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Image Compression for Wildlife Monitoring based on Wireless Multimedia Sensor Network

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Abstract: Wildlife monitoring is the basis of effective protection, sustainable use and scientific management of wildlife resources. In order to obtain image information of wildlife monitoring remotely and in real time, wireless multimedia sensor network was introduced to the field of wildlife monitoring. The key of acquiring and transmitting image through wireless multimedia sensor network is image compression. However, the traditional image compression algorithm is not suitable for wireless multimedia sensor network owing to its computational complexity, long compression time, large volume of compression data and other shortcomings. The compressed sensing theory put forward in recent years, has achieved a low-speed sampling signal coding and accurate reconstruction and greatly reduces the computational complexity and also provides a new way of thinking to improve the conventional image compression algorithm. This study demonstrates the advantages of using wireless multimedia sensor network to monitor wildlife and expounds the basic principle of compressed sensing theory and its application in image compression. On this basis, the study also discusses the possibility that image compression algorithm based on compressed sensing theory is applied to wireless multimedia sensor network. Last but not the least, it is confirmed that image compression algorithm based on compressed sensing theory is suitable for wireless multimedia sensor network by doing the simulation experiments in MATLAB.

Key words: Wildlife monitoring, Wireless Multimedia Sensor Network, Compressed sensing, Low-speed sampling, Image compression

INTRODUCTION

At present, a wide variety of wildlife dwell in different National Nature Reserves in China, the total number of which has reached as many as 355. Wildlife play a significant role in maintaining the stability and balance of ecosystem. Wildlife monitoring can provide indispensable information of the species, quantities and situation of habitats of wildlife, which establishes a solid foundation for analyzing the behaviors of wildlife. This enables us to protect and control wildlife in a more effective way. It is available for observers to adjust their supervisory methods to different environment and criteria. General wildlife monitoring methods includes: artificial exploration (Gao *et al*., 2001), GPS electronic collars (Frair *et al*., 2004; Tomkins and O'Reagain, 2007), infrared cameras (Feng *et al*., 2008) and satellite monitoring (Wark *et al*., 2009), etc. However, these monitoring methods have their own disadvantages, such as limited scope of monitoring, high stakes, insufficient accuracy, inability to obtain visual information directly. In all forms of monitoring information, images stand out as the most important one for its visualization.

However, as traditional monitoring methods can not meet with the new requirements of accuracy and instantaneity of wildlife monitoring, there is a pressing need to propose a wireless, real-time and remote monitoring method to obtain image information of wildlife. In this research context, wireless multimedia sensor network (Akyildiz *et al*., 2007) is introduced to the field of monitoring wildlife. Combined with multimedia technology, wireless sensor network can collect information-rich images and other media information and moreover, it enables wireless remote transmission.It can achieve wireless, remote and real-time wildlife image monitoring, so it can totally live up to the current requirements of wildlife monitoring. However, the amount of monitoring image data is huge and simultaneously, the resources, bandwidth and processing power of wireless multimedia sensor network are limited. In order to resolve this problem, the image must be compressed so as to accomplish guaranteeing transfer rate and instantaneity, at the same time, obtaining sufficient image information. However, the traditional image compression methods based on Nyquist criterion waste a lot of sampling resources in the encoding process, which dooms to

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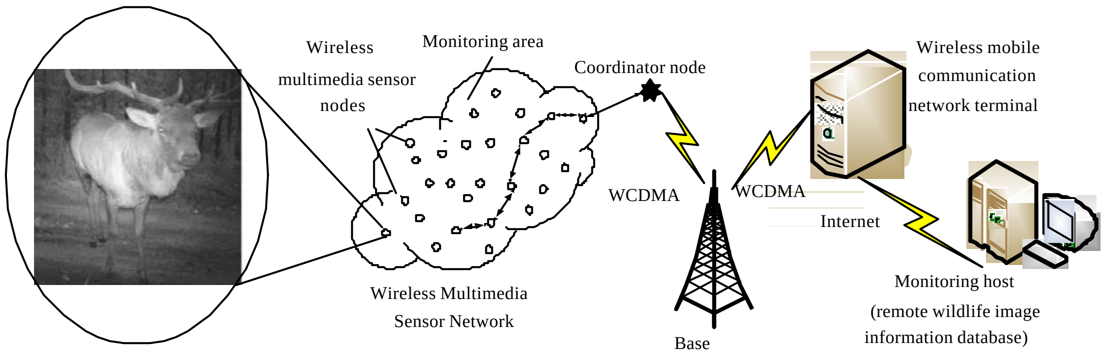

Fig. 1: Structure of wildlife monitoring system based on wireless multimedia sensor network

increase the computational complexity and also causes unnecessary waste of memory, resources, bandwidth and processing power. Therefore, an image compression algorithm with low complexity does have a say in whether wireless multimedia sensor network will be successfully used in wildlife monitoring.

WILDLIFE MONITORING BASED ON WIRELESS MULTIMEDIA SENSOR NETWORK

The Technology of Wireless Sensor Network (WSN) including the sensor, embedded system and wireless communication technology, is a hot technology in the information field. Wireless sensor network, made up of sensor nodes is used for real-time monitoring, sensing and collecting information of distributed area. It provides specific data, such as temperature, humidity, concentration of chemical components and then sends them to the observers. Compared with the traditional computer networks, wireless sensor network focuses more on communication and is an application-oriented network (Liu *et al*., 2005). A Wireless Multimedia Sensor Network (WMSN), combined with multimedia technology, is capable of obtaining, processing and transmitting images and other multimedia information. Introducing wireless multimedia sensor network to the field of wildlife monitoring can achieve wireless, remote and real-time image monitoring of wildlife. WMSN that possesses the potential of solving the problems of traditional methods, has brought new opportunities for the development of wildlife monitoring. Diagram of the structure of wild animal monitoring system based on wireless multimedia sensor network is shown as Fig. 1.

Wireless multimedia sensor network nodes, deployed in activity area of wildlife, can automatically capture videos and images, form ad-hoc network and wirelessly transfer compressed image data that the farthest nodes collect to the coordinator node one by one. Coordinator node is deployed in location with 3G network coverage. Through 3G, the image data collected by wireless multimedia sensor network is sent to researchers by e-mail or MMS, in order to facilitate researchers timely and accurately grasp the status and dynamic changes of wildlife resources . Thereby it can achieve the aim of wireless, remote, real-time wildlife image monitoring.

However, each wireless multimedia sensor node is a minimal system and it has its own independent information gathering end, processor, power supply, wireless receiver and transmitter. It means that the energy, processing power and storage space of each node are limited. Besides, the transmission between nodes is also affected by the transmission bandwidth, distance and other factors. In order to remove the major obstacles that restrict the wireless multimedia sensor network's application in wildlife monitoring, people urgently need a good image compression algorithm that has low algorithm complexity, large compression ratio and good compression quality.

COMPRESSED SENSING

In 2006, proposed by Candes *et al*. (2006) the compressed sensing (Compressed Sensing, abbreviated CS) (Donoho, 2006) theory indicates: the data of compressible signals can be sampled by the pattern which is much lower than the Nyquist sampling theorem and the original signal still can be recovered accurately. Based on compressed sensing theory, signals can be sampled at low speed and then encoded, which greatly reduces the computational complexity of compression algorithms.

Compressed sensing is based on the theoretical framework of spatial transformation, using a random measurement matrix and its key link is sparse reconstruction method of signal. Compressed sensing theory can be used to collect signals whose sample rate

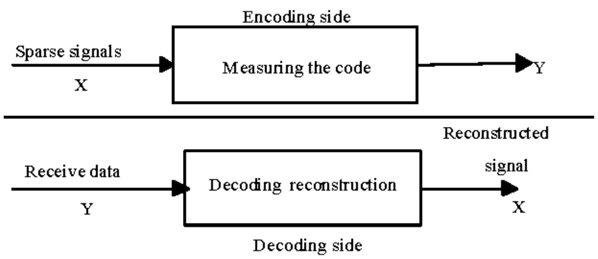

Fig. 2: Diagram of encoding/decoding theory of compressed sensing

is below the Nyquist and it can accurately restore the observed signal or image. When it takes the samples and at the same time compresses them, it can save storage space. Under the framework of compressed sensing theory, the process of signal compressive sampling is shown in Fig. 2 (Lu *et al*., 2012).

We assume there is a discrete signal X, whose length is N, it is easy to know, X can be expressed as the form of a linear combination of a group of base (Ψ^T represents the transpose of Ψ), then:

$$x = \sum_{k=1}^{N} \psi_k s_k = \Psi s \tag{3.1}$$

Among which, $S_k = \{x, \psi_k\}$, $\{x, \psi_k\}$ represents the inner product value of X and Ψ in K columns. Ψ is an orthogonal matrix with the size of N×N, X and S are both N-dimensional vector. When there is a sparse group Ψ, which causes that signal X has only K (K≤N) nonzero coefficients S_k in Ψ and then Ψ is called the sparse group of signal X. Assuming that during a linear measurement we can get a signal Y with the length of M (M<N), then:

$$Y = \Phi x \tag{3.2}$$

Φ is a measurement matrix with the size of M×N.

If the signal does not meet with the condition of sparsity, we can conduct a sparse orthogonal transform to X and obtain a sparse coefficient S and denoted as $x = \Psi s$, X has only K nonzero elements. The expression of the measurement process can be rewritten as:

$$Y = \Phi\Psi\ s = \Theta S \tag{3.3}$$

$\Theta = \Phi\Psi$ is a matrix with the size of M×N.

The converse solution which aims to obtain X of (3.2) is an underdetermined problem, which we can not solve. However, if X can be represented in the orthogonal base under the form of a sparse vector, which has the same form with S (K is the sparse matrix of S and K<M≤N) (3.3), then you can put (3.2) into a form as (3.3). By sparse reconstruction algorithm, we can reconstruct the sparse coefficients S and by solving the inverse problem of Eq. (3.3), because of reversibility of orthogonal transformation, we can use the method of the inverse transformation of S to reconstruct the signal X.

To most directly solve the sparse signal reconstruction problem is to make the l_0 of sparse coefficient S to be reconstructed minimum norm solution Eq. (3.3), the optimization model is shown as the below formula:

$$\min_x \|s\|_0 \ \text{s.t.} \Phi\Psi s = Y \tag{3.4}$$

As for time-domain sparse signals, when the signals themselves are under conditions of being sparse signals, (3.4) can be transformed into (3.5):

$$\min_x \|x\|_0 \ \text{s.t.} \Phi x = Y \tag{3.5}$$

The method described above is theoretically possible, however, since the time and space complexity of the algorithm is too high, in fact, it is difficult to achieve. Therefore, many scholars have put forward an equivalent algorithm, the greedy algorithm. Algorithm of compressed sensing reconstruction of signal which is a key part of the theory is mainly defined by the process that M-dimensional observation vector y reconstructs the recovered signal x with the length of N (M<N) and the sparsity of K. The current algorithm mainly includes iterative matching pursuit series greedy algorithm (Candes, 2006), the most l_1 norm convex optimization method (Chen *et al*., 1998), Bayesian statistics class optimization algorithm (Zayyani *et al*., 2009), iterative threshold method (Herrity *et al*., 2006) and a minimum total variation method (Lustig *et al*., 2007).

That is to say, compressed sensing theory states that: as long as the signal is compressible or sparse in a transform domain, you can use a observation matrix that is irrelevant to the transform base to project the high-dimensional signal into a low-dimensional space and then by solving an optimization problem, we can reconstruct the original signal from these small amount of projection with high possibility. It can be proved that the projection of the reconstructed signal contains sufficient information. In this theoretical framework, the sampling rate is no longer dependent on the bandwidth of the signal. It depends largely on two basic criteria: sparse or non-sparse and coherence or restricted isometry property.

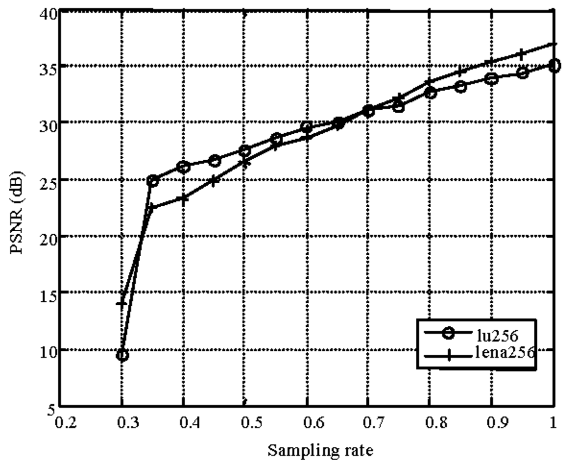

Fig. 3: Sampling rate plotted against PSNR, for, respectively using Image lu256 and Image lena256 as source image

IMAGE COMPRESSION BASED ON COMPRESSED SENSING

Compressed sensing theory receives intensive worldwide attention from the fields of mathematics and signal processing since 2006 when it is put forward in formal studys. While the theory being under development and improvement, it is also gradually applied to digital image processing, such as imaging systems, image fusion, target recognition, image tracking and single-pixel cameras. Compressed sensing signal compression technology distinguishes itself from the traditional compression methods by the asset that obtaining data sampling points and simultaneously doing the compression. This will not only reduce the time of data compression but also effectively reduce the complexity of the algorithm.

Because of the strong points that the compressing data is simple and complexity of algorithm is low, theory of compressed sensing plays a significance role in handling large scale of sparse or compressible data. Due to the limitation of the power and capacity of processing data, wireless multimedia sensor network is hard to be applied. However, compressed sensing with small acquisition and compression data, low algorithm complexity, can effectively reduce the compression time, improve the compression efficiency, save system resources. Thus it is possible to apply the compressed sensing in wildlife monitoring based on wireless multimedia sensor network.

Simulation of compressed sensing algorithm by MATLAB: This study discusses the possibility that image compression algorithm based on compressed sensing theory can be applied to wireless multimedia sensor network. Different from the traditional image compression algorithms, image compression algorithm based on compressed sensing theory can get good quality recovery image at a low sampling rate. This study did the simulation experiment in Matlab7.8 operating environment. Standard test image lena256.bmp and actual monitoring image lu256.bmp were chosen as experimental subjects. Image compression algorithm based on compressed sensing theory uses the wavelet as a sparse group, random matrix as the measurement matrix and Orthogonal Matching Pursuit (OMP) algorithm as reconstruction algorithm, to compress and reconstruct the image. We obtained Peak Signal to Noise Ratio (PSNR) relation curve of reconstructed image using image compression algorithm based on compressed sensing algorithm at different sampling rates. The Fig. 3 below is a curve graph that shows the PSNR of reconstruction of Image lena256 and lu256 while adopting different sampling rates. As can be seen, after a certain sampling rate, with the sampling rate increasing, the accuracy of reconstructed image nearly straightly lines up.

Results of reconstructed images of Image lu256 while adopting several different sampling rates are shown in Fig. 4 (The original image is also included). Taking the relation between the results of reconstructed image and the number of measurements into account, through comparing results of reconstructed images under different sampling rates, we can see little difference in the outcomes between using sampling rate 0.7 and sampling rate 0.9, which indicates that when using sample rate 0.7, the outcome of reconstructed image can totally meet with our requirements.

From the above, we can draw the conclusion that while compressing and reconstructing the same image, the value of PSNR under the compressed sensing algorithm increases along with the increment of the sampling rate, so as the accuracy of the reconstructed image, which shows a tendency of nearly a straight climb. Thus, it is not necessarily to adopt a 100% sampling rate to gain the fine reconstructed image. We can merely use a sampling rate of 0.7 or even a lower one, which reduces the compression complexity of time and space during image acquisition. The compressed sensing algorithm can easily fulfill the requirement of image reconstruction under the demand of low time and space complexity, which can be undoubtedly applied to wildlife monitoring with wireless multimedia sensor network within limited resources.

Fig. 4(a-e): Image lu256 and reconstructed images, (a) Original image, (b) Rate = 0.3, (c) Rate = 0.5, (d) Rate = 0.7 and (e) Rate = 0.8

CONCLUSION

Image compression algorithm based on compressed sensing can reduce the measured value and computational complexity of gathering end, which ideally suits for resource-constrained wireless sensor network. Compressed sensing theory research is successful to some extents but if compressed sensing were well used in the area of wildlife?monitoring , there would still be a lot of problems that need to be figured out. For instance, how to select an effective and stable observation matrix and compressed sensing algorithm simulation environment is an ideal MATLAB environment, but when it is applied to complex environment the result is still unknown. We are lacking in effective experimental data to compare compressed sensing with other traditional methods, such as JPEG compression or the classic wavelet image compression. In this study, the basic framework of compressed sensing theory and its key issues are described. It also put forward a hypothesis that applying the image compression algorithm based on compressed sensing to wildlife monitoring with wireless multimedia sensor network. In addition, relying on MATLAB simulation tool, we had the simulation experiment and the results of which shows that the image compression algorithm based on compressed sensing theory can achieve favorable recovery image quality at a low sampling rate. Despite the young age of compressed sensing theory, it has won great concern for potentially high compression ratio and good quality of the reconstructed image, it is believed that compressed sensing theory in image compression will achieve greater progress.

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