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Compressive Sensing Based Client-Cloud System for 3D Depth Reconstruction

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***Abstract*—We present a Compressive Sensing (CS) based Client-Cloud system describing the future Cloud Computing structure, which takes 3D depth reconstruction as an instance. First, a sparse representation for continuous depth data is exploited. Second, we propose a dynamic measurement generation method adapted to the variation of sparsity to reduce bandwidth requirements. Third, a feedback correction scheme is developed to detect the incorrectly reconstructed signals and perform supplementary reconstruction. According to the experimental results, the proposed system can reduce about 40% to 70% bandwidth requirements and lower about 50% error rate while reconstruction.**

I. Introduction

Cloud Computing has become popular in the field of computer science over the recent years. It mentions both the applications delivered as services and the data centers providing those services [1], [2]. A cloud-computing system usually comprises two parts: a cloud providing powerful computing capability and a data transmission client. One of the advantages of cloud computing is that each part can be designed specifically to optimize its performance. Besides, the data center can gather and process information from distributed clients efficiently.

In recent years, Compressive Sensing (CS) theory has made progress in the field of signal processing [3]–[5]. CS guarantees a relative low-cost data compression and high-flexible data reconstruction scheme. CS technique can provide a suitable computing style for a client/cloud system. It owns the beneficial transmission properties such as high error tolerance and incremental information updating that shows more measurements result in more accurate signal recovery.

In this work, we present a CS-based client-cloud system which involves information compression and reconstruction by taking 3D depth data as an example. 3D depth sensing is one of the important ways for remote device to perceive surroundings. We demonstrate a system to acquire depth data individually and process it concentratively.

II. Compressive Sensing Fundamentals

Compressive sensing acquires a signal representation with linear random projection. While a signal fulfills sparsity constraints, it can be compressed and recovered with only few compressed measurements. Supposed that a signal $\boldsymbol{x}\in\mathcal{R}^{N\times 1}$ with K nonzero elements in some basis, it is said to be K-sparse and compressible with the condition $K\ll N$. An $M\times 1$ measurement $\boldsymbol{y}$ can be computed by multiplying an $M\times N$ random matrix $\boldsymbol{\Phi}$ by $\boldsymbol{x}$

$$\boldsymbol{y} = \boldsymbol{\Phi}\boldsymbol{x} \tag{1}$$

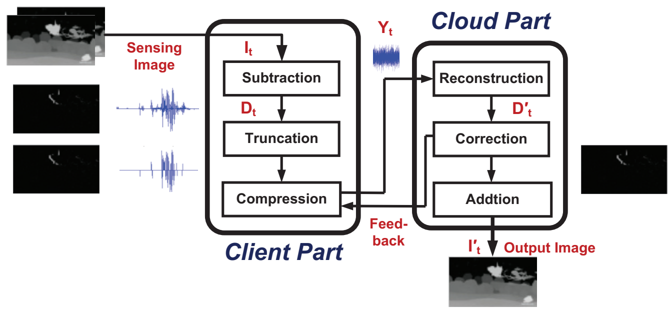


Fig. 1. Details of the proposed client-cloud system and the dataflow

In order to reconstruct the signal $\boldsymbol{x}$, we solve an underdetermined linear system with more unknowns (N) than equations (M). The CS theory states that the signal can be reconstructed with high provability if $M\geq cK\log(N/K)$ for a small constant c using the l_1-norm minimization [3]–[6]:

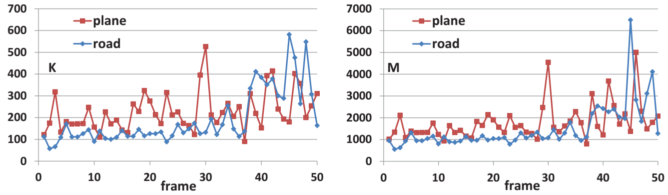
$$\min \|\boldsymbol{x}\|_{l_1} \quad s.t. \quad \boldsymbol{y} = \boldsymbol{\Phi}\boldsymbol{x} \tag{2}$$

III. Proposed System

Our client-cloud computing paradigm(Fig. 1) comprises two functional blocks: the client part and the cloud part. The successive depth information(frames) are simply transformed into a sparse representation and are compressed via random projections at the client. The compressed measurements are then transmitted to the cloud for the reconstruction of the depth signals by performing the computation-intensive l_1-minimization. A dynamic compressive measurement generation with a feedback correction mechanism is proposed to relief transmission bandwidth and to reduce reconstruction error rate.

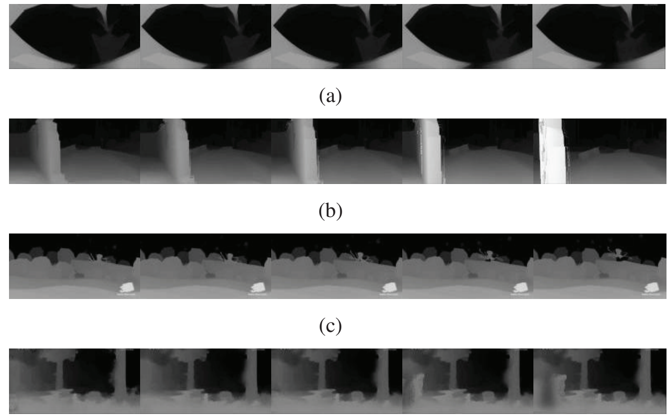
A. Sparse Representation

The overall depth data of the environment can be estimated by combining the depth data of static objects and that of dynamic objects. Suppose that the overall depth data at time $t-1$ and t can be represented as $\boldsymbol{I_t}$ and $\boldsymbol{I_{t-1}}$ respectively. The depth difference between $\boldsymbol{I_t}$ and $\boldsymbol{I_{t-1}}$, denoted as $\boldsymbol{D_t}$, is usually caused by the position or shape changes of dynamic objects along time. Because these changes are slight and smaller within a short period, $\boldsymbol{D_t}$ can be regarded as a sparse



(a) (b)

Fig. 2. Distribution of (a)the sparsity K and (b)the corresponding compressive measurements M of 3D sequences.



(a) (b) (c) (d)

Fig. 3. The reconstructed results of 3D sequences: (a)*plane*, (b)*road*, (c)*fish*, and (d)*tree*.

signal with $\boldsymbol{D_t}$=$\boldsymbol{I_t} - \boldsymbol{I_{t-1}}$. Therefore, a depth sequence is given by Eq. 3. Generally, there are some negligible values caused by insignificant motions of dynamic objects in $\boldsymbol{D_t}$. Therefore, these values are truncated to enhance the sparsity of $\boldsymbol{D_t}$.

$$\begin{aligned} \boldsymbol{I_2} &= \boldsymbol{I_1} + (\boldsymbol{I_2} - \boldsymbol{I_1}) &&= \boldsymbol{I_1} + \boldsymbol{D_2} \\ &\vdots \\ \boldsymbol{I_t} &= \boldsymbol{I_{t-1}} + (\boldsymbol{I_t} - \boldsymbol{I_{t-1}}) &&= \boldsymbol{I_{t-1}} + \boldsymbol{D_t} \end{aligned} \tag{3}$$

B. Dynamic Compressive Measurement

Since $\boldsymbol{D_t}$ is a relative sparse signal, the transmitted measurements $\boldsymbol{Y_t}$ is directly computed by

$$\boldsymbol{Y_t} = \boldsymbol{\Phi_t D_t} \tag{4}$$

where $\boldsymbol{\Phi_t} \in \mathcal{R}^{M \times N}$ is a Bernoulli random matrix. With the condition $M \ll N$, transmitting the compressive measurements rather than the original signals reduces the required transmission bandwidth. The number of compressed measurements required for each frame is decided according to $M = cK\log(N/K)$, which allows to dynamically adjusts the compressive dimensions according to the sparsity of $\boldsymbol{D_t}$. As shown in Fig. 2, we can observe the fluctuation of M is similar to that of K, which indicates that the dimension of compressive measurements varies with the sparsity of depth difference.

C. Reconstruction and Correction

After receiving the transmitted compressive measurement $\boldsymbol{Y_t}$, the cloud part performs reconstruction via l_1-minimization.

$$\boldsymbol{D_t'} = \arg\min_{\boldsymbol{D_t}} \|\boldsymbol{D_t}\|_1 \quad s.t. \quad \boldsymbol{Y_t} = \boldsymbol{\Phi_t D_t} \tag{5}$$

where $\boldsymbol{D_t'}$ is the reconstructed signal. In order to verify the reconstructed signal, the system compares the compressive measurement of $\boldsymbol{D_t'}$ and the received one.

$$\boldsymbol{E} = \boldsymbol{\Phi_t D_t'} - \boldsymbol{Y_t} \tag{6}$$

If the reconstruction is correct, the l_2 norm of $\boldsymbol{E}$ should be small. However, if the reconstruction is failed, the cloud part would require the client part transmit supplementary measurement $\boldsymbol{Y_s}$ to reconstruct the compressed signal correctly, which is given by

$$\boldsymbol{Y_s} = \boldsymbol{\Phi_s D_t} \tag{7}$$

where $\boldsymbol{\Phi_s}$ is the supplementary Bernoulli random matrix generated at the client part. The total measurements, denoted as $\boldsymbol{Y_{total}}$, used to reconstruct the depth difference is the concatenation of $\boldsymbol{Y_t}$ and $\boldsymbol{Y_s}$,

$$\boldsymbol{D_t'} = \arg\min_{\boldsymbol{D_t}} \|\boldsymbol{D_t}\|_1 \quad s.t. \quad \boldsymbol{Y_{total}} = \boldsymbol{\Phi_{total} D_t}, \tag{8}$$

where $\boldsymbol{\Phi_{total}}^T = [\boldsymbol{\Phi_t}^T \quad \boldsymbol{\Phi_s}^T]$ and $\boldsymbol{Y_{total}}^T = [\boldsymbol{Y_t}^T \quad \boldsymbol{Y_s}^T]$. Finally, the reconstructed depth data at time t, denoted as $\boldsymbol{I_t'}$, can be written as

$$\boldsymbol{I_t'} = \boldsymbol{I_{t-1}'} + \boldsymbol{D_t'} \tag{9}$$

where $\boldsymbol{I_{t-1}'}$ is the reconstructed depth data at time $t-1$. The overall depth sequence is therefore retrieved through Eq. 3.

IV. Experimental Results

To evaluate the performance of the system, four 3D sequences are used in the experiments. The size of each frame is 90×160. Note that we truncate 25% of values in the depth difference to enhance its sparsity. Besides, when $\|\boldsymbol{E}\|_2 \geq 1$, the correction process is executed by increasing M_{total} to $1.5M_t$. If the reconstruction is still incorrect, M_{total} will be increased to $2M_t$. However, if the signal recovery is failed eventually after executing correction process twice, we transmit the overall depth data at time t. We show some samples of reconstructed frames in Fig. 3. The representative frame indices are 5, 15, 25, 35, and 45.

In our experiments, we compare the dynamic compressive measurement method with the fixed compressive measurement one in three aspects: the average error, the error frame ratio, and the total transmitted measurements(Table I). The average error shows the quality of reconstruction. The smaller the average error is, the better quality the method has. It is computed by $\frac{\sum_{i=1}^{n} \|I_i' - I_i\|_2}{n}$, where n is the number of frames. The error frame ratio indicates how effective when reconstruct consecutive sequence. The total transmitted measurements represent the bandwidth requirements. The M of the fixed method is chosen to be 1000 and 3000.

When compared to fixed method(M=3000), the error frame ratio is reduced by about 50% while requiring only half of total measurements. To achieve similar error frame ratio, the fixed method requires approximated 150,000 measurements. Our

TABLE I
THE COMPARISON OF ERROR RATE AND TOTAL MEASUREMENTS

Sequences	Fixed(M=1000)			Fixed(M=3000)			Dynamic		
	Average Error	Error Frames	Total M	Average Error	Error Frames	Total M	Average Error	Error Frames	Total M
1(*plane*)	59.2	39/50	50K	0.1	1/50	150K	0	0/50	89K
2(*road*)	511.4	17/50	50K	55.1	2/50	150K	11.74	1/50	74K
3(*fish*)	3.2	4/50	50K	0	0/50	150K	0	0/50	48K
4(*tree*)	58.7	24/50	50K	6.7	4/50	150K	1.4	1/50	73K

system reduced about 41% of the required measurements for *plane*, 51% for *road*, 68% for *fish*, and 51% for *tree*. Therefore, our proposed method demonstrates promising performance including better recovery quality, lower error rate, and fewer required measurements.

V. CONCLUSION

We propose a compressive sensing based client-cloud system for 3D depth reconstruction. With dynamic compressive measurement generation and feedback correction, the overall transmission bandwidth is significantly reduced and the reconstruction accuracy increases. Generally, the proposed framework can be further applied to other signal with the similar computing manner, which performs simple compression at client and complex reconstruction at cloud.

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