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Research Article

A Camera Nodes Correlation Model Based on 3D Sensing in Wireless Multimedia Sensor Networks

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In wireless multimedia sensor networks, multiple camera sensor nodes generally are used for gaining enhanced observations of a certain area of interest. This brings on the visual information retrieved from adjacent camera nodes usually exhibits high levels of correlation. In this paper, first, based on the analysis of 3D directional sensing model of camera sensor nodes, a correlation model is proposed by measuring the intersection area of multiple camera nodes' field of views. In this model, there is a asymmetrical relationship of the correlation between two camera nodes. Then, to farthest eliminate the data redundancy and use the node collaboration characteristic of wireless (multimedia) sensor networks, two kinds of cluster structure, camera sensor nodes cluster, and common sensor nodes cluster are established to cooperate on image processing and transmission tasks. A set of experiments are performed to investigate the proposed correlation coefficient. Further simulations based on a sample of monitoring a crossing by three correlative camera nodes show that the proposed network topology and image fusion and transmission scheme released the pressure of camera node greatly and reduce the network energy consumption of communication of the whole network efficiently.

1. Introduction

The integration of low-power wireless networking technologies with inexpensive CMOS cameras and microphones is enabling the development of distributed networked systems referred to as wireless multimedia sensor networks (WMSNs) [1, 2]. The characteristics of WMSNs diverge considerably from traditional network paradigms such as the Internet and even from "scalar" sensor networks. The applications of WMSNs, such as a surveillance sensor network, environmental and industrial monitoring, intelligent traffic congestion control, health-care, and other multimedia digital entrainments, or green city applications, require the sensor network paradigm to be rethought in view of the need for mechanisms to deliver multimedia content with a predetermined level of quality of service (QoS).

Different from conventional sensor networks, WMSNs are characterized by high data rate and directional sensing range on account of multimedia nodes' field of views (FoVs). In a densely deployed WMSN, there exists correlation among the visual information observed by cameras with overlapped FoVs. These differences are calling for new approaches for sensor networking and in particular in network data processing for reduction of data redundancy. So in this paper, aiming at the issue of correlation relationship of multiple cameras, based on the analysis of 3D directional sensing model of camera sensor nodes, we present the correlation model among the camera sensor nodes and propose two kinds of cluster structure, camera sensor nodes cluster and common sensor nodes cluster to cooperate to accomplish image processing and transmission tasks in WMSNs.

The remainder of this paper is organized as follows. Section 2 discusses some previous works on correlation degree of camera nodes which motivated our work. Section 3 presents correlation model for multiple cameras, and the correlation calculate method of multiple camera nodes

based on the property of convex is proposed. Section 4 describes correlation-based hierarchical network structure and image processing and transmission scheme. The analysis of the correlation model and performance of the proposed framework are examined in Section 5. Finally conclusions and future work are derived in Section 6.

2. Related Works

There are lots of researches on correlation model of camera sensor nodes based on 2D camera sensing model. In [3], different from conventional sensing models where omnisensing area centers on the sensor node, a directional sensing model of camera sensor nodes is first employed. Meanwhile, the correlation degree of two cameras was defined as the portion of overlapped sensing areas to the entire area of the camera's FoVs. Then two sensors cooperate with each other, image processing scheme based on correlation is proposed. But this scheme is only valid when the sensing directions of the two sensors do not differ very much.

In [4], a spatial correlation model for visual information in WMSNs is proposed. Firstly, a spatial correlation function is derived to describe the correlation characteristics of visual information observed by cameras with overlapped FoVs. Then, by using this spatial correlation model, the correlation characteristics of visual information are obtained at low communication and computation costs. The shortcoming of this spatial correlation model is it just considers the angle between two cameras. But the offset angle of camera, which expresses the area of camera's FoVs, is not investigated, especially, when the offset angle of two cameras is unequivalent. In [5], based on the spatial correlation model put forward in [4], an information-theoretic data compression framework is proposed with the objective to maximize the overall compression of the visual information retrieved by a WMSN.

Papers [6, 7] show how multimedia nodes of a randomly deployed WMSN are categorized in clusters considering the FoVs as the criterion of clustering. If the FoVs of two nodes have a wide common area, sensors are grouped in a cluster since they obtain a similar vision of the monitored area. The established clusters in [6] are disjoint and nonoverlapping while in [7] they overlap each other with common nodes.

Considering the above mentioned, the correlation coefficient, or correlation degree of camera nodes based on overlapped FoVs is an important parameter to effectively divide the monitoring task between two sensors, for example, to calculate the joint entropy of multiple cameras, or to be the criterion of camera node clustering or hibernate redundant nodes, and so forth. And all the above correlation models are based on the cameras' FoVs model which is sector shaped. However, from the human eye's point of view, this simplified 2D FoVs model is reasonable, but it is not very suitable for CCD cameras in monitoring scenario in WMSNs. In practice, the imaging surface of a camera is generally a rectangle, but the shape of the human retina is much closer to a spherical surface. Objects within some range of distances (called depth of field or depth of focus) are in acceptable focus. The field of view of a camera is the portion of scene space that actually projects onto the retina of the camera. It is not defined by the focal length alone but also depends on the effective area of the retina, for example, the area of film that can be exposed in a photographic camera, or the area of the CCD sensor in a digital camera [8]. So to investigate the 3D perception model of camera node is very necessary.

In [9], since the 2D-based schemes cannot be easily extended to address the coverage issues in 3D directional sensor networks, a 3D directional sensor coverage-control model with tunable orientations is proposed to specify the actual target-detecting scene. Then, address the issue of coverage enhancement by sensors with tunable 3D orientations.

In [10], a 3D wireless multimedia sensor nodes coverage perception model with tunable tilt angle and deviation angle is designed. Through decomposing the 3D space problem to the two aspects of horizontal plane and vertical plane, which reduce the 3D problem to 2D ground. And tilt angle and deviate angle can be adjusted to change nodes' sensing direction, also particle swarm optimization is used to eliminate sensation overlapped area and blind spots, thus ultimate coverage performance of the wireless sensor network can be enhanced. In our prior work [11], based on the 3D wireless multimedia sensor nodes coverage perception model proposed in [10], a FoVs correlation model to describe the correlation characteristics for the images observed by multiple cameras with overlapping FoVs is proposed. Two algorithms, a grid-based and a relative position-based algorithm are devised to calculate the correlation coefficient of two cameras. Eight kinds of relative positions of two cameras's FoVs are shown. Then, a relative position-based approach is designed to calculate the correlation coefficient. The shortcoming of this paper is to use the proposed relative position-based approach, and all areas of cameras's FoVs must be equivalent. This is infeasible in practice.

In this paper, based on the analysis of the 3D directional sensor coverage-control model in [9], we study the correlation characteristics of camera nodes and utilize this correlation to cluster the camera nodes in WMSNs to achieve network energy conservation and prolong network lifetime.

3. Correlation Model for Multiple Cameras

3.1. 3D Sensing Model. In [9], the camera's 3D sensing model is located at a fixed 3D point and sensing direction 3D rotatable PTZ (Pan Tilt Zoom) camera. Figure 1 illustrates that 3D sensing model. This model is denoted by a 5-tuple $(P, \vec{D}, A, \alpha, \beta)$. Where P is the location (x, y, z) of the camera node in 3D space, $\vec{D}$ is the sensing orientation of the camera node, and $\vec{D} = (dx, dy, dz)$ is of unit length, where dx, dy, and dz are the components along x-axis, y-axis, and z-axis, respectively. $\vec{D}$ controls the orientation of the sensor node and can be seen as an angle for the origin of axes. To the original $\vec{D}$ in the actual scene, it is just to control the initial orientation of the camera, and it could be represented by the angle θ. γ is the value of the tilt angle γ; α and β are the horizontal and vertical offset angles of the field of view around $\vec{D}$.

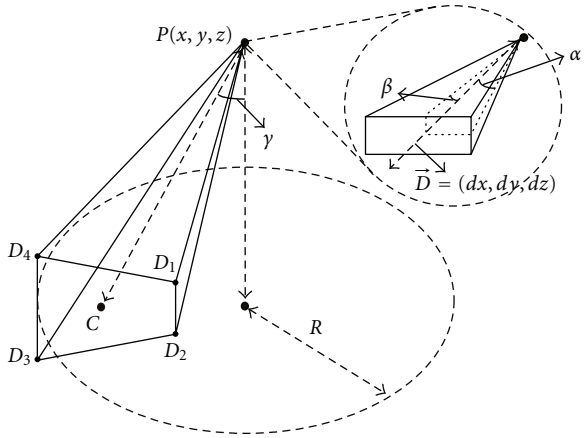

Figure 1: The 3D directional sensing model.

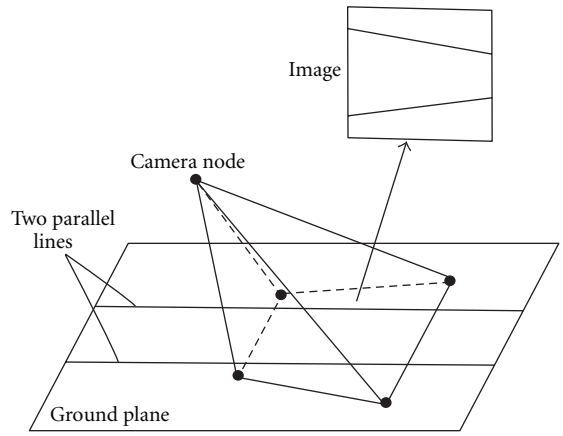

Figure 2: The projection of two parallel lines in image.

Through analyzing this camera node 3D sensing model, we can find that the FoVs of wireless camera sensor nodes is trapezium-shaped. Meanwhile, when $\vec{D}$ is represented by the angle θ, based on our priori work [10], the four vertexes in this trapezium can be calculated by:

$$\begin{aligned} D_1 &: (x + d_1 \times \cos(\theta + \alpha), y + d_1 \times \sin(\theta + \alpha)), \\ D_2 &: (x + d_1 \times \cos(\theta - \alpha), y + d_1 \times \sin(\theta - \alpha)), \\ D_3 &: (x + d_2 \times \cos(\theta - \alpha), y + d_2 \times \sin(\theta - \alpha)), \\ D_4 &: (x + d_2 \times \cos(\theta + \alpha), y + d_2 \times \sin(\theta + \alpha)), \end{aligned} \tag{1}$$

where d_1 and d_2 are calculated as

$$\begin{aligned} d_1 &= z \times \tan(\gamma - \beta), \\ d_2 &= z \times \tan(\gamma + \beta). \end{aligned} \tag{2}$$

In practice, when two parallel lines in the ground plane are taken picture by a camera, the projections of these two parallel lines lying in the image plane will converge on a point in infinity far away. Figure 2 simply illustrates the projection of two parallel lines in the image plane. This is why based on camera 3D sensing model, camera's FoVs is trapezium-shaped.

3.2. Correlation Coefficient. In WMSNs, multiple camera sensors are deployed to provide multiple views, multiple resolutions, and enhanced observations of the environment, meanwhile, they are always deployed in a field of interest, so the cameras' FoVs may overlap with each other. A camera can only observe the objects within its FoV. The observed images from cameras with overlapped FoVs are correlated with each other. For two arbitrary camera sensors C_i and C_j with FoVs F_i and F_j, suppose at a same time, their observed images are X_i and X_j, respectively. X_i and X_j are correlated when F_i and F_j overlap with each other. The definition of correlation coefficient between two cameras is given as below.

Definition 1 (correlation coefficient). Given the sensing areas of camera nodes C_i and C_j with FoVs F_i and F_j as Area(F_i) and Area(F_i), the correlation degree of X_j to X_i denoted by $\rho_{i,j}$, and the correlation degree of X_i to X_j denoted by ρ_{ji}, respectively are defined as

$$\begin{aligned} \rho_{ij} &= \frac{\text{Area}(F_i) \cap \text{Area}\left(F_j\right)}{\text{Area}(F_i)}, \\ \rho_{ji} &= \frac{\text{Area}(F_i) \cap \text{Area}\left(F_j\right)}{\text{Area}\left(F_j\right)}. \end{aligned} \tag{3}$$

Different from the correlation degree model of two cameras proposed in [3, 4, 6, 11]. In this paper, in most cases, ρ_{ij} is unequal to ρ_{ji} in (3). This is because when a WMSN is initially deployed, in order to gain better surveillance quality of service, lots of coverage-enhancing methods, for example, simulated annealing algorithm [9], particle swarm optimization [10], are used to change sensing orientation and adjust the tilt angle of camera. After network optimization, the area of each camera node's FoVs will be not always equivalent.

From Section 3.1, we know that a 3D space sensor node has trapezium-shaped FoVs in the ground plane. And those four vertexes in trapezium can be calculated by (1). Through this processing, the problem of the overlapping FoVs of two cameras has been formulated as determining the intersection polygon of two polygons in plane geometry. Once the area of the FoV of camera and intersection area of the FoVs of two cameras are calculated, we can get the correlation coefficient ρ of camera C_i and camera C_j in (3). To calculate the overlapping area of two arbitrary camera sensors, the simple and intuitive method is to divide the overall network area into small grids, then check for each grid if its center whether in the FoV of a camera [5] or assuming the sensing area of sensor is composed of discrete points, then examine every point therein and determine if it also falls in others' sensing areas [3]. The time complexity of these two methods is decided by the size of the grid or the number of discrete points. The better precision these two methods pursue, the higher complexity they increase. To remedy these deficiencies, in our priori work [11], a relative position-based approach was proposed to calculate the correlation of

```
(1) Get the FoVs of two cameras C_i, C_j are F_i, F_j, respectively. V_i and V_j are the sets
    of the four vertices of F_i and F_j, that is, V_i = {v_im | m = 1,2,3,4}, V_j = {v_jm | m = 1,2,3,4}.
    E_i and E_j are the sets of the four edges of F_i and F_j, that is, E_i = {e_in | n = 1,2,3,4},
    E_j = {e_jn | n = 1,2,3,4};
(2) Initialize the vertex set V = φ, the point of intersection of two edges v_e = φ;
(3) for m = 1 to 4 do
(4)     if v_im in F_j then
(5)         V = V ∪ v_im;
(6)     end
(7)     if v_jm in F_i then
(8)         V = V ∪ v_jm;
(9)     end
(10)    for n = 1 to 4 do
(11)        v_e = e_im ∩ e_jn;
(12)        if v_e ≠ φ then
(13)            V = V ∪ v_e;
(14)        end
(15)    end
(16) end
(17) V = Sort(V);
(18) The polygon P constructed by vertex set V is the intersection polygon of F_i and F_j;
(19) return ρ_{i,j} = (Area(F_i) ∩ Area(F_j))/Area(F_i), ρ_{j,i} = (Area(F_i) ∩ Area(F_j))/Area(F_j).
```

Algorithm 1: Correlation coefficient calculation.

multiple camera nodes, but the shortcoming of this approach is all area of cameras's FoVs must be equivalent. In this paper, we extend this approach to various sizes of the FoVs area of camera nodes in the following.

3.3. Correlation Coefficient Algorithm. In a WMSN, when some cameras are deployed and would not move anymore, these cameras are located in the variance height in 3D space, they maybe have different tilt angles γ, horizontal offset angles α, vertical angles β, and orientation of the camera angles θ. The trapezium area size of the camera's FoV is determined by the angle γ, α, β, and the height z of camera nodes. The angle θ just controls the main sensing orientation of the camera. But because every camera's FoV is project in the ground plane trapezium-shaped. As is known, trapezium is a kind of convex polygon, and the intersection of two arbitrary convex polygons still is convex polygon. So we can use the convex polygons knowledge of Computer Geometry to calculate the intersection area of two trapeziums.

Using the property of convex polygon, according to the position to calculate intersection of two trapeziums is feasible. The thought of this correlation coefficient calculate algorithm is as follows: first, judge the four vertices of a trapezium A whether located in another trapezium B. If it is true, add the vertex(s) that locate in B to a vertex set V, vice versa. Then calculate the point of intersection of the four edges in trapezium A with the four edges in trapezium B, respectively. Add the point of intersection to V. Finally, sort this vertex set V by clockwise or counterclockwise order. Now, the polygon constructed by arranged vertex set V is the intersection polygon of trapezium A and trapezium B. Algorithm 1 shows the pseudo code of correlation coefficient algorithm. From the details of this algorithm, we can obtain it has a processing time complexity of $O(1)$ per camera node.

4. Correlation-Based Clustering

The images observed by cameras with overlapped FoVs are correlated, thus leading to substantial redundancy in the network traffic. To remove such data redundancy, camera nodes can perform intercamera coding with each other by allowing a camera node to encode its image based on the reference of the image from another camera node, so that the coding rate could be reduced. The clustering strategy has been proved to be an effective way to improve network scalability and energy efficiency for sensor networks [12]. This strategy uses the hierarchical concept where the entire network is divided into regions. In many existing algorithms, the metrics for clustering are distance between nodes or node residual energy [13]. In this paper, we aim to construct clusters based on the correlation of cameras so as to minimize the redundancy of network traffic. We divide the entire network into different clustered regions. Each region corresponds to a cluster, in which a group of camera sensors collaboratively perform data processing.

4.1. Network Structure. In WMSNs, the multitier network architecture is recommended [1]. For example, many WMSN testbeds, such as the SensEye [14], adopt multitiered network topology, and it has been shown to improve energy efficiency. In this paper, we further investigate the collaborative visual information compression and transmission scheme in heterogeneous WMSNs. Two types of sensor nodes exist in our network: camera sensor nodes and common sensor nodes.

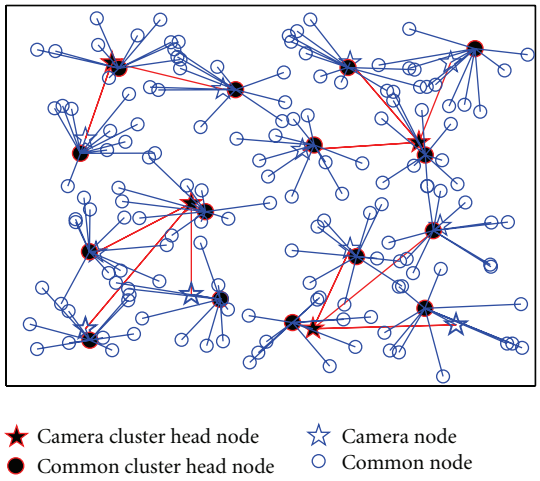

Figure 3: An example of the proposed network clustering architecture.

Camera nodes cluster based on the correlation, and common sensor nodes cluster around each camera node based on shorter distance. So there are two kinds of cluster structure in the network. The network model is illustrated in Figure 3. To construct this multitiered network topology, the following assumptions are made in first.

(1) The overall monitoring area is divided into some key regions, and more than one camera nodes are deployed to monitor a field of interest. The spatially proximal cameras could have highly overlapped FoVs, namely, some camera nodes would have correlation.

(2) There are lots of common sensor nodes randomly deployed around every camera sensor node. And the density of the common sensor nodes is sufficient for guaranteeing that every camera node in the wireless communication link connectivity within the adjacent region to the common sensor nodes is not empty.

(3) All the nodes in the network have a unique ID and the network is time synchronous.

4.2. Clustering Establishment. There are two manners to construct the hierarchical clusters, centralized and distributed. The thinking of the centralized manner is very intuitive. In centralized manner, there are always a central controller. It is sink node in WSNs or WMSNs in general. Sink node provides the full information of the network topology along with the detailed settings (e.g., location, various sensing parameters) for each camera. Sink node based on these information constructs the cluster and broadcasts the result to inform the role of each node.

However, in a large-scale distributed network like WMSN, the centralized operations have limited flexibility and scalability. Moreover, the energy constraint of sensor nodes prohibits network-wide information exchange. So, in this section, we will propose a distributed method that only needs local information exchange to accomplish nodes clustering.

Through network structure proposed in Section 4.1, we know that there are two kinds of clusters structure in the network. One kind is camera nodes cluster. The other kind is common nodes cluster. In the process of establishing the network architecture, we construct the camera node cluster firstly, then build every camera node's common nodes cluster.

In construction of the cluster of camera nodes, one camera node just needs to exchange its sensing parameters, for example, location, tilt angle γ, horizontal offset angles α, vertical angles β, and orientation angle θ to its neighbor camera nodes, which are located in its 1-hop communication range. It is a common assumption that the communication range is at least twice of the sensing range [15, 16], which is d_2 in (2). The details of the camera nodes clustering algorithm are presented in Algorithm 2.

Because one camera node just needs to exchange information with its relevant neighbor camera nodes, for each camera node to construct the cluster, it just needs to calculate the correlation coefficient between it and its neighbor camera nodes instead of all the camera nodes in the whole network. This manner can guarantee that the computational intensity would not increase considerably as the number of cameras goes up.

Once the cluster structure of camera nodes has been established, the next step is to construct the common sensor nodes adjacency cluster around each camera node. In this paper, we call these clusters neighbor clusters. We establish the neighbor cluster of each camera as follows.

(1) Taken a camera node as the center, a certain number of common nodes within this camera node's connective region compose a cluster.

(2) In this cluster, the node with sufficient energy and had best link quality of communicating with station is chosen as cluster head node.

(3) The cluster head broadcasts its ID to the surrounding cluster nodes.

(4) The surrounding nodes in the cluster inform their ID to the cluster head node.

(5) The cluster head node keeps the list of all cluster nodes' ID.

4.3. Network Transmission Scheme. When two kinds of hierarchical clustering structure have been set up already, we discuss the whole network transmission framework in this section.

(1) Based on the network structure proposed in Section 4.1, more than one camera nodes are deployed to monitor a field of interest. The spatially proximal cameras could have highly overlapped FoVs, which is measured by the correlation coefficient. So when the camera nodes cluster established, the common camera nodes send the captured pictures to the camera cluster head node. The camera cluster head node receives and fuses these pictures.

```
For a group of camera nodes C, C = {C_1, C_2, ..., C_N}, ordered by its (x, y) coordinates;
Get the FoV of each camera node F_i, F = {F_1, F_2, ..., F_N};
Initialize i = 1, correlation degree threshold ε, cluster X_i = φ;
while length (C) != 0 do
    X_i = X_i ∪ C_i;
    Check the camera nodes which distance with C_i is less than (d_i2 + d_j2);
    Add these camera nodes to a set Ct;
    for j = 1 to length (Ct) do
        Calculate ρ(C_i, Ct_j) by Algorithm 1;
        if ρ(C_i, Ct_j) ≤ ρ(Ct_j, C_i) && ρ(C_i, Ct_j) ≥ ε || ρ(C_i, Ct_j) ≥ ρ(Ct_j, C_i) && ρ(Ct_j, C_i) ≥ ε then
            if Ct_j ∈ X_other then
                X_other = X_other ∪ Ct_j;
            else
                X_i = X_i ∪ Ct_j;
                C = C − Ct_j;
            end
        end
    end
    if Area(F_k) has the bigest area in X_i then
        C_k becomes the cluster head in X_i;
    end
    i++;
end
return X_i = {X_1, X_2, ..., X_m}.
```

Algorithm 2: Distributed camera nodes clustering.

(2) For energy conservation, the camera cluster head node has no responsibility for compressing and sending the fused pictures to the sink or station. The camera cluster head node just sends the fused picture to the cluster head node of its neighbor cluster.

(3) The common cluster head node receives the picture from the camera cluster head node, then cooperatively compresses the picture with the member of common nodes cluster.

(4) The common cluster head node sends the compressive picture to the sink or station.

(5) In the camera nodes cluster, when the residual energy is less than a threshold, the cluster head of camera cluster will turn to the next camera node, which has sufficient energy and bigger area.

5. Performance Evaluation

In this section, we design some simulations to evaluate the effectiveness of correlation coefficient and the performance of the image transmission scheme we proposed.

5.1. Analysis of the Correlation Coefficient. To investigate the effect of camera's four parameters to correlation coefficient ρ. First, when the locations, α, β, θ of multiple cameras are different and fixed, we increase the value of tilt angel γ gradually to explore the change of ρ.

Figure 4 illustrates that the comparison of correlation coefficients among three cameras, denoted by i, j, k. We can find that the the correlation coefficient of a pair of camera is

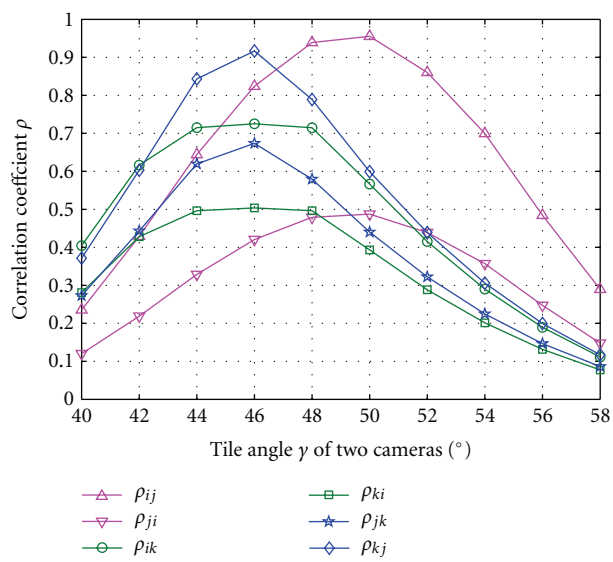

Figure 4: The effects of increasing tilt angle γ on ρ.

an asymmetrical relationship. This is because the area of the corresponding two cameras' FoVs is inequal. Meanwhile, the correlation coefficient ρ of a pair of cameras is independent of other pair of cameras, that is, ρ_{ij} (or ρ_{ji}), ρ_{ik} (or ρ_{ki}), and ρ_{jk} (or ρ_{kj}) are irrelevant with each other, but they all have the same variation tendency. As shown in Figure 4, in the beginning, the correlation coefficient ρ increases as the tilt angles γ of these three camera i, camera j, and camera k increase, but when ρ increases to a peak value, subsequently,

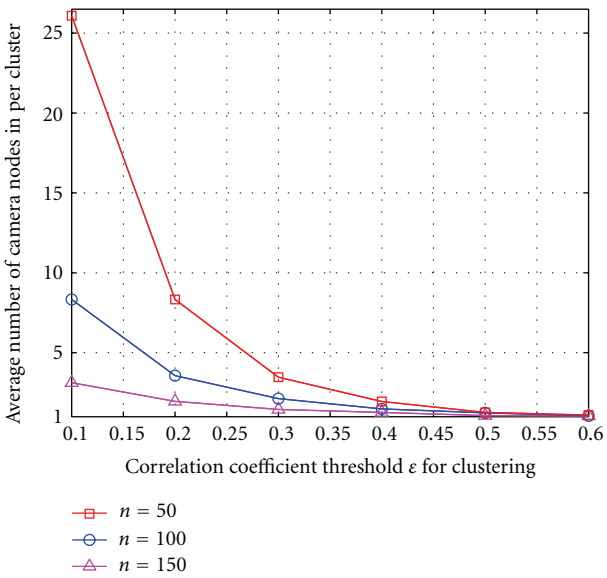

Figure 5: The effects of different clustering threshold on average cluster-size.

it would decrease. This is because correlation coefficient ρ denotes the intersection of two cameras' FoVs, and the tilt angel γ increased means that the FoV of camera increasing. Because the locations of these cameras are fixed, to increase the FoV, the overlap will became bigger. So in the beginning, the correlation coefficient ρ increases. But when the FoV of camera becomes very large, the portion of overlapped FoVs in camera's FoV is decreased, so all the curves in Figure 4 are descended eventually.

Like γ, the parameters α, β, and the height z of camera nodes have similarity property to cameras' FoVs, so these parameters have the same effect to ρ, although their influence is kind of moderate.

In Section 4.2, we use the correlation degree threshold ε as a criterion for camera nodes clustering. Next, we discuss the effects of different clustering thresholds on average cluster-size in different numbers of camera nodes in the network. In a square region $S = 100 \times 100\,\mathrm{m}^2$, we randomly deploy 50, 100, 150 camera nodes, respectively. Based on the uniform distribution model, the camera parameters are setting as follows. The horizontal offset angle is $\alpha \in [30^\circ \quad 40^\circ]$. The vertical offset angle is $\beta \in [25^\circ \quad 30^\circ]$. The tilt angle is $\gamma \in [40^\circ \quad 50^\circ]$. The sensing orientation $\vec{D}$, namely, θ, is taken from -180° to 180°, and the 3D space height z of camera nodes is taken from 5 to 8. After repeating the experiment for lots of times to take the average value, Figure 5 illustrates that the variety curves of the average cluster-size followed with the different correlation coefficient thresholds ε in three different node densities.

As shown in Figure 5, the higher correlation degree thresholds obviously restrict node memberships and decrease the number of camera nodes per cluster, while lower thresholds increase the area covered by a given cluster at the cost of complexity of coordination. It should be noted that the situation that signal camera node as a cluster by itself is quite common, even in a very densely deployed network in low correlation degree threshold. This is why in Section 4.1, we assume that every camera node must have a common node cluster around.

5.2. Performance of Network Scheme. We set up a scene to evaluate the network transmission scheme proposed in Section 4.1 as follows. Three cameras are deployed to surveillance an area of interest, for example, a crossing, lots of animals would often pass by. The FoVs of these three cameras are overlapped and by using the Algorithm 2 proposed in Section 4.2. These cameras are in a cluster, which cluster head is camera 2. These three cameras periodicity take photos from their FoVs. At a time, three photos are captured by these cameras. The captured photos are shown in Figure 6. Once the photos have been taken, based on our proposed network scheme, camera 1 and camera 3 would send the pictures to the cluster head node, camera 2, respectively. The cluster head node camera 2 will use stitching technique [17] to roughly fuse the photos, which are received from camera 1, camera 3 and captured by itself. The fused photo by camera 2 is shown in Figure 7. When the photo has fused, the camera 2 will send this photo to the cluster head of its neighbor cluster. This neighbor cluster takes the responsibility to compress and send compressive photo to the sink or station.

Based on this scene, we evaluate the performance of the proposed network transmission scheme in Section 4.3 with comparing without clustering and fusing scheme by energy consumption for communication to transmit these three photos. In Figure 6, the size of photo captured by each camera is $384 \times 512 \times 8$ bit. and in Figure 7, the size of fused photo by camera 2 is $652 \times 397 \times 8$ bit. Without considering the neighbor cluster would compress the photos and reduce the data. According to the energy model for communications in [18], in two schemes, the comparison of whole energy consumption for communication in the network is shown in Figure 8.

From Figure 8, we can see that the whole energy consumption for communication to transmit these three photos by our proposed scheme is obvious less than without clustering scheme. This is very significative in the energy-constrained WMSNs.

Camera node is the key node in the network image transmission in WMSNs. We analyze the energy consumption for communication of the camera node by the following three schemes.

(1) Scheme (A): the camera node directly sends captured photos to the sink or station.

(2) Scheme (B): the camera node sends the captured photos to the neighbor cluster head node, and the neighbor cluster takes the responsibility to compress and send compressive photo to the sink or station.

(3) Scheme (C): the camera node uses the proposed scheme in this paper, to fuse the captured photos and send the fused photos to the neighbor cluster head node.

(a) (b) (c)

Figure 6: Photos captured by distributed three cameras. (a) Camera 1. (b) Camera 2. (c) Camera 3.

Figure 7: Photo fused by the camera cluster head node.

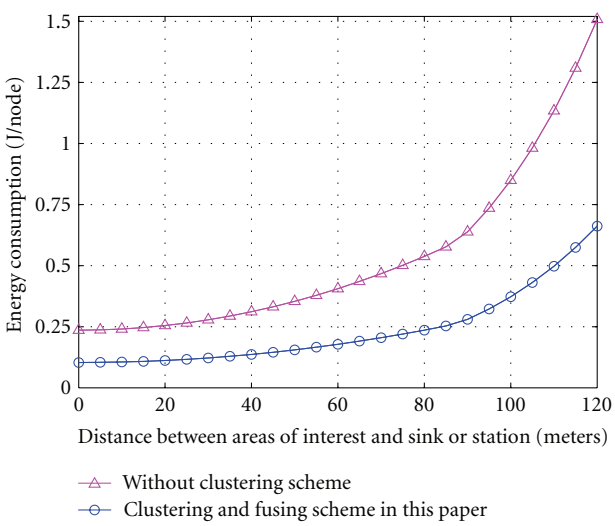

Figure 8: Energy consumption for communication in the whole network.

The comparison of energy consumption for communication of camera node in these three schemes is shown in Figure 9. Relative to Scheme (A), in Scheme (B) and Scheme (C), the camera node does not need to send data

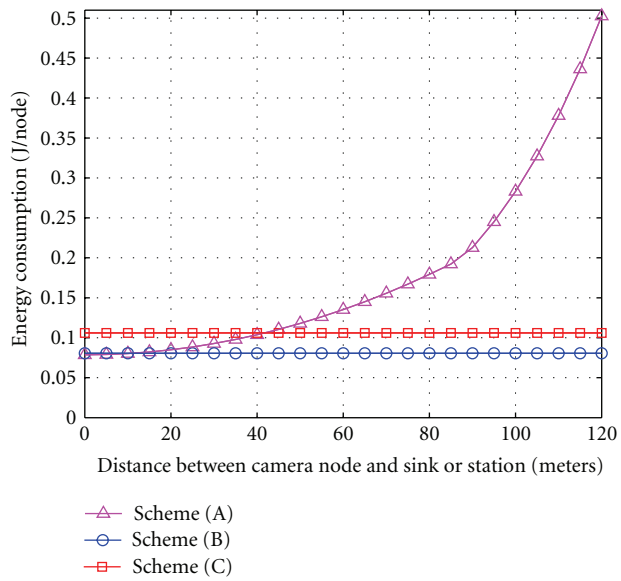

Figure 9: Energy consumption for communication of the camera node.

to the sink or station and abundant energy is saved. In the situation of Scheme (B) and (C), the energy consumption for communication of camera node only is the communication with the neighbor cluster head node. It is unrelated to the distance between camera node and sink or station. This is why the curves for Scheme (B) and Scheme (C) are almost constant in Figure 9. Meanwhile, in Scheme (C), the camera node needs to send the fused photos to the neighbor cluster head node, so its energy consumption for communication is more than camera node in Scheme (B). Although energy consumption of few camera nodes is increased in Scheme (C), the energy consumption in the whole network is greatly reduced. From this point, Scheme (C), the proposed scheme in this paper, is more suitable for image compression and transmission in WMSNs.

6. Conclusions and Future Work

In this paper, the problem of the correlation between camera nodes is investigated. Based on the 3D sensing model of the camera sensor nodes, this problem is reduced to calculate the relative position between camera nodes, and a low complexity and effective distribute method is proposed. Then, using the proposed correlation coefficient, an image fusion and transmission scheme is designed through building network hierarchy structure. A set of experiments are performed to discuss the parameters in 3D camera nodes sensing model influence on the correlation among camera nodes and analyze the perform of the devised network scheme. Simulations demonstrate that the proposed network topology and image fusion and transmission scheme reduce the network energy consumption of communication of the whole network efficiently and save the energy of camera sensor nodes.

Different from the conventional scalar WSNs, the energy consumption of data processing is very important to camera and common sensor nodes in WMSNs. So in our future work, we would consider talking about the energy consumption of data processing to design optimum image processing method to accord with the characteristic of WMSNs.

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