Dual-Channel Contrast Prior for Blind Image Deblurring

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ABSTRACT In this article, a dual-channel contrast prior (Dual-CP) is proposed for blind image deblurring. The prior is motivated by the observation that image contrast will significantly degenerate after the blurring process, which is proved in both mathematically and empirically. Based on this inherent property of the blurring process, we analyze the variation of contrast influenced by blur and research the feasibility for using contrast prior to estimate blur kernel. We model the contrast by the difference between the dark channel and the bright channel. By maximizing the contrast in the local patch, we can obtain a reliable result which contains sharp edges and is beneficial for kernel estimation. To solve this non-convex nonlinear problem, we develop an efficient optimization method with the auxiliary variable idea and alternate direction minimization. Extensive experiments on real and synthetic blurry sets demonstrate that the proposed algorithm has good performance and exhibits competitiveness compared with state-of-the-art methods. Besides, we show that the proposed method can be applied to non-uniform deblurring.

INDEX TERMS Blind image deblurring, contrast, dual-channel contrast prior.

I. INTRODUCTION
In recent years, low-level vision tasks including blind deblurring [1], denoising [2], and defogging [3] have achieved remarkable achievements. Efficient blind image deblurring methods based on the maximum a posterior (MAP) framework have been developed with different likelihood functions and image priors [4]–[11]. The success of existing blind deblurring methods can be attributed to the use of the statistical characteristics of an image, such as sparsity prior [1], low-rank prior [12] and salient edge selection [13] for kernel estimation. A large number of edge selection algorithms are widely used in the blind deblurring method. Cho and Lee [14] presented a method to recover image contour from the blurred image by a filter, which was successfully applied to image blind deblurring. Subsequently, Sun et al. [13] introduced the strategy of image block based on the fast motion deblurring method of Cho and Lee [14] and proposed a blind deblurring model based on edge selection. Because of the high computational cost of this algorithm, it is not practical. Joshi et al. [15] proposed to use the precision of sub-pixels to detect image contours for estimating blur kernels. However, due to the problem of precision, the method is only suitable for dealing with blurred images which are blurred by smaller blur kernels, not for large-scale blur kernels. In addition, for the edge based methods, the assumption that enough significant edges for kernel estimation may not always hold.

To estimate the blur kernel from the blurred image, other existing methods take advantage of the statistical characteristics of an image. Krishnan et al. [16] proposed $L_1/L_2$ norm based on image statistical characteristics. Their research shows that $L_1$ and $L_2$ norms of images are natural sparse, and $L_1/L_2$ norm is a normalized version of $L_1$, which has more sparse characteristics than $L_1$. Levin et al. [17] developed a maximum posterior (MAP) framework based on the heavy-tailed sparse distribution of image pixel histogram. Shan et al. [18] observed the sparse distribution of image gradient and introduced a probability model to fit the gradient distribution of natural images. According to the statistical properties of impulse noise, Zhong et al. [19] used a high-order variational model by replacing traditional TV (total variation)-regularized for image deblurring with impulse noise. However, these methods designed for natural images may not perform well on special scenes, such as text [20].
and low-light [21] blurred images. In this work, a blind image deblurring method is proposed for both natural and special scenes. Recently, sparse channel prior for blind image deblurring attracts much attention. He et al. [22] firstly introduced Dark Channel Prior (DCP) in image defogging. The successful application of DCP is based on the fact that in most natural scene image patches, at least one color channel has some values very close to zero. Subsequently, Pan et al. [23] enhanced the sparsity of DCP, and achieved good results in image blind deblurring. Because of the successful application of DCP, the corresponding Bright Channel Prior (BCP) is derived. BCP is just the opposite of DCP, that is, in natural scene image patches, at least one color channel has some values very close to one. Yan et al. [24] proposed an Extreme Channels Prior (ECP) for blind image deblurring algorithm in literature [24], which considers both the DCP and BCP. Intuitively, when the bright areas are blending few dark pixels, dark channel prior based method are less likely to help estimate the kernel. BCP based methods have similar drawback. To remedy this problem, we propose a dual-channel contrast prior to capturing the complex changes of pixels in local patches.

In this article, a new Dual-channel contrast prior named Dual-CP is proposed for blind image deblurrings on both natural and specific scenes. The prior is based on the observation that the contrast of an image is decreased after the blurring process. We prove this characteristic mathematically, and explore how this property can be used to estimate the blur kernel. We incorporate this property into blind deblurring model by exploiting a $L_0$ regularization term of inverse contrast. The prior can well model the complex changes of contrast in local patch, which is not captured by the dark channel and bright channel. The proposed method generates reliable intermediate results for kernel estimation without any complicated edge selection algorithms and pre-processing steps. In the proposed algorithm, the optimization of Dual-CP is challenging. To tackle this problem, we use the half-quadratic splitting (H-QS) method to solve this non-convex $L_0$ minimization problem. The main contributions of this article are summarized as follows:

- A new Dual-channel contrast prior is presented for blind image deblurring, which is motivated by the observation that the contrast of an image significantly decreased after the blurring process.
- We show mathematically and empirically that the blur decreases the contrast of clear images. We adopt $L_0$ norm to enforce sparsity on the Dual-channel term and develop an efficient optimization scheme for the deblurring model.
- We show that the proposed algorithm can effectively process natural images including text images. In addition, the proposed Dual-channel contrast prior can directly extend to non-uniform image deblurring.

The remainder of this article is structured as follows. Section II presents our Dual-channel contrast prior. In Section III, the blind image deblurring model based on Dual-CP is proposed. We extend our Dual-channel contrast prior to non-uniform deblurring in Section IV. The relationships between our algorithm and some previous works are described in Section V. Section VI reports experimental results and analysis on four benchmark datasets. Finally, conclusions are drawn in Section VII.

II. DUAL-CHANNEL CONTRAST PRIOR

The DCP is based on the observation that in most of the natural scene patches, at least one of the color channels possesses pixels with very small intensity [22], [23]. To formally describe this observation, the dark channel of an image $I$ is expressed as:

$$D(I)(x) = \min_{y \in \Omega(x)} \left( \min_{c \in \{r, g, b\}} \left( I^c(y) \right) \right)$$

where $x$ and $y$ represent the coordinates of the pixels and $\Omega(x)$ represents an image patch centered at $x$. \((r, g, b)\) denote the red, green and blue color channel of RGB image, respectively. $I^c$ is the $c$-th color channel of image $I$. As described in (1), dark channels are obtained by two minimization operations: $\min_{c \in \{r, g, b\}}$ and $\min_{y \in \Omega(x)}$. Correspondingly, Yan et al. [24] adopted bright channel prior (BCP) for image deblurring. That is, in natural image blocks, at least one color channel has very large pixel values close to one. Then the bright channel of an image is defined as:

$$B(I)(x) = \max_{y \in \Omega(x)} \left( \max_{c \in \{r, g, b\}} \left( I^c(y) \right) \right)$$

The bright channel is obtained by two maximization operations: $\max_{c \in \{r, g, b\}}$ and $\max_{y \in \Omega(x)}$. In the implementations of DCP and BCP, if $I$ is a gray image, then only the latter operation is performed. In blind image deblurring framework, blur reduces the large value and increases the small value in an image patch. This impact can be reduced by minimizing dark channel and maximizing bright channel regularization term, this is why DCP and BCP work.

A. PROPOSED DUAL-CHANNEL

Image contrast is an important indicator of image quality. Clear images often have higher contrast. We observe that the image quality and contrast decrease significantly due to blurring processing. In the proposed algorithm, the optimization of Dual-CP is challenging. To tackle this problem, we use the half-quadratic splitting (H-QS) method to solve this non-convex $L_0$ minimization problem. The main contributions of this article are summarized as follows:

- A new Dual-channel contrast prior is presented for blind image deblurring, which is motivated by the observation that the contrast of an image significantly decreased after the blurring process.
- We show mathematically and empirically that the blur decreases the contrast of clear images. We adopt $L_0$ norm to enforce sparsity on the Dual-channel term and develop an efficient optimization scheme for the deblurring model.
- We show that the proposed algorithm can effectively process natural images including text images. In addition, the proposed Dual-channel contrast prior can directly extend to non-uniform image deblurring.

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respectively, we have $N = (\text{the size of image patches}) \times (\text{blur kernel})$, and blur kernel $k$, respectively, we have $N = N_i + N_k$. According to the definition of $H(I)$:

$$H(b)(x) = \max_{y \in \Omega(x)} b(y) - \min_{y \in \Omega(x)} b(y)$$

$$= \max_{y \in \Omega(x)} \sum_{z \in \Phi(y)} I(y - z) k(z) - \min_{y \in \Omega(x)} \sum_{z \in \Phi(x)} I(y - z) k(z)$$

$$\leq \sum_{z \in \Phi(x)} \max_{y \in \Omega(x)} I(y - z) k(z) - \sum_{z \in \Phi(x)} \min_{y \in \Omega(x)} I(y - z) k(z)$$

$$= \max_{y \in \Omega^2(x)} \left( \sum_{z \in \Phi(x)} I(y - z) k(z) - \sum_{z \in \Phi^2(x)} I(y' - z) k(z) \right)$$

$$= H(I)(x)$$

Equation (4) shows that the contrast of image patch centered at $x$ after blurring is less than the value of original image. The Equation (4) demonstrates $H(b)(x) \leq H(I)(x)$.

**B. DUAL-CHANNEL CONTRAST PRIOR FOR IMAGE DEBLURRING**

The contrast of the patch centered at $x$ is smaller than that of the corresponding patch in a clear image. Therefore, we introduce a property that the high contrast of image patches is conducive to estimating accurate blur kernels. To estimate more accurate blur kernels, we hope that the larger the image contrast, the better quality of blur kernels. However, to use $H(I)$, we subtract $H(I)$ by 1, and the smaller the $1 - H(I)$ is, the higher the contrast and the sharper the image is. The prior can be expressed as:

$$P(I) = \|1 - H(I)\|_0$$

where $\| \cdot \|_0$ denotes the $L_0$ norm. This article defines such $P(I)$ as a dual-channel contrast prior, and $L_0$ norm is used for sparsity. The reason for choosing the $L_0$ norm will be analyzed in section VI-A. According to Eq. (4), Dual-CP of the clear image is less than or equal to blurred image:

$$\|1 - H(I)\|_0 \leq \|1 - H(b)\|_0$$

In the framework of MAP, by minimizing the objective function and $P(I)$, we will obtain a result that favors the clearing image. Figure 1 shows a comparison of the visual effects of dual-channel on blurry input and our result. From the figure, we can see that our Dual-channel has higher contrast, clearer outline, and sharper edges than the blurry one. Figure 2 shows the intensity histograms for Dual-channel of both clear and blurred images in the dataset [26]. Blurred images have far fewer zero dual-channel pixels than the clear ones, confirming our analysis.
III. PROPOSED BLIND DEBLURRING MODEL

Using the proposed dual-channel contrast prior, we construct a blind deblurring model based on the maximum a posteriori framework.

\[
\min_{I,k} \| I \otimes k - b \|^2_2 + \lambda P(I) + \delta \| \nabla I \|_0 + \gamma \| k \|^2_2
\]

(7)

where \( I, y, \) and \( k \) are latent clear image, blurred observation, and blur kernel respectively, and the \( \lambda, \delta, \) and \( \gamma \) are positive penalty parameters. \( \nabla \) denotes the gradient operator. \( P(I) \) is our Dual-CP. \( \| \nabla I \|_0 \) is the \( L_0 \) norm of image gradient, which is used to suppress ringing and artifacts. The first term is data fidelity, which ensures that the recovered image is as consistent as possible with the observation. The last one is the \( L_2 \) norm of the blur kernel, which increases the sparsity of the blur kernel.

We write the Bright channel prior (BCP) in the form of matrix product:

\[
B(I) = MI
\]

(8)

where \( B \) and \( I \) are vector forms of \( B \) and \( I \), respectively. \( M \) is equivalent to a selection matrix, which contains only 0 and 1 values. It defined as:

\[
M(x, z) = \begin{cases} 
1, & z = \max_{z \in \Omega(x)} I(z) \\
0, & \text{otherwise} 
\end{cases}
\]

(9)

The Dark channel prior (DCP) also has the matrix form:

\[
D(I) = GI
\]

(10)

where \( D \) is the vector form of \( D \). \( G \) is similar to \( M \), which is a linear operator and maps the pixel to dark channel in local patch. Then the difference between them, i.e. contrast:

\[
H(I) = B(I) - D(I) = MI - GI = (M - G)I = RI
\]

(11)

where \( R = M - G \), \( H \) denotes the vector form of \( H \). Let \( R \) denote the vector form of \( R \). Then the Dual-CP can be expressed as:

\[
P(x) = \| 1 - RI(x) \|_0
\]

(12)

According to formula (6), we have:

\[
\| 1 - RI(x) \|_0 \leq \| 1 - RI(y) \|_0
\]

(13)

Then, by minimizing the objective function, we will obtain a solution that is more favorable to clear images.

\[
\min_{I,k} \| I \otimes k - b \|^2_2 + \lambda \| 1 - RI \|_0 + \delta \| \nabla I \|_0 + \gamma \| k \|^2_2
\]

(14)

A. OPTIMIZATION

There are many methods to solve Eq. (7), such as [25]. In this part, to obtain the solution of the objective function, we adopt the auxiliary variable idea and ADM (alternate direction minimization) method to achieve it. By introducing auxiliary variables \( p \) and \( g \), which are related to \( 1 - RI \) and \( \nabla I \), respectively, our objective function can be rewritten as follows:

\[
\min_{I,k,p,q} \| I \otimes k - b \|^2_2 + \beta \| 1 - RI - p \|^2_2 + \varphi \| \nabla I - g \|^2_2 \\
+ \lambda \| p \|_0 + \delta \| g \|_0 + \gamma \| k \|^2_2
\]

(15)

s.t. \( p = 1 - RI, g = \nabla I \)

where \( \beta \) and \( \varphi \) are penalty parameters. By using the idea of alternating optimization, we can obtain four independent sub-problems about \( I, k, p, \) and \( g \), respectively.

\[
\min_{I,k} \| I \otimes k - b \|^2_2 + \beta \| 1 - RI - p \|^2_2 + \varphi \| \nabla I - g \|^2_2
\]

(16)

\[
\min_{p} \beta \| 1 - RI - p \|^2_2 + \lambda \| p \|_0
\]

(17)

\[
\min_{k} \| I \otimes k - \gamma \|^2_2 + \gamma \| k \|^2_2
\]

(18)

Equations (16) and (17) are \( L_0 \) norm minimization problems about \( p \) and \( g \), (18) is a classical least squares problems about \( k \). Although we can solve (19) by conjugating gradient method, it requires tremendous time to converge because of the large size of \( R \). Therefore, we introduce another auxiliary variable \( u \) related to \( I \). Then, (19) can be represented as:

\[
\min_{I,u} \| I \otimes k - b \|^2_2 + \beta \| 1 - RI - u \|^2_2 + \alpha \| I - u \|^2_2 \\
+ \varphi \| \nabla I - g \|^2_2
\]

(20)

s.t. \( u = I \)

where \( \alpha \) is a positive penalty parameter. We can solve (20) by ADM:

\[
\min_{I} \| I \otimes k - b \|^2_2 + \alpha \| I - u \|^2_2 + \varphi \| \nabla I - g \|^2_2
\]

(21)

and

\[
\min_{u} \beta \| 1 - RI - p \|^2_2 + \alpha \| I - u \|^2_2
\]

(22)

B. ESTIMATING INTERMEDIATE IMAGE \( I \)

Equation (21) contains all quadratic terms, and we can obtain its solution by the least square method. In each iteration, FFT (Fast Fourier Transform) is used to accelerate the process. Its closed-form solution is given as follows:

\[
I = F^{−1} \left( F(k)F(b) + \alpha F(u) + \varphi \overline{F(g)} \right)
\]

(23)

where \( F \) and \( F^{−1} \) are Fast Fourier Transform (FFT) and its inverse transformation. \( \overline{F} \) denotes the complex conjugates operator of FFT, \( \nabla_v, \nabla_h \) are gradients in the vertical and horizontal directions, respectively.
C. ESTIMATING U, P AND G

Given \( I \), we can compute \( u, p \) and \( g \) separately by an alternative manner. The solution to Eq. (22) is:

\[
u = \frac{\beta R^T (1-p) + \alpha l}{\beta R^T R + \alpha} \tag{24}\]

Equation (16) is a minimization problem of \( L_0 \) norm. However, the minimization of the \( L_0 \) norm is a difficult problem. We adopt the method described in [40]. The solution to (16) can be expressed as:

\[
p = \begin{cases} 
1 - RI, & |1 - RI|^2 \geq \frac{\lambda}{\beta} \\
0, & \text{otherwise}
\end{cases} \tag{25}\]

Given \( I \), the solution to Eq. (17) can be expressed as:

\[
g = \begin{cases} 
\nabla I, & |\nabla I|^2 \geq \frac{\delta}{\varphi} \\
0, & \text{otherwise}
\end{cases} \tag{26}\]

D. ESTIMATING BLUR KERNEL \( k \)

With given \( I \), we can estimate the blur kernel \( k \) independently. To decrease the effect of noise and artifacts, we solve \( k \) in gradient space as follows:

\[
\min_k \| \nabla I \otimes k - \nabla b \|^2_2 + \gamma \| k \|^2_2 \tag{27}\]

where \( \nabla \) denotes gradient operation. Note Eq. (27) is a least-square problem. We use the FFT method to accelerate:

\[
k = \mathcal{F}^{-1} \left( \frac{\mathcal{F}(\nabla I) \mathcal{F}(\nabla b)}{\mathcal{F}(\nabla I) \mathcal{F}(\nabla I) + \gamma} \right) \tag{28}\]

Similar to many previous methods (e.g. [15], [27]), we use the coarse-to-fine strategy for blur kernel estimation. For the sake of enhancing the robustness of the algorithm to noise, we restrict the small value of blur kernel by threshold at a fine scale in the process of deblurring. The main steps of latent intermediate image estimation from one level are summarized in Algorithm 1.

E. ESTIMATING LATENT SHARP IMAGE

Although we can directly obtain the latent sharp image from (7), this model is less effective for images with fine texture details. Since the blur kernel has been obtained, the latent sharp image estimation problem is degenerated to a non-blind deconvolution problem. In this article, to suppress ringing and artifacts, we use a method that estimates clear image with hyper-Laplacian prior [28] and \( L_0 \) regularized prior [9] respectively and then obtain an optimum solution through weight to trade off the smoothness and fineness of two recovered images, which is similar to Pan et al. [20] and Zhang et al. [29].

IV. DUAL-CP FOR NON-UNIFORM DEBLURRING

The blur caused by camera poses include rotation and translation. Similar to [30], let \( I \) and \( b \) denote the vector forms of latent image \( I \) and observed blurred \( b \), respectively. We can model the discrete blur of camera shakes as follows:

\[
b = \sum_{i=1}^N k_i H_i I + n \tag{29}\]

where \( I, b \) and noise \( n \) are \( N \times 1 \) vectors. \( H_i \) is a \( N \times N \) transformation matrix, which corresponds to the camera pose \( i \) and \( i \) indexes the camera pose samples. \( k_i \) is a weight and it denotes the last time of camera poses \( i \) in this function, \( k_i \geq 0 \) and \( \sum_{i=1}^N k_i = 1 \). Equation (29) models the blurred observation as the sum of latent images from all camera poses.

We apply the proposed Dual-CP to non-uniform deblurring problems based on the MAP framework directly, the non-uniform deblurring model can be written as,

\[
\min_{I,k} \left\| \sum_{i=1}^N k_i H_i I - b \right\|_2^2 + \lambda P(I) + \delta \| \nabla I \|_0 + \gamma \| k \|_2^2 \tag{30}\]

where \( \lambda, \delta \) and \( \gamma \) are the same as those in Eq. (7), \( P(\cdot) \) denotes the vector form of our Dual-CP, and \( k = \{k_0, k_1, \ldots \}^T \).

The solution to Eq. (30) can be solved by alternatively minimizing:

\[
\min_{I} \left\| \sum_{i=1}^N k_i H_i I - b \right\|_2^2 + \lambda P(I) + \delta \| \nabla I \|_0 \tag{31}\]

and

\[
\min_{k} \left\| \sum_{i=1}^N k_i H_i I - b \right\|_2^2 + \gamma \| k \|_2^2 \tag{32}\]

The optimization of Eq. (31) is described in Sec. III-A. We introduce the same auxiliary variables and rewrite the
FIGURE 3. Channels of intermediate results generated during iteration.

objective function as:

\[
\min_{I,u,p,g} \left\| \sum_{i=1}^{k_i} H_i I - b \right\|_2^2 + \beta \left\| 1 - R u - p \right\|_2^2 + \alpha \left\| I - u \right\|_2^2 + \phi \left\| \nabla I - g \right\|_2^2 + \lambda \left\| p \right\|_0 + \delta \left\| g \right\|_0
\]

\[
s.t. \quad u = I, \quad p = 1 - R I, \quad g = \nabla I
\]

where \( u, p \) and \( g \) are vector forms of \( u, p \) and \( g \) defined in Sec. III-A, \( \beta, \alpha \) and \( \phi \) are the same as those in Sec. III-A. We note that \( \| \cdot \|_0 \) is defined on each pixel. Similar to (15), the optimization problem (33) can be divided into four sub-problems. Thus, the solution to minimization problems with respect to \( u, p \) and \( g \) can be still obtained by (24), (25), and (26), respectively. The method in [27] is used to update \( I \) and blur kernel \( k_i \).

V. RELATIONSHIPS BETWEEN OUR ALGORITHM AND SOME PREVIOUS WORKS

A. THE MOTIVATION OF IMAGE PRIOR

Some recent works adopt DCP and BCP [22]–[24] because it was discovered that there is extreme pixels (0 or 1) in at least one color channel of the natural image. Dark channel is first proposed for image defogging in [22]. Then Pan et al. [23] enforced the sparsity of dark channel for image deblurring. The method [24] introduced bright channel for image deblurring, which is comparable to the dark channel. Since the extreme pixels become no longer extreme values
after blurred, we can remove the blur by minimizing the dark channel or maximizing the bright channel. However, the above methods will be less effective if large kernel blends bright part with few dark pixels or vice versa. In contrast, our Dual-CP is based on the observation that the contrast of natural images decreased after the blurring process. Our proposed Dual-CP can better capture the complex changes of an image patch even in areas where dark and bright pixels are cluttered.

**B. THE MATHEMATICAL MODEL**

Another difference between our method and [22], [23] and [24] is that our prior is computed by the difference error between bright channel and dark channel. The larger the difference, the more significant the texture, and the better for kernel estimation. The structure of an image is naturally sparse, thus the variation in the sparsity of the dual-channel is an inherent property of the blurring process. Dark channel and bright channel prior obtained by minimizing or maximizing the pixels of one patch respectively. In contrast, our Dual-channel prior is obtained by minimizing the inverse of the difference error between the bright channel and dark channel in the local patch.

**C. THE INTERMEDIATE RESULT**

Figure 3 shows the channels of intermediate results generated during iteration (from left to right). The dark channel of the intermediate image generated by [23] becomes darker and bright channels generated by [24] becomes brighter as shown in Figs. 3(f) and (g), respectively. By contrast, as shown in Fig. 3(h), the intermediate image generated by our method with Dual-channel contrast prior contains higher contrast, sharper edges, which close to clear image and is helpful for kernel estimation.

**VI. EXPERIMENT AND ANALYSIS**

In this section, we test our method on both synthetic and real-world blurred images and compare our method with state-of-the-art blind image deblurring methods. We analyze the norm constraint on the Dual-CP by dataset [31]. We also investigate the role of our Dual-CP by example and the effect of the intermediate image in the process of coarse-to-fine strategy. Furthermore, we show our method can work well on text image deblurring.

**A. NORM CONSTRAINT ON THE DUAL-CP**

According to Eq. (5), we use a $L_0$ norm to constrain our Dual-channel term. The $L_1$ norm is also reasonable since it can sparsity the model. The sparsity of Dual-channel motivates us to explore the performance of the $L_1$ norm on this term for image deblurring. We evaluate our Dual-channel with these two different constraints ($L_0$ norm, $L_1$ norm) by dataset [31]. As shown in Fig. 4, the model with Dual-channel prior achieves better results than that without Dual-channel. This indicates that the Dual-channel is naturally sparse and is helpful to estimate the blur kernel. Also, the method with $\|1 - RI\|_0$ performs the best since $\|1 - RI\|_0$ carries out more sparser solutions than $\|1 - RI\|_1$.

**B. ABLATION STUDIES**

We conduct experiments on dataset [31] to evaluate the impact of different terms in the proposed model. Figure 6 shows that the proposed method has a slightly improvement over the method without using $\|k\|_2$. The proposed algorithm does not perform well when both $\|k\|_2$ and $\|\nabla x\|_0$ terms are removed. This is because the Dual-channel contrast prior only considers the statistical characteristics of pixels in an image patch. It cannot model the complex structures of an image well, which is better constrained by the image gradient prior ($\|\nabla x\|_0$). The method without using pixel term ($\|1 - RI\|_0$) performs less effective than that with. This phenomenon reflects that the pixel term ($\|1 - RI\|_0$) can improve the performance of the blind image deblurring algorithm. The image gradient term models the main structures of image while the Dual-CP captures the pixel details.

**C. THE EFFECTIVENESS OF DUAL-CP**

To explore the role of our Dual-CP, we explore the change of intermediate image during iteration. Figure 3 shows the changes in DCP, BCP, and Dual-CP in each phase of the image. Firstly, the contrast and clarity of DCP, BCP, and Dual-CP of blurred images are very low, while the contrast of the middle layer is significantly improved, and the final

![Figure 4](image-url) Norm constraint on Dual-CP by the benchmark dataset from [31]. Comparisons in terms of cumulative error ratio.

![Figure 5](image-url) Quantitative results of our method with and without the Dual-CP prior on benchmark datasets [31]. (a) Comparisons in terms of PSNR. (b) Comparisons in terms of cumulative error ratio. The Dual-CP helps to improve the performance of blind image deblurring algorithm. Our method has 100 percent success at the error ratio 2 on this dataset.
restored images have higher contrast and clearer contour. At this time, the ringing and artifacts in the images are greatly reduced. Secondly, at the same stage, the proposed Dual-CP has a clearer outline than DCP and BCP. Comparing with literature [23], the proposed method estimates clearer blur kernels and fewer artifacts. Although the intermediate image becomes more and more clear by the coarse-to-fine strategy, large artifacts and blur edges still raise the bar of deblurring. In contrast, the intermediate image using the Dual-CP generates more sharp edges and few artifacts. Meanwhile, the contrast of the intermediate image becomes higher with more iteration in Figure (3)(h). To objectively evaluate our Dual-CP, we quantitatively measure our results on benchmark datasets [20], [31] and [26]. Figure 5(a) shows the PSNR values of our method with and without Dual-CP on benchmark datasets [26], it indicates that our Dual-CP improves the quality of the results. Besides, our method with the Dual-CP has a high success rate on the dataset [20], as shown in Figure 5(b). Overall, Figure 5 demonstrates that the Dual-CP prior improves the performance of deblurring. All the results consistently demonstrate that the Dual-CP improves the performance of deblurring effectively.

D. SYNTHETIC IMAGE DEBLURRING

We compare our method with state-of-the-art methods on the benchmark dataset [31], which includes 4 clear images blurred by 8 blur kernels. Figure 7 shows some deblurred results and estimated kernels of one challenging blurred image from the dataset [31]. Note previous method [33] fails on estimate blur kernel. The kernel estimated by [16] is near
FIGURE 10. Quantitative results of our method on text image dataset [20]. (a) blurry inputs and ground truth kernels. (b) results by [16]. (c) results by [23]. (d) results by [24]. (d) Our results.

FIGURE 11. Quantitative results of our method and the state-of-the-art methods in terms of error ratio on benchmark datasets [13].

FIGURE 12. Examples on the datasets [31] and [26]. (a) are blurry images, (b)-(e) are results generated by [16], [23] and ours.

to a delta kernel. The kernels estimated by [17], [24], [32] contain noise and artifacts. The kernels estimated by recently methods [23], [34], [35] contain trailing noise in certain directions. In contrast, our method generate a kernel that is most similar to the groundtruth and the recovered image contains less artifacts. In Table 1, we further report the PSNR and SSIM values of the images in Fig. 7 for each method. Another example is shown in the first row of Fig. 12. In addition, Figure 5(a) shows our method with $P(I)$ has a larger PSNR values of deblurred results than without using $P(I)$ and the most relevant method [24] on the dataset [31]. Figure 9(b) shows our method with the Dual-CP has a high success rate on the dataset [31]. For each ground truth kernel, we compute
the average SSD (sum of squared difference) error (Fig. 8(a)) and the average SSIM (structural similarity) values (Fig. 8(b)) of estimated blur kernels generated by different methods for quantitative evaluation. The SSD error values of kernel estimated by our algorithm with \( P(I) \) are lower than those of other methods in Fig. 8(a). And the average SSIM value, over all kernels, of our method with \( P(I) \) performs better than the evaluated methods in Fig. 8(b). Overall, our method performs better than the other state-of-the-art blind image deblurring methods.

We further implement our method on a challenging synthetic image dataset [26]. Figure 15 shows the results of our method and the comparison with several state-of-the-art methods [16], [23], [27], [33], [36], and [24]. Our method generates a clearer result and the other results have more ringing artifacts and blur contents. Another example is shown in the second row of Fig. 12, our recovered image has clear edges and containing less ringing artifacts. Figure 9 shows the average PSNR values on dataset [26], it can been seen that our method achieves the maximum PSNR value.
The image size in dataset [31] is $255 \times 255$, which lacks diversity. To further assess the limitations of the deblurring algorithms, Sun et al. introduced a large synthetic dataset [13], which contains 640 high-resolution natural blurry scenes. We compare our method with state-of-the-art methods ([9], [16], [17], [23], [24], [32], [34], [35]) on this dataset. Note for fair compare with all the methods, the kernel sizes are set to 27 (assume the blur kernel is unknown) in all the experiments. Figure 11 shows the proposed method performs better than the other competing methods in terms of cumulative error ratio on this dataset. Our method has a high success rate of the images when the error ratio is 2. We report the PSNR and SSIM values for each algorithm to further compare the performance in Table 2. According to Table 2, our method slightly perform better than state-of-the-art methods [23], [24], [35] and much better than the others. Overall, our method perform well on this dataset.

We also test our method on the text image dataset [20].
FIGURE 17. The visual comparison of state-of-the-art methods on a real blurred image. With the Dual-CP prior, the recovery image by our method contains more sharp edges.

FIGURE 18. Results on a real blurred image. With the Dual-CP prior, the recovery result by our method contains less ringing artifacts.

state-of-the-art blind image deblurring methods [12], [16], [23], [24], [34], [35]. Figure 10 shows some examples of the deblurring results on text images from [20]. The method by Krishnan et al. [16] generates kernels close to a delta function. The estimated blur kernels by Pan et al. [23] and Yan et al. [24] contain significant noise and artifacts. In the second row of 10(d), the method [24] can well estimate the blur kernel; however, the final deblurred image consistently contains unnatural color and ringing. Whereas the deblurred images and blur kernels generated by our algorithm have
clearer text, sharper edges, and less noise. For the deblurred results generated by different methods in Fig. 10, we present their PSNR values in Table 3. Our method performs best with the average PSNR value 27.55 than others. For each ground truth kernel, the average SSD error of our method and state-of-the-art methods [12], [16], [23], [24], [34], [35] is shown in Fig. 14(a). Our method with $P(I)$ has the lowest average SSD error than other evaluated methods in Fig. 14(a). And the average SSIM value of all the kernels is shown in Fig. 14(b). Our method reached the largest
average SSIM value. Figure 16 shows our method performs well on low-light text image deblurring than state-of-the-art methods [23], [24].

E. REAL IMAGE DELURRING

In this part, we test our method on real-world blurred images. Figure 17 provides one example comparing our deblurred result against those of Fergus et al. [33], Cho and Lee [14], Xu et al. [30], Levin et al. [17], Sun et al. [13] and Pan et al. [23]. As the figure shows, our result has sharper edges and fewer artifacts compared with the others.

Figure 13 shows the deblurred results on a real blurred text image by the proposed algorithm and the state-of-the-art methods [10], [13], [14], [20], [30], [33], [38]. The state-of-the-art deblurring methods [10], [20], [33], [38] can not generate clear blur kernels and latent images. Although the text image deblurring method [20] performs well on this image, it still contains ringing and artifacts. In contrast, our deblurred results have clearer text with significantly fewer artifacts.

Figures 18 and 19 show another challenging examples of real blurred image deblurring. The state-of-the-art method [16], [17] does not perform well on kernel estimation and restored unclear images. The method [13], [14], [30] performs well on kernel estimation, but the final estimated image contains ringing and artifacts. The method [23] based on the dark channel prior estimates kernel contains some noise. Overall, our algorithm estimates clear blur kernel and sharp latent image.

F. NON-UNIFORM DEBLURRING

As discussed in Section IV, our Dual-channel prior can be extended to handle non-uniform blur. We compare the proposed algorithm with the state-of-the-art methods [7], [13], [14], [17], [23], [33]. Figure 20 shows an example from [37]. Compared to the deblurred results by the state-of-the-art methods, the restored image by the proposed algorithm contains sharper edges, clear textures and fewer artifacts.

VII. CONCLUSION

In this article, a new contrast prior based on two channels is proposed, which is named Dual-CP. Dual-CP is inspired by the fact that the contrast of natural images decreases significantly after blurring. We discuss the feasibility of using contrast to estimate the blur kernel, then a novel blind deblurring model is developed by incorporating Dual-CP. The proposed Dual-CP utilizes the advantages of DCP and BCP, and regularization by $L_0$ norm. Dual-CP considers not only DCP and BCP but also the relationship between them. Then an effective optimization method is proposed. The experimental results show that our algorithm is competitive with state-of-the-art algorithms. Besides, experiments on Dual-CP show that it can significantly improve the performance of the deblurring algorithm.
[22] K. He, J. Sun, and X. Tang, “Single image haze removal using dark channel prior,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 12, pp. 2341–2353, Dec. 2011.

[23] J. Pan, D. Sun, H. Pfister, and M.-H. Yang, “Deblurring images via dark channel prior,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 40, no. 10, pp. 2315–2328, Oct. 2018.

[24] Y. Yan, W. Ren, Y. Guo, R. Wang, and X. Cao, “Image deblurring via extreme channels prior,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.* (CVPR), Honolulu, HI, USA, Jul. 2017, pp. 6978–6986.

[25] N. Xiong, R. W. Liu, M. Liang, D. Wu, Z. Liu, and H. Wu, “Effective alternating direction optimization methods for sparsity-constrained blind image deblurring,” *Sensors*, vol. 17, p. 174, Jan. 2017.

[26] R. K. O’holler, M. Hirsch, B. Mohler, B. Schikopf, and S. Harmeling, “Recording and playback of camera shake: Benchmarking blind deconvolution with a real-world database,” in *Computer Vision—ECCV*, Berlin, Germany: Springer, 2012, pp. 27–40.

[27] M. Hirsch, C. J. Schuler, S. Harmeling, and B. Schölkopf, “Fast removal of non-uniform camera shake,” in *Proc. Int. Conf. Comput. Vis.*, Barcelona, Spain, 2011, pp. 463–470.

[28] D. Krishnan and R. Fergus, “Fast image deconvolution using hyper-Laplacian priors,” in *Proc. Adv. Neural Inf. Process. Syst. Conf.*, 2009, pp. 1033–1041.

[29] X. Zhang, R. Wang, Y. Tian, W. Wang, and W. Gao, “Image deblurring using robust sparsity priors,” in *Proc. IEEE Int. Conf. Image Process. (ICIP)*, Quebec City, QC, Canada, Sep. 2015, pp. 138–142.

[30] L. Xu, S. Zheng, and J. Jia, “Unnatural L0 sparse representation for natural image deblurring,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Portland, OR, USA, Jun. 2013, pp. 1107–1114.

[31] A. Levin, Y. Weiss, F. Durand, and W. T. Freeman, “Understanding and evaluating blind deconvolution algorithms,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Miami, FL, USA, Jun. 2009, pp. 1964–1971.

[32] T. S. Cho, S. Paris, B. K. P. Horn, and W. T. Freeman, “Blur kernel estimation using the radon transform,” in *Proc. CVPR*, Providence, RI, Jun. 2011, pp. 241–248.

[33] R. Fergus, B. Singh, A. Hertzmann, S. T. Roweis, and W. T. Freeman, “Removing camera shake from a single photograph,” in *Proc. ACM SIGGRAPH Papers (SIGGRAPH)*, vol. 25, 2006, pp. 787–794.

[34] L. Pan, R. Hartley, M. Liu, and Y. Dai, “Phase-only image based kernel estimation for single image blind deblurring,” in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Long Beach, CA, USA, Jun. 2019, pp. 6027–6036.

[35] F. Wen, R. Ying, Y. Liu, P. Liu, and T.-K. Truong, “A simple local minimal intensity prior and an improved algorithm for blind image deblurring,” *IEEE Trans. Circuits Syst. Video Technol.*, early access, Oct. 27, 2020, doi: 10.1109/TCSVT.2020.3034137.

[36] O. Whyte, J. Sivic, A. Zisserman, and J. Ponce, “Non-uniform deblurring for shaken images,” *Int. J. Comput. Vis.*, vol. 98, no. 2, pp. 168–186, Jun. 2012.

[37] W.-S. Lai, J.-B. Huang, Z. Hu, N. Ahuja, and M.-H. Yang, “A comparative study for single image blind deblurring,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.* (CVPR), Las Vegas, NV, USA, Jun. 2016, pp. 1701–1709.

[38] J. Zhang, J. Pan, J. Ren, Y. Song, L. Bao, R. W. H. Lau, and M.-H. Yang, “Dynamic scene deblurring using spatially variant recurrent neural networks,” in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, Salt Lake City, UT, USA, Jun. 2018, pp. 2521–2529.

[39] D. Perrone and P. Favaro, “Total variation blind deconvolution: The devil is in the details,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Columbus, OH, USA, Jun. 2014, pp. 2909–2916.

[40] L. Xu, C. Lu, Y. Xu, and J. Jia, “Image smoothing via L0 gradient minimization,” *ACM Trans. Graph.*, vol. 30, p. 174, Dec. 2011.