Robust Face Recognition System Constructed by 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 is used to optimize routing in distributed time varying network. In this paper, swarm intelligence maintains the required BER for varied channel conditions while consuming minimal energy. A specific biometric, the face recognition, 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. Therefore 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

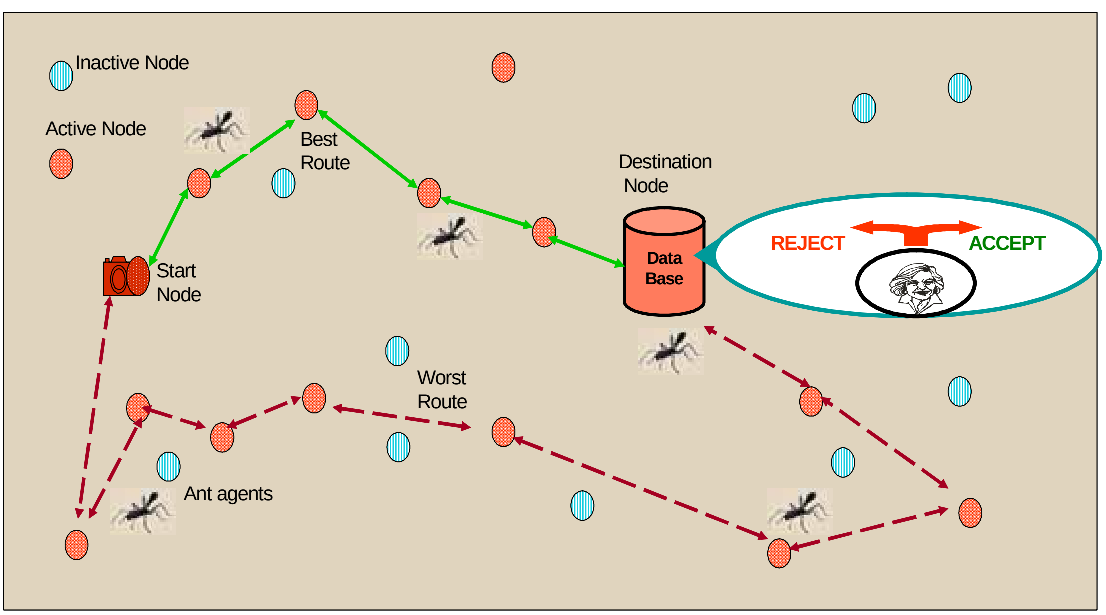

Fig. 1. Face Recognition System Using Wireless Sensor Network For Data Transmission.

by constraints. These transmissions may require a single or multi hop wireless sensor network depending on the communication ranges and transmission powers. 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, QoS [Quality of Service], 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 (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 swarm intelligence, 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. The fourth section discusses the mathematical formulation of the application in detail. Simulation results in fifth section gives an insight of the robustness of the face recognition system connected by wireless sensor network. The paper concludes with the sixth section 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.

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, 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. 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

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.

4. APPROACH - ROBUST FACE RECOGNITION BY WIRELESS SENSOR NETWORK

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)

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

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,

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

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.

$$P_{xy} = \frac{(\Psi_{xy} \cdot \Gamma_{xy})^{\alpha} \cdot (\eta_{xy})^{\beta}}{\sum_k (\Psi_{xk} \cdot \Gamma_{xk})^{\alpha} \cdot (\eta_{xk})^{\beta}} \quad (3)$$

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.

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.

$$\eta_{ij} = \sum_{i=1}^{M} \left[(W_i) \cdot \left(\frac{E_{actual} - E_{required}}{E_{actual}} \right) \right] + \ldots \quad (4)$$

$$\left[(W_i) \cdot \left(\frac{D_{actual} - D_{required}}{D_{actual}} \right) \right] + \left[(W_i) \cdot \left(\frac{H_{actual} - H_{required}}{H_{actual}} \right) \right]$$

$$\left[(W_i) \cdot \left(\frac{BER_{actual} - BER_{required}}{BER_{actual}} \right) \right]$$

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.

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

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.

5. 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.

Former work [24] shows that the contourlet transform is quite competitive to the wavelet transform for facial images. This paper focuses on the wavelet transform for computation simplicity. The left part of Figure 2 is implemented in the

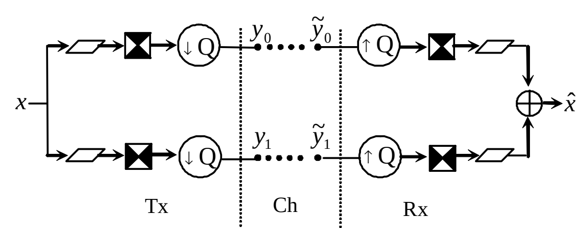

Fig. 2. Contourlet transform used in wireless image transmission.

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.

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.

Figure 3 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.

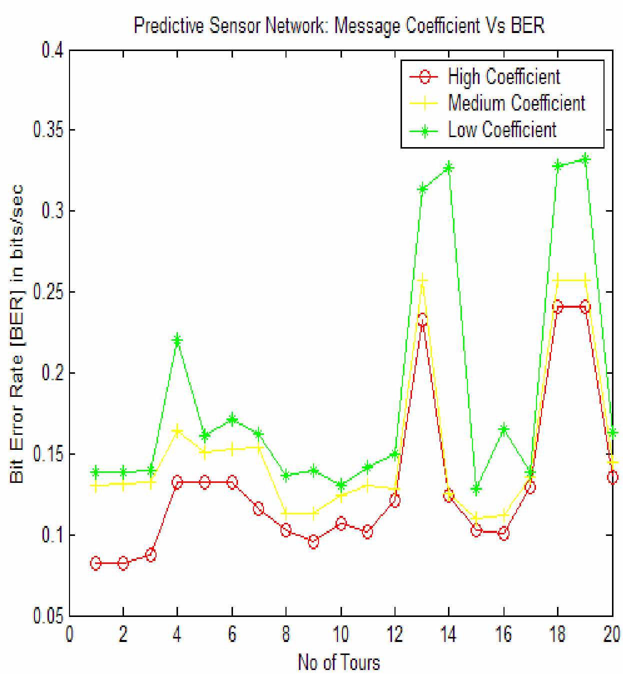

Fig. 3. BER Vs Msg Coeffcient: Routing in Predictive Sensor N/w

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 4 shows the classification performance of the face recognition system based on the transmitted wavelet coefficients.

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.

However, if the wavelet coding is first implemented to transform the image into wavelet 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 4.

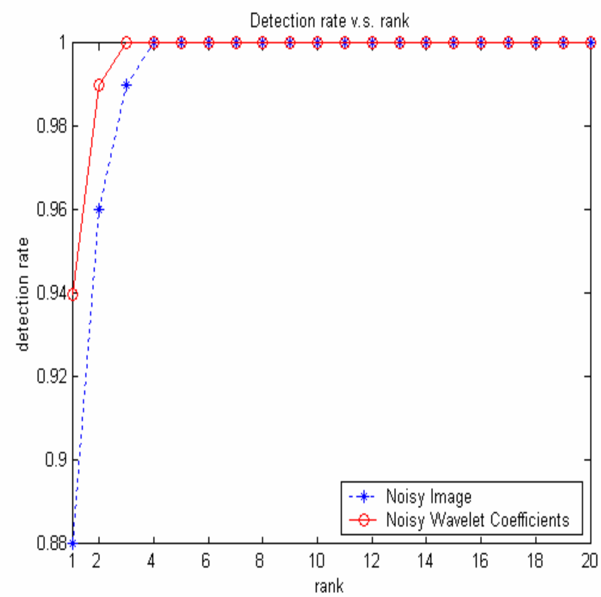

Fig. 4. Face Detection Rate v.s. Ranking

6. CONCLUSION AND FUTURE WORK

This paper proposes to use the ant system for routing the 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.

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 need to be considered as future work.

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