

A TVSCAD APPROACH FOR IMAGE DEBLURRING WITH IMPULSIVE NOISE

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Abstract. We consider image deblurring problem in the presence of impulsive noise. It is known that *total variation* (TV) regularization with L1-norm penalized data fitting (TVL1 for short) works reasonably well only when the level of impulsive noise is relatively low. For high level impulsive noise, TVL1 works poorly. The reason is that all data, both corrupted and noise free, are equally penalized in data fitting, leading to insurmountable difficulty in balancing regularization and data fitting. In this paper, we propose to combine TV regularization with *smoothly clipped absolute deviation* (SCAD) penalty for data fitting (TVSCAD for short). Our motivation is simply that data fitting should be enforced only when an observed data is not severely corrupted, while for those data more likely to be severely corrupted, less or even null penalization should be enforced. A *difference of convex functions* algorithm is adopted to solve the nonconvex TVSCAD model, resulting in solving a sequence of TVL1-equivalent problems, each of which can then be solved efficiently by the alternating direction method of multipliers. Theoretically, we establish global convergence to a critical point of the nonconvex objective function. The R-linear and at-least-sublinear convergence rate results are derived for anisotropic and isotropic TV, respectively. Numerically, extensive experimental results are given to show that the TVSCAD model improves the TVL1 significantly, especially for cases with high level impulsive noise. In addition, the TVSCAD model is also compared with a recently proposed iteratively corrected TVL1 method to illustrate its promising performance.

Key words. total variation, L1-norm, SCAD, deblurring, impulsive noise, DC programming, regularization, alternating direction method of multipliers, KL function.

AMS subject classifications. 65K05, 65K10, 65J22, 90C25

1. Introduction. We consider the problem of recovering an image degraded by blur and impulsive noise. For simplicity, we focus solely on grayscale images with square domain, and by using the multichannel *total variation* (TV) regularization introduced in [55] our discussions extend, without essential difficulties, to multichannel images with either square or rectangle domains. Let \bar{u} be a clean image of size n -by- n . By stagnating the columns of \bar{u} in an left-upper and right-lower manner, \bar{u} can be treated equally as a vector in \mathfrak{R}^{n^2} . Without loss of generality, we assume that the pixel values of \bar{u} are scaled into $[0, 1]$. The observed blurry and noisy image $f \in \mathfrak{R}^{n^2}$ obeys $f = \mathbb{N}_{\text{imp}}(K\bar{u})$, where $K \in \mathfrak{R}^{n^2 \times n^2}$ is a blurring operator corresponding to an underlying point spread function, and $\mathbb{N}_{\text{imp}}(\cdot)$ represents a procedure of impulsive noise corruption. Our aim is to approximately recover the clean image \bar{u} from the blurry and noisy observation f , with the blurring operator K given. Apparently, this problem falls into the class of linear inverse problems.

In the rest of this section, we first review briefly some impulsive noise removal methods, either with or without the degradation of blur, and then summarize the notation and the organization of this paper.

1.1. Impulsive noise and filter methods. Impulsive noise is often generated by malfunctioning pixels in camera sensors, faulty memory locations in hardware, or erroneous transmission, see [8]. Two common types of such noise are *salt-and-pepper* (SP) noise and *random-valued* (RV) noise, both of which degrade an image by changing the values of a fraction of randomly selected pixels while leaving the rest ones untouched. When degraded by SP noise, the value of the selected pixel will be replaced with half probability by either the minimum or the maximum pixel value. RV noise degrades images in a similar way, except

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that intensities of the corrupted pixels are uniformly distributed between the minimum and the maximum pixel values. They are referred to as impulsive noise because corrupted pixels are mostly distinguishable from their neighbors, and intuitively RV noise is harder to remove than SP noise. Based on these features, a number of digital filter methods have been proposed [3], which first detect likely corrupted data entries and then replace them by using the filters. Among others, the median type filters are very popular due to their favorable denoising power and high computational efficiency, e.g., the adaptive median filter [32], the multistate median filter [15], and the median filter based on homogeneity information [22, 39]. We mention that most of the aforementioned filters are merely suitable for denoising in the absence of blur.

1.2. Variational methods. An important class of methods for image deblurring is the variational approach, in which the ground truth \bar{u} is recovered approximately as the minimizer of a certain energy function. It is not uncommon that the energy function is composed of a data fitting term $\Phi(u)$ and a regularization term $\Psi(u)$, i.e., an optimization problem of the form $\min_u \Psi(u) + \mu\Phi(u)$ is solved to recover \bar{u} . Here $\mu > 0$ is a weighting parameter balancing the two terms in minimization.

The purpose of the regularization term $\Psi(u)$ is to enforce certain regularity conditions or prior constraints on the image, such as smoothness and boundedness. Indeed, image deblurring problem is very ill-posed and, as a consequence, the regularization term is indispensable in stabilizing the recovery procedure. The traditional Tikhonov regularization [51] has been widely used due to its simplicity. However, Tikhonov regularized models, though relatively easy to solve, tend to produce overly smoothed images and are unable to preserve important image attributes such as sharp boundaries. In contrast, the TV regularization pioneered by Rudin, Osher and Fatemi [44] makes image edges and object boundaries, which are generally the most important features of an image, very well preserved due to the linear penalty on the image gradient. Using finite difference operations, one can discretize the TV into different forms, e.g., the well known isotropic and anisotropic discretizations of TV are given by

$$\text{TV}_{\text{iso}}(u) = \sum_{i=1}^{n^2} \|D_i u\|_2 \quad \text{and} \quad \text{TV}_{\text{aniso}}(u) = \sum_{i=1}^{n^2} \|D_i u\|_1, \quad (1.1)$$

respectively, where $D_i \in \mathbb{R}^{2 \times n^2}$ is a local finite difference operator at the i th pixel (boundary conditions will be specified later). Exactly because of the attractive edge-preserving ability, TV regularization has been extremely widely used, see, e.g., a recent review paper up to 2013 [10] and the references therein.

On the other hand, the data fitting term penalizes the deviation of the observed data from the physical model. In the case of additive noise, i.e., $f = Ku + \omega$ for some error $\omega \in \mathbb{R}^{n^2}$, or impulsive noise as is the concern of this paper, $\Phi(u)$ usually takes the form $\|Ku - f\|_p^p$ for $p = 1$ or 2 . For additive Gaussian noise, p is usually set to 2 because minimizing $\|Ku - f\|_2^2$ corresponds to seeking the maximum likelihood estimation of \bar{u} . Combined with TV regularization, this leads to the influential TVL2 model [44, 43]. However, practical systems usually suffer from outliers, where only a fraction of data entries are corrupted by noise of some non-Gaussian distribution, e.g., impulsive noise. In such cases, nonsmooth data fitting is preferred due to its ability in fitting the uncorrupted data entries, e.g., ℓ_1 -norm data fitting was originally introduced in [1] for pure denoising problem. The importance of nondifferentiable data fitting such as the ℓ_1 -norm penalizing has been examined deeply in [35, 36].

By combining TV regularization with ℓ_1 -norm penalized data fitting $\|Ku - f\|_1$, we arrive at the well known TVL1 model, i.e.,

$$\min_u \text{TV}(u) + \mu \|Ku - f\|_1, \quad (1.2)$$

where $\text{TV}(u)$ can be either isotropic or anisotropic discretizations. In practice, the anisotropic TV is slightly

easier to process than the isotropic one. In fact, TVL1 model with anisotropic TV can be reformulated as a linear program and has been studied in [25]. Theoretically, various geometrical properties of TVL1 model have been revealed in [14, 16, 57, 58], which well justify its suitability for deblurring in the presence of impulsive noise. Numerically, very efficient algorithms have been designed for solving it, including the structure utilizing split-and-penalty method [56] and the augmented Lagrangian type methods [29, 23] which are also known as split Bregman methods. These methods can deal with both isotropic and anisotropic TV. We note that simple bound constraint can be incorporated to improve the quality of recovery, for which efficient structure-utilizing algorithms can still be designed, e.g., TVL1 model with constraint $0 \leq u \leq 1$ was considered in [13].

1.3. Two-phase method and corrected TVL1 method. The TVL1 model (1.2) fits all data entries, both corrupted and noise-free, via entry-wise absolute difference and with a unified weighting parameter μ . On the one hand, μ should be reasonably small in order to weaken the influence of fitting the corrupted data. On the other hand, if μ is not big enough, the recovered image is mostly over regularized and very blocky. As a consequence, it becomes critical to choose an appropriate weighting parameter μ so that regularization and data fitting are well balanced, particularly for the cases with high noise level. As a remedy, a two-phase method was proposed in [11] for image deblurring with impulsive and Gaussian noise. In the first stage, the outliers are approximately identified using median filters and removed from the data set. In the second stage, the image is restored by solving a regularized model with ℓ_1 -norm data fitting that applies to the remaining data entries. In [11], a regularizer that approximates the Mumford-Shah regularizer [34] was applied, and the nonsmooth ℓ_1 -norm was approximated by a smooth function, see [11, Eq. (7)]. A similar two phase approach was proposed in [12], where anisotropic TV regularizer was used to replace the nonconvex regularizer used in [11]. The resulting problem was again solved by smoothing methods. We note that solving the variational models arising from the second stage is generally much harder than solving the TVL1, which, in contrast, has very efficient algorithms [56, 29, 23, 13].

Very recently, an iteratively *corrected TVL1* (abbreviated as CTVL1) method was proposed in [7]. The CTVL1 method accomplishes deblurring and impulsive noise removal simultaneously via solving a sequence of TVL1-equivalent problems. In particular, given the current point u^k , the CTVL1 method [7] generates the next iterate u^{k+1} via

$$u^{k+1} = \arg \min_u \text{TV}(u) + \mu (\|Ku - f\|_1 - \ell^k(u)), \quad (1.3)$$

where $\ell^k(u) = \langle s^k, Ku - f \rangle$, $s^k = (s_1^k, \dots, s_{n^2}^k)^T \in \mathfrak{R}^{n^2}$,

$$s_i^k = \phi \left(\frac{(Ku^k - f)_i}{\|Ku^k - f\|_\infty} \right), \quad i = 1, 2, \dots, n^2, \quad \text{and} \quad \phi(t) = \text{sign}(t)(1 + \varepsilon^\tau) \frac{|t|^\tau}{|t|^\tau + \varepsilon^\tau}. \quad (1.4)$$

Here we adopt the convention $0/0 = 0$, and $\varepsilon, \tau > 0$ are given parameters. It has been demonstrated via extensive numerical results in [7] that the CTVL1 method performs very competitive and, in particular, outperforms the two-phase method [11].

1.4. Notation. Given a vector v , its dimension and i th component are denoted by $\dim(v)$ and v_i , respectively. The superscript “ T ” denotes matrix or vector transpositions. The standard inner product in \mathfrak{R}^n is denoted by $\langle \cdot, \cdot \rangle$, i.e., $\langle x, y \rangle = x^T y$ for $x, y \in \mathfrak{R}^n$. We follow standard notation in convex analysis [41]. The set of extended-real-valued, lower-semicontinuous, proper and convex functions on \mathfrak{R}^n is denoted by $\Gamma_0(\mathfrak{R}^n)$. The effective domain of an extended-real-valued function f on \mathfrak{R}^n is denoted by $\text{dom } f$. The conjugate function f^* of a given $f \in \Gamma_0(\mathfrak{R}^n)$ is defined by $f^*(x) = \sup_y \langle y, x \rangle - f(y)$. The indicator function

of a set Ω is denoted by χ_Ω , i.e., $\chi_\Omega(x) = 0$ if $x \in \Omega$, and $+\infty$ otherwise. The Euclidean distance of a point x to a set S is denoted by $\text{dist}(x, S)$. The gradient of a multivariate differentiable function f is denoted by ∇f . If unspecified, $\|\cdot\|$ denotes the ℓ_2 -norm. Whenever there is no confusion, we let $\sum_i := \sum_{i=1}^{n^2}$.

1.5. Organization. The paper is organized as follows. The TVSCAD model and a *difference of convex functions* (DC) algorithm are proposed in Section 2, with global convergence and convergence rate to a critical point established in Section 3. Extensive numerical results, with comparisons to both TVL1 and CTVL1, are demonstrated in Section 4. Finally, some concluding remarks are given in Section 5.

2. A TVSCAD approach. In this section, we present a TVSCAD model, reformulate it as a DC program, and propose a *DC algorithm* (DCA). A brief overview on DC programming is also included.

2.1. A TVSCAD model. The SCAD function was originally introduced in [24] as a penalty function for sparse variable selection. Let $\gamma := (\gamma_1, \gamma_2)$ be a pair of given parameters satisfying $\gamma_2 > \gamma_1 > 0$. The one-dimensional SCAD function φ_γ is defined as

$$\varphi_\gamma(x) = \begin{cases} |x|, & \text{if } |x| \leq \gamma_1, \\ \frac{-x^2 + 2\gamma_2|x| - \gamma_1^2}{2(\gamma_2 - \gamma_1)}, & \text{if } \gamma_1 < |x| < \gamma_2, \\ \frac{\gamma_1 + \gamma_2}{2}, & \text{if } |x| \geq \gamma_2, \end{cases} \quad x \in \mathfrak{R}, \quad (2.1)$$

and its graph is given in the first plot of Figure 2.1. It can be seen, from either the definition or the graph, that φ_γ coincides with the absolute value function if $|x| \leq \gamma_1$ and takes the constant value $(\gamma_1 + \gamma_2)/2$ if $|x| \geq \gamma_2$. For $\gamma_1 < |x| < \gamma_2$, the unique quadratic function, which connect $(\pm\gamma_1, \gamma_1)$ and $(\pm\gamma_2, (\gamma_1 + \gamma_2)/2)$ and make the connected parts smoothly linked, were inserted. The thresholding operator, also known as shrinkage or proximity operator, of φ_γ is defined as

$$\mathcal{T}(x, \varphi_\gamma, \tau) := \arg \min_{y \in \mathfrak{R}} \varphi_\gamma(y) + \frac{1}{2\tau} \|y - x\|^2, \quad x \in \mathfrak{R}, \quad (2.2)$$

where $\tau > 0$ is a parameter. We note that $\tau \leq \gamma_2 - \gamma_1$ must be satisfied to guarantee that the objective function in (2.2) has a unique minimizer, see [24]. In this case, the graph of $\mathcal{T}(x, \varphi_\gamma, \tau)$ is given in the second plot of Figure 2.1. It is clear from the graph that SCAD penalty function makes the resulting estimator possesses three desired properties, namely, continuity, sparsity, and unbiasedness. In contrast, the widely used hard- and soft-thresholding estimators lack continuity and unbiasedness, respectively, see [24] for detailed discussions.

To present our TVSCAD model, we define the componentwise extension of φ_γ as follows

$$\Phi_\gamma(v) = \sum_{i=1}^{\dim(v)} \varphi_\gamma(v_i), \quad v \in \mathfrak{R}^{\dim(v)}. \quad (2.3)$$

We propose the following TVSCAD model for image deblurring with impulsive noise:

$$\min_u \{ \text{TV}(u) + \mu \Phi_\gamma(Ku - f) \mid 0 \leq u \leq 1 \}, \quad (2.4)$$

where Φ_γ is defined in (2.3), $\text{TV}(u)$ can be either isotropic or anisotropic, and $\mu > 0$. The motivation of using SCAD function here is simply to enforce less or even null data fitting and more regularization whenever $(Ku)_i$ deviates significantly from f_i . This is quite reasonable as in such case the i th pixel is more likely to be corrupted. For those i such that $(Ku - f)_i$ is sufficiently small, the absolute deviation penalty is kept, as indicated by the definition of φ_γ . Note that here we also include in the model the bound constraint $0 \leq u \leq 1$, which usually improves the recovery quality [13]. It is clear that the TVSCAD model is nonconvex

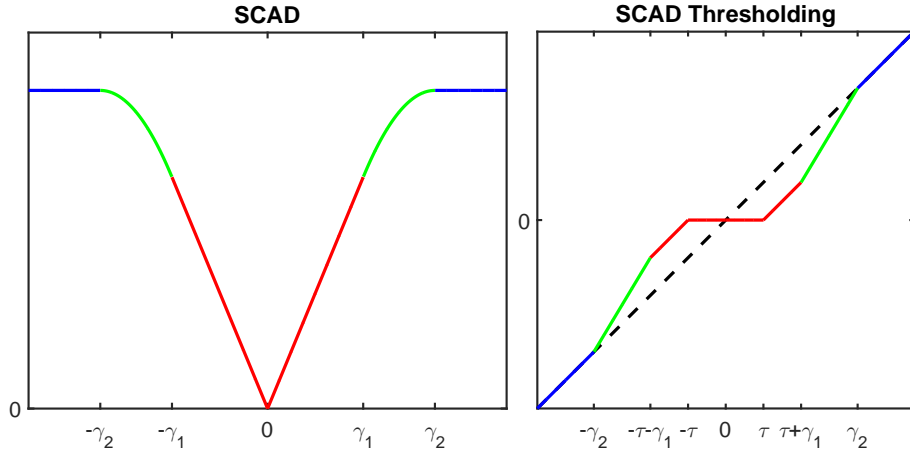


FIG. 2.1. Left: the SCAD function φ_γ . Right: the thresholding operator $\mathcal{T}(x, \varphi_\gamma, \tau)$.

and nonsmooth since φ_γ is so. The use of nonconvex and nonsmooth functions in image recovery usually results in images with better contrasts and sharper edges, see [37, 18, 19, 38], which reveal the theoretical advantages of least squares problems regularized by nonconvex and nonsmooth functions. In our setting, the nonconvex and nonsmooth SCAD function is adopted for data fitting.

2.2. Reformulation as a DC program. The TVSCAD problem (2.4) is nonconvex and nonsmooth and, in general, very challenging to solve. We reformulate the TVSCAD model as a DC program by decomposing the SCAD function (2.1) as the difference of two convex functions, where the first is the absolute value function $|\cdot|$ and the second is given by

$$\psi_\gamma(x) := |x| - \varphi_\gamma(x) = \begin{cases} 0, & \text{if } |x| \leq \gamma_1, \\ \frac{x^2 - 2\gamma_1|x| + \gamma_1^2}{2(\gamma_2 - \gamma_1)}, & \text{if } \gamma_1 < |x| \leq \gamma_2, \\ |x| - \frac{\gamma_1 + \gamma_2}{2}, & \text{if } |x| > \gamma_2, \end{cases} \quad x \in \mathfrak{R}. \quad (2.5)$$

The decomposition $\varphi_\gamma = |\cdot| - \psi_\gamma$ is illustrated in Figure 2.2. The componentwise extension of ψ_γ , denoted by Ψ_γ , is given by

$$\Psi_\gamma(v) = \sum_{i=1}^{\dim(v)} \psi_\gamma(v_i), \quad v \in \mathfrak{R}^{\dim(v)}. \quad (2.6)$$

It then follows from (2.3) and (2.6) that $\Phi_\gamma(v) = \|v\|_1 - \Psi_\gamma(v)$ for all $v \in \mathfrak{R}^{\dim(v)}$. As a result, the TVSCAD model (2.4) can be reformulated as the following DC programming problem

$$\min_u \{ \text{TV}(u) + \mu (\|Ku - f\|_1 - \Psi_\gamma(Ku - f)) \mid 0 \leq u \leq 1 \}. \quad (2.7)$$

The idea of decomposing a nonconvex function as the difference of two convex functions is not new, see, e.g., [27], where it was applied to sparse recovery problems. Before deriving our algorithm for solving the reformulated problem (2.7), we next give a very briefly overview on DC programming.

2.3. DC programming. DC programming refers to optimizing a function that can be written as the difference of two convex functions. This class of problems covers generic convex optimization and many real world nonconvex problems as special cases. The study of subgradient method for convex maximization problem in [45, 46] can be viewed as early works on DC programming. Later, DC duality theory and DCAs were developed in [49, 50] based on the nonconvex duality results in [52, 53]. Now, DC programming,

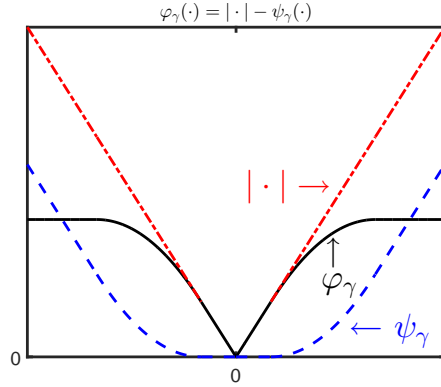


FIG. 2.2. DC decomposition: $\varphi_\gamma(\cdot) = |\cdot| - \psi_\gamma(\cdot)$.

including model, theory and algorithms have been widely used in many applications. Interested readers can refer to the review papers [47, 31, 2].

Let $g, h \in \Gamma_0(\mathbb{R}^n)$. A generic DC programming problem takes the form

$$\alpha := \inf_x g(x) - h(x). \quad (2.8)$$

It is standard result in convex analysis that the dual conjugate of $h \in \Gamma_0(\mathbb{R}^n)$ is itself, i.e., $h^{**} := (h^*)^* = h$, see, e.g., [41, Theorem 12.2]. Therefore, the DC program (2.8) can be reformulated as

$$\alpha = \inf_x g(x) - h^{**}(x) = \inf_x \left[g(x) - \sup_y \langle x, y \rangle - h^*(y) \right] = \inf_y m(y), \quad (2.9)$$

where $m(y) := \inf_x g(x) - \langle x, y \rangle + h^*(y) = h^*(y) - g^*(y)$ if $y \in \text{dom } h^*$, and $+\infty$ otherwise. Plug into (2.9), we obtain

$$\alpha = \inf_y \{h^*(y) - g^*(y) \mid y \in \text{dom } h^*\}. \quad (2.10)$$

We assume that α is finite, which implies that $\text{dom } g \subset \text{dom } h$ and $\text{dom } h^* \subset \text{dom } g^*$, and adopt the convention $+\infty - (+\infty) = +\infty$. Then, (2.10) can be equivalently simplified as

$$\alpha = \inf_y h^*(y) - g^*(y), \quad (2.11)$$

which is clearly also a DC programming problem and is known as the dual problem of (2.8). Note that there exists perfect symmetry between the primal and the dual DC programming problems (2.8) and (2.11). Interested readers can refer to [48, Sections 3.1, 3.2] and references therein for more discussions on duality results, global and local optimality conditions of (2.8) and (2.11).

The classic DCAs (cf. [45, 46] and [48, Sec. 3.3]) aim at solving the DC program (2.8) and its dual problem (2.11) to their global or local optimality. A simplified form of DCA solves (2.8) via linearizing the second part and solving a sequence of convex problems. Specifically, starting at an initial point $x^0 \in \text{dom } g$, DCA iterates as

$$x^{k+1} = \arg \min_x [g(x) - (h(x^k) + \langle y^k, x - x^k \rangle)], \quad y^k \in \partial h(x^k), \quad k = 0, 1, \dots \quad (2.12)$$

Under certain conditions, the DCA is well defined [48, Lemma 3.6], and its convergence properties were summarized in [48, Theorem 3.7] and [47, Theorem 3]. In particular, the sequence of function values $\{g(x^k) -$

$h(x^k)$ is guaranteed to be decreasing, and if α is finite and the sequence $\{(x^k, y^k)\}$ is bounded, then every limit point of $\{x^k\}$ (resp. $\{y^k\}$) is a critical point of $g - h$ (resp. $h^* - g^*$), a notion that is slightly weaker than local minimizer [48, Theorem 3.2]. We emphasize that the theoretical results derived for our DCA in Section 2.4 are much stronger than those existing ones for generic DC programming, see Section 3.

2.4. A DCA. A DCA for solving the proposed TVSCAD model (2.7) is derived in this subsection. It is easy to verify that ψ_γ defined in (2.5) is smooth, and so is Ψ_γ in (2.6). Given u^k satisfying $0 \leq u^k \leq 1$, our DCA generates the next iterate by

$$u^{k+1} = \arg \min_u \left\{ \text{TV}(u) + \mu (\|Ku - f\|_1 - \ell^k(u)) + \frac{\eta}{2} \|u - u^k\|^2 \mid 0 \leq u \leq 1 \right\}, \quad (2.13)$$

where $\eta > 0$ is a given parameter, and $\ell^k(u)$ is the linear part of $\Psi_\gamma(Ku - f)$ at u^k , i.e.,

$$\ell^k(u) := \Psi_\gamma(Ku^k - f) + \langle K^T \nabla \Psi_\gamma(Ku^k - f), u - u^k \rangle. \quad (2.14)$$

It is straightforward to verify that the DCA defined in (2.13)-(2.14) is a special case of the classic DCA (2.12) for DC programming (2.8) with

$$g(u) = \text{TV}(u) + \mu \|Ku - f\|_1 + \chi_{0 \leq u \leq 1}(u) + \frac{\eta}{2} \|u\|^2 \quad \text{and} \quad h(u) = \mu \Psi_\gamma(Ku - f) + \frac{\eta}{2} \|u\|^2. \quad (2.15)$$

DCA resulting from the above decomposition makes the objective function of (2.13) strongly convex, and thus u^{k+1} is well defined. Indeed, it is exactly because of the resulting proximal term $\frac{\eta}{2} \|u - u^k\|^2$ that makes our theoretical results in Section 3 much stronger than those in [48]. In particular, the theory of DC programming for strongly convex g and h can only guarantee that $\lim_{k \rightarrow \infty} (u^{k+1} - u^k) = 0$, see, e.g., [48, Theorem 3.7 (iii)], while we guarantee that the sequence $\{u^k\}$ converges globally to a critical point of the problem (2.4). Moreover, the addition of the proximal term also ensures R-linear convergence rate in the case of anisotropic TV. In computation, a small value of η can always be used to enhance robustness.

Next, we adapt the versatile and efficient *alternating direction method of multipliers* (ADMM, [28, 26]) to solving the subproblem (2.13). ADMM can be viewed as a practical variant of the classic augmented Lagrangian method [30, 40] or a dual application of the Douglas-Rachford splitting [17, 21] for monotone inclusion problem. ADMM has been applied to numerous applications, see, e.g., [9, 20], among others, it has been applied to TV based image deblurring problem [29] and its variants [23]. Given the encouraging performance of ADMM, especially for TV regularized image recovering problems, it is appropriate here to adopt it as the subproblem solver.

ADMM has been applied to constrained TVL1 problem in [13]. With the additional proximal term $\frac{\eta}{2} \|u - u^k\|^2$ and the linear term $\ell^k(u)$ added to the TVL1 problem, the resulting ADMM is similar. Here we present the algorithm only for completeness. We take the isotropic discretization of TV as an example, i.e., $\text{TV}(u) = \sum_i \|D_i u\|$, and the discussion for the case of anisotropic TV is completely analogous. First, we introduce a set of auxiliary variables $\{\mathbf{w}_i \in \mathfrak{R}^2 : i = 1, \dots, n^2\}$ and $v \in \mathfrak{R}^{n^2}$ to transfer $\{D_i u : i = 1, \dots, n^2\}$ and $Ku - f$ out of the nondifferentiable norms. The set of \mathbf{w}_i 's is also denoted by $w \in \mathfrak{R}^{2n^2}$. In order to treat the bound constraint, we also need to introduce an additional auxiliary variable $x \in \mathfrak{R}^{n^2}$. Define

$$\theta(w) := \sum_i \|\mathbf{w}_i\|, \quad v^k := Ku^k - f, \quad p^k := \nabla \Psi_\gamma(v^k) \quad \text{and} \quad \Omega := \{u \mid 0 \leq u \leq 1\}. \quad (2.16)$$

By omitting constant values, (2.13) can be reformulated as

$$\min_{u, v, w, x} \left\{ \theta(w) + \mu (\|v\|_1 - \langle p^k, v \rangle) + \frac{\eta}{2} \|u - u^k\|^2 \mid \mathbf{w}_i = D_i u, \forall i, v = Ku - f, x = u, x \in \Omega \right\}. \quad (2.17)$$

The augmented Lagrange function associated with (2.17) is

$$\begin{aligned} \mathcal{L}(w, v, x, u, \lambda_w, \lambda_v, \lambda_x) &= \theta(w) + \sum_i \left(\langle (\lambda_w)_i, D_i u - \mathbf{w}_i \rangle + \frac{\beta_w}{2} \|D_i u - \mathbf{w}_i\|^2 \right) \\ &+ \mu (\|v\|_1 - \langle p^k, v \rangle) - \langle \lambda_v, v - (Ku - f) \rangle + \frac{\beta_v}{2} \|v - (Ku - f)\|^2 \\ &+ \frac{\eta}{2} \|u - u^k\|^2 - \langle \lambda_x, x - u \rangle + \frac{\beta_x}{2} \|x - u\|^2, \end{aligned}$$

where $\lambda_w \in \mathfrak{R}^{2n^2}$, $\lambda_v, \lambda_x \in \mathfrak{R}^{n^2}$ are Lagrange multipliers, and $\beta_w, \beta_v, \beta_x > 0$ are penalty parameters. Given u^0 and $(\lambda_w^0, \lambda_v^0, \lambda_x^0)$, the classic 2-block ADMM iterates are

$$(w^{j+1}, v^{j+1}, x^{j+1}) = \arg \min_{w, v, x} \{ \mathcal{L}(w, v, x, u^j, \lambda_w^j, \lambda_v^j, \lambda_x^j) \mid x \in \Omega \}, \quad (2.18a)$$

$$u^{j+1} = \arg \min_u \{ \mathcal{L}(w^{j+1}, v^{j+1}, x^{j+1}, u, \lambda_w^j, \lambda_v^j, \lambda_x^j) \}, \quad (2.18b)$$

$$\begin{pmatrix} \lambda_w^{j+1} \\ \lambda_v^{j+1} \\ \lambda_x^{j+1} \end{pmatrix} = \begin{pmatrix} \lambda_w^j - \beta_w (w^{j+1} - Du^{j+1}) \\ \lambda_v^j - \beta_v (v^{j+1} - Ku^{j+1} + f) \\ \lambda_x^j - \beta_x (x^{j+1} - u^{j+1}) \end{pmatrix}. \quad (2.18c)$$

We note that both (2.18a) and (2.18b) have closed form solutions and hence can be computed efficiently. In fact, the optimization of w , v and x in (2.18a) can be carried out in parallel since they are separable from each other. Moreover, w^{j+1} and v^{j+1} are given explicitly by the proximity operators of θ and $\|\cdot\|_1$, respectively, the computations of which have linear cost. On the other hand, x^{j+1} can be computed via a projection onto Ω . The u -subproblem (2.18b) is a least-squares problem and, under the assumption of periodic boundary conditions, it can be solved very efficiently via two fast Fourier transforms. The problem structures of this type were first recognized and fully exploited in [54], where an alternating minimization algorithm was designed based on quadratic penalty method for image deblurring with Gaussian noise. Later, this splitting and alternating minimization idea was extended in [56, 55] to solve TVL1 problem and multichannel image deblurring.

2.5. Connections with the CTVL1 method. The connection between our DCA (2.13) and the CTVL1 method (1.3) recently proposed in [7] is explained in this subsection. By removing in (2.13) the bound constraint $0 \leq u \leq 1$ and the proximal term $\frac{\eta}{2} \|u - u^k\|^2$, we see that (2.13) differs from (1.3) only in the choice of $\ell^k(u)$. By letting $v^k = Ku^k - f$ and throwing away some constants, one can see that $\ell^k(u)$ for both methods has the form $\ell^k(u) = \langle s^k, Ku - f \rangle$ with $s^k = (s_1^k, \dots, s_{n^2}^k)^T$ defined by

$$s_i^k = \begin{cases} \phi(v_i^k / \|v^k\|_\infty), & \text{for (1.3),} \\ \psi'_\gamma(v_i^k), & \text{for (2.13),} \end{cases} \quad i = 1, \dots, n^2. \quad (2.19)$$

Here ϕ and ψ_γ are defined in (1.4) and (2.5), respectively. It was suggested in [7] that $\varepsilon^2 = 10^{-3}$ and $\tau = 2$ should be used in ϕ , and the derivative of ψ_γ is given by

$$\psi'_\gamma(x) = \begin{cases} 0, & \text{if } |x| \leq \gamma_1, \\ \frac{x - \gamma_1 \text{sign}(x)}{\gamma_2 - \gamma_1}, & \text{if } \gamma_1 < |x| \leq \gamma_2, \\ \text{sign}(x), & \text{if } |x| > \gamma_2, \end{cases} \quad x \in \mathfrak{R}.$$

Plots of ϕ and ψ'_γ (with $\gamma_1 = 0.15$, $\gamma_2 = 0.5$, and the practical choice of γ_1 and γ_2 will be discussed in Section 4) are given in Figure 2.3. From the figure, one may observe that if $v_i^k = (Ku^k - f)_i$ is positive and relatively large, the values of s_i^k will tend to be 1 and equal to 1 in (1.3) and (2.13), respectively. Consequently, this

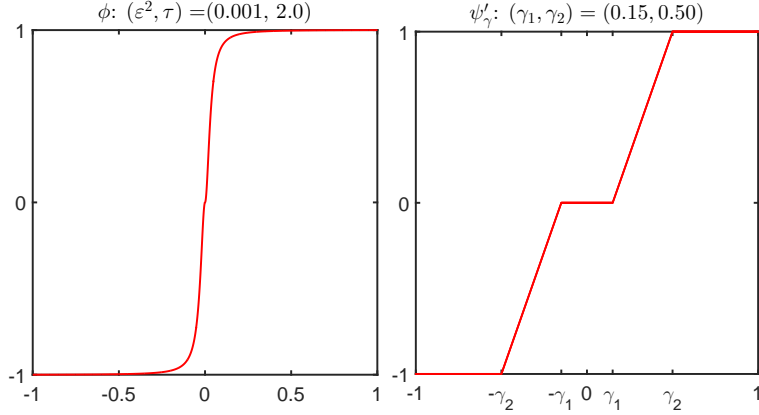


FIG. 2.3. Left: the ϕ function used by the CTVL1 method [7]. Right: the derivative of ψ_γ .

means the data fitting term $\mu(\|Ku - f\|_1 - \ell^k(u))$ being nearly or totally cancelled out from (1.3) and (2.13), respectively. In other words, nearly no or just no penalization being enforced on $v_i^k = (Ku^k - f)_i$. This coincides with our motivation as large $(Ku^k - f)_i$ means the i th pixel is more likely to be corrupted by the impulsive noise, and thus should not be fitted. When $v_i^k = (Ku^k - f)_i$ is negative with its absolute value relatively large, similar explanation applies. On the other hand, when the absolute value of $v_i^k = (Ku^k - f)_i$ is relatively small, $\mu|(Ku - f)_i|$ corresponding to ℓ_1 -norm penalized data fitting is used in (2.13) as opposed to $\mu|(Ku - f)_i|$ minus a linear term used in (1.3).

We also mention that the outer loop convergence of the CTVL1 method is unknown in [7], while our algorithm is guaranteed to converge globally to a critical point of the TVSCAD problem (2.4), as will be shown in Section 3.

3. Theoretical analysis. In this section, we establish global convergence and convergence rate for the DCA (2.13). We start with some definitions. Let F be an extended-real-valued, proper and lower semicontinuous function on \mathfrak{R}^n . The limiting subdifferential of F at $x \in \text{dom } F$ is defined by

$$\partial F(x) := \left\{ v \in \mathfrak{R}^n : \exists x^t \rightarrow x, F(x^t) \rightarrow F(x), v^t \rightarrow v, \liminf_{z \neq x^t, z \rightarrow x^t} \frac{F(z) - F(x^t) - \langle v^t, z - x^t \rangle}{\|z - x^t\|} \geq 0 \right\}.$$

A necessary condition for $x \in \mathfrak{R}^n$ to be a minimizer of F is $0 \in \partial F(x)$, and a point satisfying this condition is called a critical or stationary point of F . Readers are referred to [42] for these basics. The function F is said to have the KL property at $\bar{x} \in \text{dom } \partial F$ with an exponent of σ (cf. [6, 5]) if there exist $c, \epsilon > 0$ and $v \in (0, \infty]$ such that

$$\text{dist}(0, \partial F(x)) \geq c(F(x) - F(\bar{x}))^\sigma \quad (3.1)$$

for all x satisfying $\|x - \bar{x}\| \leq \epsilon$ and $F(\bar{x}) < F(x) < F(\bar{x}) + v$. If F has the KL property with the exponent σ at any $x \in \text{dom } \partial F$, then F is called a KL function with an exponent of σ . We continue using the notation of v^k and Ω as defined in (2.16), and according to (2.4) and (2.7), we define

$$F(u) := \text{TV}(u) + \mu\Phi_\gamma(Ku - f) + \chi_\Omega(u) = \text{TV}(u) + \mu(\|Ku - f\|_1 - \Psi_\gamma(Ku - f)) + \chi_\Omega(u).$$

LEMMA 3.1. For any $u^0 \in \Omega$ and $\eta > 0$, the sequence $\{u^k\}$ generated by (2.13) satisfies

$$F(u^k) - F(u^{k+1}) \geq \eta\|u^{k+1} - u^k\|^2, \quad \forall k \geq 0. \quad (3.2)$$

Proof. By definition, (2.13) implies that $u^k \in \Omega$ and thus $\chi_\Omega(u^k) = 0$ for all $k \geq 0$. Let $k \geq 0$ be fixed. The convexity of Ψ_γ implies that $\Psi_\gamma(v^{k+1}) \geq \Psi_\gamma(v^k) + \langle \nabla \Psi_\gamma(v^k), v^{k+1} - v^k \rangle$. Thus,

$$F(u^k) - F(u^{k+1}) \geq (\text{TV}(u^k) + \mu \|v^k\|_1) - (\text{TV}(u^{k+1}) + \mu \|v^{k+1}\|_1) + \mu \langle \nabla \Psi_\gamma(v^k), v^{k+1} - v^k \rangle \quad (3.3)$$

It follows from (2.13) that

$$s^{k+1} := \mu K^T \nabla \Psi_\gamma(v^k) + \eta(u^k - u^{k+1}) \in \partial [\text{TV}(u) + \mu \|Ku - f\|_1 + \chi_\Omega(u)] \Big|_{u=u^{k+1}}.$$

Further considering the convexity of $\text{TV}(u) + \mu \|Ku - f\|_1 + \chi_\Omega(u)$, we obtain from (3.3) that

$$F(u^k) - F(u^{k+1}) \geq \langle s^{k+1}, u^k - u^{k+1} \rangle + \mu \langle \nabla \Psi_\gamma(v^k), v^{k+1} - v^k \rangle = \eta \|u^{k+1} - u^k\|^2,$$

which completes the proof. \square

LEMMA 3.2. *If the TV is anisotropic as given in (1.1), then for any fixed $\mu > 0$ the function F is a KL function with exponent 1/2.*

Proof. According to the definitions of anisotropic TV (1.1) and Ψ_γ (2.6), F is a piecewise linear-quadratic function, and every piece is defined on a closed polyhedral set. Denote by m the number of pieces of F , F_i the linear-quadratic function on the i th piece, and C_i the domain of F_i . Then, it holds that $F(u) = \min_{1 \leq i \leq m} \{F_i(u) + \chi_{C_i}(u)\}$. Since χ_{C_i} is a proper closed polyhedral function, it follows from [33, Corollary 5.2] that F is a KL function with exponent 1/2. \square

Now we are ready to establish the global convergence and convergence rate results for our DCA. In the general theory of DC programming, see, e.g., [47, Theorem 3.7 (iv)], it is only guaranteed that, if α in (2.8) is finite and the generated sequence is bounded, then any accumulation point is a critical point. The same result is derived in part (i) of the following Theorem 3.3, while the rest of the theorem, namely part (ii)-(iv), are much stronger than existing results for generic DC programming.

THEOREM 3.3 (Global convergence and rate of convergence). *Let $u^0 \in \Omega$, $\eta > 0$ and $\{u^k\}$ be the sequence generated by (2.13). Then*

- (i) *any accumulation point of $\{u^k\}$ is a critical point of (2.4);*
- (ii) *$\{u^k\}$ converges globally to a critical point of (2.4), and furthermore $\sum_{k=0}^{\infty} \|u^{k+1} - u^k\| < +\infty$;*
- (iii) *if the TV is anisotropic, then there exist $h > 0$ and $\tau \in (0, 1)$ such that $\|u^k - u^*\| \leq h\tau^k$ for all $k \geq 0$, i.e., the convergence rate is R -linear;*
- (iv) *if the TV is isotropic, then $\{u^k\}$ converges to u^* at least sublinearly.*

Proof. (i) It follows from (2.13) that

$$d^{k+1} := \mu K^T (\nabla \Psi_\gamma(v^k) - \nabla \Psi_\gamma(v^{k+1})) - \eta(u^{k+1} - u^k) \in \partial F(u^{k+1}). \quad (3.4)$$

Since $u^k \in \Omega$ for all $k \geq 0$ and $\text{TV}(u) + \mu \Phi_\gamma(u)$ is bounded below (by 0), it follows from (3.2) that

$$\sum_{k=0}^{\infty} \|u^{k+1} - u^k\|^2 \leq F(u^0)/\eta < +\infty.$$

It thus follows that $\lim_{k \rightarrow \infty} (u^{k+1} - u^k) = 0$. Let u^* be any accumulation point of $\{u^k\}$ and $\{u^{n_k}\}$ be a subsequence such that $\lim_{k \rightarrow \infty} u^{n_k} = u^*$. Then, $\lim_{k \rightarrow \infty} u^{n_k+1} = \lim_{k \rightarrow \infty} [(u^{n_k+1} - u^{n_k}) + u^{n_k}] = u^*$. By replacing k by n_k and letting $k \rightarrow +\infty$ on the both sides of (3.4), we obtain immediately from the upper semicontinuity of ∂F and the continuity of $\nabla \Psi_\gamma$ that $0 \in \partial F(u^*)$, which completes the proof of part (i).

(ii) According to [6, Theorem 2.9], it suffices to guarantee that the sufficient decrease condition of $\{F(u^k)\}$, the relative error condition on $\{d^k\}$ and the boundedness of $\{u^k\}$ hold for all k . In fact, $\{F(u^k)\}$ is sufficiently

decreasing due to (3.2), and $\{u^k\}$ is bounded since $0 \leq u^k \leq 1$. Moreover, since $\nabla\Psi_\gamma$ is Lipschitz continuous, we know from (3.4) that there must exist $M > 0$ sufficiently large such that

$$\|d^{k+1}\| \leq M\|u^{k+1} - u^k\|. \quad (3.5)$$

Thus, all the conditions required to guarantee the global convergence of $\{u^k\}$ to a critical point have been fulfilled. The global convergence of $\{u^k\}$, as well as the inequality $\sum_{k=0}^{\infty} \|u^{k+1} - u^k\| < +\infty$, follows directly from [6, Theorem 2.9].

(iii) From (3.2), we see immediately that

$$F(u^{k+1}) - F(u^*) \geq \sum_{i=k+1}^{\infty} \eta \|u^{i+1} - u^i\|^2. \quad (3.6)$$

By Lemma 3.2, F has the KL property at u^* with $\sigma = 1/2$. It thus follows from (3.1) and (3.5) that there exists a sufficiently large K such that

$$F(u^{k+1}) - F(u^*) \leq \frac{1}{c^2} \text{dist}^2(0, \partial F(u^{k+1})) \leq \frac{M^2}{c^2} \|u^{k+1} - u^k\|^2, \quad \forall k \geq K. \quad (3.7)$$

Define $A_k = \sum_{i=k}^{\infty} \|u^{i+1} - u^i\|^2$. Combing (3.6) and (3.7), we get $A_{k+1} \leq \frac{M^2}{\eta c^2} (A_k - A_{k+1})$, or equivalently $A_{k+1} \leq \tau^2 A_k$ for all $k \geq K$, where $\tau := M/\sqrt{M^2 + \eta c^2} \in (0, 1)$. Hence, there exist a constant $\rho > 0$ sufficiently large such that $A_k \leq \rho^2 \tau^{2k}$ for all $k \geq 0$, and hence $\|u^{k+1} - u^k\| \leq \rho \tau^k$, for all $k \geq 0$. Thus,

$$\|u^k - u^*\| \leq \sum_{i=k}^{\infty} \|u^{i+1} - u^i\| \leq \frac{\rho}{1-\tau} \tau^k := h \tau^k, \quad \forall k \geq 0.$$

(iv) Since the isotropic TV is semialgebraic, so is F . It then follows that F is a KL function with certain exponent $\sigma \in [1/2, 1)$, see [6] for details. If $\sigma > 1/2$, then it is straightforward to show by following [4, Theorem 2] that $\|u^k - u^*\| \leq h k^{-\frac{1-\sigma}{2\sigma-1}}$ for some $h > 0$ and all $k \geq 1$, i.e., the convergence rate is sublinear. If $\sigma = 1/2$, then similar to the proof of (iii), we can derive that the sequence $\{u^k\}$ converges to u^* with the faster R-linear rate. \square

4. Numerical results. In this section, numerical results are presented to demonstrate the performance of the proposed TVSCAD model (2.4) and the corresponding DCA (2.13). The superior performance of CTVL1 compared to the two-phase method [11] in terms of recovery quality has been demonstrated in [7] via extensive numerical results. Therefore, we only compare TVSCAD with CTVL1. For reference purpose, we also present results of TVL1.

Let \bar{u} and u be the original and the recovered images, respectively, and denote the mean intensity of \bar{u} by $\text{mean}(\bar{u})$. The quality of recovered images will be evaluated by *signal-to-noise ratio* (SNR, in dB), which is defined by

$$\text{SNR} := 20 \times \log_{10} (\|\bar{u} - \text{mean}(\bar{u})\| / \|\bar{u} - u\|). \quad (4.1)$$

According to our experiments, adding the bound constraint $0 \leq u \leq 1$ can generally stabilize the compared algorithms and improve the recovery quality. Therefore, we incorporate this constraint into all the compared algorithms, and the resulting algorithms will still be referred as TVL1 and CTVL1. In our experiments, constrained TVL1-equivalent problems, e.g., (2.18) for TVSCAD, were always solved by ADMM with the same set of parameters. It is also our experience that the isotropic and anisotropic discretizations of TV do not result in significantly different recoveries in terms of both visual quality and SNR. Thus, we simply chose the anisotropic TV in our tests, which has favorable theoretical guarantee for TVSCAD.

All algorithms were implemented in Matlab, and the experiments were executed on a Lenovo Thinkpad laptop with an Intel Core i7-3667U CPU at 2.00 GHz and 8 GB of memory, running 64 bit Microsoft Windows 8 and Matlab v8.6 (R2015b).

4.1. Details of setting. The details of our experiments are summarized below.

- *Tested image.* In our experiments, we mainly tested the popular Lena image of size 512-by-512, which has both smooth region and sharp boundaries. The original Lena image is given in Figure 4.1. In fact, a few other nonabnormal images are test as well. Since the results remain largely similar provided that relevant parameters are properly set and also due to the limitation of space, only results of the Lena image are included. The only reason that we choose to present results of this image is because it seems to be the most widely used one in imaging science.



FIG. 4.1. *Tested image: Lena (512-by-512).*

- *Tested blur.* We tested three types of blur, i.e., Gaussian, motion and average blurs, which were generated by the Matlab function `fspecial`. For Gaussian and average blurs, the tested kernel sizes were `hsize` = 7, 11, 15. For motion blur, we tested `len` = 7, 13, 19 and `angle` = 45°. For Gaussian blur, we set the standard deviation of kernel to be 5. We have also tested disk and pillbox blurs. Since the comparison results remain largely alike, we only present recovered results of Gaussian, motion and average blurs.
- *Impulsive noise.* We tested the two common types of impulsive noise, i.e., SP and RV noise. In general, RV noise is much harder to remove than SP noise. In our experiments, we tested 90% and 80% as the highest noise levels for SP and RV noise, respectively.
- *Parameters: μ , τ , ε , γ_1 , γ_2 , η , and others.* Now we specify the model and algorithmic parameters used in our tests.
 - (i) The “best” choice of the parameter μ is known to be problem dependent and very hard to find. In fact, this is largely an open problem, even for the simpler TVL2 model [44]. In our experiments, we first solved a sequence of bound constrained TVL1 problems to search for each specific case the “best” choice of μ , i.e., a value that gives nearly the highest possible SNR. These “best” parameters for different blurs and noise are plotted in Figure 4.2. Generally, more noise implies smaller μ .
 - (ii) For TVSCAD and CTVL1, the model parameter μ is set by $\mu = \frac{c\mu^*}{1-r}$. This simple rule for setting μ is based on numerical experiments. Here μ^* denotes the “best” μ found for constrained TVL1 model, $c > 0$ is a constant, and r denotes the noise level defined by noise level := (# corrupted pixels)/(# total pixels). We set $c = 4$ and $c = 1$ for SP and

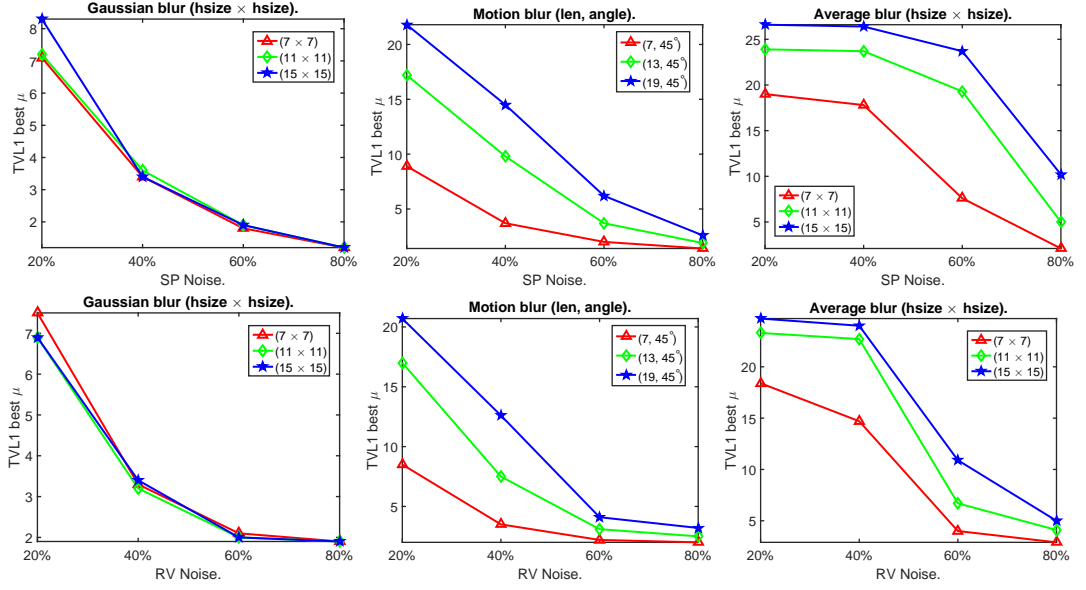


FIG. 4.2. The “best” choice of μ for different settings.

RV noise, respectively, which may be suboptimal but performed favourably in our tests. We emphasize that both TVSCAD and CTVL1 are much less sensitive in the choice of μ than TVL1 due to the additional correction term $\ell^k(u)$ at each iteration, see detailed discussions in [7]. Continuation on μ , i.e., starting from a small value and increasing it gradually, is also applied to enhance the stability of the algorithms.

- (iii) Parameters τ and ε , which define ϕ in (1.4) for CTVL1, and parameters γ_1 and γ_2 , which define the SCAD function φ_γ in (2.1), are also problem dependent. Consequently, the “best” choices of these parameters are very difficult to determine. For CTVL1, we set $\tau = 2$ and $\varepsilon = 10^{-3}$, as recommended by the authors of [7]. For TVSCAD, we set $\gamma_2 = \max(0.2 \times 0.85^{k-1}, 0.1)$ and $\gamma_1 = 0.08/k$, where $k \geq 1$ denotes the iteration counter. Our choice of γ_2 is based on experiments, which performed favourably in all the tested cases. It is definitely possible to adjust the rule for choosing γ_2 case by case. However, a uniformly defined γ_2 is preferred.
- (iv) The proximal term $\frac{\eta}{2} \|u - u^k\|^2$ is added mainly to facilitate the theoretical analysis. In practice, the presence of this term also prevents u^{k+1} from deviating too much from u^k , and thus stabilizes the algorithm. We set η to be 10^{-5} throughout. For solving the constrained TVL1 problem like (2.17), we set $\beta_w = 5$, $\beta_v = 50$ and $\beta_x = 50$ uniformly for all cases, and ADMM performs very stable and efficient.

- *Initialization.* For solving TVL1 problem by ADMM, we set $u^0 = f$ always. For TVSCAD and CTVL1, u^0 is set to be the solution obtained from solving TVL1. To compute u^{k+1} from u^k by solving the TVL1-equivalent problem like (2.13), ADMM (2.18) is initialized from u^k . Each time we launched ADMM, all the starting Lagrange multipliers are set to zero.
- *Stopping rule.* For solving each TVL1-equivalent subproblem, the ADMM (2.18) was terminated by $\|u^{j+1} - u^j\| / (1 + \|u^j\|) \leq 10^{-4}$. According to our experiments, in many cases (though not always) the quality of recovered images does not change significantly after no more than 15 iterations for both TVSCAD and CTVL1, see [7] for a similar conclusion. Therefore, we terminated both methods after 15 iterations. For TVSCAD, a more practical stopping rule could be introduced depending

on detecting the stagnation of objective function values in (2.4). However, this is not possible for CTVL1 since the convergence of its outer loop is unknown.

4.2. Comparison results with TVL1 and CTVL1. In this section, we present comparison results with CTVL1. For reference purpose, results of TVL1 are also presented. We emphasize that we have modified TVL1 and CTVL1 by adding the bound constraint $0 \leq u \leq 1$ to improve the recovery quality. Without this constraint, pixel values of recovered images may fall out of $[0, 1]$, in which truncation or rescaling technique need to be incorporated.

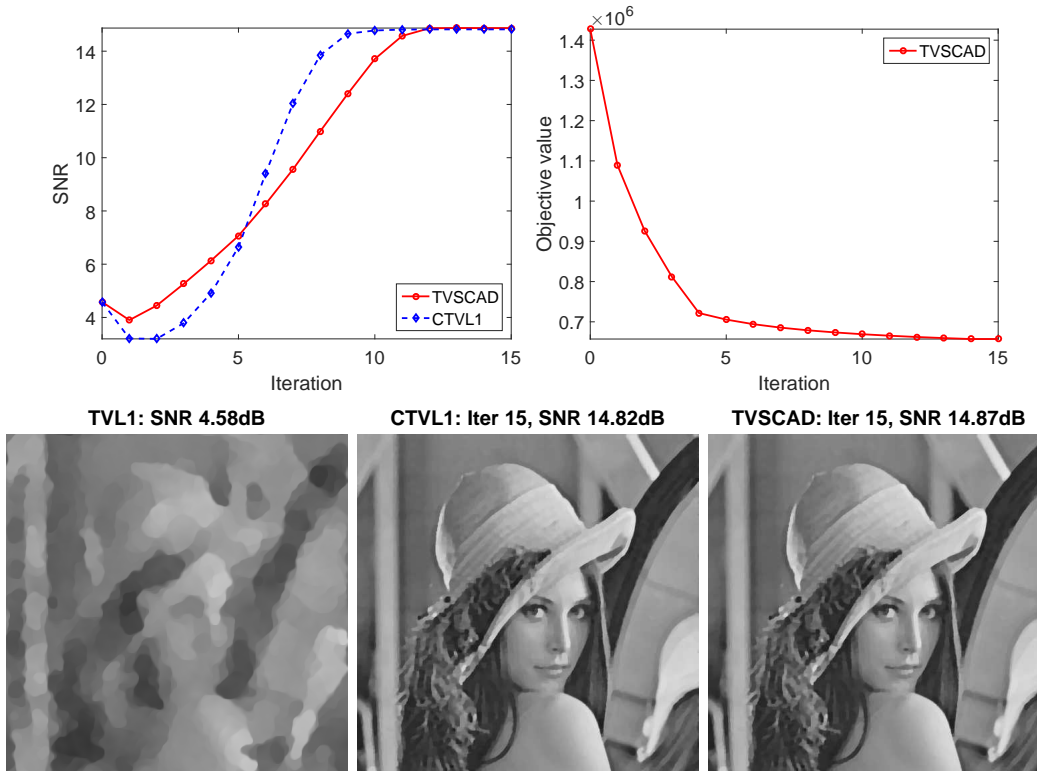


FIG. 4.3. *Gaussian* (9×9), 90% SP noise.

Here we present two classes of experimental results. In the first class, we tested three blurs, i.e., Gaussian blur ($\mathbf{hsize} = 9$, $\mathbf{std} = 5$), motion blur ($\mathbf{len} = 7$, $\mathbf{angle} = 45^\circ$) and average blur ($\mathbf{hsize} = 9$). For each blur, 90% SP noise and 70% RV noise were tested. Detailed experimental results are given in Figures 4.3-4.8, including evolutions of SNR values and objective function values and the recovered images for all the compared algorithms. In the second class, we tested Gaussian blur ($\mathbf{hsize} = 7, 11, 15$, $\mathbf{std} = 5$), motion blur ($\mathbf{len} = 7, 13, 19$, $\mathbf{angle} = 45^\circ$) and average blur ($\mathbf{hsize} = 7, 11, 15$). For each blur, 20%, 40%, 60% and 80% SP and RV noise were tested. We note that this class of experimental results contain much more information than the first class. For each instance, the SNR values of restored images by TVL1, CTVL1 and TVSCAD are demonstrated by bar plots, see details given in Figure 4.9.

It can be seen from Figures 4.3-4.9 that both TVSCAD and CTVL1 outperform TVL1 significantly for all the tested cases. For low noise level, TVL1 performs reasonably well, while TVSCAD and CTVL1 perform better. For high noise level, TVSCAD and CTVL1 can improve the results of TVL1, and sometimes the improvements are significant. This is desirable and easy to understand because both methods enforce less fitting on likely noisy data, as a result of which the likely uncorrupted data can be fitted more sufficiently

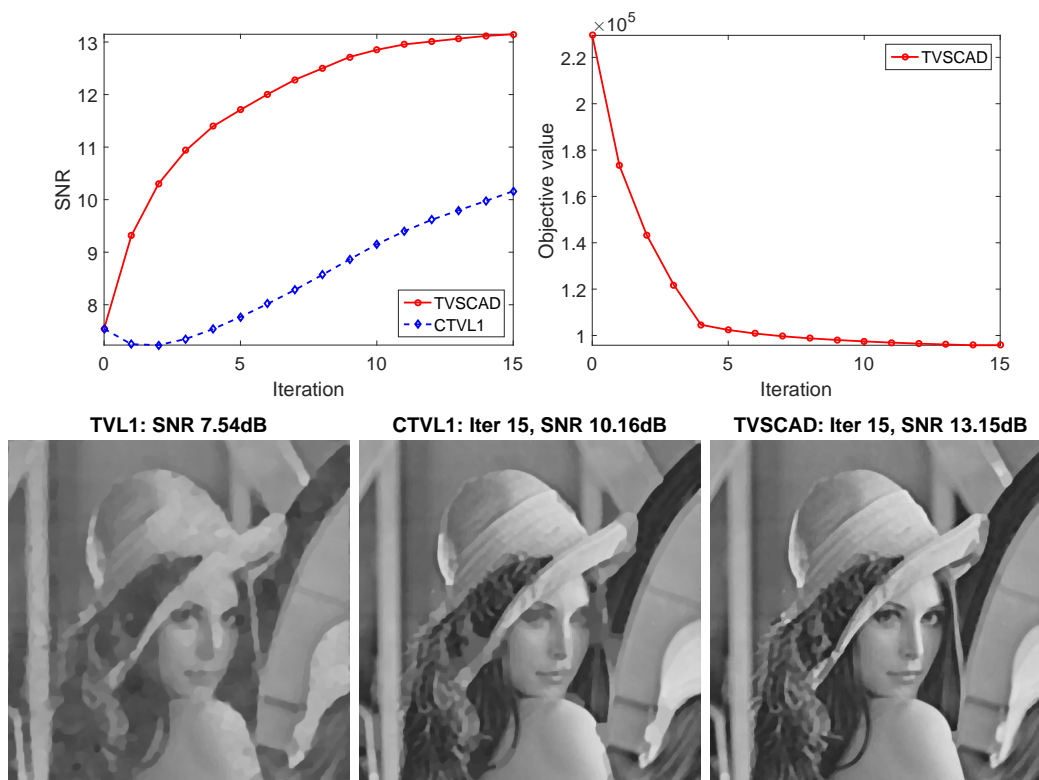


FIG. 4.4. Gaussian blur (9×9), 70% RV noise.

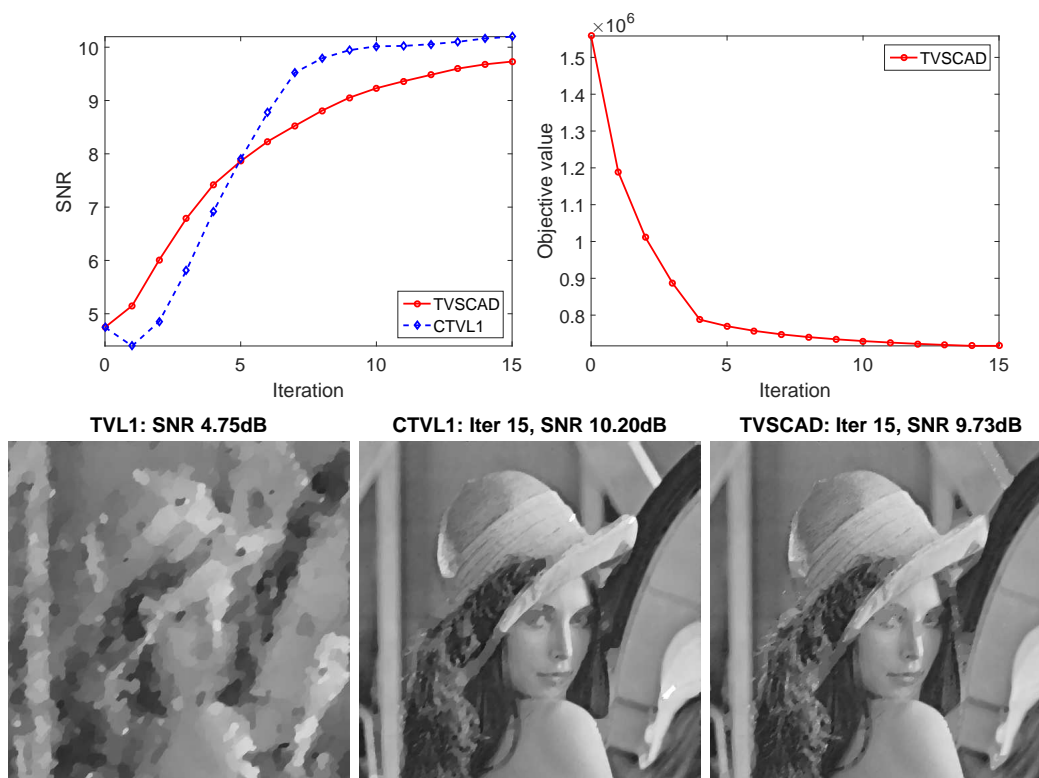


FIG. 4.5. Motion blur ($len = 7$, $angle = 45^\circ$), 90% SP noise.

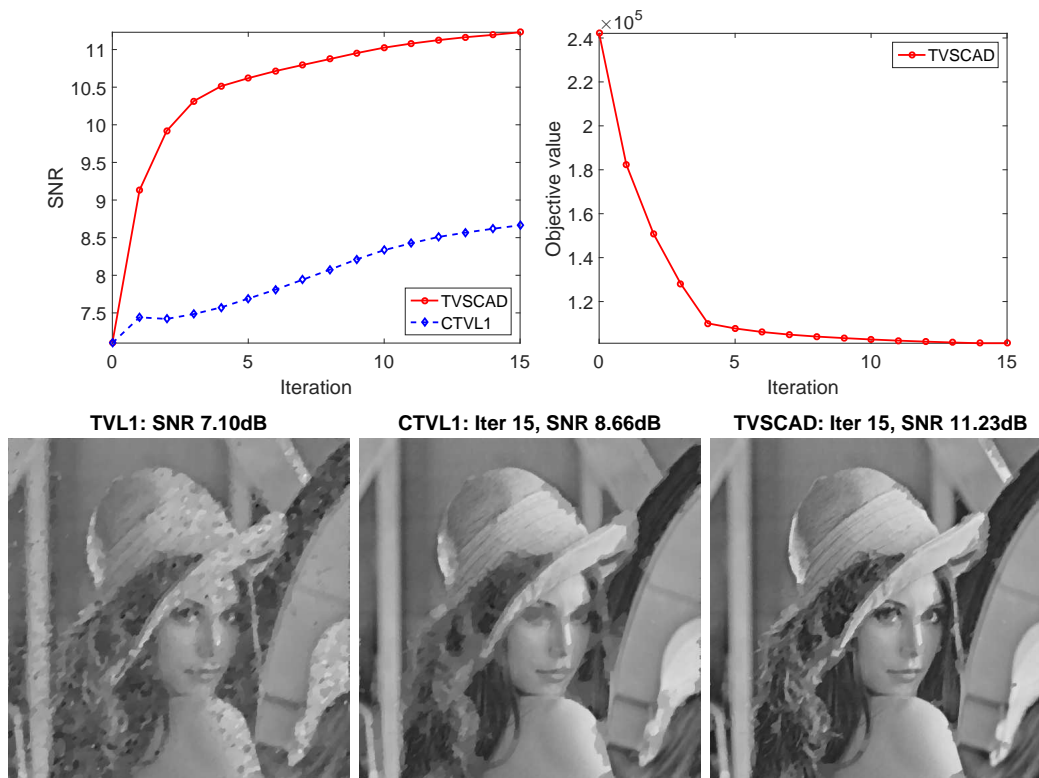


FIG. 4.6. Motion blur ($len = 7$, $angle = 45^\circ$), 70% RV noise.

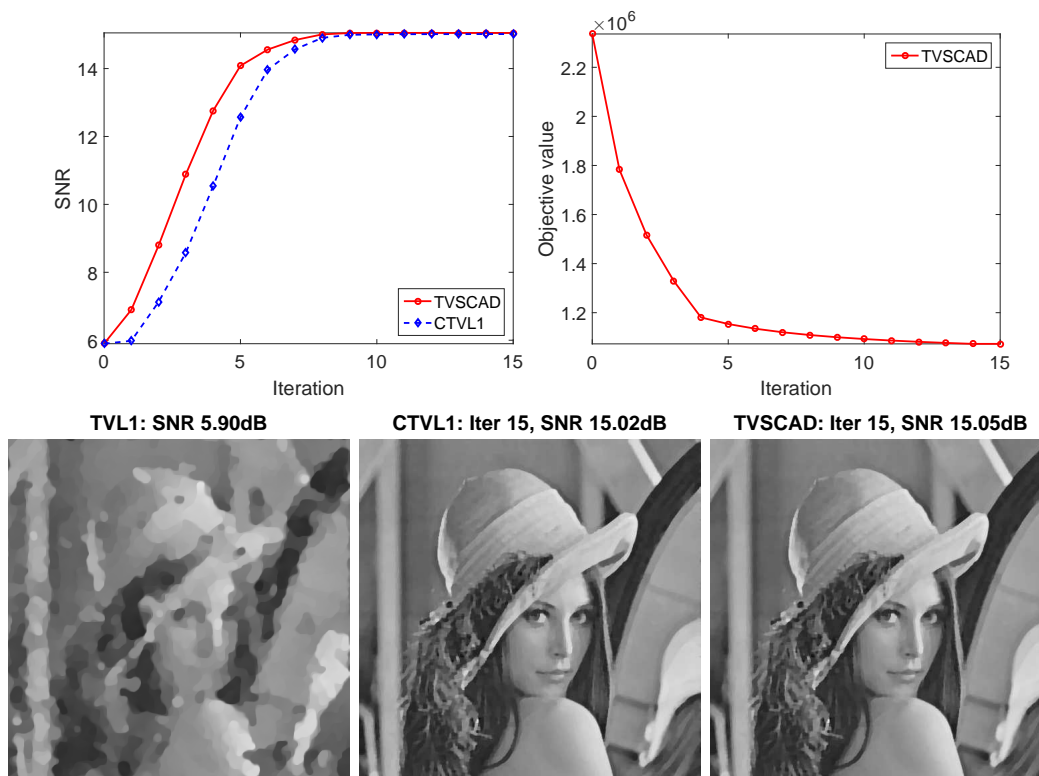


FIG. 4.7. Average blur (9×9), 90% SP noise.

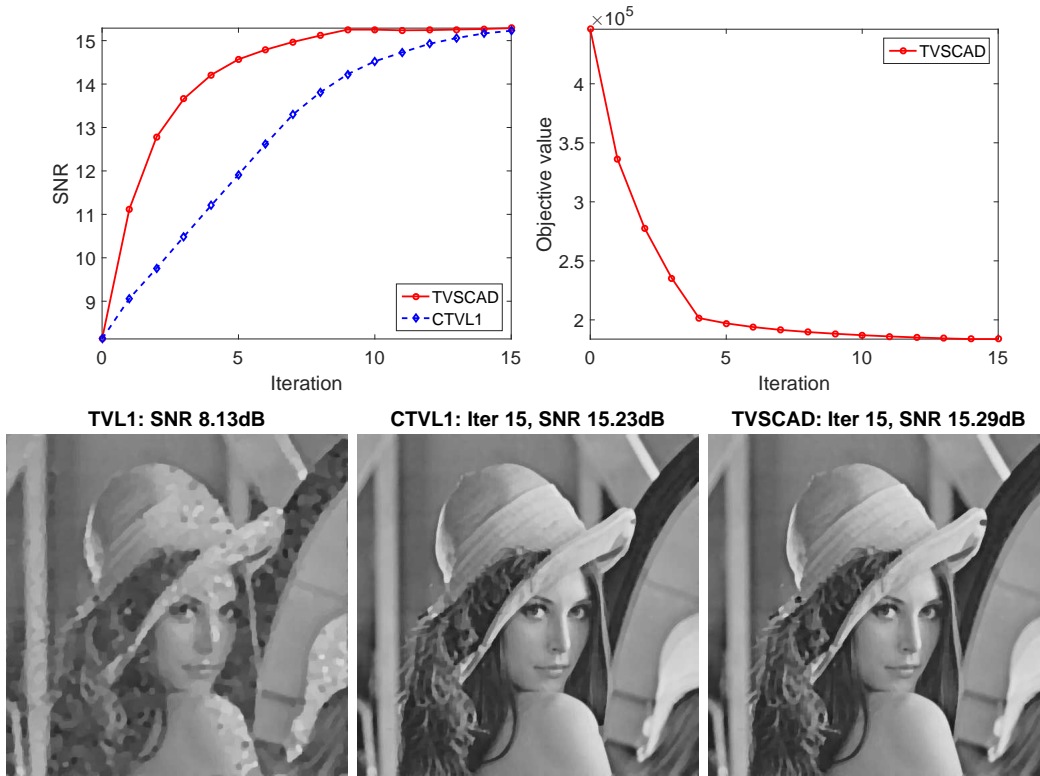


FIG. 4.8. Average blur (9×9), 70% RV noise.

by attaching a parameter μ larger than that of TVL1. From Figures 4.3-4.8, the images recovered by both CTVL1 and TVSCAD are apparently much better than those recovered by TVL1 in terms of both visual quality and SNR. Moreover, both TVSCAD and CTVL1 improve SNR as the algorithms proceed. In four of the six cases tested in the first class experiments, the SNR values of restored images stagnated for both methods after around 15 iterations. Two exceptions are Gaussian and motion blur with 70% RV noise, in which case CTVL1 converges much slower and needs more iterations, see Figures 4.4 and 4.6. The objective function value $\text{TV}(u) + \mu\Phi_\gamma(Ku - f)$ of (2.4) also decreases monotonically and quickly. Comparing the results of CTVL1 and TVSCAD, we see that TVSCAD obtained better or comparable results in all the tested cases. In particular, it can be seen from the results of Gaussian and motion blur with 70% RV noise that TVSCAD increases SNR much faster than CTVL1, as shown in Figures 4.4 and 4.6. The only case that CTVL1 wins with slightly higher SNR is motion blur with 90% SP noise, as shown in Figure 4.5. For other cases, as given in Figures 4.3, 4.7 and 4.8, TVSCAD is either faster than or comparable with CTVL1. For the large set of experimental results presented in Figure 4.9, TVSCAD is a clear winner since in about half of the tested cases TVSCAD obtained noticeably higher SNR values than CTVL1, while for the rest half cases, TVSCAD and CTVL1 perform very closely.

5. Concluding remarks. In this paper, we proposed, analyzed and tested a nonconvex TVSCAD model for image deblurring with impulsive noise corruption. To solve the nonconvex TVSCAD model, we proposed a DCA, which enjoys favorable convergence properties, namely, global convergence to a critical point of the nonconvex objective function, R-linear rate of convergence in the case of anisotropic TV, and at-least-sublinear convergence rate for isotropic TV regularization case. These results are much stronger than existing results for general DC programming. Extensive numerical results demonstrated that TVSCAD

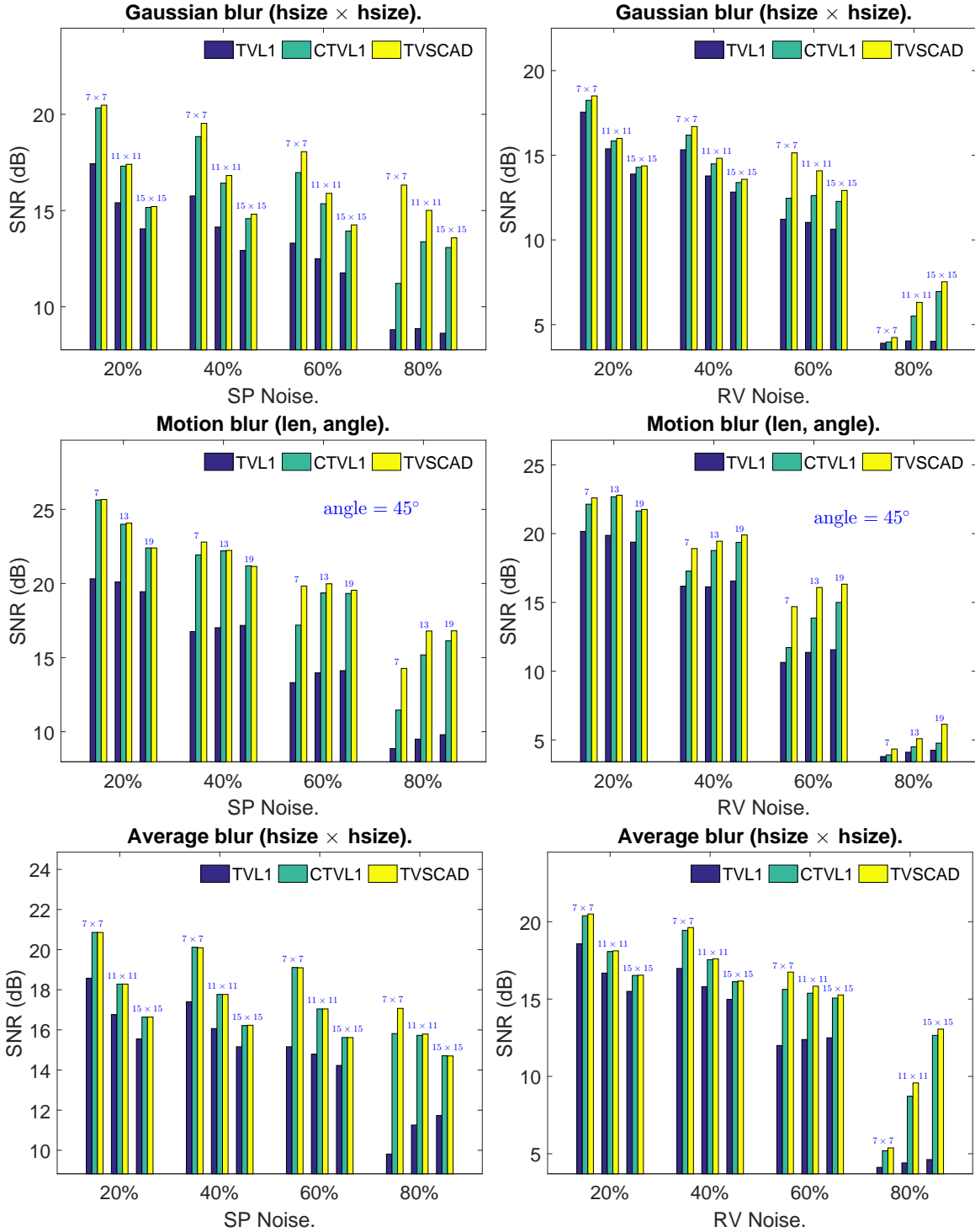


FIG. 4.9. More comparison results with TVL1 and CTVL1.

performs favorably. In particular, it outperforms the recently proposed CTVL1 method [7] in many cases.

We note that the idea of this paper can be extended to solve more problems. For example, color image processing based on the multichannel TV regularization proposed in [56]. The idea of DCA can also be extended to solve problems with other nonconvex penalty function, such as folded concave functions [27]. At

present, it remains largely unexplored on how to adaptively choose the weighting parameter μ and the SCAD parameters γ_1 and γ_2 , which are clearly problem dependent. Our choice in this paper could be far from optimal for certain specific instances. Another problem is how to determine a “better” DC decomposition of the objective function. Our choice in (2.15) was motivated by the easiness of subproblem and better convergence properties of the whole algorithm. In fact, this problem is known as regularization technique in DC programming and kept open for a long time. Moreover, the theoretical properties of the TVSCAD model is definitely very important in understanding its performance and deserves further investigations. Related results for regularized least squares problem have been presented in [37, 18, 19, 38]. We leave these issues to further research.

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