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Wavelet Transforms of Image Reconstruction Applied in Internet of Things

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Abstract. A wavelet technique is adopted in image communication in this paper. With the development of The Internet of things and 3G, more and more image information used in communication. Therefore it is necessary to take wavelet technique to image compression. Firstly, wavelet is used in sending image to decomposition, Then decomposed image is sent ,Finally ,the recessive image is the decomposed image, so those decomposed images will be reconstruction. We test the one, two and three layer wavelet transform, Experimental results show that the two layer wavelet transform compares favorably in high-compressive ratio and the rapid processing speed, and the reconstruction image is better.

Keywords: wavelet transform; The Internet of things; image reconstruction; image communication

1. Introduction

The internet of things is the third revolution after the computer and internet. IBM company proposed the “sapiential earth” in 2008, the Europe propose the “the internet of things project” in 2009, at the same time, the Japan propose the “i-Japan project” .And the China propose the “Apperceive China project” in 2010. the things of internet will develop in the future 10 years[1].

With the development of the things of internet, the image communication is the important factor in the future. so This paper deals with the machine-to-machine (M2M) image communications. M2M is telemetry that is accomplished using networks, especially public wireless networks, in which billions of electronic and electromechanical devices being connected to the Internet. The global economy is improved by the cost savings of M2M growth [2].

Compressing Sampling is the first step of the image communication. In the traditional signal sampling process, Shannon theorem must be fit for preventing signal distortion. It is well known that the Nyquist sampling theorem which that the sampling rate must be at least twice the max frequency of the signal is a golden rule used in image acquire. But such an image will lead to an increased sampling frequency, which substantially increase the data storage and transmission costs [31]. To solve this problem, compressive sensing theory, which is a new theory, captures and represents compressible signals at a sampling rate significantly below the Nyquist rate. It first employs wavelet projections that preserve the structure of the signal, and then the signal reconstruction is conducted using an optimization process from these projections. It is meaningful that Using compressive sensing application in medical image compression. In 2006,Candés proves the truth of the restoration signal from FFT in theory, which is the foundation of the compression sensing [4]. Following the Donoho proposed the compression sensing theory in formally [5]. Recently, many researchers work in this field. Chun-Yang Chen applies the compressed sensing in the radar system [6], Sivan Gleichman and Yonina C. Eldar studies on the Blind compressed sensing is achieved by simultaneously measuring several signals [7]. Recently, the idea of compressed sensing has been used in many fields.

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2. Wavelet Transform

2.1. Wavelet Theory

Wavelet transform based on flourier transform , appearance in 80thof 20 century, with such better characters in time and frequency fields, it is widely applied in image processing ,model identify and robot vision and so on. In 1989, Mallat promote the tower algorithm [8], which can disassemble the image into some sub images according to different scale, orientation and space field. In particular, this material is used in this book for image data compression and for pyramidal representation, in which images are subdivided successively into smaller regions.

2.2. Relationship Between The Image And The Wavelet

Image signal is the two-dimension signal, therefore secondary wavelet to analysis multiple resolution is used in this paper. Because of the image is disperse signal, the wavelet transform is the two dimension wavelet disperse transform, which is derived from the one-dimension wavelet transform. The principle of wavelet transform is multiple resolute decomposing. The image is divided into some sub images in different space and frequency, then quantization and coding. The total of sub images data is equal to the original image data, but the statistical characteristics of them are different. In this processing, the key point is the best optimum wavelet base.

2.3. Selection and Optimization of Wavelet Base

Wavelet base collection is important for image compressing. Image is different from other images in quality, any losing details will lead mistake diagnose. Wavelet transforms can comeback original image signal, but different wavelet bases have different results, the compressed ratio is different. The algorithm of wavelet base collection is not the unique, but every wavelet base has it own characteristic.

3.Wavelet Transforms of Image Reconstruction

3.1. Wavelet Transforms

If $\varphi(x)$ is a one-dimension scale function， $\psi(x)$ is corresponding wavelet quotiety. Then the two-dimension wavelet transform function is like eq1 to eq4.

$$\psi^1(x,y) = \varphi(x)\psi(y) \tag{1}$$

$$\psi^2(x,y) = \psi(x)\varphi(y) \tag{2}$$

$$\psi^3(x,y) = \psi(x)\psi(y) \tag{3}$$

$$\varphi(x,y) = \varphi(x)\varphi(y) \tag{4}$$

At the two dimension conditions, there is a scale function $\varphi(x,y)$, which flex and translation will become a group of V2j orthogonal base. Assumption that $\varphi_{2^j}(x)$ is the orthogonal base of the set $(2^{-j}\varphi_{2j}(x-2^{-j}n, y-2^{-j}m)),(n,m)\in Z^2$ of the V2j.

For a cluster of detachable multi-resolution approximation on L2（R×R）, every vector space disassemble to the same two subspace tensor product of L2（R）, while the V12j compose the multi-resolution approximation of L2（R）， the vector sequence V2j compose the multi-resolution approximation of L2（R×R）. That is $\varphi(x,y) = \varphi(x)\varphi(y)$ is true. Among this $\varphi^*(x)$ is the corresponding one-dimension scale function. Then the figure $f(x,y)$ is in the 2j resolution approximation the following.

$$A_{2j}^d f = (f(x,y), \varphi_{2j}(x-2^{-j}n)\varphi_{2j}(y-2^{-j}m)) \tag{5}$$

The resolution is 1, which N is global pixel. Obviously, the disperse image approximation have 2j pixel, liking the one dimension circumstance, hypothesis the level and the perpendicularity is symmetry of the image. In 2j resolution, the detail signal is the projection of orthocomplement space Q2j of $f(x,y)$ of V2j base.

The information difference between $A_{2j+1}^d f$ and $A_{2j}^d f$ is equal to projection of $f(x,y)$ Q2f, which can express by inner product as following.

$$D^1_{2j+1}f = f(x,y),\psi^1_{2j}(x-2^{-j}n, y-2^{-j}m) \tag{6}$$

$$D^2_{2j+1}f = f(x,y),\psi^2_{2j}(x-2^{-j}n, y-2^{-j}m) \tag{7}$$

$$D^3_{2j+1}f = f(x,y),\psi^3_{2j}(x-2^{-j}n, y-2^{-j}m) \tag{8}$$

Therefore, two main information is the $A^d_{2j}f$, and the detail is the convolution of $D^1_{2j+1}f$ 、 $D^2_{2j+1}f$ 、 $D^3_{2j+1}f$.

$$A^d_{2j}f = f(x,y) * \varphi_{2j}(-x)\varphi_{2j}(-y)\varphi_{2j}(-2^{-j}n, -2^{-j}m) \tag{9}$$

$$D^1_{2j}f = f(x,y) * \varphi_{2j}(-x)\psi_{2j}(-y)\varphi_{2j}(-2^{-j}n, -2^{-j}m) \tag{10}$$

$$D^2_{2j}f = f(x,y) * \psi_{2j}(-x)\varphi_{2j}(-y)\varphi_{2j}(-2^{-j}n, -2^{-j}m) \tag{11}$$

$$D^3_{2j}f = f(x,y) * \psi_{2j}(-x)\psi_{2j}(-y)\varphi_{2j}(-2^{-j}n, -2^{-j}m) \tag{12}$$

From the eq9 to eq12, the two dimension image can disassemble the main part of $A^d_{2j}f$ and the details of $D^1_{2j+1}f$ 、 $D^2_{2j+1}f$ and $D^3_{2j+1}f$, which the details can acquire by filtering along the x direction, y direction and diagonal orientation, thus filtering disassemble is a group of signals disassemble in frequency direction. Which resolution frequency is lowest in 2j and $A^d_{2j}f$, and then given the x and y direction low frequency, while $D^1_{2j+1}f$ 、 $D^2_{2j+1}f$ and $D^3_{2j+1}f$ given the level perpendicularity and the diagonal direction high frequency separately. Finally, the image $A^d_{2j}f$ can disassemble the 3J+1 dispersed sub images.

$$(A^d_{2j}f, f(D^1_{2j}f)_{-J<j<J}, f(D^2_{2j}f)_{-J<j<J}, f(D^3_{2j}f)_{-J<j<J}) \tag{13}$$

This is the processing of wavelet biorthogonal disassemble, which 2J is sketchy approximation, $D^1_{2j+1}f$ 、 $D^2_{2j+1}f$ and $D^3_{2j+1}f$ is the detail signal in the same resolution of different directions. In this algorithm, the total pixel is invariability.

4.Experiments and Conclusion

We test the two image use wavelet transform, the 1st image is 256x256 pixels gray image. Fig. 1 is image 1. And the 2nd image is 240x320 pixels color image. Fig . 2 is the image 2. Firstly we transform the input image to a index image. Then the biorthogonal wavelet base is used in the wavelet transform to first disassemble and the second disassemble. Finally, we will see the compressive ratio of 1st, 2nd and 3rd wavelet disassemble, compared the compressed ration and image restoration based on biorthogonal wavelet base.

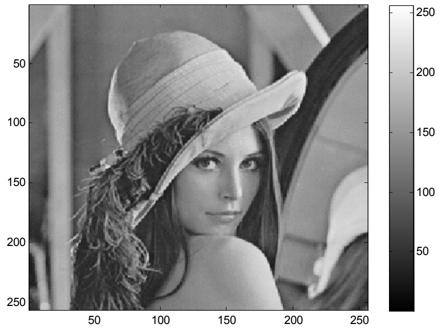

Fig.1 The Input Image I

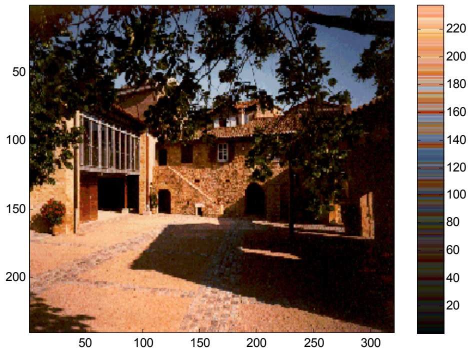

Fig.2 The Input Image II

The total elapsed time of image I is 2.648412 seconds. From the pictures, we see that three wavelet transform have three results. The 1st image of 1st line is the restoration image of the following images in the 1st line. Liking the line 1, the 1st image of line 2 or 3 is also the restoration image of the following images. The compressive ratio of the 1st of line 3 is the best ,but the image is blur. At the same time , the compressive ratio and the result will be better of the 1st image of image 2 which is the 2nd wavelet transform.

The total elapsed time of image I is 2.043718 seconds. In every group the restoration image is the first image of every line, which is the main image from the wavelet transform, the first line is the 1 layer wavelet disassemble, the second line is the 2 layers disassemble, and the third line is 3 layers disassemble image.

5.Conclusion

In this algorithm, the wavelet transform including the three layers approximation information and the details at vertical, horizontal and the diagonal directions. The 3rd, 2nd and 1st approximation .From the restoration picture of every algorithm, we find that the restoration result is well in the line 2. In fact, the restoration image is well in vision and the compressive ration is better.

Image Compressive is a necessary to image processing. Compared the traditional method, we adopt three methods to image compression and restoration. Experimental results show that 2nd wavelet transform compares favorably in high-compressive ratio and the preserve the characters of the image.

6. Acknowledgment

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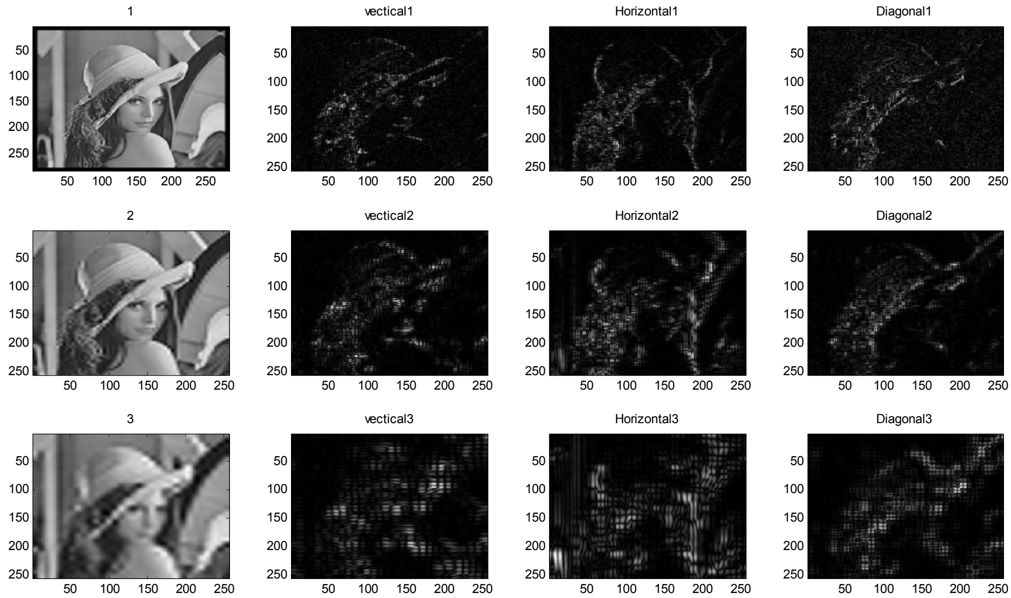

Fig.3 1^{st} ,2^{nd} and 3^{rd} wavelet transform of image I

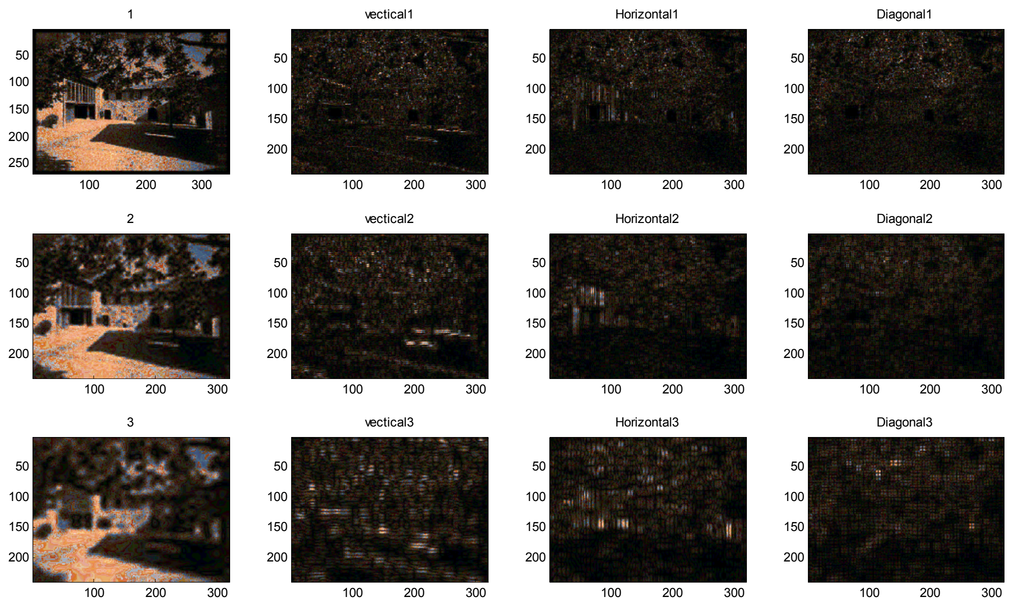

Fig.4 1^{st} ,2^{nd} and 3^{rd} wavelet transform of image II