A Study on Compressive Sensing based Clustering algorithms in Wireless Sensor Networks for reduced data transmissions

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1. Introduction

Wireless Sensor Networks (WSN) is an emerging technology playing a great role in many applications of science & technology including Internet of Things (IoT). Due to its limited battery, communication process should be made effectively to preserve energy. Basically, sensor nodes sense the required physical scalar quantity such as temperature or pressure variation over a geographical region. Each node in the network senses the parameter and transmit the sensed data to the Base station. Most effective method of data gathering is exploiting hierarchical structures which improves network lifetime and proved to be effective in terms of energy consumption[1]. Usually, in hierarchical technique, nodes perform different tasks which include sensing, data collection and forwarding, and data aggregation. Nodes in the middle hierarchy may perform data aggregation or compression to remove redundancies. One such method of performing data gathering is Compressive Sensing (CS) in WSN[2]. The real time information collected by sensor nodes may be sparse in some domain. Overruling the concept of Nyquist criterion, the minimum data required to perform data recovery with acceptable error rate is less. Instead of collecting all original sensor data information, fewer measurements are sufficient to retrieve the information. In large scale networks, the concept of CS has its increasing use to prolong network lifetime [3] and to lessen the communication cost. Instead of

https://doi.org/10.33292/ijarlit.v3i1.45

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transmitting original data, the projections of data can be transmitted with fewer transmissions which can be determined using the measurement or sensing matrix. Thus, the notion of CS is that even with lesser number of measurements than stated in Nyquist criteria, the data can be reconstructed accurately provided that the signal is sparse in some domain [4]. Exploiting CS technique in multi-hop or hierarchical WSN for data gathering, data collection, data aggregation or data compression results in energy efficiency, lesser transmissions, improved network lifetime and reduced cost [5]. In these techniques, CS measurements are forwarded through tree or cluster heads towards the sink which performs data recovery using various schemes. The reconstruction of data at the sink highly depends on the sensing matrix. So, prudent selection of the sensing matrix is mandatory. Most works consider the use of Gaussian random matrix as the measurement matrix to perform compressive sensing. Figure 1 depicts the architecture of clustered WSN using compressive sensing technique.

![Architecture of Compressive Sensing in clustered WSN](image)

**Fig. 1. Architecture of Compressive Sensing in clustered WSN**

Due to the reason that clustering has proved to be an energy saving and load balancing technique in WSN, CS technique is applied over clustering to enhance the performance. Various algorithms have been proposed for clustering by utilizing compressive sensing for data collection process in WSN. While applying CS based data gathering over clustered WSN, it can be categorized into three cases: plain-CS, hybrid-CS and tree based hybrid-CS technique. In plain-CS technique, each sensor node transmits the product of the data and measurement vector coefficient to the CH and the CH transmits the linear combination of all products to the base station. In hybrid-CS, intra-cluster communication does not employ CS whereas inter-cluster communication does. In tree based hybrid-CS, in addition to the earlier case, measurements from CH will be transmitted to the base station through the inter-cluster routing tree. Figure 2 shows the data transmission using plain-CS technique in cluster based WSN during its first round of data transmission.

This paper presents the recent algorithms which employ Compressive sensing techniques in the cluster based WSN and are discussed in brief. A comparison of such algorithms is also presented in terms of sparse representation, measurement matrix and reconstruction techniques.

The section 2 provides the fundamentals of compressive sensing in detail. Section 3 presents the various clustering algorithms using compressing sensing in brief and provides the comparison of the same. Section 4 concludes the work.
2. Compressive Sensing Background

This section provides the prologue of the compressive sensing process. The sparse representation of the data vector, measurement matrix for perfect recovery and the possible reconstruction algorithms have been discussed.

Fundamentals of compressive sensing

In WSN applications, most real time information provided by sensor nodes in dense network exhibits data correlation or redundancy among them. Transmitting all such information towards the Base station utilizes more energy resulting in earlier battery drain. In CS theory, it is stated that a sparse signal is sampled and can be exactly recovered from smaller number of data projections than Nyquist sampling rate. Let us consider a WSN with 'n' number of sensor nodes and a Base Station. When each node (n) transmits data towards the BS, the number of transmissions will be 'n' and the sensor data will be \{d_1, d_2, d_3, ..., d_n\}; d_i \in \mathbb{P}^n. The data vector can be represented as n×1 vector, D=[d_1 d_2 d_3 ... d_n]^T which contains scalar values of sensor measurements. A vector is said to be sparse if it has sparse representation in some domain[6]. The vector D may be represented as a sparse signal in some domain. Let D be sparsely represented in some \(n \times n\) orthonormal basis \(\Psi = \Psi_1, \Psi_2, ..., \Psi_n\) as

\[
D = \psi \mu
\]

\[
D_k = \sum_{k=1}^{n} \psi_k \mu_k
\]

The vector \(\mu\) is the coefficient vector of D in \(\Psi\) domain. With \(\mu\) being the sparse vector representation of D, the data vector D is said to be \(x\)-sparse if the vector \(\mu\) has \(x\) number of non-zero coefficients where \(x \ll n\) and other D\(x\) coefficients are zeroes or closer to zeroes. Instead of transmitting 'n' data directly to the base station, we can transmit 'm' projections, \(M=\Omega D\) where 'M' is of size \(m \times 1\) and '\(\Omega\)' denotes the measurement matrix of size \(m \times n\). After receiving these 'm' projections, the base station performs data reconstruction of 'n' original data. The accuracy of data recovery depends on the selection of the measurement matrix. The projection is given by,
\[ M_{m\times1} = \Omega_{m\times n}D_{n\times1} \]  
\[ M_i = \sum_{j=1}^{m} \Omega_{i,j}D_j \]  
\[ \begin{bmatrix} M_1 \\ M_2 \\ M_3 \\ \vdots \\ M_m \end{bmatrix} = [\Omega_1 \ \Omega_2 \ \Omega_3 \ \ldots \ \Omega_m]^T \begin{bmatrix} D_1 \\ D_2 \\ D_3 \\ \vdots \\ D_n \end{bmatrix} \]

where each \( \Omega_i \), \( i=1,2,...,m \) denotes the \( n\times1 \) vector. Each value of projection is determined by multiplying the sub-matrix of the measurement matrix and its corresponding data. The theory of CS states that if a signal \( D \) is \( x \)-sparse in some basis (\( \Psi \)), it can be reconstructed with \( 'm' \) linear measurements (\( m<<n \)) with acceptable error. It is clear that number of transmissions has reduced from \( 'n' \) to \( 'm' \) since \( m<<n \) [7].

2.2 Sparse Representation

According to sparse representation theory, the sparse data can be exactly recovered from a small number of measurements. A signal can be said as sparse if it can be expressed as a linear combination of small number of basis vectors. In CS, measurements can completely summarize the information in a sparse signal. The sensed physical data is not sparse in real time always but it can be sparse if represented in some domain. The possible options for the sparsifying the sensor data includes Discrete Cosine Transform (DCT) [22], Discrete Wavelet Transform (DWT), Discrete Fourier Transform (DFT) [8], Laplacian Eigen vector and Kernel based transform.

Normally, there are two different types of sparsity which includes \textit{temporal sparsity} and \textit{spatial sparsity}. In a network of \( 'n' \) nodes, let the time samples collected from each sensor node be \( d_i \in \mathbb{R}^n; i \in (1,n) \) and the data vector be \( D=[d_1, d_2, d_3,..., d_n]^T \). The data collected from many types of sensors such as pressure, temperature, humidity, etc. can be sparse in some orthonormal basis. This type of sparseness is known as temporal sparsity. Spatial sparsity refers to the sparsity of data collected from distributed sensor nodes. Information collected from distributed nodes can be sparse since nodes close to the source/event can have significant sensor data while distant nodes cannot have. Spatial sparsity can be utilized in data gathering, sparse event monitoring and localization of sources [16].

2.3 Measurement Matrix Design

The selection of the measurement matrix plays a vital role in the data reconstruction process. If data vector \( D \) is adequately sparse, then it is possible to recover data from \( m\)-\textit{compressed} projections under certain conditions. For the perfect reconstruction of the compressed data, the measurement matrix should follow the following properties:

1) \textit{Restricted Isometry Property (RIP)}

A matrix \( \Omega \) is said to follow RIP(otherwise known as Uniform Uncertainty Principle), if there exists an isometric constant \( \delta_s \in (0,1) \) such that

\[ (1 - \delta_s)\|D\|_2^2 \leq \|\Omega D\|_2^2 \leq (1 + \delta_s)\|D\|_2^2 \]  

for all \( x \)-sparse vectors \( D \) [9], non-zero elements lesser than \( s \). The RIP provides the near optimal recovery of the sparse vector from compressed vector using \( l_1\)-\textit{norm} minimization. It is a NP-hard problem to determine the measurement matrix which satisfies the RIP principle. Nevertheless, a \( m\times n \) random matrix \( \Omega \) whose entries are i.i.d realizations of random variables with zero mean and \( 1/m \) variance satisfies RIP.

2) \textit{Mutual Coherence}:
The rows of the measurement matrix $\Omega_{m \times n}$ should be incoherent with the columns of the sparsity basis orthonormal matrix $\psi_{n \times n}$. The mutual coherence (MC) between $\Omega$ and $\mu$ can be defined as,

$$MC(\Omega, \psi) = \sqrt{n} \max_{1 < k, j < n} |\langle \Omega_k, \psi_j \rangle|$$

(7)

where $MC \in (1, \sqrt{n})$. The coherence is large if both matrices have more correlated elements [10]. The smaller the coherence, lesser is the number of measurements required for reconstructing the signal.

Some of the commonly used measurement matrices are the random Gaussian matrix, Bernoulli matrix, Toeplitz structured matrix [19], Block Diagonal matrix [11]. Among this, random Gaussian matrix is the most basically used one which provides matrix of random elements which follow Gaussian distribution.

2.4 Reconstruction Algorithm

Given a compressed vector of data $M = \Omega D$, the s-sparse signal $D$ can be reconstructed using the $l_1$-norm minimization technique by solving

$$\arg\min_{\mu \in P_+} \|\mu\|_1 \quad s.t \quad M = \Omega D = \Omega \psi \mu$$

(8)

This can be solved by using some greedy techniques such as Basis Pursuit (BP) [6], Subspace Pursuit[12], Orthonormal Matching Pursuit [13], Compressive Sampling Matching Pursuit (CoSaMP)[14] and Hard Thresholding Pursuit (HTP)[15].

3. Compressed sensing in clustered WSN

Being a proved technique for energy efficiency, clustering plays a main role in WSN data collection. Employing the concept of CS in the clustered WSN enhances the energy efficiency since compressive sensing reduces the number of data transmissions towards the base station. The general structure of data collection in clustered WSN using the compressive sensing is shown in the figure 3.

![Fig. 3. Hybrid CS in clustered Wireless Sensor Networks (WSN)](image-url)
Compressibility based Clustering Algorithm (CBCA) for Hierarchical Compressive Data Gathering [17]:

Lan et al. proposed a compressibility based clustering algorithm for hierarchical WSN. Initially, nodes are formed as a chain as in PEGASIS. A sliding window of size ‘Z’ is used to slide through the chain by advancing one node. The Compression Ratio (CR) is predicted for all possible \( n-Z+1 \) windows and a set of windows which have CR greater than the threshold (ICT) is determined. The Incompressible windows (ICW) are selected using this ratio and clustering is performed over them using sliding concept. The clustering is performed using a default window (DW) of size ‘Z’ by sliding it over the ICW-marked chain of nodes as given below.

Case-(i): \( DW \) is disjoint with any ICW

Nodes in the DW are formed as a cluster

Case-(ii): \( DW \) is completely overlapped with a ICW

Nodes in the DW are formed as a cluster

Case-(iii): \( DW \) is partially overlapped with a ICW

Clustering is performed based on the non-overlapped nodes (NO) and most formed cluster (MC). Let \( NO_{DW} = DW \setminus (DW \cap ICW) \) and \( NO_{ICW} = ICW \setminus (DW \cap ICW) \). The possible cases are:

(i). \( CR_{MC} > ICT \):

If \( CR_{NO_{DW}} < ICT \), then set of NO nodes and nodes in ICW will be formed as clusters separately, else they will be together formed as a cluster.

\[
cluster = \begin{cases} 
Cluster_1(NO_{DW}) + Cluster_2(ICW) & \text{if } CR_{NO_{DW}} < ICT \\
Cluster(NO_{DW} + ICW) & \text{otherwise} 
\end{cases}
\] (9)

(ii). \( CR_{MC} < ICT \):

\[
cluster = \begin{cases} 
Cluster_1(NO_{DW} + MC) + Cluster_2(ICW) & \text{if } CR_{NO_{DW}} < ICT \\
Cluster(NO_{DW} + ICW) & \text{otherwise} 
\end{cases}
\] (10)

Once clusters are formed, the CR for each cluster is determined. If \( CR_{cluster} < ICT \), Compressive Data Gathering is employed else Random Data Gathering is employed for data transmission. Gaussian matrix is utilized as a sensing matrix and three sparse representations such as Difference Transform, DFT and DWT are utilized. The algorithm has less number of transmissions compared to that of the Random Clustering method.

Unbalanced Expander based Compressive Data Gathering in clustered WSNs [18]:

In [18], authors have proposed an energy efficient Compressive Sensing-Data Gathering (CS-DG) algorithm for addressing the higher energy consumption during clustered data transmission in WSN. Here, a sparse random sensing matrix is constructed by jointly applying random sampling and random walks. The sensing matrix makes use of the concept of adjacency matrix of unbalanced expander to solve the \( l_1 \)-minimization problem. Initially, nodes in the network are organized into clusters using HEED algorithm. The sensed data is represented sparsely using Laplacian eigen vector basis and Identity matrix. The sensor data are collected in the form of measurements from cluster heads in the random walk. The sensory data are randomly sampled before random walk. The reconstruction quality, probability of successful reconstruction and energy consumption parameters of the algorithm were determined. The experiment was performed over real data sets and performance was compared with different algorithms to show its improvement.

Effective data gathering method using Compressive Sensing for WSN[19]:

Zhang et al. proposed an effective data aggregation method for WSN. This hybrid compressive sensing data aggregation method consists of four phases which includes clustering the nodes, building routing tree, perform CS within clusters and inter-cluster data transmission. Initially, nodes in the network are organized into \( N \) clusters. In the second step, inter-cluster routing tree is
determined for forwarding data towards the sink. The tree is formed between CHs with the number of hops, starting from the sink. The sink sets the seed vector value and transmits to the cluster head nodes. Each CH node determines its position in the seed vector and generates the corresponding sub-matrix. The CH determines measurements of received sensor data and transmits to the base station. The base station determines the entire measurement matrix based on the seed vector and recovers the original data after receiving all measurements. The hybrid CS is utilized in this work where CS technique is not used in intra-cluster data transmission whereas CS is incorporated in the inter-cluster data transmission. The energy consumption is analyzed for the proposed data aggregation method in comparison to the existing techniques. The method shows performance improvement in terms of energy consumption, network lifetime and normalized transmission overhead.

![Fig. 4. Data transmission over hybrid CS in clustered Wireless Sensor Networks (WSN)](image)

- Transmission Efficient Clustering method in WSN using Compressive Sensing:
  
  In [20], authors proposed a transmission efficient clustering algorithm which employs hybrid compressive sensing for WSN. Following the poisson distribution process for deployment and by dividing the network into small grids of edge length ‘a’, the optimal cluster size is determined as follows.

\[
N_c = \begin{cases} 
\frac{3M - \lambda a^2}{1 - \frac{3M}{2N}}; & M < \frac{2}{9}N \\
N; & \frac{2}{9}N \leq M \leq N 
\end{cases}
\]

where 'M' denotes number of projections, 'a' denotes the grid edge length, 'λ' is the density of poisson distribution and 'N' represents the number of nodes. Based on the optimal cluster size, clustering is performed. A backbone tree connecting all CHs and the base station is determined using the Minimum Spanning Tree algorithm. This method provides reduction in the number of transmissions compared to the existing algorithms.

- Dynamic Clustering and Compressive data gathering algorithm for energy efficient WSN
  
  Zhang et al. proposed an algorithm using dynamic clustering for energy efficient WSN. Authors have utilized distance based attenuation matrix (ψ) for sparsification which is defined as,
\[ \psi_{ij} = \psi_{ji} = a \cdot \left[ \sqrt{\left( x_i' - x_j' \right)^2 + \left( y_i' - y_j' \right)^2} \right]^n \] 

where 'a' denotes constant, 'n' represents the signal attenuation coefficient, \((x_i',y_i')\) and \((x_j',y_j')\) denotes the location of nodes i and j respectively. The clustering is performed using the event sources in a way that the node closest to the event source will be selected as the cluster head. This process repeats after every particular time interval 't' and so it is a dynamic clustering process. The joint sparsity model-1 (JSM-1) is utilized in this work. Depending on the seed vector from the sink, each cluster head determines the measurement matrix and calculates measurements of all received data. After receiving data from all cluster head nodes, with the help of measurement matrix using seed vector, the sink reconstructs the original data corresponding to each cluster head. The reconstruction is followed by dynamic clustering with rotation of cluster heads. This work differs from conventional CS based algorithms in such a way that clustering is performed using spatial correlation and reconstruction of compressed data is done individually for each cluster. The network lifetime and signal to noise ratio parameters were compared for the proposed work with that of existing algorithms [21].
and are forwarded. That is, each node multiplies its data with random Gaussian coefficients and transmit the product to the respective CH. On receiving from all of its cluster members, the CH adds its data with the received ones and forwards to the base station. Given the measurement matrix and collected measurements, the original data is reconstructed at the sink. The DCT is used as the sparsifying matrix and simulations were carried out for the work and compared with other K-means clustering and LEACH protocol.

- CCS: Energy Efficient data collection in clustered WSN using block-wise CS

Nguyen et al. [24] have proposed the CCS algorithm for energy efficient WSN which employs CS technique in clustered WSN. Initially, uniform selection of cluster heads at random and allocating closer nodes to them results in clustered WSN. Block Diagonal Matrix (BDM) is used for sparsification and based on that, measurements are generated at CHs with received data from their cluster members. The way it differs from the earlier work [G] is that BDM is used as sparsifying matrix. The simulation was performed over random sparse signal and real sensor data set. The former one is sparse in the canonical form whereas the latter in DCT and wavelet basis. The measurements are then transmitted directly to the base station and this is known as D-CCS(case 1). In ICCS (Inter-cluster data transmission using CCS), a tree will be formed between CHs for forwarding data towards the base station (case 2). A greedy algorithm is utilized to construct the routing tree for inter cluster data transmission. This tree formation utilizes the number of hops form the base station to construct the tree. In both these cases, M measurements are forwarded to the base station. In the third case, instead of transmitting M measurements, k<M measurements are used from which the data can be reconstructed. Initially, nodes transmit their raw data to their respective CHs and sorting of data is done in CHs. After multiplying them with the DCT sparsifying coefficients, only k-large values are transmitted to the base station directly instead of 'M'. This further reduces the energy consumption. The total power consumption is given as follows:

\[
P_{tot} = \left(\frac{N}{N_c} - 1\right) \frac{L^2}{2\pi} + \frac{ML^2}{6} \text{(case 1)}
\]

\[
P_{tot} = \left(\frac{N}{N_c} - 1\right) \frac{L^2}{2\pi} + \frac{KL^2}{6} \text{(case 3)}
\]

- Effective algorithm for Optimizing Compressive Sensing:

Aziz et al.[25] proposed a Cluster Size Load Balancing for CS algorithm (CSLB-CS) for IoT based sensor network. In this work, optimization is done for CS matrix using Chicken Swarm Optimization (CSO) algorithm. It involves the setup phase, cluster size load balancing phase and data transmission phase. The network is setup using a clustering algorithm such as LEACH and data is collected. With the transform matrix \( \Psi \), \( \Psi^T \) is computed and then eigen values decomposition \( \Lambda \) and \( \Lambda \) are computed such that \( \Psi^T = \text{VAV}^T \). From the collected data, perform optimization over the \( T \) matrix which helps in determining the optimized CS matrix \( T = \Phi \) using CSO algorithm where \( \Phi \) is a random matrix initially. Then, the optimization is done for CS matrix by optimizing \( \Gamma \). With \( X \) being the matrix which represents the position of chickens by \( \Gamma \), fitness value is determined for each row. With those fitness values, chickens are grouped into roosters, hens and chicks. In CSO algorithm [26], The mobility of roosters, hens and chicks in each iteration are updated respectively as,

\[
R_{i,j}^{t+1} = R_{i,j}^t \ast (1 + \text{randn}(0, \sigma^2))
\]

\[
\sigma^2 = \begin{cases} 
1; & \text{if } f_i < f_k \\
\exp\left(\frac{f_k - f_i}{|f_i| + \epsilon}\right); & \text{otherwise} \\
\end{cases} \quad k \neq i; k \in [1,N]
\]
where randn(0,σ²) is a Gaussian distribution with mean 0 and standard deviation σ², 'f' refers to the fitness value, ε refers to smallest constant used to avoid zero-division-error, 'k' refers to the rooster index.

\[ H_{ij}^{t+1} = H_{ij}^t + S_1 \times \text{rand} \times (H_{r1,j}^t - H_{ij}^t) + S_2 \times \text{rand} \times (H_{r2,j}^t - H_{ij}^t) \] (17)

\[ S_1 = \exp \left( \frac{f_i - f_{r1}}{|f_i| + \varepsilon} \right); S_2 = \exp (f_{r2} - f_i) \] (18)

where r1 refers to the corresponding group-mate rooster of the ith hen, r2 refers to randomly chosen hen/rooster such that r1≠r2.

\[ C_{i,j}^{t+1} = C_{i,j}^t + FL \times (C_{m,j}^t - C_{i,j}^t) \] (19)

where \( C_{m,j}^t \) refers to the mother of the ith chick and FL∈(0,2). Once the maximum iterations are reached, the optimized CS matrix can be determined and sub-matrixes are sent to each cluster. Then data transmission occurs in the form of measurements. The optimal cluster size is determined based on the number of measurements. Thus, load balancing is achieved in clustering and reduction in transmissions is achieved through compressive sensing.

- Hierarchical data aggregation using Compressive Sensing in WSN [27]:

In [27], authors have proposed a data aggregation method for hierarchical WSN using compressive sensing. Initially, nodes are organized into hierarchical clusters using their geographical location and area. Then data transmission starts from leaf nodes which transmits the sensed data directly to their respective cluster heads. These cluster heads transmit projections of all received data to cluster heads at higher level. In this way, the data transmission occurs through CS. For sparse representation of original data vector, Discrete Cosine Transform is utilized. The simulation is performed on the real data set and noiselets are employed as the sensing matrix because of its self-productive and scalable property. Instead of transmitting the entire sensing matrix for supporting data recovery, only indexes of the rows of the matrix are forwarded which reduces the cost. A signal reconstruction algorithm is proposed based on the Compressive Sampling Matching Pursuit (CoSaMP) by examining the characteristics of the DCT. This method provides improvement in terms of the energy efficiency and signal recovery.
### Table 1. Comparison of compressive sensing based clustering algorithms

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<th>Reconstruction algorithm</th>
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<td>Gaussian matrix</td>
<td>Orthonormal Matching Pursuit (OMP)</td>
</tr>
<tr>
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<tr>
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### 4. Conclusion

In Wireless Sensor Networks, clustering algorithms have proved to have various advantages such as energy efficiency, load balancing and data aggregation. Compressive Sensing is a signal processing technique which also has proved to be energy efficient in WSN by reducing number of transmissions. Integrating compressive sensing technique and clustering process in WSN provides improved energy efficiency over the multi-hop compressive sensing and tree-based compressive sensing. This paper provides a comparison of various contemporary clustering algorithms which have employed compressive sensing for either data gathering, data collection or data aggregation process. Few algorithms have utilized hybrid compressive sensing which provides better improvement. Comparison has been done for sparsity, measurement matrix and reconstruction algorithms used in such algorithms. Since measurement matrix plays a vital role in perfect recovery of the original data, focus can be made on the best selection of measurement matrix. In future, algorithms ensuring no packet loss while reconstruction can be designed by maintaining sparsity in time critical applications. This CS reconstruction algorithm can be designed for exact reconstruction without any error and can be extended to applications like healthcare.
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