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Compressive Perception Image Reconstruction Technology for Basic Mixed Sparse Basis in Metal Surface Detection

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Abstract. Applying Compressed Sensing (CS) technology to robot vision image transmission, an effective method for image reconstruction in robot imaging is proposed to improve the accuracy of reconstruction. Reconstructing images using a mixed sparse representation of DCT and circularly symmetric contour wave transform, the basic algorithm used is the Smoothed Projection Landweber (SPL) algorithm, which optimizes the coefficients under different sparse transformations by incorporating hard thresholding and binary thresholding methods for different sparse bases during iterations. The experiment shows that compared with single sparse base image reconstruction, the proposed reconstruction method has improved reconstruction accuracy.

Keywords: robot vision, mixed sparse basis, reconstruction accuracy, SPL

1 Introduction

With the advancement of technology, the application and research of robots are gradually increasing [1]. At present, the signals transmitted by robots mainly include image signals, which are used for determining walking paths or performing operations through image recognition. However, during the transmission process, the image signal is first collected based on Whittaker Hannon sampling theory, then compressed and transmitted, and the original signal is reconstructed at the decompression end. In this way, the behavior of first sampling to obtain a large number of samples and discarding most of the information for transmission in order to reduce the requirements on hardware devices during compression not only wastes the storage space of image acquisition devices, but also poses a challenge to hardware devices during signal processing. Therefore, it is considered that Compressed Sensing (CS) [2] can be applied to image transmission in robot systems. During sampling, only important information of the image signal is collected and transmitted, and then reconstructed based on the prior conditions of the image at the decoding end. At present, some scholars have conducted research on this aspect [3], among which constructing reconstruction methods suitable for robot systems is crucial, and reconstruction accuracy and time are key factors characterizing system performance. Therefore, this article focuses on three key factors that affect the reconstruction effect: conduct research on sampling methods, sparse representation, and reconstruction algorithms, evaluate using two indicators, Peak Signal to Noise Ratio (PSNR) and reconstruction time, to find an effective reconstruction method and propose a reconstruction effect to reduce reconstruction time.

For the sampling method, the widely used method is the observation matrix formed by independent and identically distributed random variables. Based on this, block sampling [4], adaptive sampling [5], emi tensor product sampling [6-7], etc. have been proposed successively. Among them, the principle of adaptive sampling is the simplest and the most convenient to operate. Considering the problems applied to real systems, this article applies the adaptive sampling method to collect robot vision images. In terms of sparse representation, Fourier transform, wavelet transform, and multi-scale geometric analysis are commonly use [8]. Many scholars have also used complete redundant dictionaries for sparse representation of images, taking into account factors such as the need for training an overly complete dictionary, this paper defines the sparse basis selection range

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of the reconstructed model in wavelet transform and multi-scale geometric analysis, find suitable sparse bases through comparison. For reconstruction algorithms, there are currently four main types: greedy algorithms, convex optimization algorithms, approaching algorithms, and homotopy algorithms [9], many scholars have also made further improvements on the basis of the four categories, such as the A * orthogonal matching tracking algorithm and reconstruction algorithms based on prior knowledge of image smoothness, low rank, and sparsity. In this article, considering the reconstruction accuracy, the SPL algorithm is mainly studied, with a focus on its threshold processing process and the combination of multiple sparse bases.

2 CS Model

In CS theory, the sampling process only captures partial information of the original signal, that is, for a one-dimensional signal x (length N) that can be expressed using sparse basis Ψ, it can be measured Φ by a measurement matrix that satisfies the Restricted Isometric Property (RIP) [10].

$$y = \Phi x \,. \tag{1}$$

Among them, $\Phi \in R^{M\times N}$, $M \le N$, $y \in R^{M\times 1}$.To recover the signal, it is necessary to constrain the above formula during reconstruction, that is, the reconstruction process must incorporate other prior knowledge such as signal sparsity.

When the sparse representation of a signal on a certain basis is used as a constraint, the essence of signal reconstruction is an optimization problem for solving the l_0-norm. However, solving the l_0-norm is clearly an NP hard problem, so the problem can be transformed into an equivalent optimization problem under the l_1-norm, as shown in equation (2):

$$\min \| \Psi^{\mathrm{H}} x \|_{l_1} \text{ and meet the requirements of } \Phi x = y \,. \tag{2}$$

When using sparse prior knowledge of images as constraint conditions for image reconstruction, if only one sparse basis is used to represent an image, the reconstruction effect will vary greatly depending on the content of the image, because the optimal sparse basis corresponding to the texture and edge parts of the image are different. In this article, in order to best represent the image, two different base representations of the image are selected, and the representation of the image under different sparse bases is used as the reconstruction constraint. The refactoring model can be written as the following disclosure:

$$\min \| \Psi_i^{\mathrm{H}} x \|_{l_1} \text{ and meet the requirements of } \Phi x = y \,. \tag{3}$$

3 Overall Reconstruction Plan

3.1 Acquisition

In order to improve the sampling speed of the image, it is possible to divide the image into blocks, that is, use block compression sensing method for image acquisition, and construct the measurement matrix Φ_{B} for each sub image. The overall measurement matrix is shown below.

$$\Phi = \begin{bmatrix} \Phi_{\mathrm{B}} & & \\ & O & \\ & & \Phi_{\mathrm{B}} \end{bmatrix} . \tag{4}$$

In this way, it can solve the problem of transforming the image into a one-dimensional signal for overall measurement, which leads to excessive dimensionality of the measurement matrix and excessive computation.

3.2 Sparse Basis Selection

The effect of selecting different sparse bases on image representation varies. Due to the use of block sampling, the content of each sub image is different. When using the same sparse base for expression, it is not possible to consider the expression effect of each block of image. Therefore, in order to improve the reconstruction effect, a mixed sparse base form is needed.

Generally speaking, for images with rich textures, DCT basis and wave atoms are commonly used to express the image. However, the image artifacts generated by wave atom reconstruction are too severe, so DCT basis is chosen in this article. For images with many contours, wavelet transform DWT, Curvelet, Contourlet transform, etc. are commonly used. Among them, Contourlet transform has better expression effect, but there is often spectral confusion problem in Contourlet transform. Therefore, it is proposed to use Circular Symmetric Contourlet Ttransform (CSCT) [11-12] to enhance the directionality of Contourlet transform for image expression. The specific transformation principle of circular symmetric contour waves is shown in Fig. 1.

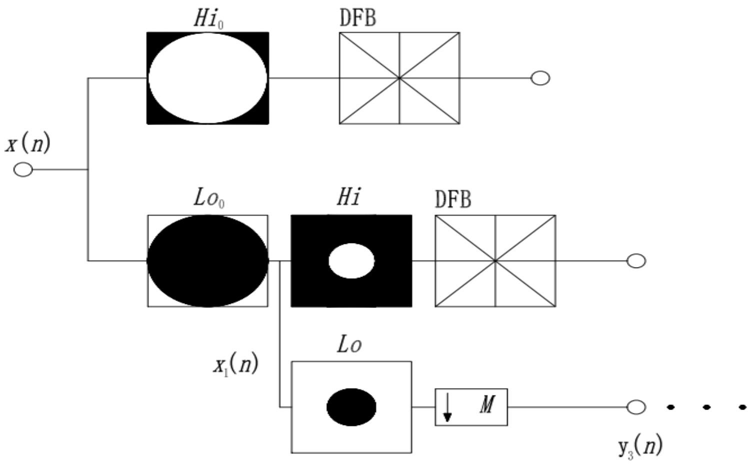


Fig. 1. The transformation principle of circular symmetric contourlet transform

Among them, Hi is the decomposed high-frequency sub-band, Lo is the low-frequency sub-band, and DFB is the directional filter bank. Except for the directional sub band with the highest resolution, each directional sub band support area of the circularly symmetric contour wave is a fan-shaped support area, which is more in line with human visual characteristics compared to the Contourlet transform. Meanwhile, the redundancy of circular symmetric contour waves is relatively small, at 2.33.

3.2 Reconstruction Algorithm

The basic principle of using the Smoothed Projection Landweber (SPL) framework for robot image reconstruction is to continuously project onto a certain closed convex set to ultimately find the optimal solution. The closed convex set is composed of the system's constraint information. In this article, due to the prior information being the sparsity of the image after DCT and circularly symmetric contour wave transformation, the composition of a closed convex set is the 0 norm of the image's coefficients in different sparse domains. Specifically, the iterative process of the SPL algorithm based on mixed sparse basis is as follows:

Input: Construct a sampling matrix Φ and compress the one-dimensional signal Y obtained from sampling. Set the parameter E_0 to control the stopping of iterations and the maximum number of iterations $K_{\max}$. Set the number of initialization iterations $k = 1$ and the approximation error $e_0 = 0$. Obtain the initial image $I_0 = \Phi^{+} \bullet Y$ through the method of pseudo inverse solution.

Output: Reconstruct the image as I_k.

Iteration process:

Step 1: Perform Wiener filtering on the image I_{k-1} obtained from the $k-1$-th iteration, then divide it into blocks, and transform each image sub block into a one-dimensional signal.

Step 2: Project the one-dimensional signals of each sub block onto a convex set, and arrange and combine the obtained signals to form a new image I'_k .The formula for convex set projection is $\hat{I}_{i,k} = I_{i,k-1} + \Phi_B^T (y_i - \Phi_B I_{i,k-1})$, where $\hat{I}_{i,k}$ represents the one-dimensional signal formed by the i -th block image in the k -th iteration, y_i is the value measured by the sub images, and Φ_B is the measurement matrix for each sub image.

Step 3: Use a certain coefficient transformation to process image I'_k and obtain the sparse coefficient θ'_k of image I'_k .

Step 4: Perform threshold processing on θ'_k to obtain sparse coefficient θ_k, and perform sparse inverse transformation on θ_k to obtain image I_k .

Step 5: Perform convex optimization on image $\tilde{I}_k$ again to obtain image I_k .

Step 6: Calculate the approximation error $e_k = \frac{1}{\sqrt{N}} \left\| I_k - I_{k-1} \right\|_2$ for the k -th iteration and determine whether the condition $e_k < e_0$ or $k > k_{max}$ for stopping the iteration is met. If satisfied, stop the iteration and reconstruct the image as I_k . If not satisfied, continue iteration.

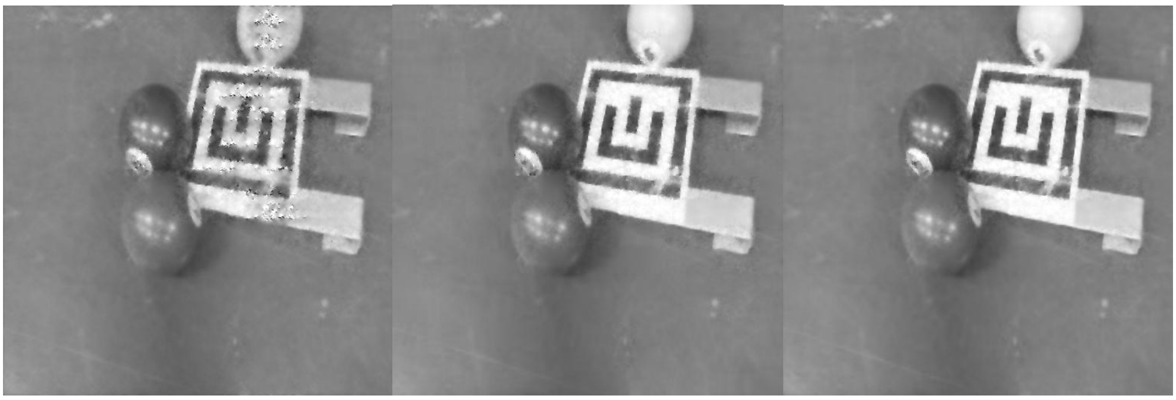
4 Experimental Results and Analysis

In order to verify the effectiveness of the proposed method, three comparative experiments were conducted with different sparse basis reconstructions at the same average sampling rate, namely the reconstruction of a single sparse basis DCT (SPL-DCT), the reconstruction of a single sparse basis CSCT (SPL-CSCT), and the reconstruction based on a mixed sparse basis DCT and CSCT (SPL-DCT+CSCT). The experimental image is shown in Fig. 2, and the image size is uniformly adjusted to.

Fig. 2. The experiment images

4.1 Reconstruct Subjective Effects

The image block size is 32 * 32, and the sampling matrix is a random Gaussian matrix. In reconstruction, the parameters of the Wiener filter are set to 3 * 3. The parameter for stopping iteration is $E_0 = 0.00005$, the maximum number of iterations is $K_{max} = 260$. The control constants for hard threshold processing and binary threshold processing are 6 and 10, respectively. The objective indicators for evaluating the reconstruction effect are the Peak Signal to Noise Ratio (PSNR) and reconstruction time of the reconstructed image. In the experiment, each reconstruction process was repeated 10 times, and the average of the objective evaluation indicators was obtained.

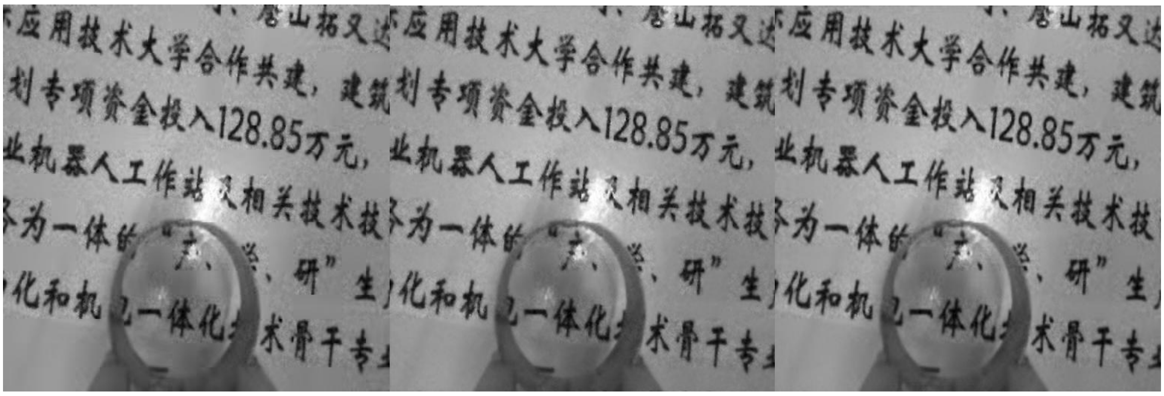


(a) SPL-DCT (PSNR=25.2 dB) (b) SPL-CSCT (PSNR=28.33 dB) (c) SPL-DCT+CSCT (PSNR=30.24 dB)

Fig. 3. Reconstruction performance of image a under different algorithms with an average sampling rate of 0.1

(a)SPL-DCT (PSNR=28.43 dB) (b) SPL-CSCT (PSNR=29.13dB) (c)SPL-DCT+CSCT (PSNR=29.88dB)

Fig. 4. Reconstruction effect of image b under different algorithms with a sampling rate of 0.1



(a) SPL-DCT (PSNR=28.23 dB) (b) SPL-CSCT (PSNR=29.89dB) (c) SPL-DCT+CSCT (PSNR=30.92dB)

Fig. 5. Reconstruction effect of image c under different algorithms with a sampling rate of 0.2

At different sampling rates, the reconstruction effects of different images are shown in Fig. 3, Fig. 4, and Fig. 5. Subjectively speaking, at a sampling rate of 0.1, due to the very little information obtained from sampling, the reconstruction effects of different methods are subjectively poor. However, relatively speaking, when using SPL-DCT alone for reconstruction, the reconstructed image contains more noise and the visual effect is worse, while the image reconstructed using SPL-CSCT is smoother, the details are ignored, and the reconstruction algorithm of SPL-DCT+CSCT can balance well, resulting in the best visual effect of the reconstructed image, especially in image a. When the sampling rate is 0.2, due to the large amount of data obtained through sampling, the reconstruction effect is significantly better. However, the image reconstructed by SPL-DCT+CSCT is also the best among the three algorithms. Therefore, these three results clearly demonstrate that the reconstruction accuracy of the reconstruction model based on mixed sparse basis is the highest at different sampling rates, with a maximum reconstruction accuracy of 2dB higher than that of the reconstructed image under a single sparse basis. At the same time, this fully demonstrates that mixed sparse basis is more effective in expressing images, and can balance smooth and detail rich sub blocks of the image to ultimately achieve better reconstruction results, The binary threshold processing method during the iteration process also takes into account the relationship between coefficients, which can better screen out more important parameters.

4.2 Reconstruct Objective Effects

In order to further verify the reconstruction effect based on DCT and CSCT, the reconstruction results of experimental images at different sampling rates were analyzed and calculated to obtain the reconstruction accuracy at various sampling rates. The experimental results are shown in Table 1.

Table 1. PSNR values of reconstructed images at different sampling rates (dB)

Sampling rate		Method	0.1	0.2	0.3	0.4	0.5
Image	a	SPL-DCT	25.2	30.89	38.15	40.45	43.21
		SPL-CSCT	28.33	30.77	34.12	40.23	43.98
		SPL-DCT+CSCT	30.24	34.45	37.26	41.98	44.01
	b	SPL-DCT	28.43	32.21	35.02	37.22	40.13
		SPL-CSCT	29.13	32.64	34.23	38.39	40.78
		SPL-DCT+CSCT	29.88	33.99	35.78	38.66	40.89
	c	SPL-DCT	23.51	28.23	32	34.93	37.55
		SPL-CSCT	23.94	29.89	31.64	35.15	38.29
		SPL-DCT+CSCT	24.61	30.92	33.46	36.02	39.64

Comparing the PSNR values of images reconstructed using different algorithms, it is evident from an objective perspective that the PSNR value of images reconstructed using mixed sparse basis is higher than that of images reconstructed based on DCT, and about 1dB higher than that of images reconstructed based on CSCT. Therefore, overall, it can be proven from both subjective and objective perspectives that images reconstructed based on alternating sparse representations of DCT and NSCT are superior to those reconstructed using a single sparse basis.

5 Conclusion

This article proposes an image reconstruction algorithm based on alternating sparse representations of two-dimensional DCT and CSCT from the perspective of the impact of different sparse bases on image reconstruction, in order to improve the efficiency and accuracy of robot imaging. The experimental results show that when using two alternating sparse bases to reconstruct images, the reconstruction effect is better than using a single sparse base to reconstruct images. However, there are still many issues that need to be addressed in this algorithm, such as the impact of different iteration times on experimental results, and the use of random matrices with different experimental times may not always yield consistent results. Therefore, obtaining more accurate results under the premise of integrating the optimal iteration times is a problem that we need to study.

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