Cluster-based Distributed Compressed Sensing for QoS Routing in Cognitive Video Sensor Networks

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Abstract. Compressed sensing based in-network compression methods to minimize the data redundancy are critical to cognitive video sensor networks (CVSNs). However, most existing methods require a large number of sensors for each measurement, resulting in significant performance degradation in energy efficiency and quality-of-service (QoS) satisfaction. CDCS, a cluster-based distributed compressed sensing approach for QoS routing is proposed to efficiently deliver visual information in CVSNs. To begin with, the correlation among adjacent video sensors is utilized to determine the suitable set of video sensors that participate in a cluster. On this basis, a sequential compressed sensing approach is applied to determine whether enough measurement have been obtained to limit the reconstruction error between decoded signals and original signals under a specified reconstruction threshold, thereby maximizing the removal of redundant traffic without sacrificing video quality. Lastly, the compressed data is transmitted by a distributed QoS routing scheme, with an objective to minimize energy consumption subject to delay and reliability constraints. Simulation results demonstrate that compared with exiting QoS routing schemes, CDCS can achieve energy-efficient data delivery and reconstruction accuracy of visual information.

1. Introduction

QoS sensitive multimedia applications require more spectrum and transmission resources [1], [2]. With the provision of cognitive radio, the underutilized spectrum resources could be exploited to gain more bandwidth used for multimedia applications [3]. In addition, cognitive radio networks can adapt transmission parameters according to application requirements. While CVSNs have received more attention, the transmission of multimedia incurs challenging technological issues. In addition to resource constrains such as limited energy and processing capacity, the transmission of visual information requires high-bandwidth, high-fidelity and more processing energy. These challenges and constraints, along with the complex network environment, make video transmission and in-network processing over CVSNs a challenge issue.

In CVSNs, correlation exists among the observations of distributed video sensors with overlapped field of views (FoVs), leading to considerable data redundancy. DCS [4]–[6] can exploit both intra- and inter-signal correlation to compress data to a large extent, thereby reducing the amount of data needed to reconstruct the signal in traditional compressed sensing. According to DCS theory, the signal can be reconstructed by a small number of linear observations as long as the signal can be represented sparsely on some bases.
Most QoS routing protocols in wireless sensor networks are designed to support two performance metrics: delay and reliability. MMSPEED [7] takes a cross-layer design approach to distinguish the communication flows and provide end-to-end QoS guarantee. SCEEM [8] is proposed for CRSNs that jointly overcomes the formidable limitations of energy and spectrum without damaging multimedia quality.

The above works provide QoS guarantee by properly distributing network traffic, without considering the removal of unnecessary multimedia loads. In-network compression [9] can effectively reduce the number of packets transmitted in the network and guarantee the accurate reconstruction of compressed data at the sink. The work in [10] takes advantage of high spatial correlation of observation retrieved from proximal video sensor to process in-network video in routing, which can reduce much redundant data of network.

This paper proposes CDCS, a cluster-based distributed compressed sensing for QoS routing in CVSNs, focusing on energy-efficient transmission of visual information in presence of QoS constraints. The main contributions are as follows:

• A correlation metric for adjacent video sensors with overlapped FoVs is utilized to determine which video sensor can participate in a cluster. The purpose is to enhance video compression efficiency.
• A QoS routing framework is presented to transmit the compressed data with an objective to minimize energy consumption subject to delay and reliability constraints.
• The effectiveness and superiority of CDCS are validated through extensive simulations. It is showed that CDCS can achieve energy efficient QoS communication without damaging video frame quality.

This paper is organized as follows. Section II explains the reason why DCS can reduce redundancy. The main design is presented in Section III. Performance evaluation is given in Section IV, followed by the conclusions in Section V.

### 2. Motivation

Due to the huge size of raw visual information, images and video sequences are compressed prior to transmission. We present an example to show the impact of DCS on the removal of redundancy. Consider a length-N, real-valued signal of one dimension indexed as $x$, its coefficient $\theta$ is sparse in wavelet basis $\psi$, that is $x = \psi \theta$, where $\theta$ is an $N \times 1$ column vector with $k$ nonzero elements and $k$ is the sparsity of $\theta$.

![Figure 1. Sparsity coefficient of signals observed by adjacent sensors](image)

![Figure 2. Cluster-based distributed compressed sensing for QoS routing](image)

Take Fig. 1 as an example of sparsity coefficient of signals observed by different sensors, where the signals are processed under three situations: non-compression, CS and DCS. The size and location of sparsity coefficient are same for all $\theta_i$, but sparsity coefficient of the noise are not. Consider first a simple case where no encoder processes these three signals. If the length of a signal is 40, 120 signal samples need to be transmitted for three signals. Next, consider a simple case where the encoder processes these three signals by CS. Based upon the CS machinery, $M = c \cdot k$ (where $c = 4$) measurements are required to reconstruct the signal $x$. accordingly, we need to transmit 60 signal...
samples for three signals totally. If the encoder processes these three signals by DCS, measurements are expected to reconstruct the signal \( x \), where \( K \) represents the common sparsity of three coefficients and \( k_i \) represents the unique sparsity of coefficient \( \theta_i \). As a result, only 36 signal samples are transmitted for these three signals.

The above analysis indicates that DCS can largely reduce unnecessary redundancy of data transmission compared with compressed sensing.

3. Main Design
This section presents a cluster-based distributed compressed sensing approach for QoS routing, the main mechanism of which is comprised of the following parts (shown in Fig.2).

1) Event-driven clustering: The video sensors will be triggered and the clustering process is generated when an event is detected within their vicinity. The cluster consisting of several member nodes is formed in the dashed circles.

2) Collaborative nodes selection: SCS determines how many collaborative nodes are selected to participate in DCS so as to meet the needs of the reconstruction error.

3) QoS-aware routing selection: Each node respectively selects the optimal next hop with the objective of minimizing energy consumption and satisfying QoS requirements in delay and reliability. Afterwards, compressed data is transmitted to the sink along the chosen path.

3.1 Event-Driven Clustering
Video sensors can only observe the object in their FoVs [10]. As shown in Fig.3, the FoVs of video sensor is determined by four parameters: the location of the video sensor (L), the sensing radius (r), the sensing direction (v) and the offset angle (α). For two sensors \( v_i \) and \( v_j \) with FoVs \( F_i \) and \( F_j \), suppose at the same time, their observed image information are \( X_i \) and \( X_j \), both of which are correlated if \( F_i \) and \( F_j \) are overlapped with each other.

Two metrics which characterize the correlation between adjacent video sensors are introduced to select member nodes.

Overlapped Ratio of FoVs: The overlapped ratio of FoVs for \( v_i \) and \( v_j \), denoted by \( r_{ij} \), is defined as

\[
 r_{ij} = \frac{S(F_{ij})}{S(F)}
\]

where \( S(F_{ij}) = F_i \cap F_j \) is the overlapped area of \( F_i \) and \( F_j \), and \( S(F) \) is the area of \( F_i \). If two video sensors have large overlapped ratio of FoVs, large portions of the two observed images are correlated and they are likely to observe the same event concurrently.

Condition Entropy of Observed Images: For a pair of nodes \( v_i \) and \( v_j \), the condition entropy of observed images information is defined as

\[
 H(X_i | X_j) = H(X_i, X_j) - H(X_j)
\]

which quantifies correlation between \( v_i \) and its adjacent nodes. With the decrease of conditional entropy, the correlation of images captured by \( v_i \) and \( v_j \) increases.
Assume that sensing direction \( v \) is fixed. Let each video sensor report its focal length and FoVs parameters to the sink. After receiving these parameters, the sink calculates \( r_{i,j} \) between any two video sensors using (1), and send calculation results to each node. The clustering process is generated when an event is detected. Event detecting nodes become member nodes directly. Then, a request message is send by these member nodes to non-member one-hop neighbors. Upon receiving this request, each non-member node determines whether they join clustering. The condition for becoming member nodes depends on the correlation between nodes. The member nodes newly elected send message to their non-member one-hop neighbors and the process continues until the event is not within nodes’ FOVs. Assume member node \( v_i \) sends request message to its neighbor node, i.e. \( v_j \). The weight between \( v_i \) and \( v_j \), denoted by \( w_{i,j} \), is calculated by

\[
w_{i,j} = \frac{r_{i,j}}{H(X_i | X_j)}
\]

(3)

The node \( v_j \) with highest weight \( w_{i,j} \) in the neighborhood of \( v_i \) is chosen as member node. We define a set \( \gamma \) that represents member nodes within a cluster. Clusters are formed only when an event takes place, when event moves to another place, a new clustering process begins.

After selecting member nodes, the cluster head is responsible to compress observed images and then sends compressed data to the sink. Due to the existence of PUs, the channel availability of each node is different, which causes big influence on the data transmission of cluster head. Thus, how to select a cluster head which does not influence PUs activities to transmit compressed data is significant in CVSNs. To characterize dynamics of channel availability, PUs activity in each data channel can be modeled as two-state birth-death process with birth rate \( b \) and death rate \( a \) [11]. The ON state indicates that the channel is occupied by PUs, whereas the OFF state implies that the channel is idle. By the help of assumed PUs activity model, the probability of channel \( c \) being occupied and idle are defined as \( u_{on}^c = \frac{b}{a+b} \) and \( u_{off}^c = \frac{a}{a+b} \). A larger \( u_{off}^c \) indicates that \( c \) is better and more suitable for data transmission.

When an event moves, nodes within the scope of event should participate in compressed sensing. This corresponds to the follow-ing optimization problem:

\[
v_i^* = \arg \max_{v_i \in \gamma} E_i
\]

(4)

Subject to:

\[
d(v_i, s) < d(e, s)
\]

(5)

\[
d(v_i, e) < r
\]

(6)

\[
u_{off}^c \geq U
\]

(7)

\[
\beta - \pi < \arctan \left( \frac{y_i - y_e}{x_i - x_e} \right) < \beta
\]

(8)

Constraint (5) ensures that the distance between cluster head and the sink is less than the distance between the sink and the event. Constraint (6) demands that the distance between cluster head and event is less than sensing radius of video sensor. The cluster head selection depending on Constraint (8) requires that cluster head and the sink should be located on the same side of the event movement locus, where \((x_0, y_0)\) is the location of event \( e \) whose the moving direction is \( \beta \) and \((x_i, y_i)\) is the coordinate of \( v_i \).

We provide a probabilistic cluster head selection guarantee, in which the probability that the channel being idle should not be below \( \gamma \), expressed by

\[
P(u_{off}^c \geq U) \geq \gamma
\]

(9)
Where $U$ is the channel availability threshold. Let $f_{\text{off}}$ be $1 - u_{\text{off}}$. Equation (9) can be changed to

$$ P\left(f_{\text{off}} \geq 1-U\right) \leq 1- \gamma $$

(10)

By applying the Markov’s inequality on Eq. (10), we have

$$ P\left(f_{\text{off}} \geq 1-U\right) \leq \frac{f_{\text{off}}}{1-U} $$

(11)

and

$$ 1-U > 0 $$

(12)

Comparing (10) and (11), if the following inequality holds,

$$ \frac{f_{\text{off}}}{1-U} \leq 1- \gamma $$

(13)

The probabilistic guarantee inequality (10) for cluster head selection can be satisfied, from which constraint (7) is obtained. The probabilistic guarantee we provide can ensure the probability of channel being idle be larger than a given channel availability threshold. Hence, cluster head selection can be realized without influencing PUs activities.

### 3.2 Selection for Collaborative Nodes

It can be concluded from the above analysis that the number of measurements $m$ required in DCS is preset according to the assumed signal sparsity. In practice, however, the signal sparsity is often unknown or even time-varying. In the DCS process, with the help of sequential compression sensing technology that unaware of the signal sparsity, the number of measurements required to satisfy the reconstruction error is determined, and these nodes are selected in the cluster to carry out DCS. Hence, the redundant information in routing transmission can be minimized to achieve QoS.

Benefiting from SCS [12], we decide whether enough samples have been obtained, with which reconstruction error can be limited to a specified threshold. Assume the sparsity of signal $x$ is $k$, SCS first obtains an initial measurement vector $y^m = (y_1^m, ..., y_s^m) \in \mathbb{R}^m$ based on experience, and then accept $G$ additional measurements. The distance between the current reconstruction $x_m$ of $m$ measurements and the affine space $H_{m+G}$ determined by $m+G$ measuring is

$$ d(x^m, H_{m+G}) = (\Phi^{m+G})^\times (\Phi^{m+G}x^m - y^{m+G}) $$

(14)

where $\Phi^{m+G} \in \mathbb{R}^{(m+G) \times d}$ represents measurement matrix, $(\Phi^{m+G})^\times$ is pseudo inverse matrix of $\Phi^{m+G}$. The reconstruction error of $m$ measurements with probability at least $1-1/a^2$ is

$$ \| x - x^m \|_2 \leq C_G d(x^m, H_{m+G}) $$

(15)

In eq.(15), the value of $C_G$ is computed by

$$ \sqrt{\frac{Q-2}{G-2}} + 2 \sqrt{\frac{Q}{G-2}} \frac{Q}{G} $$

(16)

where $Q = k - m$. $C_G d(x^m, H_{m+G})$ represents the estimated value of reconstruction error. In the following, we stop taking new measurements once the estimated value of reconstruction error in (6) falls below a desired threshold. Otherwise, taking $G$ as the step and increasing the number of measurements sequentially until the reconstruction error is under a specified reconstruction threshold, we get measurement vector $y^{m+Gs}$, where $s=0,1, ..., S$. 


After m collaborative nodes are selected, their observed images are jointly compressed at cluster head. And then cluster head sends compressed data to sink hop by hop.

### 3.3 Distributed QoS Routing

Suppose a cluster head needs to forward a video frame to the sink. We define the set of selectable neighbors that closer to the sink than itself and on the same side of the track of the event with the sink by $F_i$. The next hop node $v_j$ is selected from $F_i$ according to the following rules.

Given: $v_i, v_j \in F_i, c \in C_{i,j}, r_{i,j}^c \in R$

Find: $v_j^*, c^*$

Minimize:
$$E\left(\frac{L}{r_{i,j}}, d(v_i, v_j)\right)$$

Subject to:
$$\frac{L}{r_{i,j}^c r_{i,j}^e} < T_{i,j}$$
$$p_{i,j}^e \geq P_{i,j}$$

The local optimal next hop $v_j^*$ is the node that results in the minimum energy consumption under local delay, local reliability constraints. A channel transmission rate, i.e. $r_{i,j}^e$ is chosen from a set of channel transmission rates $R$ belonging to $\{R_1, R_2, ..., R_n\}$.

The objective of (16) is to minimize energy consumption for transmitting a packet of L bits data with channel transmission rate over a distance of $d(v_i, v_j)$. An equation (17) is the local delay requirements, (18) is the local reliability requirement.

1) Energy consumption

We use a model in [13] for the data communication energy dissipation. Suppose that one sensor node transmits l bits of data over a distance d to another node. The energy consumption for transmission is

$$E_t(l, d) = l \cdot E_{elec} + \varepsilon_{amp} \cdot l \cdot d^a$$

while the energy consumption for receiving these bits is

$$E_r(l, d) = l \cdot E_{elec}$$

The electronics energy, $E_{elec}$, is the energy needed by the transceiver circuitry to transmit or receive one bit, whereas $\varepsilon_{amp}$ is a constant for communication energy. The total energy consumption for transmitting and receiving l bits over a distance d is given by

$$E(l, d) = E_t(l, d) + E_r(l, d) = 2 \cdot l \cdot E_{elec} + \varepsilon_{amp} \cdot l \cdot d^a$$

The energy consumption for processing can be modeled as a function of supply voltage. Suppose the execution of a task consisting of Ncyc clock cycles, the energy consumption for processing is estimated as

$$E_{proc}(N) = N_{cyc} C_{total} V_{dd}^2 + V_{dd} \left( I_0 e^{\frac{V_{dd}}{n f}} \right) \left( \frac{N_{cyc}}{f} \right)$$

The first term in (22) is the switching energy, where $C_{total}$ is the total capacitance switched by the computation per cycle, and $V_{dd}$ is the supply voltage. The second term stands for the leakage energy, where f is the clock speed, and $I_0, n$ are processor-dependent parameters [14].

2) Local Reliability Guarantee:
Consider a multi-channel CVSN. A redundancy scheme is incorporated in transmission to adapt to varying wireless channel conditions. Cluster head will add an appropriate amount of redundancy to the packet according to the delivery rate of the link. Higher link delivery rate means less redundancy added to packets.

To calculate reliability, we use the packet delivery ratio, the percentage of packets successfully send to the destination. If we require that each hop on a route should provide the same level of reliability, the required packet delivery ratio from vi and vj, can be estimated as

$$P_{i,j} = \frac{P}{\hat{N}_{i,s}}$$

(23)

where P is the required packet delivery ratio given by the applications and $\hat{N}_{i,s}$ can be calculated as follow:

$$\hat{N}_{i,s} = \max \left( \left\lfloor \frac{d(v_i, s)}{d_{hop}} \right\rfloor, 1 \right)$$

(24)

In Eq. (24), the average single hop distance, denoted by $d_{hop}$ can be estimated as the sample arithmetic mean of the distance between $v_i$ and all its forwarding neighbor nodes:

$$d_{hop} = \frac{\sum_{v_j \in F_i} d(v_i, v_j)}{|F_i|}$$

(25)

Next we explain how to obtain the required packet delivery ratio P. The biggest problem to be considered in the transmission process of encoded data is whether data packets can be decoded successfully at the sink. Hence, we use the probability that a video frame is successfully decoded as a metric to evaluate reliability. We denote this probability by PD. A video frame X is packed into n packets for transmission. The packet will be decodable only when enough video frames are received correctly. We introduce frame decodable threshold, denoted by DT, to represent the percentage of video frames needed to decode a frame. The probability that at least DT percent of packets are successfully delivered, denoted by $\omega(X)$, is estimated from n, DT, and P, given by

$$\omega(X) = \omega(n, DT, P)$$

$$= \sum_{r=\lceil DT \rceil}^{n} \binom{n}{r} P^r (1-P)^{n-r}$$

(26)

A video frame is decodable if at least DT percent of the packets are delivered to the sink. If a video sensor has generated a frame X, the probability that X is successfully decoded is given by

$$P_D(X) = \omega(X) = \omega(n, DT, P)$$

(27)

The probability that the frame is successfully decoded PD(X) is correlated with the process of compressed sensing of data, which is limited by the decoded effect of packet, i.e.

$$P_{D}(X) = 1 - \frac{1}{\|x^* - x\|}$$

(28)

In this work, given a required PD(X) from an application, the number of packets for X (n), and the frame DT, the required packet delivery ratio P is estimated and assigned to each packet.

3) Local Delay Guarantee:

Local delay requirement also needs to be considered in data transmission. A node knows its neighbors, available channels and transmission rates when it chooses a next hop. So it can choose one from a set of channel transmission rates $\{R_1, R_2, \ldots, R_n\}$. The higher the channel transmission rate, the shorter time data transmission spends.
A geographic mechanism is used to map end-to-end delay requirements to local delay requirement. Suppose a packet with a length of $L$ at $v_i$ needs to be delivered to the sink within delay $T$. The local delay constraint, denoted by $T_{i,j}$, is expressed as

$$T_{i,j} = \frac{T}{N_i}$$  \hspace{1cm} (29)$$

The transmission delay for a packet from $v_i$ to $v_j$ is $\frac{L}{p_{i,j} \cdot c_{i,j}'}$, where $p_{i,j}'$ is the packet length after redundancies are added.

4) Protocol Operation:

The next hop is selected by performing Algorithm 1. The channels of $v_j$ in $F_i$ are put in set $J$ only if the local delay requirement and local reliability requirement can be satisfied. By computing (16), the optimal channel of $v_j$ is selected from the channels selected above. After all nodes in $F_i$ find their optimal channel, the node $j^*$ that results in the smallest energy consumption among all nodes in $F_i$ is selected as the next hop node. The channel $c_{i,j}^*$ of the optimal node $j^*$ becomes transmission channel correspondingly.

4. Performance Evaluation

We evaluate the performance of CDCS under varying traffic load and QoS requirements. For performance comparison, we choose two baselines, i.e., multi-channel MMSPEED (referred as M3SPEED) and CDCS without correlation-aware design (referred as DCSR). Because M3SPEED fails to support cognitive radios, we extend its capabilities in terms of spectrum sensing and channel selection so as to make it comparable.

**Algorithm 1 QoS-Guaranteed Next-hop Selection**

1. for $v_j \in F_i$ do
   2. $J = \emptyset$
   3. for $c \in C_{i,j}$ do
      4. if $\frac{L}{p_{i,j}' \cdot c_{i,j}'} < T_{i,j}$
         5. $J \leftarrow c$
     6. end if
   7. end for
   8. $c_{i,j}^* = \arg \min_{c \in J} E \left( \frac{L}{p_{i,j}' \cdot c_{i,j}'} \cdot d(v_i, v_j) \right)$
   9. end for
10. $j^* \leftarrow \arg \min_{v_j \in F_i} E \left( \frac{L}{p_{i,j}^\sigma} \cdot d(v_i, v_j) \right)$ where $\sigma = c_{i,j}^*$
11. $c^* \leftarrow c_{i,j}^*$

4.1 Compression Efficiency

200 video sensors are deployed in a field and their transmission range is 15m. The number of channels is 10. The video sensors’ sensing radius is set to be 30m and the offset angle is set to be 60°. The locations and sensing directions of each video sensor are fixed. Each sensor captures one image at
each deployment, and the size of each image is 256×256. Each image is segmented to blocks of 8×8 before DCS. The results on DCS compression efficiency under different node number are shown in Fig. 4.

The reconstruction error rate of X is calculated by 1−PD (X). From Fig. 4, the reconstruction error rate of image declines with the increase of node number. When the number of node in the network is high, the reconstruction error tends to zero, and the image shows a good reconstruction effect. Without considering correlation, nodes will be clustered randomly, and some nodes that have not observed the objects will appear in the cluster. Because there is no object in the observation of these nodes, the compression for the object cannot be realized. Consequently, the number of nodes that can participate in DCS is reduced and the reconstruction error is larger. When the number of node is high, more nodes can be selected. This increases the probability of the node to observe the object, making up for the disadvantage without consideration of the correlation to a certain extent.

4.2 Energy Efficiency

The purpose of the next experiment is the energy utilization efficiency of the proposed algorithm, where the deadline is set to be 1s and the required packet delivery ratio i.e. P, is set to be 0.85. The parameters $E_{elec}$, $\epsilon_{amp}$ and $\alpha$ in Eq. (21) are 50nJ/b, 10 pJ/b/m2 and 2 respectively. Correspondingly, $I_0$, $N_{cyc}(encoder)$, $C_{total}$ and $N_{cyc}(decoder)$ in Eq. (22) are 1.196 mA, 2.3M cycles, 0.69 nF, 0.14M. Fig. 5 illustrates the result on energy consumption.

Compared with M3SPEED, CDCS and DCSR need more processing energy consumption for encoding local video frames. However, the primary problem for M3SPEED is that it lacks a control for redundant data, so there is much energy consumption in routing decisions. The proposed CDCS algorithm is designed to reduce energy consumption by reducing the transmission of redundant information and selecting energy efficient next hops. Hence, in contrast to M3SPEED, CDCS and DCSR consume less energy. Without considering FoVs correlation, DCSR has less number of nodes that observes object in a cluster. This leads to limited video compression, and thus the energy consumption of DCSR is less than CDCS.
4.3 QoS Provisioning

Fig. 6 gives the frame delivery under reliability requirements with respect to different deadlines. For each reported image frame, we count the number of received packets within the deadline. If the percentage of received packets for a frame is above the frame decodable threshold (DT=0.8), we show that it is successfully decoded at the sink. Based on the number of decoded frames, we can obtain the percentage of successfully decoded video frames (frame delivery ratio). From Fig. 6, CDCS can meet reliability requirements in most cases.

5. Conclusions

A cluster-based distributed compressed sensing approach that combines network coding and QoS routing is proposed in this study. The purpose is to minimize energy consumption while satisfying QoS requirements in delay and reliability. Based on the correlation degree among adjacent video sensors with the overlapped field of views, the video sensor that observes the object is selected as a member node. Then SCS is used to determine enough number of collaborative nodes that can meet the requirements of the reconstruction error to participate in DCS. Finally, a QoS routing framework is presented where each node respectively selects the optimal next hop with the object of minimizing energy consumption. Simulation results show that by integrating FoVs correlation operations in DCS process, CDCS can realize high energy-efficient delivery and reconstruction accuracy of visual information.

6. Acknowledgement

The authors gratefully acknowledge the support and financial assistance provided by the National Natural Science Foundation of China under Grant Nos. 61502230, 61501224 and 61073197, the Natural Science Foundation of Jiangsu Province under Grant No. BK20150960, the National Science Foundation of the Jiangsu Higher Education Institutions of China under Grant No. 15KJB520015.

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