A Distributed Compressive Sensing Scheme for Event Capture in Wireless Visual Sensor Networks

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Abstract. Image signals which acquired by wireless visual sensor network can be used for specific event capture. This event capture is realized by image processing at the sink node. A distributed compressive sensing scheme is used for the transmission of these image signals from the camera nodes to the sink node. A measurement and joint reconstruction algorithm for these image signals are proposed in this paper. Make advantage of spatial correlation between images within a sensing area, the cluster head node which as the image decoder can accurately co-reconstruct these image signals. The subjective visual quality and the reconstruction error rate are used for the evaluation of reconstructed image quality. Simulation results show that the joint reconstruction algorithm achieves higher image quality at the same image compressive rate than the independent reconstruction algorithm.

1. Introduction

1.1. Wireless visual sensor networks

Wireless Visual Sensor Networks (WVSNs) is a sensor network composed of a large number of visual sensor nodes to monitor a certain area. It captures and monitors certain event in the field of view by means of image acquisition and processing, and transmits event information via wireless communication.

In general wireless sensor networks, scalar data such as temperature, humidity, illuminance and pressure, or speed and other vector data have relatively simple data types and small amount of data. The raw data can be transmitted directly, and finally the event is captured by the sink node, for example, the sink node can capture such event as "temperature exceeding the threshold" through temperature data.. Image data contain richer information, the use of a variety of image processing algorithms (such as pattern recognition, target tracking, behavior recognition, etc.), can achieve the capture of a lot of certain events [1]. For example, the use of target tracking algorithm can achieve the event capture of "the emergence of a human target" in the field of view.

However, the amount of data in the image is too large, in the wireless visual sensor network, if the event capture is completed by the sink node, the bandwidth of the wireless communication network cannot meet the demand. In addition, the power consumption of data processing is much lower than the power consumption of wireless transmission of data [2], therefore, WVSNs should use the underlying node to complete the event capture as much as possible and transmit event information in the communication network rather than the raw image data, thus avoiding a large amount of raw data being transmitted in the network.
In the video monitoring system, each camera independently and continuously transmits video data stream to the video server, and the higher resolution of the video is, the better it will be [3]. Different from the video monitoring system, WVSNs takes the event collecting rather than capturing clear video (or images) as the primary purpose. After the underlying nodes capture events, the WVSNs transmit event information directly to the network rather than the video stream. Therefore, the ability to flexibly deploy the wireless communication mode can meet the requirements of the transmission bandwidth.

1.2. Distributed compressive sensing
As a new signal processing method, CS (Compressive Sensing) can reconstruct the original signal at a signal receiving end with a small number of measurements. The requirements of compressive-sensing method for the signal are quite sparse [4-5]. The image signal can be sparsely represented, such as by domain transformation. For example, smooth images are sparse in Fourier basis, while piecewise smooth images are sparse on wavelet basis. Thus, for N-pixel images, it can be represented by K sparsity [6].

D. Baron et al. proposed a distributed compressive sensing based on the theory of compressive sensing, a compressive sensing which extends the single signal to the signal ensemble.

The DCS theory is based on the joint sparsity concept of the signal ensemble by using the correlation of the signals. In a typical DCS scenario, if the sensor's measurement signal is sparse and relevant under a certain basis, each sensor encodes the measurement signal through an incoherent bases (eg, a random matrix), and transmits the small amount of encoded data to the decoding side. Under appropriate conditions, the decoder can accurately reconstruct the measurement signal of each sensor [7].

DCS can further reduce the demand for communication bandwidth. The image signals collected by VSNs nodes deployed in the field of view usually have spatial correlation, so DCS provides an efficient image processing method for VSNs for capture events [8-9].

2. Scenario model
As shown in Figure 1, a scenario model for WVSNs can be represented as two parallel planes: Field of View (FoV, Field of View ) Plane $\pi$, Sensor Node Deployment Plane $\pi_1$. In order to capture Event E in $\pi$, it is necessary to monitor the event area (EA, Event Area). The image acquisition area of the node of $S_i$ ($i = 1,2,3,4$) in $\pi_1$ can cover EA after splicing, then $S_i$ ($i = 1,2,3,4$) and the cluster head $C_1$ together constitute a cluster of capturing Event E.

![Figure 1. A scenario model for WVSNs.](image)

The sensor node, cluster head, and sink make up a cluster tree network. The sensor node collects the original image as the encoding end of compressive sensing and generates the measurement and transmits it to the cluster head. As the compressive-sensing decoding terminal, the cluster head is used
to reconstruct the original signal and capture the event through the image processing algorithm. And then the captured event is transmitted to the Sink node data through the multi-hop routing.

3. A distributed compressive sensing algorithm for event capture

**Step 1:** The sink node calculates the Event Area (EA) based on the coverage area required for the capture event, and selects the sensors node of the camera within the EA. These nodes form clusters and select head node. The multi-hop routing of head node and sink nodes is established to form cluster tree type of WVSNs.

**Step 2:** The head node generates random seed and measurement length (Default measurement length is used for the first time) and broadcasts within the cluster. The sensor node generates the measurement matrix after receiving the random seed and the measurement length. The sensor node measures (encodes) the acquired image signals and then transmits the measurement to the cluster head.

**Step 3:** The cluster head generates the joint measurement matrix according to the random seed, the length of the measurement and the number of nodes, and calculates the sparse base matrix according to the node acquisition signal length and the number of nodes to obtain the joint mapping matrix. The measurement of each node received are combined according to the EA image acquisition area splicing sequence, and the OMP algorithm is used to reconstruct (decode) the measured signal ensemble.

**Step 4:** The cluster head uses the image processing algorithm to capture the events in the reconstructed EA spliced image signal, and passes the event data to the sink node through the multi-hop route.

**Step 5:** The sink node increases or decreases the measurement length based on whether the capture event succeeds or not. After receiving the instruction, the cluster head regenerates the random seed and the new measurement for the next measurement. Assuming that the image quality threshold required for successful capture event is \( q_0 \), the reconstructed image quality \( q \geq q_0 \) is the condition for terminating the sink node and cluster head scheduling.

4. Measurement of image signal and joint reconstruction algorithm

Assuming that the image obtained in the acquisition event area EA is represented by I, the pixel is represented as \( I \times I \). As shown in Fig. 1, it is stitched by the image \( B_i \) \((i = 0,1,\cdots,N - 1)\) collected by the sensor node \( S_i \) \((i = 0,1,\cdots,N - 1)\) in EA. Assuming that the image \( B_i \) \((i = 0,1,\cdots,N - 1)\) is in the same size; the pixels are \( B \times B \). After the distributed sensing begins, the node receives the random seed and the measurement length indicated by the cluster head to generate the measurement matrix \( \phi_i \in \mathbb{R}^{M \times B} \) \((i = 0,1,\cdots,N - 1)\), wherein, \( M \) is the measurement length.

\( S_i \) uses \( \phi_i \) to perform a random measurement. The measurements \( y_i \) \((i = 0,1,\cdots,N - 1)\) are as follows:

\[
Y = \begin{bmatrix}
    y_0 \\
    \vdots \\
    y_{N-1}
\end{bmatrix} = \begin{bmatrix}
    \phi_0 B_0 \\
    \vdots \\
    \phi_0 B_{N-1}
\end{bmatrix} = \begin{bmatrix}
    \phi_0 \\
    \vdots \\
    \phi_{N-1}
\end{bmatrix} \begin{bmatrix}
    B_0 \\
    \vdots \\
    B_{N-1}
\end{bmatrix}
\]

(1)

4.1. Independent reconstruction

\( S_i \) sends \( y_i \) to the cluster head. When the independent reconstruction algorithm is used, the cluster head receives \( y_i \) and respectively generates the mapping matrix \( \theta_i \) according to the random seed, the signal length and the measurement length, then:

\[
\theta_i = \phi_i \rho_i
\]

(2)

Wherein, \( \phi_i \in \mathbb{R}^{M \times B} \) is the measurement matrix, \( \phi_i \in \mathbb{R}^{B \times B} \) is a sparse base matrix. And then the optimization problem is solved as:
Wherein, \( s_i \) is the sparse coefficient of \( B_i \) in the base of \( \phi_i \in \mathbb{R}^{B \times B} \), \( \vec{B}_i = \phi_i s_i \), then the recovery image \( \vec{B}_i \) is obtained and then the recovered \( \hat{I} \) is obtained through the image splicing.

**4.2. Joint reconstruction**

\( S_i \) sends \( y_i \) to the cluster head. When the joint reconstruction algorithm is used, the cluster head receives the measurement of all nodes and generates the joint measurement matrix according to the random seed, the number of nodes, the length of the node signal and the length of the measurement [10].

\[
\Phi = \begin{pmatrix} \phi_0 \\ \phi_1 \\ \vdots \\ \phi_M \end{pmatrix}, \quad \hat{\Phi} \in \mathbb{R}^{M \times l}
\]

Wherein, \( \hat{M} \) is the length of the joint measurement, then \( \hat{M} = \frac{I}{B} \times M \). And then the joint mapping matrix is obtained:

\[
\Theta = \hat{\Phi} \Psi
\]

Wherein, \( \Psi \in \mathbb{R}^{l \times l} \) is the joint sparse base matrix; And then the optimization problem is solved:

\[
\min \| s \|_0 \quad s. t. \quad Y = \Theta s
\]

Wherein, \( s \) is the sparse coefficient of \( I \) in the base of \( \Psi \in \mathbb{R}^{l \times l} \), \( \vec{I} = \Psi s \), then the recovery image \( \hat{I} \) is obtained.

**5. Simulation results and analysis**

The method of computer simulation is used to verify the scheme proposed in this paper. The image obtained by collecting the event area EA by 256-order gray-scale image is used to transform the sparse image signal by using DWT [11]. The stochastic measurement matrix is used for signal mapping; and the OMP algorithm is used to solve the optimization problem of the joint reconstruction [12].

**5.1. Evaluation index**

The reconstruction error is selected as the evaluation index of the reconstructed image quality to reflect proximity between the reconstructed image \( \hat{I} \) and the original image \( I \). The reconstruction error rate is calculated as follows:

\[
rer = \frac{\| \hat{I} - I \|_2}{\| I \|_2}
\]

Namely, the ratio of the difference between the pixel values \( \hat{I} \) and \( I \) and the square root of the \( I \) pixel value.

**5.2. Quality comparison of reconstructed images between independent reconstruction and joint reconstruction**

Figure 2 is a local satellite image of a city; the image name is "innoway" with 256 * 256 pixels, 256-order gray-scale image to analog EA image \( I \). When there are four nodes in EA, \( I \) is stitched by the images collected by the four sensor nodes, and the image collected by each camera sensor node is 128 * 128 pixels.
If the measurement $M = 64$, then the original image $B_i$ with $128 \times 128$ pixels progressively projects through the mapping matrix, then $64 \times 128$ measurement matrix is obtained. At this point, the image compressive rate is:

$$r = \frac{M \times B}{B \times B} = \frac{64 \times 128}{128 \times 128} = \frac{1}{2} \quad (8)$$

Independent reconstruction (IR) method is to receive the measurement matrix to reconstruct the original image $B_i$ and then is spliced into $I$.

Joint reconstruction (JR) method is to receive the measurement matrix for splicing, and then directly obtain the reconstructed EA image $\tilde{I}$ through the joint mapping matrix reconstruction.

Figure 3 is the reconstructed EA image $\tilde{I}$ of the independent reconstruction (left) and joint reconstruction (right) respectively, when the measurement is the same. As can be seen from the Figure, when $M = 48$, IR cannot distinguish things in the figure, and JR can roughly distinguish between streets and buildings; when $M = 64$, JR can distinguish between streets and buildings, IR can only roughly distinguish between streets and buildings.

Figure 4 is the reconstruction error curve of independent reconstruction and joint reconstruction, it can be seen that in the same measurement, the error of joint reconstruction is lower than that of the
independent reconstruction. When the measurement is close to 128, the compression rate is close to 1, and the reconstruction error is close to but less than 0, and then a platform is as follows.

![Figure 4. Comparison of reconstruction errors for independent reconstruction and joint reconstruction.](image)

5.3. The influence of the number of nodes in EA on the reconstructed image quality

We use the image "lujiazui" as the EA image I with 512 * 512 pixels and 256-order gray-scale image. The image $B_i$ (i = 0, 1, ⋯, N – 1) acquired by each node is 64*64 pixels, then N=64. If the measurement is M = 32, the compression rate is 1/2, the cluster head uses the joint reconstruction algorithm to restore the original image. There are three networking schemes:

a) Each four nodes make up a cluster, each cluster covers 1/16 area, with a total of 16 clusters;

b) Each 16 nodes make up a cluster, each cluster covers 1/4 area, with a total of 4 clusters;

c) 64 nodes form a cluster covering the entire EA area.

Because the compression rate of each node is the same, the data volume of the three networking schemes is the same, but the transmission method of the cluster head to the sink node is different. As can be seen from Fig. 5, the quality of the whole EA area image $I$ is better than the upper left corner 1/4 region, which is better than the 1/16 region of the upper left corner. It is shown that the more the number of nodes in the cluster is, the higher the quality of the cluster head reconstruction image is in the case of collecting the same amount of EA image I data.

![Figure 5. Cluster head reconstruction image of scheme a), b) and c) vs. Figure 6. Comparison of the reconstruction errors for the different number of nodes.](image)

Figure 6 is the reconstruction error curve with different numbers of nodes; we can see that in the case of the same measurement, the more the number of nodes, the lower the reconstruction error.
6. Conclusions
DCS is one of the distributed source codings (DSC) [13]. The sensor node acquires the original image signal by compression sensing coding, thereby reducing the amount of data. In the same EA, when the number of nodes increases, the spatial correlation of the image signal collected by the node increases. And the reconstruction error decreases when the compression rate is constant. In this paper, a DCS scheme is proposed in this paper, through analysis and simulation, it is verified that the scheme can reconstruct the original image with lower reconstruction error.

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