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Super-resolution Algorithm for Passive Millimeter Wave Imaging Based on Maximum Likelihood and Neighbor Wavelet Transform

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Abstract: In passive millimeter wave imaging system, the problem of poor resolution of acquired image stems are mainly from system antenna size limitations. In order to improve the resolution of passive millimeter wave images, a super-resolution algorithm based on Maximum Likelihood estimation and neighbor wavelet transform are proposed in this paper. This algorithm first restores the spectrum in the pass-band and de-noises the image based on neighbor wavelet transform, then extrapolate the spectrum by using the non-linear projection operation Richardson-Lucy (RL) algorithm. Experimental results demonstrate the algorithm improve the convergent rate, enhance the resolution and reduces the ringing effects which are caused by regularizing the image restoration problem. Furthermore, the algorithm is easily implemented for passive millimeter wave imaging.
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Keywords: Passive millimeter wave (PMMW) imaging, Radiometer, Super-resolution, Maximum likelihood.

1. Introduction

On this account that MMW can penetrate severe weather like cloud rain and fog, it is mainly used at the field of aircraft navigation and airport check under all-day and all-weather situation. MMW is mainly imaged by using differences of objects' millimeter wave radiation.

In many imaging applications, acquiring a scene image with high spatial resolution is not possible, because of a number of theoretical and practical limitations. These limitations include for instance the sensor resolution, the Rayleigh resolution limit, the increased cost, data transfer rate and the amount of shot noise due to the size of the digital sensor, among others [1].

Due to the restriction of actual antenna aperture, spatial resolution of MMW is very low, this leads to vague image. Its transfer function is equivalent to a low pass filter [2]. Traditional image restoration methods can just improve spatial resolution limitedly, so, the further improvement of resolution can only be achieved by super-resolution algorithm. At present, main super-resolution algorithms applied to passive millimeter wave (PMMW) imaging are project onto convex set (POCS) [3], maximum likelihood (like Richardson-Lucy) [4], regularization algorithms [5], and so on.

Because of the existence of noise, although RL algorithm can extrapolate some of high-frequency component, at the same time it destroys low frequency component in pass-band of image, the ability to enhance resolution is limited. For this reason that image itself and RL algorithm both bring unknown obscureness and this method has a poor noise reduction ability, in addition the imaging system itself is disturbed by various of noise inevitably, so it is necessary to choose suitable methods to do de-blurring and de-noising, to recover low frequency component in pass-band in order to remedy the lack of this method and get super-resolution result with high quality.

Owing to its ability to provide favorable time-frequency localization property, wavelet transform [6] is widely applied to signal and image processing field. Literature [7] points out that comparing with traditional wavelet de-noising method, neighbor wavelet de-noising method has obvious advantage.

We combine Richardson-Lucy (RL) algorithm and neighbor wavelet transform (NW), using NW to cover the lack of RL, we put forward a super-resolution algorithm of passive millimeter wave images based on maximum likelihood algorithm and Neighbor wavelet transform for the first time, called NWRL algorithm. This algorithm is mainly based on iterative process, it uses the recuperative frequency spectrum to instead of the frequency spectrum which was in pass-band through the algorithm of NW, then it ensures low frequency component of the image safe at the time when it extrapolates high-frequency component of the image.

2. Mathematical Model of Super-Resolution

All objects in nature are always radiating electromagnetic, for millimeter-wave imaging radiometer, antenna temperature which is obtained by the radiometer is,

$$T_A = \iint_{4\pi} T_{AP} G d\Omega = T_{AP} \otimes G , \quad (1)$$

in the equation, T_{AP} is the apparent temperature, G is the normalized antenna gain.

Consider the influence of shake, pan, and so on, assuming imaging system is linear and constant displacement, the mathematical model can be expressed as,

$$T_R = T_{AP} \otimes H + n , \quad (2)$$

where T_R is the output signal of radiometer, n is the noise, H is the point spread function of the system.

The difficulty of image de-blurring comes from the fact that the original image spectrum is damaged by the blur. Therefore, a recovery of the distorted image spectrum by using all available information is a major challenge of image de-blurring.

The imaging model can be further expressed in a familiar way as,

$$g(x,y) = h(x,y) \otimes f(x,y) + n(x,y) , \quad (3)$$

where $f(x,y)$ is the original image, $g(x,y)$ is the image obtained by the system, $n(x,y)$ is the noise, $h(x,y)$ is the point spread function (PSF) of the system, $\otimes$ is the convolution computing. The scheme of the system is as Fig. 1.

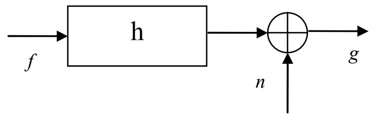


Fig. 1. Scheme of the system.

PSF has the following properties:

1) Certain and negative;
2) With limited support domain;
3) $\sum\sum h(x,y) = 1$.

The formula can be expressed in vector form as

$$g = Hf + n , \quad (4)$$

if the original image is an M×N matrix, than the vectors g, f, n are MN×1, and H is a MN×MN Toeplitz matrix.

The imaging model in frequency domain is

$$G(u,v) = H(u,v)F(u,v) + N(u,v) , \quad (5)$$

where u and v are the discrete frequency component, $G(u,v)$, $H(u,v)$, $F(u,v)$ and $N(u,v)$ are the discrete Fourier transform of g , h , f , and n . The question of super-resolution is to give h and g , solve f .

$$F(u,v) = \frac{G(u,v)}{H(u,v)} + \frac{N(u,v)}{H(u,v)} \quad (6)$$

By equation (6), because $H(u,v)$ is zero beyond the cut-off frequency of the imaging system, it seems impossible to restore high frequency components beyond the cut-off frequency only from the frequency domain, but by the theory of analytical continuation and airspace boundedness [8], as long as there is enough priori information, it is possible to restore high frequency components.

3. Analysis of NWRL Algorithm

3.1. Analysis of RL Algorithm

Super-resolution algorithm [9] of Richardson-Lucy is based on maximum likelihood method. The algorithm tries to find an estimate $\tilde{f}$ to maximize likelihood function $p(g \mid f)$, that is

$$\tilde{f} = \arg\max_f p(g \mid f) \quad (7)$$

The key of the method is to choose a statistical model that reflects the distribution of scene radiation. Different models have different estimate methods.

If $p(g\,|\,f)$ meets the Poisson distribution, the iterative equation got by Picard iteration is as follows

$$\tilde{f}^{n+1}(x,y)=\tilde{f}^{n}(x,y)\bullet \left(\frac{g(x,y)}{h(x,y)\otimes\tilde{f}^{n}(x,y)}\otimes h(x,y)\right) \quad (8)$$

$\sum_{x,y}h(x,y)=1$, $h(-x,-y)=h(x,y)$, initial condition is generally set as $\tilde{f}^{0}(x,y)=g(x,y)$.

It can be seen from the above analysis that super-resolution ability of the algorithm is from nonlinear processing by each iteration step. In noisy environment, the RL algorithm destroys the low frequency component, enlarges the influence of noise.

3.2. Neighbor Wavelet De-noising

The construction of discrete wavelet depends on the scaling function $\phi(x)$, the function follows the following equation,

$$\phi(x)=\sqrt{2}\sum c_k\phi(2x-k), \quad (9)$$

c_k is a real number sequence, and follows [9]

$$\sum c_k=\sqrt{2} \quad (10)$$

$$\sum c_k c_{k+2m}=\delta(m) \quad (11)$$

$$\sum(-1)^k k^m c_k=0, m=0,1,...,M-1 \quad (12)$$

The wavelet $\psi(x)$ is defined as equation (13),

$$\psi(x)=\sum d_k\phi(2x-k) \quad (13)$$

and $d_k=(-1)^k c_{M-1-k}$.

It is known that the wavelet coefficients are interrelated in a small neighborhood, and a large wavelet coefficient in the neighborhood will also have a big factor. C_{ai} and Silverman propose a 1-D wavelet de-noising scheme through combine the domain value and neighborhood coefficient [7]. The project merges the coefficient of neighborhood through the domain value. Assume $d_{j,k}$ is a 1-D wavelet coefficient with noise. If the value of $S^2{}_{j,k}\times d^2{}_{j,k-1}\times d^2{}_{j,k}\times d^2{}_{j,k+1}$ is less than or equal to λ^2, then we assume $d_{j,k}=0$, otherwise, the coefficient is compressed by formula $d_{j,k}\times d_{j,k}(1-\lambda^2/S^2{}_{j,k})$. $\lambda=\sqrt{2\sigma^2\log n}$, is length of signal, Liu and Zhu propose a 2-D wavelet de-noising scheme [10], domain values are selected by the following formula,

$$E(C,\lambda)\times\sum_{i,j}(A_{i,j}-B_{i,j})^2/n^2, \quad (14)$$

where C represents wavelet filter, λ represents the field value, n^2 is the image pixels. Window size affects the de-noising effect. Experiments show that the best size of the window is 3×3.

In actual passive millimeter wave image, different airspace spectral components suffering from different noise pollution. In the cut-off frequency of passive millimeter wave imaging system, the low-frequency components suffering from the noise pollution are relatively small, and the signal to noise ratio is high. The high-frequency contains more noise components, so the signal to noise ratio is low. There is basically only the noise component out of the system cut-off frequency.

It can be seen that neighbor wavelet transform algorithm can better restore the pass-band spectral components, filter the spectral components out of the cut-off frequency, and have the ability of de-blurring and de-noising which can keep details of image.

In order to combine the advantage of neighbor wavelet transform and RL algorithm, we propose NWRL algorithm. The algorithm uses RL algorithm as the main iterative process, and correct the restore spectrum. It uses the restored low-frequency components by neighbor wavelet transform instead of the pass-band spectral components. The algorithm flow chart is as shown in Fig. 2, and the mainly iterative process consists of the following three steps:

Step1. Format the initial high resolution image.

Step2. Calculate the restored image by neighborhood wavelet transform.

Step3. Set the initial value of the restore image as a constant, achieve the iterative process, obtain the recovery image f_k.

4. Experiments

In order to verify the validity of the algorithm, we adopt two synthetic images to simulate actual millimeter wave images to do experiment, and compare the results with RL algorithm.

The first experiment is a ring diagram composed by five concentric, used to simulate images generated by the simple scenarios.

To simulate lower clarity effect of the imaging system, we convolute Fig. 3 (a) with a circular aperture antenna generated a point spread function with 16 pixels diameter, and then we increase the zero-mean Gaussian white noise. The original image, the original image spectrum, the reduction clarity image with noise, and the reduction clarity image with spectrum noise are shown in Fig. 3 (a) to Fig. 3 (d), Fig. 3 (e) to Fig. 3 (h) are shown the image and spectrum after 150 iterations by RL algorithm and NWRL algorithm respectively. Seen from four figures, both two algorithms have obvious super-resolution ability. Under the condition of same numbers of iterations, NWRL algorithm is better than RL algorithm.

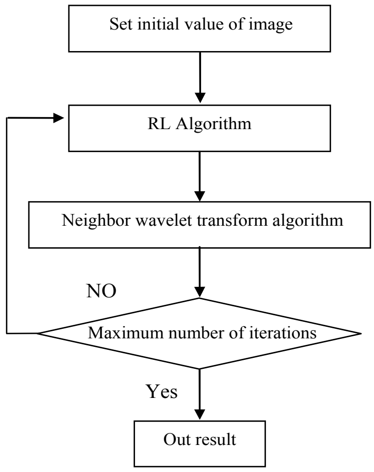


Fig. 2. Algorithm flow chart.

The second experiment is an image with complex scene, and the original image, the original image spectrum, the reduction clarity image with noise, and the reduction clarity image with spectrum noise are shown in Fig. 4 (a) to Fig. 4 (h).

An objective evaluation standard is brought in to measure the quality of restored image by minimum mean square error (MSE). It is defined as

$$\Delta MSE = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}[f(m,n) - f'(m.n)]^2 , \qquad (15)$$

$f(m,n)$ is original image, $f'(m,n)$ is restored image. The smaller MSE is, the better the algorithm is.

Table 1 shows the results with two experiments. It can be seen from Table 1 that the algorithm this paper proposed is much better than the original algorithm.

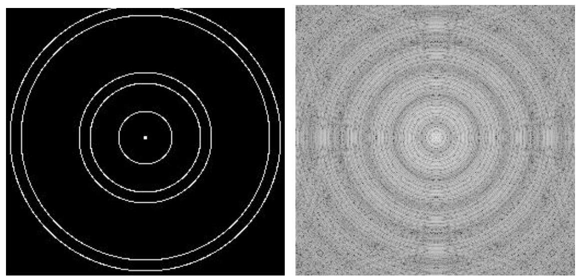
Table 1. MSE of two experiments.

No.	RL	NWRL
Experiment 1	0.0308	0.0296
Experiment 2	272.53	233.67

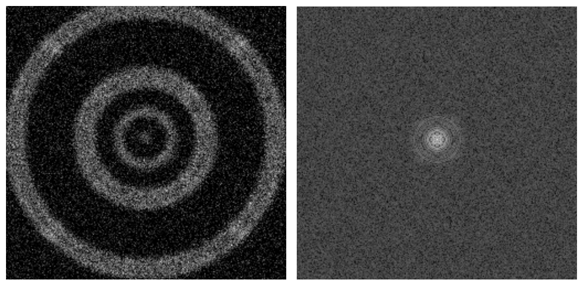
5. Conclusions and Future Work

This paper proposes a super-resolution algorithm by combining RL algorithm and neighbor wavelet transform for passive millimeter wave imaging. The algorithm first uses neighbor wavelet transform to recover the spectrum instead of the pass-band spectrum, then it uses RL algorithm as the main iterative process, which ensures the low-frequency of the image not damaged when extrapolating high-frequency component. It shows the super-resolution ability of the algorithm is better than RL algorithm with simple and complex synthetic images experiment results, and the ability of neighbor wavelet transform is better than wiener filter. The algorithm can reduce and remove noise and oscillating fringe in restored image. The algorithm can be used for passive millimeter wave imaging.

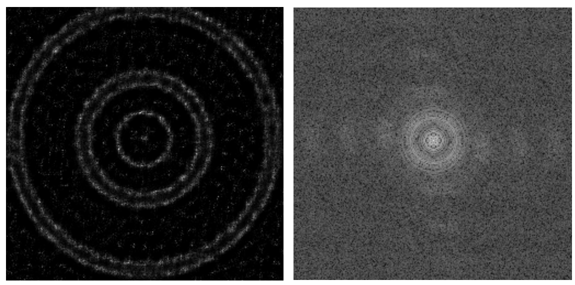
In the future work, we will study more methods to improve the image resolution ratio, and the ability of the algorithm in real passive millimeter wave image will be researched in the future.



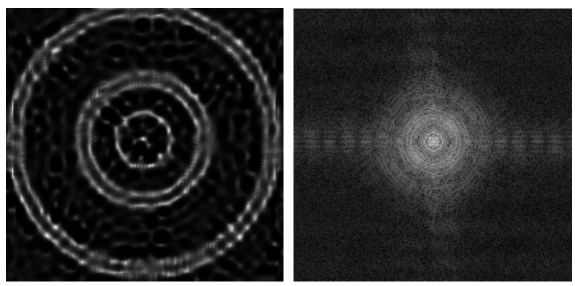
(a) Origin image. (b) Origin spectrum.



(c) Noise blurred image. (d) Noise blurred image spectrum.



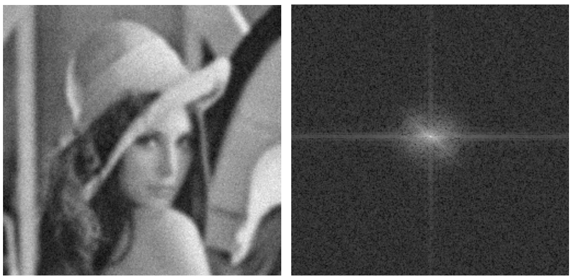
(e) Restored image by RL. (f) Restored image spectrum by RL.



(g) Restored image by this paper (NWRL). (h) Restored image spectrum by this paper (NWRL).

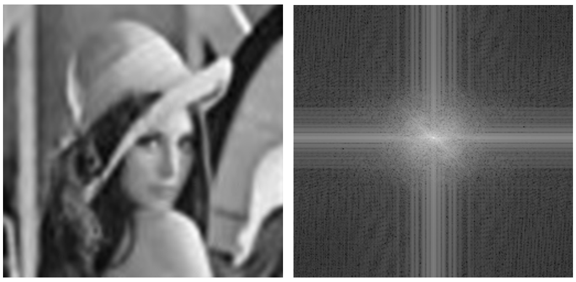
Fig. 3. Results of Experiment 1.

(a) Origin image. (b) Origin spectrum.



(c) Noise blurred image. (d) Noise blurred image spectrum.

(e) Restored image by RL. (f) Restored image spectrum by RL.



(g) Restored image by this paper (NWRL). (h) Restored image spectrum by this paper (NWRL).

Fig. 4. Results of Experiment 2.

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