Progressive Sparse Image Sensing using Iterative Methods

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Abstract— **Progressive image transmission enables the receivers to reconstruct a transmitted image at various bit rates. Most of the works in this field are based on the conventional Shannon-Nyquist sampling theory. In the present work, progressive image transmission is investigated using sparse recovery of random samples. The sparse recovery methods such as Iterative Method with Adaptive Thresholding (IMAT) and Iterative IKMAX Thresholding (IKMAX) are exploited in this framework since they have the ability for successive reconstruction. The simulation results indicate that the proposed method performs well in progressive recovery. The IKMAX has better final reconstruction than IMAT at the cost of requiring sparse signal with extra information about the sparsity number. However, the IMAT has the ability to recover the compressible signals. Furthermore, two sampling strategies, random sampling and uniform sampling are exploited. The simulations show that IMAT is a better choice for random sampling and IKMAX behaves better than IMAT in the case of uniform sampling.**

Keyword: IMAT; sparse; IKMAX; progressive transmission; compressed sensing; random sampling; uniform sampling

I. INTRODUCTION

The progressive image transmission provides the ability to reconstruct higher quality images successively as more samples are received. The goal of progressive transmission is to have an acceptable recovery at each step in addition to efficient overall compression. The progressive transmission schemes are robust to data rate. In a way that, if the available rate is too low a poor quality recovery of the image would be available for the user and as the available data rate increases the user is provided with more fidelity replicas of the image. The progressive transmission makes the possibility of quick browsing. In the sense that low- or medium-resolution replicas of the image can be available for the user to interrupt the transmission before downloading an undesired high resolution one. The progressive image transmission emerges in many applications such as telemedicine, teleastronomy or database retrieval.

The various progressive transmission schemes proposed in the literature are based on Shannon-Nyquist sampling theory [1-4] and there are very few works which investigate the progressive transmission schemes for sparse signals. Progressive quantization of compressive sensing [5-7] measurements is suggested in [8]. In [9], an adaptive joint source-channel coding method has been proposed for progressive transmission of medical images based on compressed sensing.

In this paper, we wish to develop a progressive method for randomly sampled sparse image recovery. To achieve this goal, we should seek for sparse recovery methods that have the ability for successive reconstruction. There are various recovery algorithms for compressively sampled sparse images such as Orthogonal Matching Pursuit (OMP) [10], Gradient Projection for Sparse Reconstruction (GPSR) [11]. However, none of them can be useful in progressive sparse signal recovery. For instance, OMP recovers the signal using the correlation of the measurement vector with the columns of the measurement matrix. When some new rows are added to the measurement matrix (new samples of the image are taken), it is impossible to use the recovered samples of the previous stage and the whole of the recovery procedure should be repeated. The iterative methods such as Iterative K MAX Thresholding (IKMAX) [1] and Iterative Method with Adaptive Thresholding (IMAT) [12-14] are suitable for progressive Sparse Signal recovery. Whenever a new subset of samples is derived from the image, the reconstructed image in the previous stage is enhanced by adding the effect of the new samples to it. In these methods, there is no need to repeat the whole stage of the reconstruction procedure. Two sampling strategies, uniform and random sampling [15-17] are exploited for sparse signals. The simulation results indicate that iterative methods are successful in progressive recovery. Comparing the results of the two recovery methods simulated in this paper, we observe that IMAT outperforms IKMAX in terms of quality for random sampling case. Also, the IKMAX behaves better than IMAT in the case of progressive reconstruction of uniformly sampled signals.

The rest of the paper is organized as follows: Section II gives an overview of sparse recovery methods, including IKMAX and IMAT. The proposed method is presented in Section III. The simulation results are given in Section IV. Finally, Section V concludes this work.

II. SPARSE RECOVERY METHODS

A. Iterative Method with Adaptive Thresholding (IMAT)

IMAT, introduced in [13] and [14], is an iterative sparse recovery method that reconstructs the randomly sampled signals. Despite of most of the existing reconstruction methods which are designed to deal with 1-D signals, IMAT can be easily adapted to be used for 2 and 3-D signals. Figure 1. depicts the steps of IMAT in details.

[1] we mistakenly named this method IHT in [12]

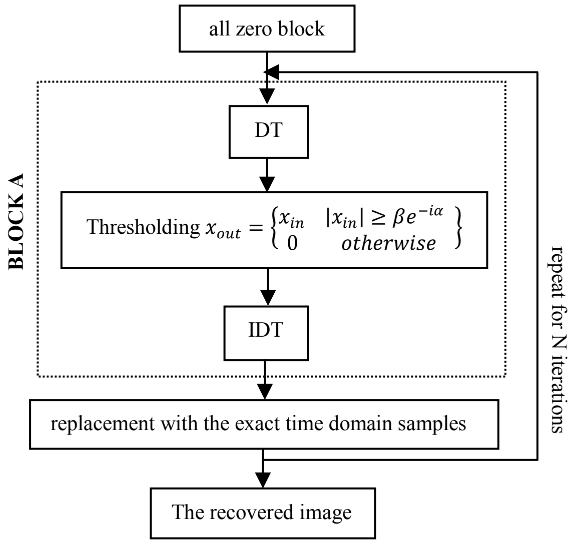


Figure 1. Block diagram of IMAT.

The block diagram explains reconstruction of a signal which is randomly or uniformly sampled using a mask. In this block diagram, the DT and IDT blocks are Discrete Transform (such as DCT) and its inverse, respectively. Let x be a sparse signal in an arbitrary domain (DCT domain) where we have a subset of its samples in another domain (time domain). The DT block is used for transforming the signal from the sparsity domain to time domain. To initialize, the signal is estimated as an all-zero block. After taking the discrete transform of the signal, sparsity is enforced by using an adaptive threshold which keeps the components above a specific threshold value. In order to retrieve all the coefficients of the signal, the threshold is set to a large value at first and decays exponentially as the iteration number increases (the reverse can also be performed). The inverse discrete transform is applied after thresholding and the exact time domain samples of the signal are replaced. After a number of iterations in time and frequency domain, the estimated signal becomes more similar to the original one.

The parameter selection of IMAT is illustrated below:

There are three parameters (α, β , N) that should be selected. The first step is to find the best β. To that end, we calculate the largest DCT coefficient of different images and set the mean value of that for β. Then, the α parameter is set a small value say 0.1 to produce all probable DCT coefficients. The N is set to a large value like 1000. Then, the β is reduced to the extent that the quality of the recovered signal does not change. This would be the optimum value for β. The next step is to increase α to the extent that the recovered signal is not distorted. As the last step, the N parameter is set to the value at which the curve of PSNR versus the iteration number becomes steady. That would be the best value for N. Using this way, we set the parameters as $\beta = 200$, $\alpha = 0.15$, N= 10 .

B. IKMAX

The IKMAX method is similar to the IMAT except that it requires the sparsity number to recover the signal. The block diagram of the IKMAX method is depicted in Figure 2.

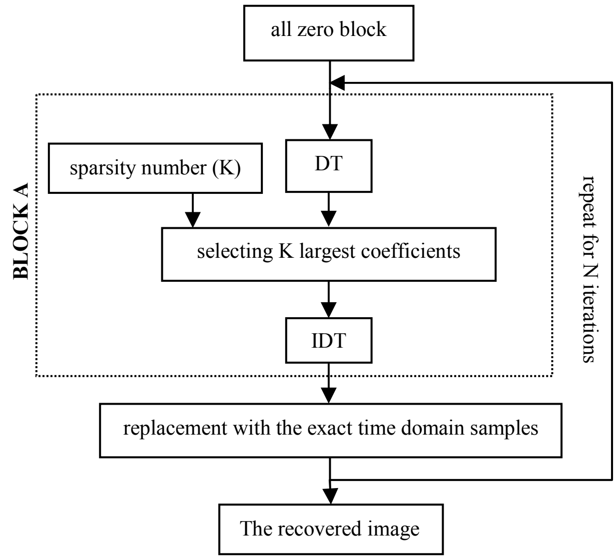


Figure 2. Block diagram of IHT.

According to this diagram, K (the sparsity number) of the largest coefficients of the DT representation of the signal (for example, DFT representation) is selected in each iteration. After performing the IDT (inverse DFT), non-distorted samples of the received signal are replaced in the time domain signal. After several iterations, the original signal can be recovered. For simulating, we sparsify the test images at first and apply the IKMAX method on the sparse images.

III. PROPOSED METHOD

The paper proposes a method to progressive transmission of images when you have an imaging system working based on random sensing. If you want to implement the traditional progressive transmission schemes in such a system, you firstly have to recover the signal using a sparse recovery method and then calculate its DCT or DWT coefficients, sort and send them according to one of the transmission schemes in the literature. Therefore, you will waste a large amount of energy in the encoder side to the recovery of the whole image from its random samples. However, the proposed method in this paper progressively transmits the random samples of the image without any need to obtain the whole image in the encoder side. Consequently, the suggested method saves the energy to a large amount and prepares a simple structure for the encoding system. Hence, the proposed method would be useful in the applications where a simple progressive encoder is needed for example in a sensor network system where the energy saving in the encoder side is a crucial factor. However, it should be noted that in the applications where the simplicity of the encoder is not of great importance, the ordinary progressive encoders based on Shannon theory may become more effective.

At this part, the proposed method of the progressive sparse image sensing is illustrated. At each stage, a mask is applied to the signal to take random or uniform measurements (instead of a linear combination of the signal pixels). A fixed-size non-overlapping subset of pixels are added to the mask at each stage, i.e., the mask of the a^{th} stage is the addition of the mask of the $(a-1)^{th}$ stage and a subset of new pixels. The pixels at each stage are sent to the receiver which exploits the IMAT or IKMAX for progressive sparse recovery. The block diagram of the proposed method is depicted in Figure 3.

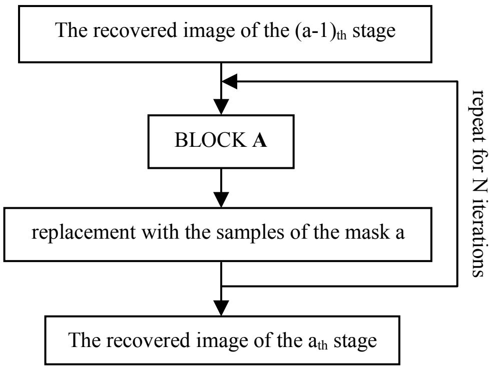


Figure 3. Block diagram of the proposed method.

According to this diagram, at the a^{th} stage of progressive reconstruction, the recovered image of the $(a-1)^{th}$ stage is used as the initial value for the a^{th} stage. Then, the BLOCK A (which is shown in Figure 1 and 2) is applied to the image and the exact pixels of the mask a are replaced. Therefore, the quality of the recovered signal improves stage by stage as new samples are received and reconstructed. An important point is that the recovery process corresponding to the pixels of the $(a-1)^{th}$ mask has been done in the $(a-1)^{th}$ stage and in the a^{th} stage only the newly derived pixels (the ones added to the mask at the current iteration) are recovered.

The sampling strategies used for designing the masks such as uniform and random sampling are explained below. Let P be the number of required progressive stages. P uniform sampling masks are generated as follows:

$$Mask(a)_{i,j} = \left\{ \begin{matrix} 1 & 1 \leq \left\lfloor \frac{i}{P} \right\rfloor \leq a \; or \; 1 \leq \left\lfloor \frac{j}{P} \right\rfloor \leq a \\ 0 & otherwise \end{matrix} \right\}, 1 \leq a \leq P$$

In the case of random sampling, each of the P masks takes random non-overlapping pixels of the image.

In any practical sampling system, the samples should be quantized before sending to the receiver. In this work a uniform quantizer is exploited with q bits.

The progressive compression method used in this work can be categorized as the spatial progressive transmission method since the image is spatially divided into some planes which are transmitted successively.

IV. SIMULATION RESULTS

In this section, the simulation results are reported. The proposed progressive image recovery algorithm has been applied to the lena, boat and baboon images. In the case of IKMAX method, the images are sparsified at first (20% of the largest coefficients are preserved and others are set to zero), however the original non-sparse images are applied for the IMAT method. The parameter P, the number of progressive stages, has been set to 10. The parameter N, the number of iterations at each step, is 10. The Mean Square Error (MSE) versus the progression step for random sampling and uniform sampling are depicted in Figure 4 and 5, respectively.

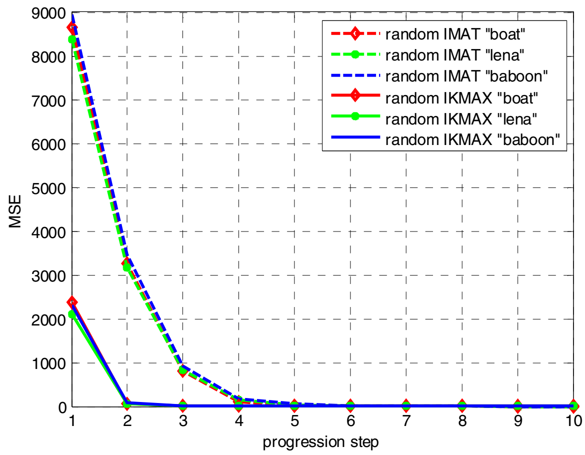


Figure 4. The MSE of the proposed method versus the progression step for random sampling.

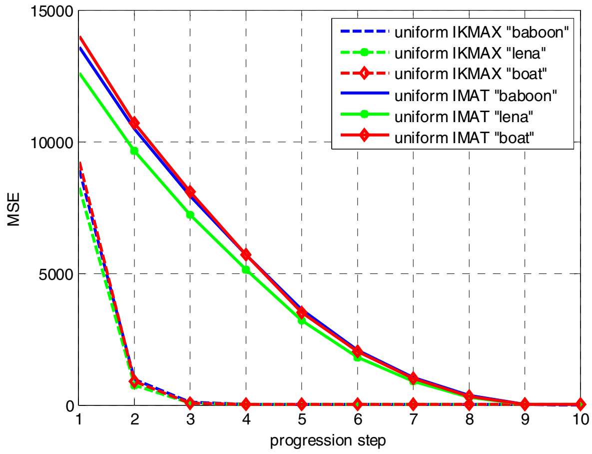


Figure 5. The MSE of the proposed method versus the progression step for uniform sampling.

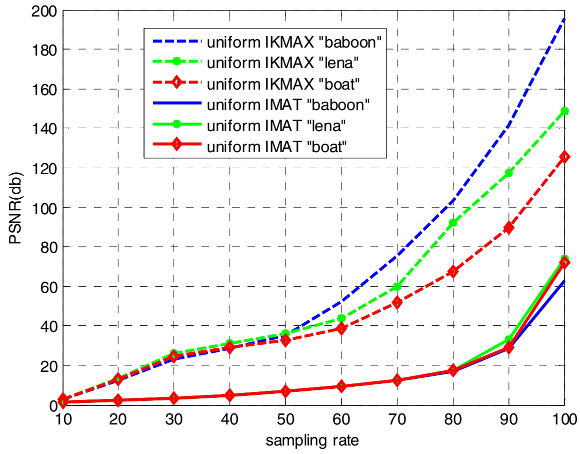


Figure 7. The rate distrortion performance of the proposed method for uniform sampling.

As it was predicted, the MSE curve has a decreasing trend in all of the case. The IMAT method outperforms IKMAX in the case of random sampling in a way that the MSE approaches zero in the first few steps, while IKMAX behaves better than IMAT in progressively recovering uniform sampled signals.

Applying the quantization step, we investigate the performance of the proposed method with $q = 7$ bits. The PSNR versus sampling rate curves for random and uniform sampling are depicted in Figure 6 and 7.

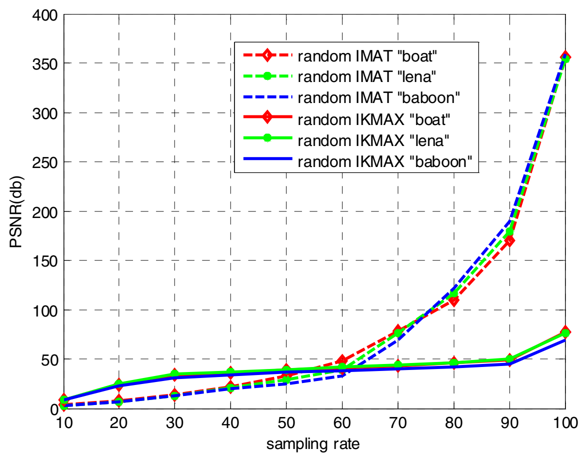
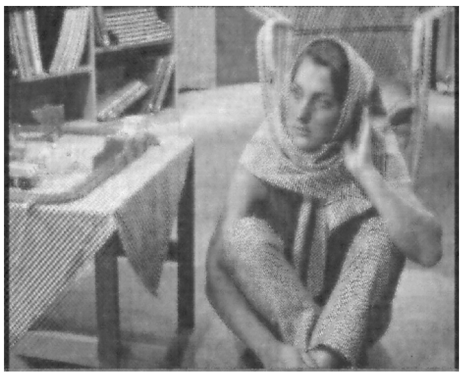


Figure 6. The rate distrortion performance of the proposed method for random sampling.

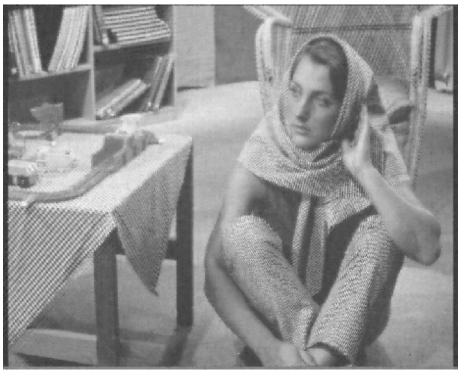
As it can be seen in the Figure 6 and 7, the final reconstruction of the IKMAX method is extremely better than that of IMAT. This significant outperformance of IKMAX over IMAT is at the cost of requiring a sparse image with extra information about its sparsity number. Actually, the IKMAX can be used for reconstruction of sparse signals, while IMAT can recover the compressible (and not necessarily sparse) signals. Moreover,

The average simulation time of the progressive IMAT is 2.5 seconds while that of IKMAX is 4.9 seconds. Hence, the IKMAX method is more complex than IMAT.

In order to have a subjective comparison, the recovered images at various progression steps of the IMAT method with random sampling are shown in Figure 6.



(a)



(b)

(c)

Figure 8. progressive IMAT with random Mask, (a) step 4,(b) step 6, (c) step 9

As it can be seen from the Figure, the recovered images at each step have satisfactory results and the quality of the recovered image increases at each iteration.

V. CONCLUSION

In this paper, progressive compressed image sensing using iterative methods is proposed. IKMAX and IMAT methods have been exploited in progressive recovery using random or uniform sampling. The simulation results prove that in the case of random masks, IMAT method is better choice for progressive reconstruction. Furthermore, when uniformly sampling the signal, the IKMAX performs better in the rate distortion performance.

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