2D gray scale images or 2D RGB color images. Whereas, the 2D facial images are affected by many factors such as lighting conditions, poses, facial expressions, and age[1].

The desired face recognition system should tolerate the intra-person variations while distinguishing the inter-person variations. In this paper, a robust wireless face recognition system is constructed while optimizing the network transmission limited by constraints. These transmissions may require a single or multi hop wireless sensor network depending on the communication ranges and transmission powers.

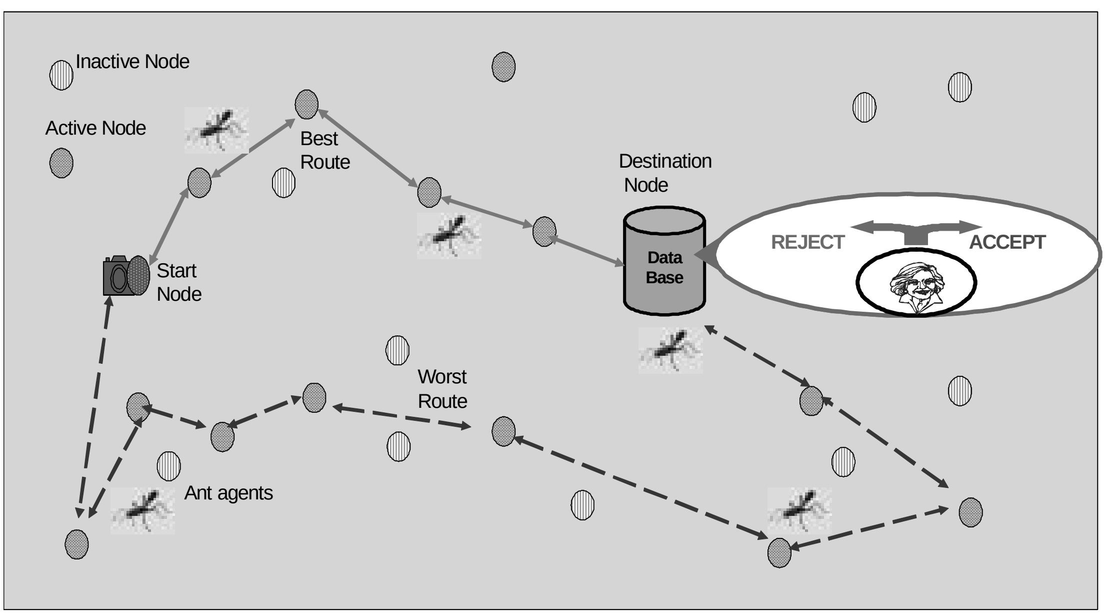

Fig. 1. Face Recognition System Using Wireless Sensor Network For Data Transmission.

Sensor networks with self organizing techniques that optimize nodes based on their capabilities and energy capacities are best suited for deployment in remote area, where batteries often cannot be recharged. Power efficiency and optimization, power scavenging, are the only approaches viable in such an environment[2]. A sensor network with capabilities such as efficient routing, healthy prediction and self-healing is preferable. The state of the sensors may change from active to idle to disconnected.

Typical issues related to a wireless network are energy conservation, stability, convergence of the routing algorithm, scalability, Quality of Service (QoS), real time adaptation, and reliability[3, 4]. The routing algorithm must optimize these performance parameters while monitoring the state of the communication links among sensors. The performance parameters considered in this paper are hops, distance, energy and transmission error i.e., BER. The functionality of nodes is to sense, collect and distribute the dynamic information from one sensor to the other. Energy is a key issue, as the sensor's battery have limited power supply leading to difficulties during computation[5]. An optimal and reliable communication is vital under the above constraints.

Apart from optimization of the network performance, communication delays and sensor failure also requires priority. To handle all these issues efficiently an evolutionary algorithm known as swarm intelligence[6] is used as they could sense the network link and update the link status thus enabling a robust network in a decentralized manner. This optimization problem is shown to be a Nondeterministic Polynomial (NP) hard problem [7].

The Ant system[9], developed from the SI, is a learning algorithm which uses local information interactively to reach a global optimum by a group of agents, the ants. The manner of local interaction gives the ant system robustness and versatility to solve the NP hard problems. In the third section, the justification for swarm intelligence and its performance on a sensor network is discussed. Section 4 discusses the ant system algorithm in detail.Section 6 discusses mathematical formulation of the application in detail. Simulation results in Section 6 gives an insight of the robustness of the face recognition system connected by wireless sensor network. The paper concludes with the Section 8 discussing conclusions and future work.

2. APPLICATION - ROBUST FACE RECOGNITION

In temporarily enhanced security situations, a wireless constructed security system is more flexible and cost effective by designing a communication network that adapts to the environment and the sensors. This paper takes face recognition system as an example of such security systems.

A temporary face recognition system can be set up easily by placing a camera near the region of interest and transmitting the data by wireless channel to the processing center placed at convenience. Data that is either the full image or representative coefficients, need to be transmitted with high fidelity to the remote processing center, where the face recognition database is stored. Former work [24] shows that the wavelet transform is more robust to transmission loss, so the data in transmission is preferred to be the wavelet coefficients rather than the original image. In this paper, the contourlet transform is experimentally shown to be able to further decrease the mean square error from the wavelet transform, and their performance is tabulated.

Figure 1 illustrates the routing of image coefficients to construct a robust face recognition by a wireless sensor network. The message is transmitted from the start node, denoted by a circle attached with a camera icon, to the destination node marked as "DataBase". The active sensor nodes are denoted by dotted orange circles and inactive nodes are denoted by blue circles with vertical stripes. The green lines show the actual route taken by the swarm agent. The dotted red lines show the alternative route that the agent could have taken. The swarm agents travel through the route with less load, energy consumption, and transmission error. The selected route is evident to be shorter and more efficient. The data collected at the destination is processed and the acceptance or rejection decision is made.

Within the camera sensor near the region of interest there's a small chip for image compression and preliminary face tracking. The chip includes a small buffer to store the raw image in case a finer raw image is needed later on. By discrete wavelet transform or contourlet transform, a coarser image at a lower resolution can be produced to locate a face with less computation resources and to transmit the coarse face to the face recognition system with less bandwidth and energy. Once the face recognition system determines that there's a possible target, it will require the camera to send in the finer raw image and scrutinize it in more detail.

For data coding efficiency, the coarse scale image is derived by wavelet decomposition or contourlet transform. The coarser image is lossy by zeroing out the detailing coefficients. If all coefficients are used in reconstruction, the reconstructed image is lossless. But the bandwidth requirement increases from coarse scale to fine scale since the finer scale image needs more nonzero coefficients to represent it. The detailing coefficients are usually very small and dense near zero; entropy coding is very efficient in representing them. This improves the efficiency of transmitting the encoded coefficients describing the facial details as well. This kind of architecture increases the speed, and efficiency with reduced energy consumption and transmission error. In eigenface classification system, the basis vectors are stored in the destination node to compare with the reconstructed face based on received coefficients. If the transmission network can maintain the speed and efficiency of the system, then the face recognition system is robust in nature. In the next section, choosing an efficient algorithm for communication routing is discussed

3. SWARM INTELLIGENCE

Evolutionary algorithms (EA) are formulated based on phenomena found in nature. There are many algorithms available for routing optimization such as genetic algorithm, simulated annealing[10, 11], travelling salesman[12], asymmetric travelling salesman, swarm intelligence[14, 15, 16, 17, 18] and others. An evolutionary algorithm may not always result in a global solution. Each algorithm possess its advantages and trade-offs related to adaptive routing. Optimality and reachability are the two important factors in choosing an appropriate algorithm.

Swarm intelligence, is the collective behavior of a group of social insects, namely the ants, bees, birds, etc. Ant system and particle swarm optimization (PSO) [19 20,21] are algorithms that evolved from swarm intelligence. In Ant system, our algorithm of choice, the agents [swarms] in the system communicate interactively either directly or indirectly in a distributed problem solving manner to achieve an optimal solution. The choice of algorithm is not limited to performance only but also on its processing time. A trade-off between the factors affecting overall performance of a system is application dependent

G'omez in [28] provides reasons for the success of Ant Colony Optimization (ACO) in comparison to GAs on the Travelling Salesman Problem (TSP) benchmark problem, The TSP solution space has a globally convex structure [29]. The presence of one dominant solution in GA results in a behavior like a single point search algorithm. GAs can easily produce a local solution rather than a global solution. Therefore when multiple solutions dominate a particular problem's population, the reduced diversity of GA may result in an errored solution. Thus, GA falls short in situations like this where ACO, using positive correlation approaches where promising solution is located, may easily succeed.

"The Job Shop Scheduling Problem (JSSP) is a strongly NP-hard problem of combinatorial optimization and one of the best-known machine scheduling problem"[30]. The job shop scheduling problem can be represented with a disjunctive graph [31]. A disjunctive graph G=(N, A, E) is defined as follows: N is the set of nodes representing all operations, A is the set of arcs connecting consecutive operations of the same job, and E is the set of disjunctive arcs connecting operations to be processed by the same machine.

Moraglio et al in [31] applied an hybrid algorithm (GTS) combining Genetic Algorithms and Tabu Search for solving JSSP. The Genetic Local Search scheme has been used to hybridize the GA with an effective TS algorithm for JSSP. The experimental results of this approach show that on large size problem GA falls short. GAs are far more profitably hybridized with Tabu search than with Simulated Annealing(SA) as in terms of time required and solution quality a difference of one order of magnitude was achieved.

Table I summarizes performance comparisons of the algorithms, the GA requires 71 generations to obtain the optimal distance for the problem with 5.9715seconds CPU time, whereas the AS obtained the optimal result in 3.4140secs without exhibiting any stagnation behavior unlike SA algorithm. AS is best suited for solving any discrete problems, for continuos solution space another EA called Particle Swarm Optimization (PSO) works best. A combination of AS and PSO giving a hybrid algorithm can be used to solve any kind of NP hard problems.

TABLE I.OVER ALL PERFORMANCE OF ANT SYSTEM IN BENCHMARK PROBLEM

Algorithm	CPU Time (In secs)	# of Generations	Optimal Distance
Genetic Algorithm	5.9715	71	2.8865
Simulated Annealing	3.4140	30	2.015
Ant System	12.5014	112	4.9203

The advantages of using Evolutionary algorithms are, the population is searched in a parallel manner and not in an one-one basis. They do not require any derivative information or any auxiliary knowledge only the objective function and the fitness level for performing a directive search is required. It uses only probabilistic transition rules, not deterministic ones. Therefore, EAs are generally more straightforward to apply and also they can provide a number of potential solutions to a given problem. They could lead to a pre-mature solution too, but its up to the user to define the fitness function in a way to obtain a global optima rather than a local optima.

4. ANT SYSTEM

The ant agents are designed based on their real life characteristics. Figure 2 illustrates an example of how the agents find different routes to reach their final destination (food). In sub-figure (a) the ant agents travel to their destination without any obstacles. But once a obstacle is introduced in part (b), there are two ways to go around the obstacle. Few agents try to travel the long route and the others using shortest obstacle route. As time passes by, the pheromone deposition over one route increases over time and this becomes the frequently used route as shown in part (c). The ants are blind yet they use a chemical substance called 'pheromone' which helps them in sensing its neighbors movements.

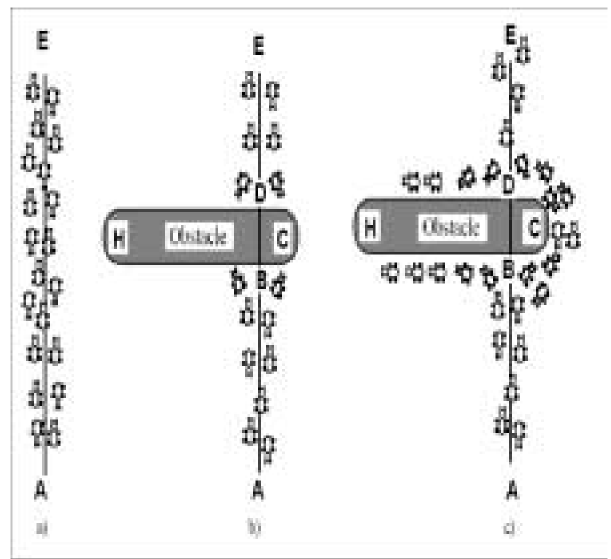

Fig. 2. Ants in real life [14]

The agents move towards an optimal solution by sharing their knowledge among neighbors. The initial set of agents traverse through the nodes in a random manner. and once they reach their destinations they leave trails by depositing pheromones on the sensor nodes, a means of communicating with the other ants, that traverse the system to determine appropriate route.

The level of pheromone accumulation is directly proportional to the number of agents traversed through the same path with respect to the time taken. The pheromone evaporation plays an important role in keeping the current state of the route with respect to the time. Thus by determining the amount of pheromones left by the ants, which in turn shows the optimal route taken by recent agents, the current agent's probability of choosing the same route is higher. In this manner, the group behavior leads to an optimal solution in a network, where time is an important constraint.

There are three different kinds of swarm (ant) agents which performs functions like allocating, sensing and de-allocating the sensed values, which make the system flexible. These learning features allow the system to be more robust, decentralized and intelligent.

In the sensor network, the agents function in order to minimize the energy and also keep track of the network requirements. The allocator ants are responsible for allocating the resources required by the network and monitors the allocation process among active network links. The sensing agent’s function is to traverse the network and communicate with its neighbors to reach the destination using an optimal route. The deallocator ant agents are responsible for deallocating trails laid by sensing agents and the sensed values. These agents ensure optimal route to the destination using limited resources and also learning the network environment. In the initial stages computational tasks are high but once after the agents learn to adapt to the network the computational time, costs and the tasks involved are minimized drastically.

5. WIRELESS FACE RECOGNITION SYSTEM

Face Recognition, as one of the non-intrusive, non-contact biometric identification methods, has developed rapidly since early 1990's, and is gradually being accepted by the general public. The appearance-based methods take the 2D images as inputs, and make certain transformations to find the features.

The common diagram for face recognition systems is shown in Figure 3. In enrollment, the images of the registered users are processed into templates of caricatures by the specific algorithms of the face recognition system, and these templates are stored. The templates can be regarded as the transformed user images encoded by the corresponding processing techniques. The processing techniques and the templates are adjusted, concurrently.

In verification or identification, the face recognition system receives a new image, defines and stores the new image by the same algorithm, and compares to the templates. The decision process may incorporate all kinds of classifiers. If the classifier is a learning algorithm and its structure needs to be trained such as the neural network or bayesian network, the enrollment database may be split into two parts, one for constructing the templates, and one for learning the classifier structure. Appearance-based face recognition algorithms, derived from PCA or LDA and their variants, have gained great success in modern face recognition systems, and they can be unified in a single framework for clear comparison.

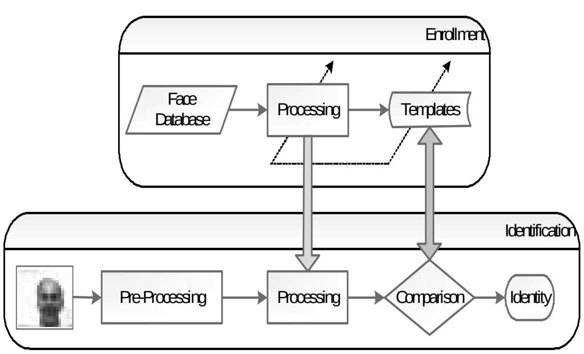

Fig. 3. General Diagram of Face Recognition System

A face recognition system gains flexibility and efficiency through wireless configuration. Our goal is to make the wireless face recognition system as robust as a wired one. This paper discusses what kind of configuration is suitable for the wireless setup in the sense of mean square error of reconstructed images after the wireless transmission; Further, the transmission properties also dictates what kind of face recognition algorithms are more suitable for a wireless face recognition system. Development in the face recognition algorithms helps improve the performance of the wireless system as well.

Face recognition systems usually have a centralized processing unit, and the flexibility can be gained by placing remote image acquisition devices or remote template database. A wireless face recognition system replaces the image transmission channel in Figure 3 by a wireless channel, which introduces bit errors from the channel fading etc.

6. APPROACH - ROBUST FACE RECOGNITION BY WIRELESS SENSOR NETWORK

Former work[24] shows that the contourlet transform is quite competitive to the wavelet transform for facial images. Despite of the coding techniques to combat the fading in wireless communications, the wireless channels can not be error-proof, and a specialized transmission scheme designed for the face recognition system is discussed here by the ant system.

In wireless sensor network, the nodes are deployed randomly on a two-dimensional plane. The sensor network is spread with ant agents in a random manner across the nodes to speed up the search process. The distance between the sensor nodes is evaluated based on euclidean metric as in (1)

$$D_{xy} = \sqrt{(X1 - X2)^2 + (Y1 - Y2)^2} \quad \textbf{(1)}$$

The ant agents accumulate pheromones as they traverse through the nodes, hence the distance travelled by the agents is one of the critical parameter’s that needs to be considered while depositing the trails. The pheromone is updated upon completing a tour by every agent and is given by,

$$\psi_{ij}(t) = \rho(\psi_{ij}(t-1)) + \frac{Q}{D_t \cdot E_t \cdot BER_t \cdot Link_t \cdot Hop_t} \quad \textbf{(2)}$$

where Dt is the total distance of the current tour of the agent.

The link status, hops and BER in a tour taken by an agent is incorporated in the pheromone (2). Thus the trails formed by the ant agent is now dependent on both the physical and MAC layer of a network. The Partially ordered sets (POSets) [8] or a user could weigh the performance factors.

In our face recognition system application, the primary goal is to attain less BER value with minimal energy, hence these two factors are weighed more than the number of hops, link status and distance. The wireless channel assumed here is Rayleigh flat and slow fading.

In the face recognition center, there is a “snapshot” for each stored face feature, which is a coarse scale faceprint in eigenface space. The face image is first segmented from the received image, and then it's transformed into the eigenface space for comparison with the snapshots. A similarity score is computed by finding the difference between the current face’s eigenface coefficients and the stored face’s eigenface coefficients. The similarity score of the coarse scale image is reconstructed from the prominent approximation coefficients. Once it reaches above a certain threshold, a further comparison with the finer scale image is demanded. The finer-scale similarity score is therefore computed and it's compared with a slightly higher threshold to make a final decision on whether this face belongs to a person to deny access to (on the blacklist).

Using the (3) (ACS - see [14, 15, 16]), transition probability for the pheromone is calculated. where Q (arbitrary parameter), ρ (which controls trail memory of the ant system), α (used in probability function for pheromone deposited by the ants), β (used to weight distance in probability function) and η the performance factor as varying parameters of the swarm agents. The transition probability in the ant system includes an objective function, which is influenced by weights reflecting the objective's importance to the system. The weights on each of the performance parameters greatly affects the decisions made by ant system.

$$P_{xy} = \frac{(\Psi_{xy} \cdot \Gamma_{xy})^{\alpha} \cdot (\eta_{xy})^{\beta}}{\sum_{k} (\Psi_{xk} \cdot \Gamma_{xk})^{\alpha} \cdot (\eta_{xk})^{\beta}} \qquad (3)$$

Γ_{xy} is the priority given to coefficients. By wavelet decomposition, the image is transformed to approximation coefficients and detailing coefficients in several levels. The higher the level, the more influence of the coefficients on the reconstruction. Therefore for the high level coefficients, the priority is set to high; similarly for medium and low level coefficients, the priority is set to medium and low respectively.

The performance factor plays a key role for the path selection by the agent. An additional factor Pe, which, is the bit error rate for the corresponding signal to noise ratio (SNR) value is added to the transition probability, P_{xy}. Formulation of (3) shows that the physical layer factors are important in making routing decision for the network layer. Figure 4 provides the pseudo code of ant system in the wireless face recognition system.

```
Initilization of AS parameters
  Initialization of N/w
   for each node
     Generate arrival time
    for each ant
      for each hop
       next node = select (node, destn node, tabu-list,p
       if msg_priority = high
           break;
      elseif msg_priority = medium
       if msg_atnode > msg_received
          put msg_on_stack
         else
           break;
        end if
        else
       put msg_on_stack;
      end if
     lay pheromones
   end for loop (hop)
  update pheromone deposition, transition probabili
 end for loop (ant agent)
 update tabu-list
end for loop (node)
```

Fig. 4. Pseudo code - Ant System Algorithm

Once the network is set up, the ant agents are randomly placed on the network with their initial parameters configured to default settings. The simulation is performed for a defined number of iterations or unless a global optimal is reached.

Energy, distance, BER, and the number of hops determines the performance of the network. Hence, these factors need to be normalized using the weights. The normalized energy E_{norm} is defined as dividing the difference between actual and required energy (a threshold, beyond which the node becomes inefficient) by the actual energy. Similarly the normalized distance D_{norm} is defined as dividing the difference between the actual distance (normal route by traversing all the route) and the required distance (distance taken by taking shortest route) by the actual distance. The normalized number of hops H_{norm} is defined as dividing the difference between the actual hops (total number of nodes, using TSP rule) and required hop (user specified) by the actual hops. And finally the normalized BER, BER_{norm}, is defined as dividing the difference between the required BER (typical BER of wireless system, 10^{-4}) and simulated BER in bits/sec (given in (4)) by the simulated BER. W_i is the weight with respect to the node and M is the number of factors used in the network.

$$\eta_{ij} = \sum_{i=1}^{M} \left[(W_i) \cdot \left(\frac{E_{actual} - E_{required}}{E_{actual}} \right) \right] + \dots \qquad (4)$$
$$\left[(W_i) \cdot \left(\frac{D_{actual} - D_{required}}{D_{actual}} \right) \right] + \left[(W_i) \cdot \left(\frac{H_{actual} - H_{required}}{H_{actual}} \right) \right]$$
$$\left[(W_i) \cdot \left(\frac{BER_{actual} - BER_{required}}{BER_{actual}} \right) \right]$$

The tabu list consists of updated values of the average energy, BER, distance travelled and the response time. R_t is defined in (5) for the particular sub-optimal route with high reachability.

$$R_t = \text{No of Hops} \times P_t \times Msg_t \qquad (5)$$

where P_t is the fixed processing time and Msg_t is the time taken for traversing the message.

The sensor nodes that are inefficient (node which dissipates energy greater than a desirable threshold) are neglected by taking an alternate route. Thus the network is kept functional even if some individual sensors fail.

Given an efficient transmission scheme by the ant system, further improvement on the facial image transmission can be achieved by constructing a practical transform. Three schemes are evaluated on their performance in a wireless face recognition system: in the raw format, in compressed transforms by wavelets, or by contourlets. The transformed coefficients have different importance levels when reconstructing the images. Therefore, different priority levels can be specified to coefficients with different importance levels. An ant system is utilized to realize such customized and automatic priority adjustment.

The contourlet coefficients are transmitted through the wireless channel as shown in Figure 5: the parallelogram represents the shearing operator, the quincunx represents the vertical or horizontal filter, and the circle with Q inside represents downsampling or upsampling. The left half is to expand the image by the contourlet transform and the right half is the reconstruction. In multi-resolution analysis, such process can be done iteratively to realize the multi-scale and multi-direction expansion or reconstruction. The contourlet coefficients are transmitted through the wireless channel for reconstruction later on.

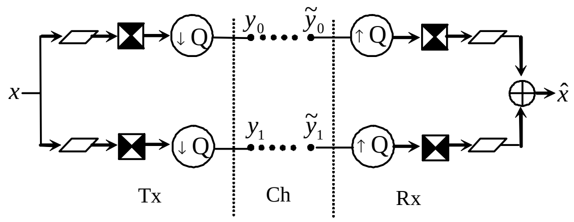

Fig. 5. Contourlet transform used in wireless image

The wavelet coefficients are transmitted similarly as the contourlet coefficients. Only the processing techniques are different for these two compression methods.

The left part of Figure 5 is implemented in the transmission, transmitter (Tx) or start node and the right part is implemented at the receiver (Rx) or the destination node. The messages pass through the fading channel (Ch) while communicating between sensor nodes on the route until it reaches the destination.

The Channel is Raylaigh faded as in common wireless systems as shown in Figure 6, where the signal is distorted by the fading and contaminated by the AWGN noise.

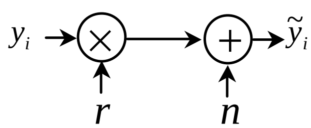

Fig. 6. Wireless Channel Model

After the transmission, the data (either coefficients or original images) are thresholded by Stein's thresholding method [25] as shown in Figure 7, where the input is shown along the x axis, and the thresholded result is shown along the y axis. Stein's thresholding method nulls the small coefficients, which are very commonly caused by the noise, and it preserves the actual values of the big coefficients without distortion.

(6)

$$\gamma_j = (1 - t\sigma / |\hat{\alpha}_j(x)|^2)_+$$

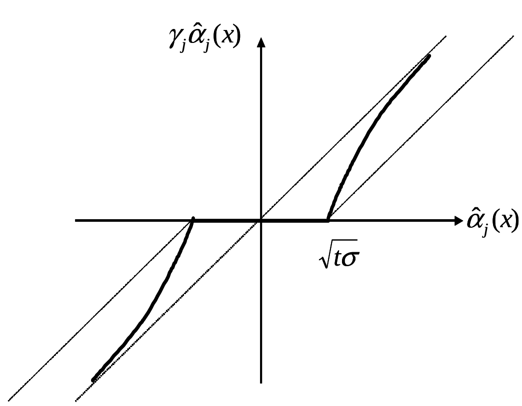

Fig. 7. Stein's Thresholding

In the receiver end, the image could be reconstructed directly from the received coefficients, but the reconstruction suffers from channel distortion. If the received coefficients are hard thresholded or processed by other more delicate denoising schemes, the reconstructed image is denoised and it will be a better estimate of the true image.

The training face images are used to derive the eigenface [26] or LDA-faces [27] as the basis of the feature space. Different users span a sphere in this feature space, and the probing images are transformed into the feature space to compare with the known users.

In eigenface method, the face images are vectorized and the covariance matrix is denoted as Σ, then the eigenface features Φ are the principle components of Σ as illustrated below:

(7)

$$\Phi_{Eigenface} = arg\max_{\Phi} \Phi^T \Sigma \Phi$$

In LDA method, the within class scatter S_w and the between class scatter S_b are first calculated, then the LDA features are derived as following

(8)

$$S_w = \sum_{i=1}^{c} \sum_{j=1}^{n_i} (a_{i,j} - \mu_i)(a_{i,j} - \mu_i)^T$$

(9)

$$S_b = \sum_{i=1}^{c} n_i \cdot (\mu_i - \mu) \cdot (\mu_i - \mu)^T$$

(10)

$$\Phi_{LDA} = arg\max_{\Phi} \frac{\Phi^T S_b \Phi}{\Phi^T S_w \Phi}$$

where c is the number of classes, or users; n_i is the number of available face images for the ith user; $a_{i,j}$ is the jth image of the ith user; μ_i is the mean of the ith user; μ is the group mean for all users.

The flow of the algorithm from the transmitter to the receiver end is explained in detail in Figure 8 . The image sensed by the camera at the transmitter end is processed depending on the bandwidth and power available for pre-processing. Three different methods (wavelet compression, contourlet compression and raw-image) are compared to see which one works best in the wireless transmission system. After the pre-processing stage the data is communicated to the destination node using the ant agents as described in Figure 4 . The performance parameters on the agents decides the priorities of the messages that needs to be transmitted. In raw image the priorities are uniformly distributed, whereas in wavelet and contourlet images coefficients are set to high, medium and low priorities depending on their importance. In contourlet and wavelet transform, the lower-band coefficients are bigger and more important in preserving the shapes and outlines of the face images, which are useful in face recognition; whereas, the higher-band coefficients are prone to noise contamination and may obscure the intrinsic features for face recognition. At the receiver end, the image is reconstructed and is compared against the database for verification. The performance of three different methods is stored and compared.

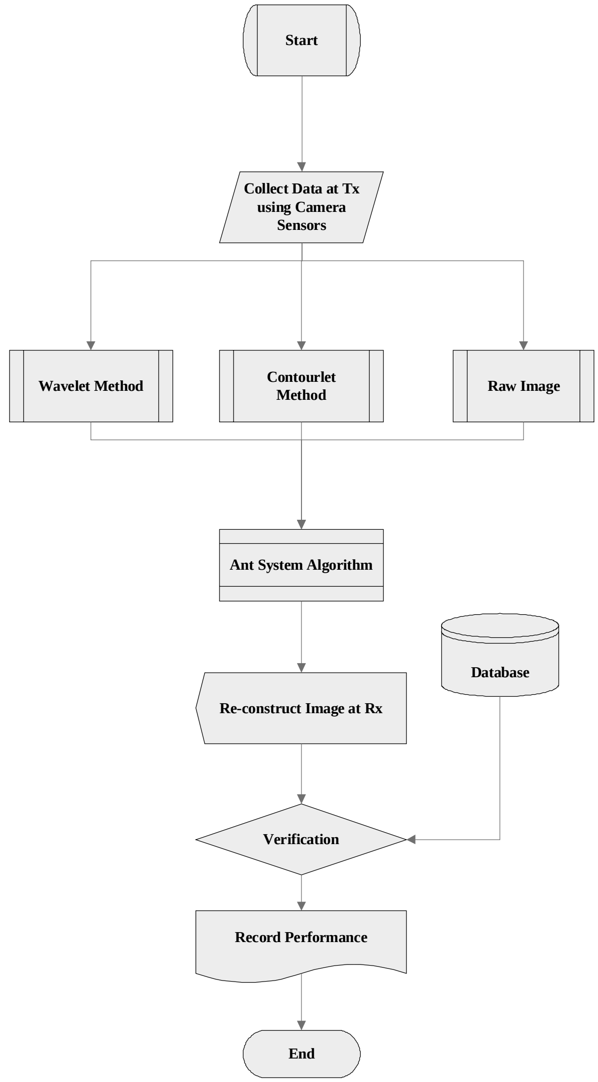

Fig. 8. Flowchart - Wireless FRS

7. SIMULATION RESULTS

A sensor network with 16 nodes is considered in this simulation run. Agents are randomly placed on the nodes. It is evident that more ant agents leads to less computation time and higher performance. To ensure fairness, the network consists of equal number of agents and nodes. The total hops for all simulations is assumed to be the same as the number of nodes in the network, that is 16. The actual number of hops is user defined, which varies depending on the problem assigned.

The predicted BER (bits/sec), energy and distance helps in making a decision whether the nodes in the current route are capable of communicating with its peers on the next iteration. The memory of the sensor nodes are very limited hence, the messages are limited to 10 per stack.

The performance of prioritized transmission is evaluated by the mean square error of the reconstructed images. The performance is averaged over 1000 trials. The performance of coefficients v.s. original images is evaluate by the face recognition rate based on the distorted coefficients and images with manually added error, where the BER is ensured by the ant system transmission. After the transmission, the data (either coefficients or original images) are thresholded by Stein's thresholding method [25] for denoising.

Table II lists the mean square error of the reconstructed images with or without the prioritization setup. It also compares the contourlet compression and the wavelet compression. The result shows that the contourlet compression is quite competitive to the wavelet compression, and it's slightly better in both cases. Meanwhile, the prioritization of the coefficients realized by the ant system can decrease the MSE in both cases.

TABLE II.MSE COMPARISON OF THE COEFFICIENTS TRANSMISSION WITH OR WITHOUT PRIORITIZATION

	Prioritization	With	Without
Coefficients	Contourlets	4.1349	4.3653
	Wavelets	4.7108	4.9863

Table III lists the rank-1 face recognition rates based on different transmission schemes. The transmission of coefficients, either contourlets or wavelets, is more robust than transmitting the original images, because the compression compacts the information in fewer coefficients, and less prone to channel error; meanwhile, the prioritization preserves the most important information more accurately, and it can improve the performance further. What's more, comparing the effect of contourlet compression and the wavelet compression on the face recognition, the two schemes are again comparable, and the contourlets scheme is slightly more robust.

TABLE III.**RANK-1 FACE RECOGNITION RATES BASED ON THE TRANSMITTED COEFFICIENTS AND IMAGES**

Contourlets		Wavelets		Image
With Prioritization	Without	With Prioritization	Without	
91.7949%	90.2564%	91.2821%	89.7436%	89.2308%

Figure 9 shows the BER of DSSS-BPSK model for image coefficients with three different priority levels. The normalized BER for high priority coefficients is given by red circles, the normalized BER for the medium priority coefficients is denoted by yellow '+' and the normalized BER for the low priority coefficients is denoted by green '*' symbols respectively.

The BER achieved for high priority coefficients is much less compared to messages of low priority coefficients. Therefore the limited network resources are allocated more on the more important data and less distortion is exerted on the original message by channel.

After the analysis of the data transmission in the wireless sensor network, Figure 10 shows the classification performance of the face recognition system based on the transmitted wavelet coefficients. The contourlet coefficients achieve the same performance as the wavelet coefficients, therefore the curve is not shown.

In the traditional wired face recognition system, the data transmission is expected to be more reliable than the wireless transmission, and the 1st ranking face detection rate based on eigenface method is 94%. This paper proposes to use a wireless sensor network for data transmission to make the face recognition system more flexible in watching the dynamic region of interest, in the specific deployment of devices, and in sharing the face database. But with the extra link of wireless fading channel, the imperfect data transmission is lowering the 1st ranking detection rate down to 88% as shown by the blue dashed line in Figure 10.

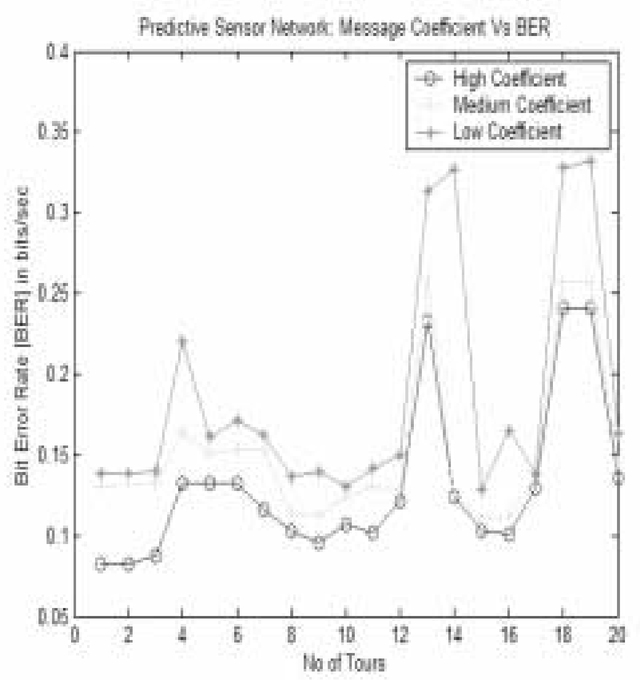

Fig. 9.   BER v.s. Msg Coefficient: Routing in WFRS

However, if the contourlet or wavelet coding is first implemented to transform the image into coefficients to assign different priorities in transmission, more channel source is allocated to the more important data, and final 1st ranking detection rate can be still maintained at 94% as shown by the red solid line in Figure 10.

The face recognition system provides not only the rank-1 candidate, but also other lower-rank possible identities. This property is useful for pre-screening and multiple combination with other modalities.

8. CONCLUSION AND FUTURE WORK

This paper proposes to use the ant system for routing the contourlet or wavelet coefficients of the face images to the processing center with minimum energy consumption and reliable transmission, thus the performance of the wireless face recognition system achieves 94% accuracy, the same performance of a wired system, with a short response time. Meanwhile, the wireless channel make the face recognition system more flexible, more efficient and still robust. Jamming attacks can make a sensor unsuitable for any kind of transmission, hence choosing FHSS and DSSS helps in avoiding denial of service attacks (DoS) to an extend.

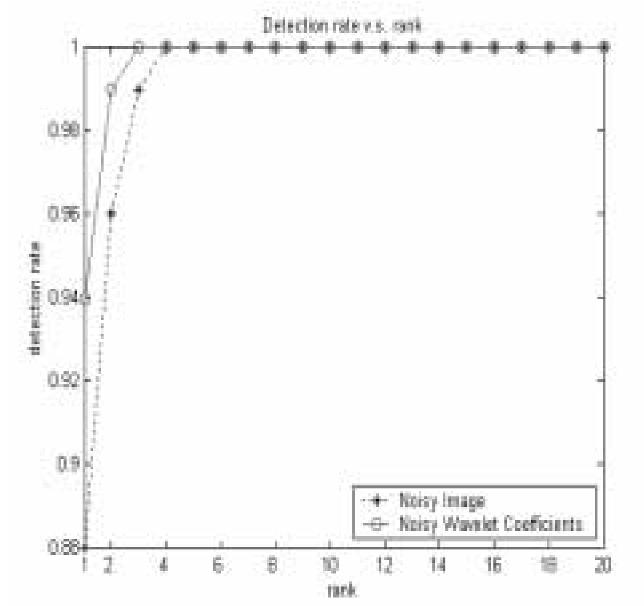

Fig. 10. Face Detection Rate v.s. Ranking

In the future, diversity schemes can be used for higher transmission accuracy. A combination of artificial intelligence and evolutionary algorithm increases the performance of the system. Hence, Bayesian network could be introduced to enhance the learning ability of the ant system. The sensor nodes considered here are assumed to be under a secure environment, which is not true in reality. Secure transmission of messages under worm hole and sybil attack[32] need to be considered as future work. Knowledge of different jammers and predicting the attacks keeps the network efficient and reliable. This security feature will also be added to the Wireless Face Recognition System, making the network secure, reliable and efficient.

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