Computers and Electrical Engineering 44 (2015) 67–79

Contents lists available at ScienceDirect

Computers and Electrical Engineering

journal homepage: www.elsevier.com/locate/compeleceng

Energy-efficient image transmission in wireless multimedia sensor networks using block-based Compressive Sensing ☆

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A R T I C L E I N F O

Article history:
Received 14 May 2014
Received in revised form 14 January 2015
Accepted 14 January 2015
Available online 7 February 2015

Keywords:
WMSN
CS
Mica2
Atmega 128
Encoding

A B S T R A C T

Wireless multimedia sensor networks (WMSNs) are capable of retrieving audio, image and video data in addition to scalar sensor data. The lifetime of these networks is mainly dependent on the communication and computational energy consumption of the node. In this paper, compressed sensing (CS)-based image transmission is proposed to reduce the energy consumption considerably with acceptable image quality. A unique encoding algorithm is formulated for the CS measurements attained with the Bernoulli measurement matrix. The proposed CS method produces better results at a lower sparsity range. Experimental analysis is performed using the Atmega 128 processor of Mica2 to compute the execution time and energy consumption in the hardware platform. The proposed CS method has a considerable reduction in energy consumption and better image quality than the conventional CS method. The simulation results show the efficiency of the proposed method.

1. Introduction

WMSN is a network of wirelessly interconnected sensor nodes equipped with multimedia devices capable of retrieving video streams, images, audio streams and scalar sensor data. The availability of inexpensive hardware such as CMOS cameras and microphones has led to the development of WMSNs. WMSNs are able to store, process in real-time, correlate and fuse multimedia data originated from heterogeneous sources [1]. WMSNs are resource constrained and have high bandwidth demand. It is essential to reduce both computational and communication energy consumptions involved in image transmission to increase the lifetime of these networks. Recently, CS has been widely used, allowing the entire signal to be determined from relatively few linear measurements. It is used to capture and represent compressible signals at a rate significantly below the Nyquist rate. It simultaneously senses and compresses the data at low complexity. In this paper, CS is used for reducing the energy consumption in WMSNs.

Candes and Wakin [2] proposed a new sampling theory that simultaneously combines sampling and compression procedures during acquisition. The use of CS theory can recover sparse signals and images from far fewer samples or measurements than traditional methods present in the WMSN. The hardware architecture proposed for the real-time implementation of CS acquisition has less complexity compared to the conventional digital camera [3]. Hence, the implementation of a CS-based real-time image acquisition system has a promising future. The sparse vector can also be estimated

☆ Reviews processed and recommended for publication to the Editor-in-Chief by Guest Editor Dr. Raja K. Murugesan.
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http://dx.doi.org/10.1016/j.compeleceng.2015.01.011
0045-7906/

from coarsely quantized and noisy measurements by CS [4–6]. This can further reduce the energy consumption of the image transmission process.

Romberg [7] described the combined usage of the low-pass discrete cosine transform (DCT) and the noiselet coefficients for image acquisition. The image is reconstructed by minimizing the total variation (l_1 minimization). Han et al. [8] proposed that the image could be divided into dense and sparse components, which are encoded by the CS technique. The correlation between these two components is studied by using an autoregressive model. Projection onto convex sets (POCS) is used to reduce the decoding computational complexity and the number of random measurements needed for CS. Xiong et al. [9] suggested an adaptive measurement matrix to reduce the dimension of block compressed sensing (BCS)-based image representation and to improve the recovered image quality. CS-based image transmission and recovery for wireless sensor network (WSN) applications are discussed in [7–9]. However, the energy consumption of the transmission is not evaluated in any target platforms. Chen et al. [10] used CS for image compression and implemented the CS-based compression algorithm on the Intel XScale PXA270 processor. Mamaghanian et al. [11] proposed a CS-based solution for electrocardiogram signal compression in wireless body area networks. The lifetime evaluation of the mote has been performed in the shimmer platform.

Karakus et al. [12] proposed a framework for CS-based signal recovery, and the energy consumption was determined by using the Atmega processor. The effects of acquiring, processing and communicating CS-based measurements on WSNs are analysed and compared to conventional approaches. CS prolongs the network lifetime for sparse signals, and it is more advantageous for WSNs with a smaller coverage area. Based on the programming logic, operations are decided and the energy consumption is analysed. The total energy consumption has been computed based on the energy consumed by each instruction. However, the entire process is not validated in the target platform. Alternatively, we have extended the energy analysis procedure to incorporate image transmission in WMSNs. However, for image applications, the sparsifying basis and measurement matrix plays a major role in determining the energy consumption. The optimal measurement range required to achieve an acceptable image quality suitable for WMSN applications is also suggested. Further, a new encoding algorithm is developed that uniquely suits the unquantized measurements obtained using the Bernoulli sensing matrix. Experiments are performed on the Atmel Atmega 128 Processor of Mica2 for analysing the energy consumption.

The rest of the paper is organized as follows. Section 2 provides an overview of CS. In Section 3, the proposed framework is discussed in detail. In Section 4, the performance evaluation is explained. Image recovery analysis and the corresponding simulation results are discussed. Energy analysis for image transmission and its validation in the target platform is also explained. Conclusions are provided in Section 5.

2. Overview of CS

Consider a real valued, finite length, one-dimensional signal $X \in R^N$. Using the $N \times N$ basis matrix $\psi = [\psi_1|\psi_2|\ldots|\psi_N]$ with the vectors$\{\psi_i\}$ as columns, a signal X can be expressed as

$$X = \sum_{i=1}^{N} S_i \psi_i = \psi S \tag{1}$$

where X is an $N \times 1$ column vector with coefficients X_i, $i = 1, 2, \ldots, N$ and S is a vector of coefficients representing X in ψ basis. The process of measurement in CS [13] can be defined as,

$$y = \varphi X = \varphi \psi S = \Theta S \tag{2}$$

where φ is an $M \times N$ random matrix, $\Theta = \varphi\psi$ and y is an $M \times 1$ measurement vector. It is assumed that $M < N$. The number of measurements depends upon the sparsity and incoherence [14]. Low coherence between measurement basis φ and representation basis ψ results in fewer measurements. The number of measurements M for the perfect reconstruction of a K-sparse N dimension signal [13] is given by

$$M \geqslant \alpha \cdot K \cdot \log\left(\frac{N}{K}\right) \tag{3}$$

where α is some positive constant affecting the probability of recovery. Signal X could be recovered exactly by solving the minimum l_1-norm optimisation problem. The reconstruction process is formulated as,

$$\widehat{S} = \min_S \|S\|_{\ell_1} \text{ subject to } y = \Theta S, \quad X = \psi \widehat{S} \tag{4}$$

This methodology can be made in-built during the acquisition process itself. The signal can be recovered at the receiver with the help of measurements by using recovery techniques such as convex optimisation, linear programming, POCS [7] and greedy algorithms – orthogonal matching pursuit (OMP) [13], regularized OMP (ROMP) [15], stage wise OMP (STOMP) [16], basis pursuits (BP) [17], and compressive sampling matching pursuit (CoSaMP) [18]. The Bernoulli measurement matrix (±1 entry with equal probability) and OMP are used for acquisition and recovery of an image in this paper.