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Power-driven Image Compression in Wireless Sensor Networks

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Abstract. In WSNs, wirelessly interconnected devices enable multimedia content such as video and audio streams to be ubiquitously retrieved, and still images along with scalar data from surroundings for a wide range of applications are constrained by the processing, memory, and power resources. Image compression through low-complexity and resource-efficient transforms has been addressed by several researchers to prolong the network lifetime where power conservation is achieved through sharing computational load among sensor nodes and by adjusting the transmission ranges of camera nodes. However, these schemes are not adaptive to the presence and changes in the power-level of computational sensor nodes or to the amount of computational load. We propose a resource and power efficient distributed image compression algorithm that dynamically configures the network according to the power levels, and a forwarding strategy that is based on the entropy of the image. The simulation results show that our adaptive distributed image compression scheme significantly prolongs the network lifetime and improves the network utilization efficiency, while maintaining an adequate image quality.

Keywords: Wireless sensor networks, image compression, power efficiency, network lifetime

1 Introduction

A wireless sensor network (WSN) consists of sensor nodes deployed over a geographical area for monitoring physical phenomena such as temperature, humidity, vibrations, and seismic events [1, 6, 7]. In WSNs, a sensor node is a tiny device that includes three basic components: a sensing subsystem for data acquisition from the physical surrounding environment, a processing subsystem for local data processing and storage, and a wireless communication subsystem for data transmissions. Moreover, a power source supplies the power needed by the device to perform sensing and report tasks. The power source often consists of a battery with limited power. In an unattainable environment, it may be impossible or inconvenient to recharge the battery. Therefore, the sensor network should have a long enough lifetime to fulfill the application requirements. A single node failure, owing to a

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limited amount of power, can affect the WSN lifetime and/or overall utilization.

To prolong the network lifetime during environmental monitoring and process the control applications, the bulk amount of monitored multimedia data needs to be efficiently compressed before transmission [5]. However, multimedia compression algorithms for image compression are constrained based on the processing and communication efficiency of sensor nodes in WSNs.

In this paper, we consider power-driven distributed image compression in environmental monitoring and process control applications. Our scheme uses a distributed lapped bi-orthogonal transformed(LBT)-based compression scheme to compress and transmit the data to a base station.

2 Power-driven Clustering and distributed Image Compression

2.1 Power Consumption Model

In the cluster, all nodes are assumed to control their transmission power. We also assume that a member node(*MN*) is part of the cluster and shares the clustering tasks. The nodes have to transmit the final compressed data toward a remote *BS* through a Cluster Header(*CH)*. The transmission power $\boldsymbol{E_{TX}}$ in (1) depends on the amplifier and transmission distance, $\boldsymbol{d}$, between two communicating nodes.

$$E_{TX} = \begin{cases} E_{elec} + \epsilon_{fs} d^2, & d < d_0 \\ E_{elec} + \epsilon_{mp} d^4, & d \geq d_0 \end{cases} \tag{1}$$

where the power consumed by receiving a bit of data is equal to the power consumed by the circuitry of a sensor node, i.e., $\boldsymbol{E_{TX}} = \boldsymbol{E_{elec}}$. We used the power model in [2], where $\boldsymbol{E_{pre}}$ is the power for 1-D pre-processing, $\boldsymbol{E_{DCT}}$ is the power for DCT, and $\boldsymbol{E_{encode}}$ is the encoding power added to the total LBT-based compression computational power, $\boldsymbol{E_{cp}}$, as given in (2).

$$E_{cp} = 2\left(E_{pre} + E_{DCT}\right) + E_{encode} \tag{2}$$

2.2 Power-driven Node Clustering

It is assumed that every node is able to operate as a camera node, intermediate node, and *CH*, and switches its role depending on the power level. For the power level of the node, three different classes, $\boldsymbol{Class_0}$, $\boldsymbol{Class_1}$, and $\boldsymbol{Class_2}$ exist with the order of highest power level. It becomes extensible to multiple classes as the number of nodes is increased.

We now propose a clustering algorithm that considers the power level at each node. For the first step, nodes communicate with neighbor nodes within radio coverage and exchange node information, including the current power consumption defined in (2) and the distance between nodes. After receiving information on its neighbors, each node updates its neighborhood table with the given information. In this step, unit functions, ($\boldsymbol{E_{cp}}$, $\boldsymbol{d}$), are applicable for the evaluation of power consumption in each sensor node. Additionally, the reachability of the nodes is included in this neighborhood table for the path computation. Next, each sensor node calculates its availability, which indicates how this node can handle compression and forwarding and produce power computation scale; compares it with a pre-defined power scale; and defines whether the mode is a *CH* or not. For example, if the calculated power scale is smaller than the threshold, nodes can be selected as a *CH*. A smaller power scale implies that this node can handle an additional operation. This is one way to select a *CH* to balance the power consumption of a node, and various approaches to determine a *CH* can be applied. A node selected as a CH sends a cluster advertising message with information such as the current power scale, number of hops the message can deliver, and so on. When an MN receives a cluster advertising message, it responds and becomes a member of the cluster.

When an MN receives multiple advertising messages from multiple *CHs*, it responds to the *CH*, which has the least power consumption scale. After receiving a cluster join message from an *MN*, a *CH* updates the neighborhood table, and calculates the power class of an *MN* as in the following procedure. $\boldsymbol{Class_0}$ nodes that have the highest power level among the clustering nodes, and have transmission constraint, i.e., $\boldsymbol{d} < \boldsymbol{d_0}$. On the other hand, as $\boldsymbol{Class_1}$ has sufficient power but is distanced from the camera nodes, i.e., $\boldsymbol{d} \geq \boldsymbol{d_0}$. Finally, the clusters are configured and are assumed to be idle node as $\boldsymbol{Class_2}$.

2.3 Distributed LBT

Our distributed LBT shown in Fig. 1 is adaptive to the power levels of the computational helpers and the entropy of the sensed image. We used these two parameters as forwarding decisions and the distribution of computational load among the computational helpers. The *X* rows of the image data from the camera node are forwarded to the computational helper sub-trees, with |***m***| such that $m = 1, 2, 3, \cdots, N$ computational helpers, to further distribute or/and compress them. Our scheme is highlighted in both Fig.1 and ***Proc (1).***

	Procedure (1) $distributedLBT()$
1	**do if** (entropy $< l$)
2	$CHClass \leftarrow CLASS_0$;
3	$forwardtoCH$;
4	**for** each $class_0$ node
5	$LBTCoefficients \leftarrow lbtBasedCompression\left(\frac{X}{m}\right)$;

$m = |class_0|$
6 $compressedData \leftarrow sCoding(LBTCoefficients)$
7 $transmitToCH(compressedData)$;
8 **elseif** (entropy $> l$)
From $class_i$ to $class_{i+1}$ of CH
9 $forward\{(n * X - X)$ rows image from $CameraNode, MNList$, entropy};
where $n = \sum_{i=0}^{|classes|} |class_0|$
10 On each CHs perform the steps 5, 6 and 7

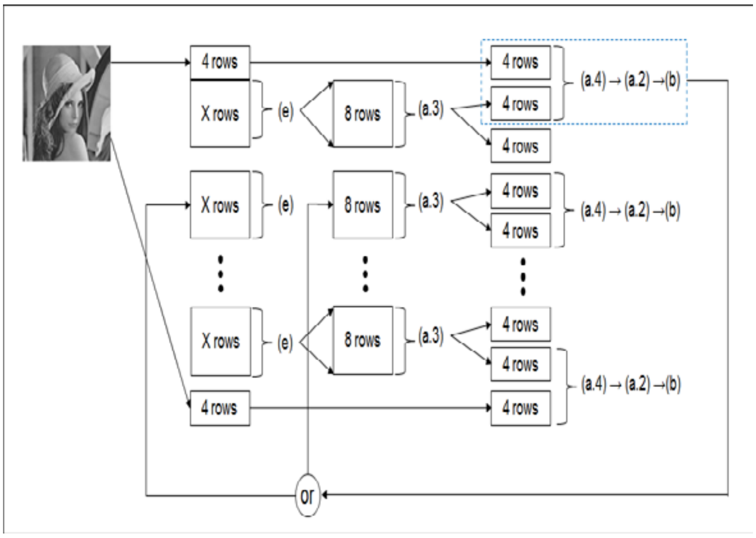

Fig. 1. Adaptive and distributed LBT-based compression using computational helpers.

4 Performance Evaluation

We assumed a WSN of ***N* = *100*** randomly distributed over an area of 500x500(m^2) and standard images of ***lena***, ***camera man***, and ***peppers*** at 512x512(pixels), and 8 bit/pixels are used for the distributed LBT-based compression experiments. We analyzed our distributed image compression scheme for the optimal network lifetime L and utilization efficiency η . We observed that the network lifetime is related to the initial power, ζ_0 , of the sensor nodes; the power consumption from the distributed image compression algorithm, P_C, the average power left with sensor nodes when the sensor network dies out, $\mathrm{E}[E_w]$, and the average computational and communication power needed for the sensor to compress and transmit an image {active computational helpers in image compressions},

$$\begin{aligned}\mathrm{E}\left[E_w\right] &= \sum_{i=1}^{k}(E_{cp}^{i} + E_{cm}^{i}) \\ &= \sum_{i=1}^{k}\mathrm{E}(E_r^i) = \sum_{i}^{k} p_i \text{挲} \le \sum_{i}^{k} p_i \;_i, \forall k \subseteq N\end{aligned} \tag{3}$$

Whereas the communication power for a computational helper ***i*** is constrained as $E_{cm}^{i} \le E_{TX}^{i} + E_{RX}^{i}$.

$$\mathrm{L} = \frac{\zeta_0 - \mathrm{E}[E_w]}{P_C + \lambda \mathrm{E}[E_r]}, \eta = \frac{\mathrm{L}}{|k|} = \frac{E_0 - \frac{1}{N^2}\mathrm{E}[E_w]}{N^2 P_S + \lambda \mathrm{E}[E_r]} \tag{4}$$

The simulation is halted when a certain percentage of computational nodes die out. *MNs* choose the best *CHs* to compress the ***lena***, ***camera man***, and ***peppers*** images in a distributed fashion. The steady state performance improvements of our scheme, shown in Figs. 2 reveal that the power-level classification of the computational help in stripping out the idle but weak and power-starved sensor nodes from the computational loads hence contribute to a prolonged network lifetime. From Figs. 2, it can be deduced that transmission range adjustments alone are insufficient to increase the network lifetime with sparsely located diverse sensor (in the sense of power) nodes. Combining the power classification scheme with entropy-based forwarding helps in reducing the power consumption by allowing the forwarding role to stronger nodes in the cluster. Moreover, pruning out low-power nodes from the compression and communication process significantly improves the network lifetime and network utilization efficiency.

5 Conclusion

To prolong the network lifetime and utilization, and hence provide useful applications, WSNs require an efficient image compression scheme. In this paper, we propose an improved distributed image compression scheme for WSNs. Our scheme is based on a lapped bi-orthogonal transform that requires fewer resources and less memory and processing power, as compared with JPEG2000, on an individual sensor node. Based on the available power of the sensor nodes, we classified and clustered them into computational clusters to distribute the computational load, i.e., image compression. This approach sensibly selects a sufficient number of power nodes for computation, and as a result, prolongs the lifetime and network utilization in WSNs. We are working on incorporating the throughput efficiency and QoS support along with a broader analysis of our scheme.

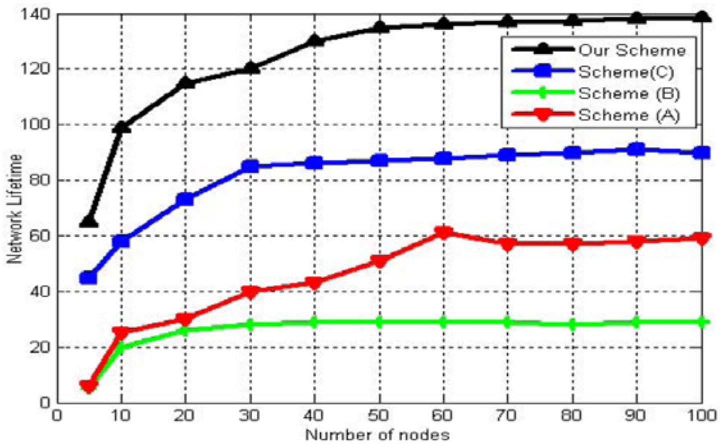

Fig. 2. Network lifetime comparison of our scheme with the schemes in [2]

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