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### ► To cite this version:

Ningning Zhao, Qi Wei, Adrian Basarab, Denis Kouamé, Jean-Yves Tournet. Single image super-resolution of medical ultrasound images using a fast algorithm. 13th IEEE International Symposium on Biomedical Imaging: From Nano to Macro (ISBI 2016), Apr 2016, Prague, Czech Republic. pp.473-476, 10.1109/ISBI.2016.7493310 . hal-01566911

**HAL Id: hal-01566911**

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**To cite this version** : Zhao, Ningning and Wei, Qi and Basarab, Adrian and Kouamé, Denis and Tournet, Jean-Yves *Super-resolution of medical ultrasound images using a fast algorithm*. (2016) In: 13th IEEE International Symposium on Biomedical Imaging: From Nano to Macro (ISBI 2016), 13 April 2016 - 16 April 2016 (Prague, Czech Republic).

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# SINGLE IMAGE SUPER-RESOLUTION OF MEDICAL ULTRASOUND IMAGES USING A FAST ALGORITHM

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## ABSTRACT

This paper addresses the problem of super-resolution (SR) for medical ultrasound (US) images. Contrary to device-based approaches, we investigate a post-processing method to invert the direct linear model of US image formation. Given the ill-posedness of single image SR, we proposed an  $\ell_p$ -norm ( $1 \leq p \leq 2$ ) regularizer for the US tissue reflectivity function/image to be estimated. To solve the associated optimization problem, we propose a novel way to explore the decimation and blurring operators simultaneously. As a consequence, we are able to compute the analytical solution for the  $\ell_2$ -norm regularized SR problem and to embed the analytical solution to an alternating direction method of multipliers for the  $\ell_p$ -norm regularized SR problem. The behavior of the proposed algorithm is illustrated using synthetic, simulated and *in vivo* US data.

**Index Terms**— Ultrasound, single image super-resolution, circulant matrix, ADMM,  $\ell_p$ -norm regularization.

## 1. INTRODUCTION

Medical ultrasound imaging (USI) has been widely used for clinical diagnosis, especially for soft tissue applications including cardiovascular medicine and obstetrics [1]. USI has many advantages compared to other medical imaging modalities such as X-ray computed tomography and magnetic resonance imaging including its harmless, cost-effective, portable and noninvasive properties. However, US images suffer from a relatively low contrast, reduced spatial resolution and low signal-to-noise ratio. Even though advances in ultrasonic hardware have improved the resolution of US images during the last 15-20 years, e.g., [1, 2], post-processing techniques enhancing US image resolution are still appealing due to the physical limitations of device-based solutions. In an ultrasound system, there are

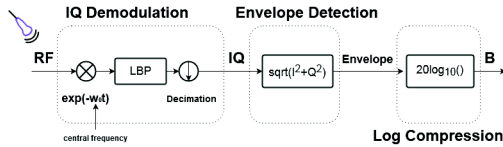


Fig. 1. Relationship between different US image modes.

basically three image modes available for analysis, including *radio-*

*frequency* (RF) data, *in phase/quadrature* (IQ) data and B-mode image (also called displayed image) [3], whose relationships are shown in Fig. 1. In this work, we focus on the complex IQ data. Due to the linearity of the demodulation process, the convolution model classically used for RF data can be used to describe the IQ image formation [4]. This model is defined as

$$\mathbf{y} = \mathbf{S}\mathbf{H}\mathbf{x} + \mathbf{n} \quad (1)$$

where the vector  $\mathbf{y} \in \mathbb{C}^{N_l \times 1}$  ( $N_l = m_l \times n_l$ ) is the observation and  $\mathbf{x} \in \mathbb{C}^{N_h \times 1}$  ( $N_h = m_h \times n_h$ ) is the vectorized tissue reflectivity function (TRF), i.e., the image to be estimated, with  $N_h > N_l$ . These vectors are obtained by stacking the corresponding images into column vectors using a lexicographic order. The vector  $\mathbf{n} \in \mathbb{C}^{N_l \times 1}$  is classically supposed to be an independent identically distributed (*i.i.d.*) additive white Gaussian noise (AWGN). The matrices  $\mathbf{S} \in \mathbb{R}^{N_l \times N_h}$  and  $\mathbf{H} \in \mathbb{C}^{N_h \times N_h}$  are associated with the decimation and blurring/convolution operators. More specifically,  $\mathbf{H}$  is a block circulant matrix with circulant blocks (BCCB) corresponding to cyclic convolution boundaries, and left multiplying by  $\mathbf{S}$  corresponds to down-sampling with an integer factor  $d$  ( $d = d_r \times d_c$ ), with the relationships  $N_h = N_l \times d$ ,  $m_h = m_l \times d_r$  and  $n_h = n_l \times d_c$ .

The US image super-resolution (SR) problem consists of estimating the TRF vector  $\mathbf{x}$  from the observation vector  $\mathbf{y}$ , which requires additional prior information to regularize this well-known ill-posed problem. An  $\ell_2$ -norm regularized method is known to produce over-smoothed results, the TV regularized method produces piecewise smoothing results, whereas the  $\ell_1$ -norm regularizer can be used when the solution is known to be sparse [5]. In this paper, we consider an  $\ell_p$ -norm regularizer with  $1 \leq p \leq 2$  for the TRF  $\mathbf{x}$ , which obviously generalizes the  $\ell_1$ -norm and  $\ell_2$ -norm regularizers [6, 7].

The single image SR problem was solved in [8] with the alternating direction method of multipliers (ADMM) by separating the SR problem into up-sampling and deconvolution steps that can be solved efficiently and iteratively. First order gradient-based algorithms were also investigated for the image SR problem in [9]. However, these algorithms assume that the function to be optimized is differentiable, which limits their applications. In this paper, we propose to handle the decimation and blurring matrices simultaneously by exploring their specific properties in the Fourier domain [10]. Note that similar properties were mentioned in [11, 12] in different contexts.

## 2. PROPOSED SUPER-RESOLUTION ALGORITHM

### 2.1. Problem formulation

Similar to the traditional image reconstruction problems, accounting for the AWGN and the prior information for the TRF, we consider

Part of this work has been supported by the Chinese Scholarship Council and the thematic trimester on image processing of the CIMI Labex, Toulouse, France, under grant ANR-11-LABX-0040-CIMI within the program ANR-11-IDEX-0002-02.

the following optimization problem

$$\min_{\mathbf{x}} \frac{1}{2} \|\mathbf{y} - \mathbf{S}\mathbf{H}\mathbf{x}\|_2^2 + \tau \|\mathbf{x}\|_p^p \quad (2)$$

where  $\|\mathbf{x}\|_p = \sqrt[p]{|x_1|^p + \dots + |x_{N_h}|^p}$  is the  $\ell_p$ -norm and  $\tau$  is the regularization parameter balancing the weights of the data fidelity and regularization terms. Under the cyclic boundary assumption, the blurring matrix  $\mathbf{H}$  is diagonalizable in the Fourier domain leading to

$$\mathbf{H} = \mathbf{F}^H \mathbf{\Lambda} \mathbf{F} \text{ and } \mathbf{H}^H = \mathbf{F}^H \mathbf{\Lambda}^H \mathbf{F} \quad (3)$$

where  $\mathbf{F}/\mathbf{F}^H$  are the Fourier and inverse Fourier transform operators and  $\mathbf{\Lambda} = \text{diag}\{\mathbf{F}\mathbf{h}\}$ , where  $\mathbf{h}$  is the first column of the matrix  $\mathbf{H}$ .

## 2.2. Estimation of the TRF $\mathbf{x}$

As mentioned in the introduction, we propose to handle the decimation and blurring matrices simultaneously by taking into account the properties of the decimation matrix in the Fourier domain. More precisely, the following result can be obtained [12]

$$\mathbf{F}\mathbf{S}\mathbf{F}^H = \frac{1}{d} \mathbf{J}_d \otimes \mathbf{I}_{N_l} \quad (4)$$

where  $\mathbf{J}_d \in \mathbb{R}^{d \times d}$  is a matrix of ones,  $\mathbf{I}_{N_l} \in \mathbb{R}^{N_l \times N_l}$  is the identity matrix,  $\mathbf{S} = \mathbf{S}^H \mathbf{S}$  and  $\otimes$  is the Kronecker product. Using (4), an analytical solution to (2) for  $p = 2$  is

$$\begin{aligned} \mathbf{x} &= (\mathbf{H}^H \mathbf{S}^H \mathbf{S} \mathbf{H} + 2\tau \mathbf{I}_{N_h})^{-1} \mathbf{r} \\ &= \mathbf{F}^H (\mathbf{\Lambda}^H \mathbf{F} \mathbf{S} \mathbf{F}^H \mathbf{\Lambda} + 2\tau \mathbf{I}_{N_h})^{-1} \mathbf{F} \mathbf{r} \end{aligned} \quad (5)$$

where  $\mathbf{r} = \mathbf{H}^H \mathbf{S}^H \mathbf{y}$ . The computation of (5) is complicated due to the huge and non-diagonalizable matrix to be inverted. The existing methods to solve this problem include iterative optimization [8] and sampling [13] methods that are still computationally intensive. The main contribution of this paper is the derivation of the analytical solution (5) (i.e., the solution of (2) for  $p = 2$ ) presented in Theorem 1.

**Theorem 1.** *The solution of (5) can be computed as*

$$\hat{\mathbf{x}} = \frac{1}{2\tau} \mathbf{r} - \frac{1}{2\tau} \mathbf{F}^H \mathbf{\Lambda}^H \left( 2\tau d \mathbf{I}_{N_l} + \mathbf{\Lambda} \mathbf{\Lambda}^H \right)^{-1} \mathbf{\Lambda} \mathbf{F} \mathbf{r} \quad (6)$$

where  $\mathbf{\Lambda} = \underbrace{(\mathbf{I}_{N_l}, \dots, \mathbf{I}_{N_l})}_{d} \mathbf{\Lambda} \in \mathbb{C}^{N_l \times N_h}$ .

*Proof.* Use the Woodbury inversion lemma, see [10] for more details of the proof.  $\square$

Moreover, the analytical solution (6) can be embedded into an ADMM framework for  $1 \leq p < 2$ . Precisely, by introducing an additional variable  $\mathbf{u} = \mathbf{x}$ , (2) can be rewritten as

$$\begin{aligned} \min_{\mathbf{x}, \mathbf{u}} \quad & \frac{1}{2} \|\mathbf{y} - \mathbf{S}\mathbf{H}\mathbf{x}\|_2^2 + \tau \|\mathbf{u}\|_p^p \\ \text{subject to} \quad & \mathbf{u} = \mathbf{x}. \end{aligned} \quad (7)$$

The augmented Lagrangian function associated with (7) is

$$L(\mathbf{x}, \mathbf{u}, \boldsymbol{\lambda}) = \frac{1}{2} \|\mathbf{y} - \mathbf{S}\mathbf{H}\mathbf{x}\|_2^2 + \tau \|\mathbf{u}\|_p^p + \boldsymbol{\lambda}^T (\mathbf{x} - \mathbf{u}) + \frac{\mu}{2} \|\mathbf{x} - \mathbf{u}\|_2^2$$

or equivalently

$$L(\mathbf{x}, \mathbf{u}, \mathbf{d}) = \frac{1}{2} \|\mathbf{y} - \mathbf{S}\mathbf{H}\mathbf{x}\|_2^2 + \tau \|\mathbf{u}\|_p^p + \frac{\mu}{2} \|\mathbf{x} - \mathbf{u} + \mathbf{d}\|_2^2 \quad (8)$$

where  $\mathbf{d} = (1/\mu)\boldsymbol{\lambda}$  is the scaled dual variable with  $\mu > 0$ . Then, the problem (8) can be solved iteratively as

For  $k = 0, \dots$

$$\begin{cases} \mathbf{x}_{k+1} \in \arg\min_{\mathbf{x}} \frac{1}{2} \|\mathbf{y} - \mathbf{S}\mathbf{H}\mathbf{x}\|_2^2 + \frac{\mu}{2} \|\mathbf{x} - \mathbf{u}_k + \mathbf{d}_k\|_2^2 \\ \mathbf{u}_{k+1} \in \arg\min_{\mathbf{u}} \tau \|\mathbf{u}\|_p^p + \frac{\mu}{2} \|\mathbf{x}_{k+1} - \mathbf{u} + \mathbf{d}_k\|_2^2 \\ \mathbf{d}_{k+1} = \mathbf{d}_k + (\mathbf{x}_{k+1} - \mathbf{u}_{k+1}) \end{cases} \quad (9)$$

The optimization problems w.r.t.  $\mathbf{x}$  and  $\mathbf{u}$  involved in (9) are detailed below

- Update  $\mathbf{x}$ : The analytical solution of the MAP estimator of  $\mathbf{x}$  can be calculated as follows

$$\begin{aligned} \mathbf{x}_{k+1} &= (\mathbf{H}^H \mathbf{S}^H \mathbf{S} \mathbf{H} + \mu \mathbf{I}_{N_h})^{-1} \mathbf{r}_1 \\ &= \mathbf{F}^H (\mathbf{\Lambda}^H \mathbf{F} \mathbf{S} \mathbf{F}^H \mathbf{\Lambda} + \mu \mathbf{I}_{N_h})^{-1} \mathbf{F} \mathbf{r}_1 \end{aligned} \quad (10)$$

where  $\mathbf{r}_1 = \mathbf{H}^H \mathbf{S}^H \mathbf{y} + \mu(\mathbf{u}_k - \mathbf{d}_k)$ . Theorem 1 can be finally used to compute the solution (10).

- Update  $\mathbf{u}$ : The MAP estimator of  $\mathbf{u}$  can be calculated with the following proximal operator since  $\mathbf{u}$  is pixel-wise decoupled [14]

$$\text{prox}_{|\cdot|_p}(\nu) = \arg\min_{\mathbf{u}} \tau |\mathbf{u}|^p + \frac{\mu}{2} \|\nu - \mathbf{u}\|_2^2 \quad (11)$$

where  $\nu$  is an element from the vector  $\boldsymbol{\nu} = \mathbf{x}_{k+1} + \mathbf{d}_k$ . Note that when  $p$  belongs to  $\{1, 4/3, 3/2, 2\}$ , the analytical solution of the proximal operator (11) can be found in [14].

## 2.3. Proposed algorithm

The SR algorithm resulting from the previous derivations is summarized in Algo. 1. Note that the regularization parameters used in this paper have been adjusted manually by cross-validation.

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### Algorithm 1: fast SR algorithm for US images

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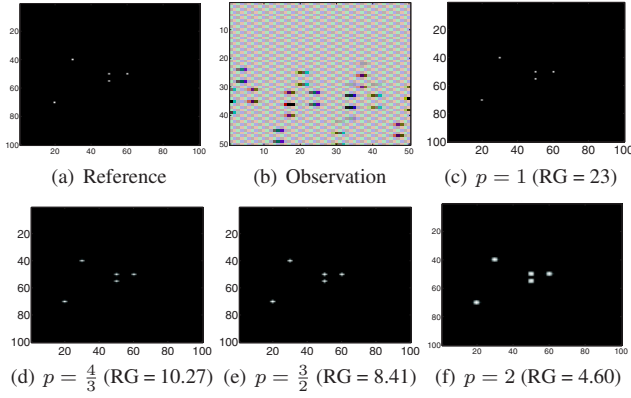
- 1 Set  $k = 0$ , choose  $\mu > 0$ ,  $\tau > 0$ ,  $\mathbf{x}_0$ ,  $\mathbf{d}_0$ ;
  - 2 Repeat
    - // 1) Update  $\mathbf{x}$  using (10)
    - 3  $\mathbf{r}_1 = \mathbf{H}^H \mathbf{S}^H \mathbf{y} + \mu(\mathbf{u}_k - \mathbf{d}_k)$ ;
    - 4  $\mathbf{\Lambda} \leftarrow \text{Dec}(\mathbf{H})$ ;
    - 5  $\mathbf{\Lambda} \leftarrow \mathbf{\Lambda} \mathbf{\Lambda}^H$ ;
    - 6  $\mathbf{x}_f \leftarrow (\mathbf{\Lambda}^H (\mu d \mathbf{I}_{N_l} + \mathbf{\Lambda} \mathbf{\Lambda}^H)^{-1} \mathbf{\Lambda}) \mathbf{F} \mathbf{r}_1$ ;
    - 7  $\mathbf{x}_{k+1} \leftarrow \frac{1}{\mu} \mathbf{r}_1 - \frac{1}{\mu} \mathbf{F}^H \mathbf{x}_f$ ;
    - // 2) Update  $\mathbf{u}$  using the proximal operator
    - 8  $\boldsymbol{\nu} = \mathbf{x}_{k+1} + \mathbf{d}_k$ ;
    - 9  $\mathbf{u}_{k+1} = \text{prox}_{|\cdot|_p}(\boldsymbol{\nu})$ ;
    - // 3) Update the dual variables  $\mathbf{d}$
    - 10  $\mathbf{d}_{k+1} = \mathbf{d}_k + (\mathbf{x}_{k+1} - \mathbf{u}_{k+1})$ ;
    - 11  $k \leftarrow k + 1$
    - 12 until stopping criterion is satisfied.
- 

## 3. SIMULATION RESULTS

In this section, we evaluate the proposed algorithm on synthetic data, simulated and *in vivo* US images. The performance of the algorithms is assessed using the resolution gain (RG), whose definition is the ratio of the normalized auto-correlation (higher than 3 dB) of the interpolation of the observed US data to the normalized auto-correlation (higher than 3 dB) of the restored TRF. Note that RG is widely used in US image reconstruction problems [5, 15].

### 3.1. Synthetic data

We first tested the proposed algorithm on synthetic data, as shown in Fig. 2 (a)-(b). The synthetic sparse data (isolated Diracs) was convolved by a PSF represented by a Gaussian function modulated by a 3.4 MHz cosine sampled at a rate of 20 MHz. Note that the observations have been scaled for better visualization in this paper (i.e., the LR images contain  $d$  times fewer pixels than the corresponding HR images). In this group of experiments, we studied the efficiency of the  $\ell_p$ -norm regularizer for  $p \in \{1, 4/3, 3/2, 2\}$ . The regularization parameter  $\tau$  was set to 0.001 and the decimation factors were  $d_r = d_c = 2$ . The restored images and the numerical RG results are reported in Fig. 2 (c)-(f). As illustrated in Fig. 2, the smaller the value of  $p$  is, the higher RG we can obtain. The results are coherent since the  $\ell_1$ -norm regularized problem favors a sparse solution.



**Fig. 2.** Synthetic data and SR results with the proposed method with  $\ell_p$ -norm regularization terms.

### 3.2. Simulated US image

This section evaluates the performance of the proposed algorithm on simulated images of size  $78 \times 88$ , as shown in Fig. 3 (a)-(c). The observation (Fig. 3 (a)) has been generated from the decimation of the convolution between a TRF of size  $156 \times 196$  (Fig. 3 (c)) and a standard US PSF with decimation factors  $d_r = d_c = 2$ . The regularization parameter is  $\tau = 0.0001$ . The restored images using  $\ell_p$ -norm regularization terms with the proposed algorithm are shown in Fig. 3 (e)-(h). The corresponding numerical results are reported in Table 1. Compared to the synthetic data in Section 3.1, the simulated US image is not sparse explaining why the restored image using the  $\ell_p$ -norm regularizer with  $p = 4/3$  outperforms the others. Thus, we emphasize that the choice of the value of  $p$  highly depends on the statistical properties of the TRF. Furthermore, we also show that our method outperforms, in terms of RG, the super-resolution technique introduced in [8] using a TV regularizer (see Fig. 3 (d)).

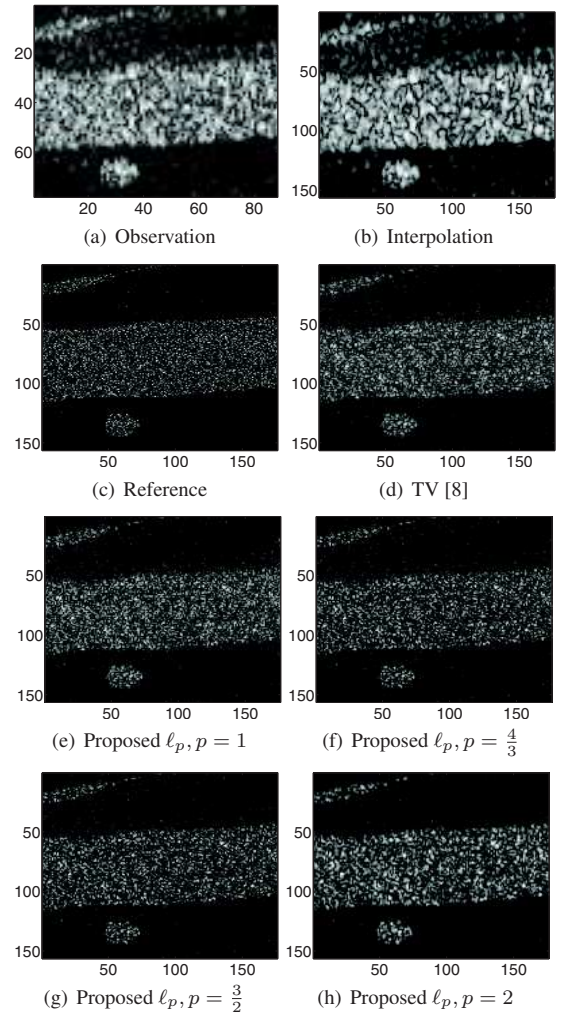
### 3.3. In vivo US image

Finally, the proposed SR algorithm was tested on *in vivo* US data using  $\ell_p$ -norm regularization. The image displayed in Fig. 4 (a) is a mouse kidney image acquired with a probe of 25MHz central frequency. We carried out SR experiments on the region located inside the red box, shown in Fig.4 (b). The up-sampling factors were set to  $d_r = d_c = 2$ . The PSF was estimated directly from the data following [16]. Finally, the regularization parameter  $\tau$  was set to 0.1 in this section. For the real data, we compared the proposed

algorithm with a classical ADMM implementation [8, 10]<sup>1</sup>. The restored images obtained with the proposed method are shown in Fig. 4 (c)-(f), while the ones estimated with the classical method are shown in Fig. 4 (g)-(j). The numerical results are reported in Table 2. According to the graphical and numerical results, the restored images with the proposed algorithm and the classical method are similar in terms of RG. However, the proposed algorithm needs less CPU time and a reduced number of iterations (when compared to the classical method) to converge.

**Table 1.** SR of the simulated US image

Prior $\ell_p$	RG	Time (s)	Iters.
$p = 2$	2.37	0.004	-
$p = 1$	9.56	1.55	317
$p = 4/3$	<b>26.01</b>	2.98	300
$p = 3/2$	22.63	2.20	329
TV [8]	2.24	2.70	289



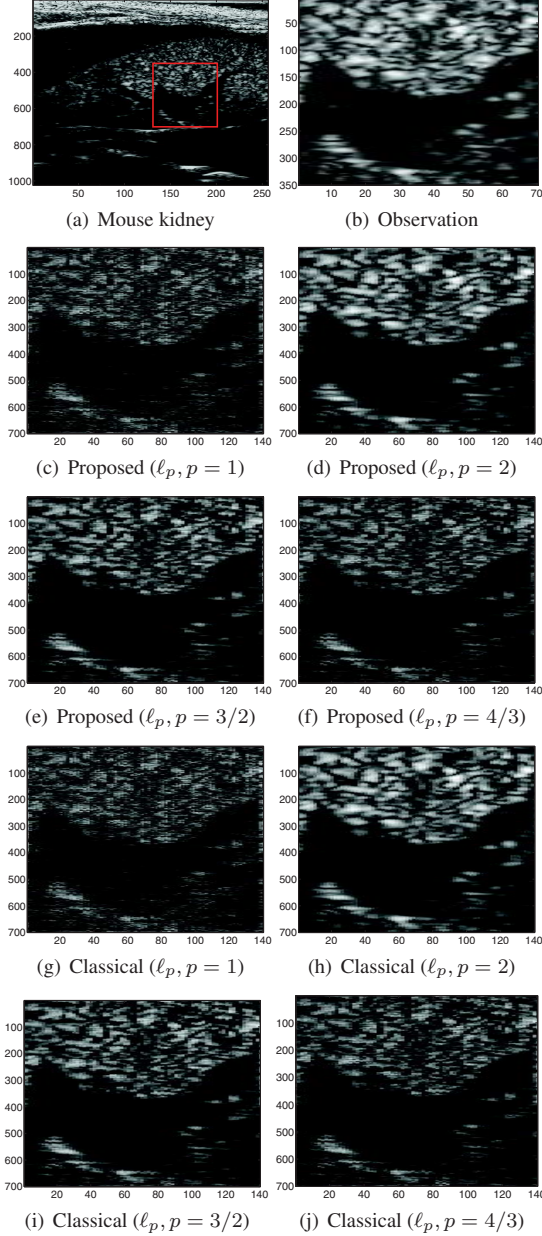
**Fig. 3.** Simulated US image and the SR results using  $\ell_p$ -norm and TV regularizers.

<sup>1</sup>The classical method needs to split the SR problem into deconvolution and up-sampling problems.



**Table 2.** SR of the real US image

$\ell_p$	Method	RG	Time (s)	Iters.
$p = 2$	Proposed	1.78	<b>0.009</b>	-
	Classical	1.78	0.53	55
$p = 1$	Proposed	<b>16.26</b>	<b>2.42</b>	190
	Classical	<b>16.50</b>	2.58	199
$p = \frac{4}{3}$	Proposed	9.72	<b>0.76</b>	28
	Classical	10.04	1.12	37
$p = \frac{3}{2}$	Proposed	5.55	<b>0.31</b>	14
	Classical	5.72	0.75	33



**Fig. 4.** *In vivo* US image and the restored images with the proposed and classical methods using  $\ell_p$  norm regularizers.

#### 4. CONCLUSION

This paper studied a new super-resolution algorithm for ultrasound images. By exploring the properties of the decimation matrix in the Fourier domain, we were able to calculate an analytical solution of the super-resolution problem with an  $\ell_2$ -norm regularizer and were able to embed this analytical solution into an ADMM framework for a more general  $\ell_p$ -norm regularizer ( $p \in [1, 2]$ ). Due to the implementation of the analytical solution, the proposed method allowed to reduce the computation time comparing with the classical method. Our results also showed that better restoration performance can be obtained with the  $\ell_p$ -norm regularizer, depending on the image structure.

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