Theory and Applications of Compressive Sensing in Visual Sensor Networks

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Abstract -

Wireless Visual Sensor Networks (WVSNs) is a network of camera-equipped sensor nodes which can capture, process and transmit image/video information. VSNs have become an emerging multidisciplinary research area as the use of camera in sensor nodes powered by batteries poses a lot of new challenges. The visual data is much larger and complicated and therefore intelligent schemes are required to capture/process and transmit visual data in limited resources. Many energy aware compression algorithms for VSN had gained wide attention. Compressive Sensing (CS) is a new paradigm that combines both acquisition and compression and is totally different from conventional compression algorithms. Conventional compression methods do not consider image acquisition while encoding. CS is a promising method to reduce power consumption and is highly requested for VSN applications. The implementation of CS for VSN reduces the amount of data to be processed and it reconstructs the image/signal using fewer samples. This paper explores the theory, basic principle and applications of compressive sensing mechanism in VSN.

Key Words: Compressive Sensing, Visual Sensor Network.

1. INTRODUCTION

A Wireless Visual Sensor Network (WVSN) is a wireless network of camera based sensor nodes that is widely used for surveillance purposes. As in Fig.1.1, the network normally has a large number of sensor nodes to monitor and detects critical events in a broad physical area. The development of image sensors and wireless technologies has greatly increased the surveillance capacity of wireless visual sensor networks.

Visual processing before transmission can achieve a considerably improved results in terms of energy consumption which in turn reduces the bandwidth utilization. To reduce the energy used in transmission, the size of the images should be made small by applying a large compression ratio, which may reduce the image quality. Each node in a visual sensor network should be capable of extracting, processing and transmitting the visual data.

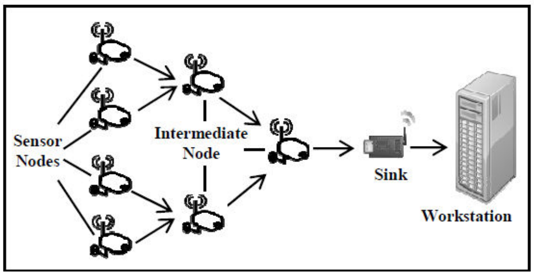

Fig. 1.1 Visual Sensor Network architecture

Therefore, a node consists of an image sensor, an embedded processor and a wireless transceiver. Since the sensor nodes are usually battery-operated the power consumption is one of the main concerns in the design, data processing and data transmission.

In some applications, the entire sensing process should be real-time, thus requiring fast and less complex imaging and processing units. Therefore, each node should extract only useful and new data from the scene. Also, redundant information should be locally removed at each node to improve the efficiency and reduce the amount of the transmitted data. This leads to the use of local image processing and data compression algorithms. Therefore, low cost, low power and smart image sensor structures which are compatible with on-chip signal processing are required in visual sensor network applications. In conventional schemes, all samples of the original signal are acquired and it considers the redundancy in the acquired signal/image for representation.

The Compressive Sensing scheme allows that a signal can be acquired and reconstructed with fewer samples. Combining acquisition and compression of input image helps to considerably reduce the overall energy consumption of a visual sensor. This paper provides a survey on the theory and practical applications of CS in Visual sensor networks.

2. COMPRESSIVE SENSING

In a traditional acquisition system, all samples of the original signal are acquired. This number of signal samples can be in the order of millions, as is the case for instance with digital images. The acquisition process is followed by compression, which takes advantage of the redundancy in the signal to represent it in a domain where most of the signal coefficients can be discarded with little or no loss in quality. For instance, for a typical image of a natural scene, an almost lossless approximation can be achieved with only about 5% of the frequency (e.g., wavelet, DCT) coefficients.

Hence, traditional acquisition systems first acquire a huge amount of data, a significant portion of which is immediately discarded (compression). This creates inefficiency in many practical applications. Compressive sensing addresses this inefficiency by effectively combining the acquisition and compression processes as shown in Fig. 2.1

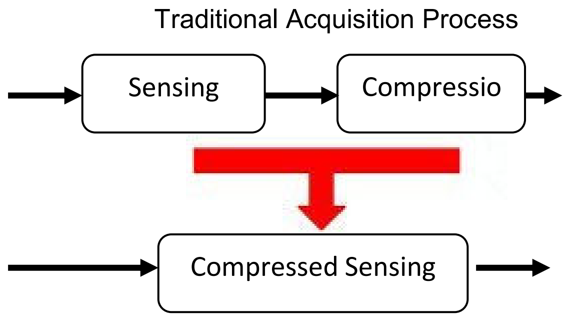

Fig. 2.1 Traditional acquisition Vs Compressive Sensing

Traditional decoding is replaced by recovery algorithms in CS that exploit the underlying structure of the data (Fig. 2.2).

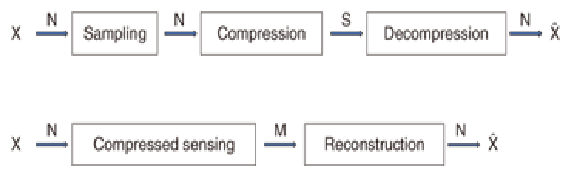

Fig.2.2 Conventional Vs Compressive Sensing

2.1 Nyquist Sampling Vs Compressive Sampling

Conventional approaches to sampling signals or images follow Shannon's theorem: the sampling rate must be at least twice the maximum frequency present in the signal (Nyquist rate). In the field of data conversion, standard analog-to-digital converter (ADC) technology implements the usual quantized Shannon representation - the signal is uniformly sampled at or above the Nyquist rate. Compressed sensing or CS is a novel sensing/sampling paradigm that goes against the common wisdom in data acquisition.

Compressed sensing is a revolutionary signal acquisition scheme that allows a signal to be acquired and accurately reconstructed with significantly fewer samples than required by Nyquist-rate sampling. Unlike Nyquist sampling, which depends on the maximum rate-of-change of a signal, compressed sensing relies on the maximum rate-of information in a signal. Compressed sensing has been emerging in research for low-power data acquisition methods.

2.2 Theory of Compressive Sensing

CS theory states that a signal can be sampled without any information loss at a rate close to its information content. The theory of CS seeks to recover a sparse signal from a small set of linear and non adaptive measurements. The most remarkable idea is that compressive sensing is possible to capture the useful information embedded in a sparse signal and condense it into a small amount of measurements without comprehending the signal. The full-length signal can later be reconstructed from the small amount of measurements by solving a numerical optimization problem. Therefore, it could save a lot in sampling rate and energy when compressive sensing is used in image and video compression in sensor networks.

A sampled signal can be modeled as

$$y = \Phi x$$

--- (1)

where y is an m dimensional vector of sampled values, x is an n dimensional vector of the exact signal, and Φ is a m by n matrix which samples the exact signal. Φ represents the acquisition process Compressive sensing combines these two stages, sensing (sampling) and compression

Let $x \in R$ be real-valued, finite-length, compressible in transform basis, one-dimensional, discrete-time signal with sparse representation S in orthonormal basis Ψ. Mathematically,

$$y = \Phi x = \Phi\Psi s = \Theta s$$

--- (2)

Where Ψ is a compression basis (DCT / DWT) and Θ is the compressive sensing matrix-the product of the compression and sensing bases. So, we can take some small number of samples y, compute the sparse representation s of our exact signal x, and then apply the inverse compression approximation to recover x.

To achieve reconstruction of signal x from y, the sensing matrix $\mathbf{\Phi}$ has to satisfy few properties.

1. Stable measurement matrix $\mathbf{\Phi}$ such that the salient information is preserved during dimensionality reduction
2. A reconstruction algorithm to recover x from only M ~ S log (N) measurements y

Measurements in compressive sensing are random projections (Fig. 2.4)

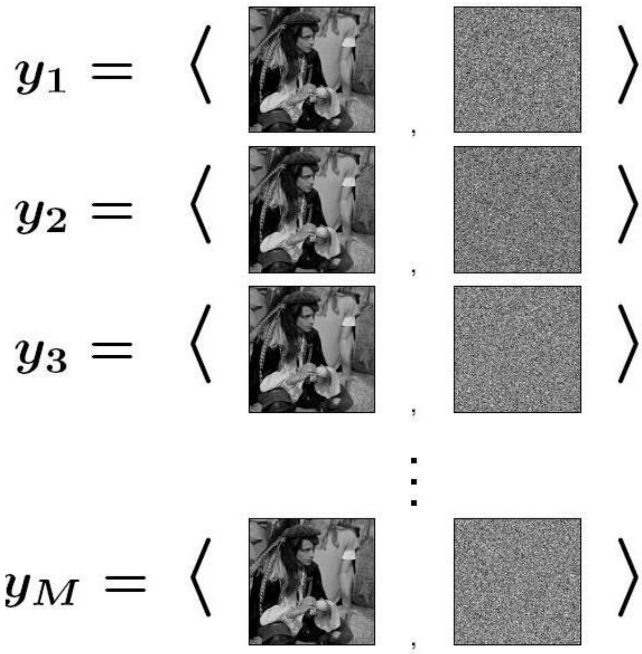

Fig.2.4 Random projections

2.3 Terms and Definitions

CS relies on following properties of signals and their representation and measurement basis:

- Signal sparsity
- Mutual coherence and
- Restricted Isometry Property(RIP)

2.3.1 Signal Sparsity

The sparsity or compressibility of a signal means that most coefficients are zeros or close to zeros when the signal is expressed in proper basis. Take natural images as an example, even though pixels of a image have zero values, wavelet coefficients of the image are much more concise, which means that most wavelet coefficients are close to zeros and only a few coefficients are large which contain most of the information.

2.3.2 Mutual coherence

Signal cannot be sparsely synthesized from both the frequency side and from the time side at the same time if two bases are mutually incoherent.

It measures the largest correlation between any two elements of Φ and Ψ(*i.e.*, any row of Φ and column of Ψ), can be defined as:

$$\mu(\Phi,\Psi) = \sqrt{N} \max \left|(\Phi_k,\Psi_j)\right|$$

--- (3)

where $i \le k$, $j \le n$

The coherence μ , can range between 1 and $\sqrt{N}$ [5]. As it is shown in [2], the minimum number of measurements
needed to recover the signal with over whelming probability is as follow:

$$M \geq C\mu^2(\Phi,\Psi)K\log N \quad \text{--- (4)}$$

where, C is a positive constant, K is the number of significant non-zero coefficients in x, and N is the dimension of the signal to be recovered. In other words, the less coherence between Φ and Ψ the fewer number of measurements needed to recover the signal. Hence, to minimize the required number of measurements, it is required to have the minimum coherence between Ψ and Φ. Random matrices are a good candidate for sampling matrix as they have low coherence with any fixed basis, and, as a result, the signal basis Ψ is not required to be
known in advance in order to determine a suitable sampling matrix, Φ [7].

2.3.3 Restricted Isometry Property (RIP)

The restricted isometry property characterizes matrices which are nearly orthonormal, at least when operating on sparse vectors. The concept was introduced by Emmanuel Candès and Terence Tao [2] and is used to prove many theorems in the field of compressed sensing.
Let Φ be a matrix of dimension M x N with its row vectors € R^N.For each integer S = 1,2,…N, S-Restricted Isometry Constant ∂S of matrix Φ is defined as the smallest number such that

$$(1-\delta_S)\|x\|_{\ell_2}^2 \leq \|\Phi x\|_{\ell_2}^2 \leq (1+\delta_S)\|x\|_{\ell_2}^2 \quad \text{--- (5)}$$

holds for all S-sparse vectors x.
The above theorem is called restricted isometry property (RIP) [6]. RIP guarantees that with a proper matrix A, all subsets of K columns taken from A are in fact almost orthogonal.

2.3.4 Sensing Matrices

For stable reconstruction of S-Sparse signals the sensing matrix Φ must satisfy Restricted Isometry Property for 3S sparse signals.

- Φ must be incoherent to representation basis
- Sensing matrices satisfy RIP in probabilistic sense

Sensing Matrices may be Random or Deterministic matrices. Most popular random sensing matrices are generated by identical and independent distributions Gaussian Sensing Matrix, Symmetric Bernoulli Distribution. Random sensing matrices ensure high probability in reconstruction; they also have many drawbacks such as excessive complexity in reconstruction, significant space requirement for storage, and no efficient algorithm to verify whether a sensing matrix satisfies RIP property with small RIC value. Hence, exploiting specific structures of deterministic sensing matrices is required to solve these problems of the random sensing matrices. Recently, several deterministic sensing matrices have been proposed [14]-[16]. We can classify them into two categories. First are those matrices which are based on coherence [14]. Second are those matrices which are based on RIP or some weaker RIPs.

2.3.5 Reconstruction Algorithms

The signal reconstruction algorithm must take the M measurements in the vector **y**, the random measurement
matrix ϕ (or the random seed that generated it), and the basis Ψ and reconstruct the length-N signal **x** or, equivalently, its sparse coefficient vector **s**. For K-sparse signals, since $M < N$ in (2) there are infinitely many **s** that satisfy Θ **s'**= **y**. This is because if Θ **s** = **y** thenΘ (**s** + **r**) = **y** for any vector **r** in the space N(null Θ) of Θ. Therefore, the signal reconstruction algorithm aims to find the signal's sparse coefficient vector in the $(N - M)$-dimensional translated null space $H = N(\Theta) + \mathbf{s}$.

- **Minimum *l*2 norm reconstruction:**

Define the $l\,p$ norm of the vector **s** as

$$(\|s\|_p)^p = \Sigma_t N\, |s_i|^p$$

t ranges from 1 to r
The classical approach to inverse problems of this type is to find the vector in the translated null space with the smallest $l2$ norm (energy) by solving

$$\mathbf{S = argmin\|s`\|_2 \text{ such that } \theta s' = y}$$

Unfortunately, $l2$ minimization will almost never find a K-sparse solution, returning instead a nonsparse **s** with
many nonzero elements.

- **Minimum *l*0 norm reconstruction:**

Since the $l2$ norm measures signal energy and not signal sparsity, consider the $l0$ norm that counts the number of non-zero entries in **s**. (Hence a *K*-sparse vector has *l*0 norm equal to *K*.) The modified optimization

$$\mathbf{S = argmin\|s`\|_0 \text{ such that } \theta s' = y}$$

can recover a *K*-sparse signal exactly with high probability using only $M = K + 1$ iid Gaussian measurements [5]. Unfortunately, solving (5) is both numerically unstable and NP complete, requiring an exhaustive enumeration of all possible locations of the nonzero entries in **s**.

■ **Minimum *l*1 norm reconstruction:**

Surprisingly, optimization based on the *l*1 norm

$$\mathbf{S = argmin\|s`\|1 \text{ such that } \theta s' = y}$$

can exactly recover *K*-sparse signals and closely approximate compressible signals with high probability using only $M \geq cK \log(N/K)$ iid Gaussian measurements [8], [9]. This is a convex optimization problem that conveniently reduces to a linear program known as basis pursuit [8], [9] whose computational complexity is about $O(N3)$. Other, related reconstruction algorithms are proposed in [11] and [12].

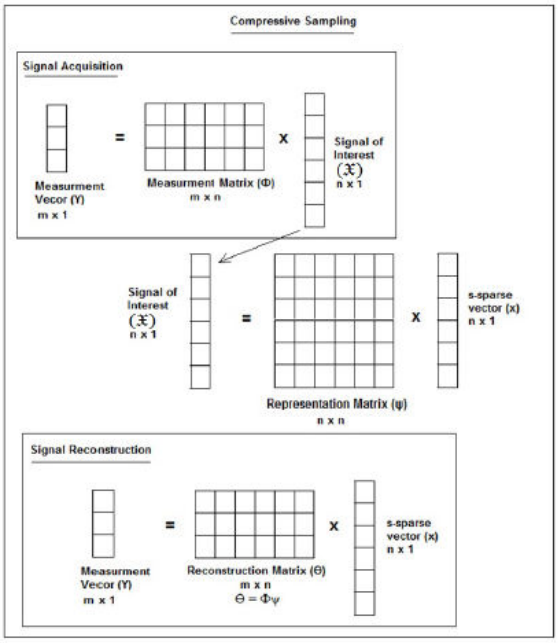

Fig. 6 Compressive Acquisition and reconstruction

3. MOTIVATION FOR COMPRESSIVE SENSING IN VSN:

VSN deal with larger amount of data and the acquisition and processing of images requires mechanisms to control the cost, complexity and bandwidth.

Data processing in Visual sensor network demands

- Faster Sampling
- Acceptable Compression rate
- Low computational complexity
- Larger Dynamic Range
- Reducing the Higher Dimensional Data
- Lower Energy consumption
- Embedded Encoding

Therefore it is critical to use a model that summarizes information regarding the input where N-samples can be described by using only K parameters, where K<<N. The compressive sensing proves a promising technique for reducing sensing cost, data compression, parameter estimation, feature extraction and channel estimation.

3.1 Features of Compressive Sensing

The theory of CS seeks to recover a sparse signal from a small set of linear and non adaptive measurements. The tremendous advantage of CS is to exhibit recovery methods that are computationally feasible, numerically stable, and robust against noise and packet loss over communication channels.

The features of Compressive sensing are

- Single Sensor
- Universality
- Robustness
- Scalable
- Computational asymmetry

Thus the Compressive sensing is highly requested for high dimensional data systems such as VSN.

Table1. Performance analysis of CS based schemes

Parameters	Performance
Compression	High compression ratio.
Complexity	Low complexity with simple encoder.
Memory	Only few sample values that are needed for reconstruction are taken and thus low memory usage
Power	Few samples are measured thereby reducing the data processing and thus high power efficiency
Time	Moderate execution time.

4. APPLICATIONS OF COMPRESSIVE SENSING PARADIGM IN VSN

The recent years have witnessed the emergence of a new sensing and acquisition modality that offers the means to succinctly and effectively represent the salient information of signals with no loss. This emerging sensing modality, emblematically known as Compressive Sensing, has been shown to have a myriad of applications ranging from signal, image and video compression and processing, to communications and medical applications.

4.1 Imaging via CS

Linear measurements cannot adapt to changes in structure from one image to the next; they are stuck recording the same M transform coefficients for every image. CS matches the adaptive approximation performance with a predetermined set of linear measurements. The difference between compressive and linear imaging is dramatic; not only are the reconstructions uniformly better, but they are improving at a faster rate as measurements are added. CI reconstruction is cleaner around the edges than the linear reconstruction. Compressive sensing has far reaching implications on compressive imaging systems and cameras [22]. It reduces the number of measurements, hence, power consumption, computational complexity and storage space without sacrificing the spatial resolution.

4.2 Multi focus Image Fusion

Image fusion is a technique that combines images of a scene from different sensors to discover knowledge that is not apparent from any single image alone. Image fusion finds applications in analysis of satellite images, surveillance and security.

Fusion rule is guided by clarity measures. Fused image is reconstructed based on blocked CS. Because the compression takes place during sensing, fusing less data and reconstructing only one image takes less time in fusing a pair of multi focus source images on a PC. So it greatly improves the efficiency of processing for multi focus Image fusion.

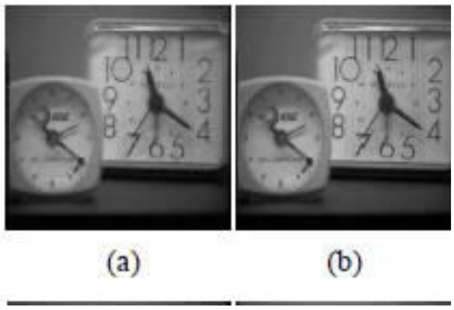

Fig.7 Fusion result of Clock: (a) and (b) Sampling rate 0.3, 0.5 with block-size 16;

4.3 Object Tracking in Surveillance applications

Surveillance application for WVSNs is one of the important applications that require high detection reliability and robust tracking, while minimizing the usage of energy as visual sensor nodes can be left for months without any human interaction. In surveillance applications, within WVSN, only single view target tracking is achieved to keep minimum number of visual sensor nodes in a 'wake-up' state to optimize the use of nodes and save battery life time, which is limited in WVSNs.

CS is investigated in designing target detection and tracking techniques for WVSNs based surveillance applications, without compromising the energy constraint which is one of the main characteristics of WVSNs. Results have shown that with compressive sensing (CS) upto 31% measurements of data are required to be transmitted, while preserving the detection and tracking accuracy which is measured through comparing targets trajectory tracking using LMS (Least Mean Square) tracking. CS is a strong applicant to reduce the size of images as WVSNs are resource constrained In addition, for different schemes where the sparsity nature of each image differs, CS chooses the compression rates accordingly. Moreover, surveillance application within

WVSNs is one of the important applications that require high detection reliability and robust tracking.

4.4 Image representation

The objective of image representation is to signify and express the resulting aggregate of segmented pixels in a form suitable for further computer processing after segmenting an image into regions. Compressing sensing theory have been favourable in evolving data compression techniques, though it was put forward with objective to achieve dimension reduced sampling for saving data sampling cost. CS uses sparse representation of the signal of interest in some basis (Representation Basis). BCS (Block Compressive Sensing) based image representation improves the recovered image quality. The BCS based image representation scheme could be an efficient alternative for applications of encrypted image compression and/or robust image compression.

4.5 Multi-view Image Compression

A multiview image compression framework, which involves the use of Block-based Compressive Sensing (BCS) and Joint Multiphase Decoding (JMD), can be used for a Visual Sensor Network (VSN). In [18], one of the sensor nodes is configured to serve as the reference node, the others as nonreference nodes. The images are encoded independently using the BCS to produce two observed measurements that are transmitted to the host workstation. In this case, the nonreference nodes always encoded the images (I_{NR}) at a lower sub rate when compared with the images from the reference nodes (I_R).

The idea is to improve the reconstruction of I_{NR} using I_R. After the two observed measurements are received by the host workstation, they are first decoded independently, and then image registration is applied to align I_R onto the same plane of I_{NR}. Subsequently, the difference between the measurements of the I_P and I_{NR} is calculated. The difference is then decoded and added to I_P to produce the final reconstructed I_{NR}.

4.6 Dynamic Resource Allocation

For compressed data of lightweight encoding, compression sensing technology is able to further optimize the signal sampling and data transfer, to facilitate further optimization of resource management. In reality, the number of hops between sensor and sink node is often less than the number of samples of compression sensing. This leads to that data transmission frequency based on compressed sensing was significantly greater than that of the traditional way. Therefore, the combination of lightweight encoding and compression sensing is used to simultaneously reduce the number of hops in the compressed data transmission.

The resource-aware scheduling, the combination of light weight coding and compressed sensing is used to improve the real-time performance of acquisition of system resource and reliability of resource management in this paper. Compressed sensing scheme based on the adaptive frame format definition of lightweight coding is able to set up the parameters such as sample signal, signal and hops. The nonlinear relationship matrixes between resource information of sensors or system and quality of services are built to manage the global or local network resource scheduling. The parameters of compressed sensing, such as number of sample signals and measurement matrix, are selected based on resource information defined in the frame format.

4.7 Image In-painting

Inpainting images with corruption is a challenging task. Most existing algorithms are pixel based, which construct a statistical model from image features. However, in these algorithms, the frequency component is not sufficiently addressed. Compressed sensing (CS) in frequency domain can be used to reconstruct corrupted images. In order to reconstruct image, image can be decomposed into two functions with different basic characteristics — structure component and textual component. A sparse representation for the function and DCT coefficients of this representation can be used to generate an over-complete dictionary. In painting can also be done using the sparsity in transform domain.

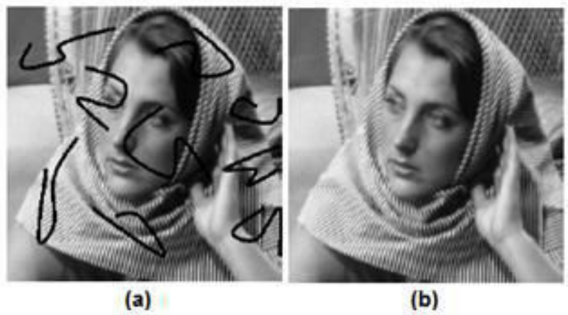

Fig.8 Image In-painting

5. CONCLUSION

The remarkable benefit of CS is to exhibit recovery methods that are computationally feasible, numerically stable, and robust against noise and packet loss over communication channels. The mathematical theory underlying CS, however, is deep and beautiful, and draws from diverse fields including harmonic analysis, convex optimization, random matrix theory, statistics, approximation theory, and theoretical computer science. Compressive sensing has been in use for acquisition, sampling, encoding and analysis of multimedia data and to optimize the efficiencies of these systems. There has been a great demand recently to apply CS to communications and networks domain. In this paper, we have provided a survey of the novel compressive sensing paradigm and its applications. We have traced origins of this technology and presented mathematical and theoretical foundations of the key concepts and have presented few applications of CS in VSN.

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