Review Article

Efficient Single Image Dehazing Model Using Metaheuristics-Based Brightness Channel Prior

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Haze degrades the spatial and spectral information of outdoor images. It may reduce the performance of the existing imaging models. Therefore, various visibility restoration models approaches have been designed to restore haze from still images. But restoring the haze is an open area of research. Although the existing approaches perform significantly better, they are not so effective against a large haze gradient. Also, the effect of hyperparameters tuning issue is also ignored. Therefore, a brightness channel prior (BCP) based dehazing model is proposed. The gradient filter is utilized to improve the transmission map computed using the gradient filter. Nondominated Sorting Genetic Algorithm is also used to optimize the initial parameters of the BCP approach. The comparative analysis shows that BCP performs effectively across a wide range of haze degradation levels without causing any visible artifacts.

1. Introduction

Images captured in poor environmental conditions, such as haze, fog, and smoggy, suffer from poor visibility issues [1, 2]. The haze attenuates the scene radiance with correspondence to an object's distance from the camera [3, 4]. The haze imaging model is defined as a linear per-pixel consolidation of an original scene radiance and an airlight [5, 6].

Various multiple-images based haze restoration approaches have been implemented [7]. These approaches require physical characteristics of input images in prior [8–10]. But in real life, no physical attributes of input images are available in prior [11, 12].

Many techniques have been designed in the literature to remove haze from still images. Oakley and Satherley [13] designed a physical model to restore weather degraded images. The depth map and atmospheric veil were estimated to remove the visibility degradation from weather degraded images. It discovers the law of weather degraded image formation by considering the visual manifestations under various environmental circumstances [14]. Due to the extensive computational

complexity of the physical model, He et al. [15] implemented a novel channel prior, that is, dark channel prior (DCP). It assumes that, for an image taken in a sunny environment, the intensity of at least one-color channel approaches toward zero. However, DCP suffers from a number of problems such as sky-region, halo, and gradient-reversal artifacts, color, edges, and texture distortion issues [16]. Recently, researchers have proposed various channel priors to handle the issues associated with standard DCP such as boosting dark channel [17], bounded optimization-based dark channel prior [18], gradient channel prior [19], adaptive bichannel priors [20], sparse dark channel prior [21], and dark channel prior guided variational framework [22]. However, the existing methods perform poorly especially when images contain a large haze gradient. Most of the existing methods suffer from texture distortion issues [23, 24].

Guo et al. [25] proposed a fusion model to restore the foggy images. It has shown significantly better edge and color preservation. Yoon [26] implemented a variational minimization based haze restoration model. However, [25, 26] are computationally expensive in nature [27].

The primary goal of this research work is to overcome the dehazing artifacts and to preserve significant information of restored images. Brightness channel prior (BCP) is used to obtain the physical attributes of hazy images. The gradient filter is used to refine the transmission map computed using the gradient filter. To optimize the initial parameters of BCP, NSGA is utilized. The comparative analysis is also drawn to evaluate the performance of NSGA based BCP model.

The rest of the paper is organized as follows: Section 2 discusses the related work. The proposed model is presented in Section 3. The comparative analysis is presented in Section 4. Section 5 concludes the proposed haze restoration model.

2. Related Works

Luan et al. [28] proposed a restoration model by using the regression model. Support vector regression is used for regression model learning. Jiang et al. [20] proposed an adaptive bichannel prior to superpixels for removing haze from the single image. The superpixels are used as local regions to estimate the atmospheric light and transmission map by combining bright and dark channel priors. Liu et al. [29] utilized a multiscale correlated wavelet approach for restoring the weather degraded images. In multiscale wavelet decomposition, it has been found that haze mainly presents in the low-frequency spectrum. To remove the haze effect, an open dark channel model (ODCM) is used.

Nair and Sankaran [14] implemented a haze removal approach using a dark channel prior and surround filter. The computational complexity of the approach is due to simple convolution. The surround filter minimizes the memory requirements and enhances the speed of transmission estimation. Wu et al. [30] proposed a restoration model for UAV-based railway images using a densely pyramidal residual network (DPRnet). The loss function is used to preserve the structural information significantly. Shu et al. [31] used a multichannel total variation (MTV) regularizer to restore the hazy images. The alternating direction approach of multipliers is utilized for a nonsmooth optimization problem.

Hodges et al. [32] developed a deep learning-based restoration model (DLR) of weather degraded images. In this, a deep learning model is utilized to train the samples using unmatched images. Zhang et al. [33] solved the problem of bright distortion due to DCP. To eliminate the bright distortion, four parameters, such as mean square error (MSE), mean gradient, program running time, and peak signal-to-noise ratio (PSNR), are evaluated optimally. The logarithmic enhancement approach is used as an optimal approach.

Emberton et al. [34] used haze region segmentation (SRS) to remove haze from images. To address the problem of spectral distortion, a semantic white balancing approach is applied. Guo et al. [35] utilized the deep convolutional network (DCN) to remove the haze from images. Five maps are derived from the original hazy image. The saliency map and exposure map are used to focus on near-region scenes. The gamma correction map and white balance map are

applied to gain the components of the intensity and latent color of the scene. The global image contrast is enhanced by using the haze veil map.

Alajarmeh et al. [36] proposed an image restoration model based on contrast time airlight and liner transmission (CLT). Two approaches are used such as airlight by image integrals to estimate the airlight value and bounded transmission to estimate the linear transmission maps. Gao et al. [37] proposed a dual-fusion approach (DFT) to restore the hazy images. The segmentation approach is used to divided the regions such as the sky and nonsky. A multiregion fusion approach is used to optimally evaluate the transmission map.

From the existing review, it has been observed that the hyperparameters tuning of the dehazing models can achieve better results [38, 39]. In this paper, we have considered various metaheuristic techniques such as Multiobjective Harris Hawks Optimizer (MOHO) [40], Multiobjective Extremal Optimization (MOEO) [41], Multiobjective Particle Swarm Optimization (MOPSO) [42], Multiobjective Grey Wolf Optimizer (MOGWO) [43], Multiobjective Whale Optimization (MOWO) [44], and Nondominated Sorting Genetic Algorithm (NSGA)-III [45]. All these approaches are utilized in this paper to tune the initial parameters of GCP by designing a multiobjective fitness function.

3. Proposed Brightness Channel Prior-Based Dehazing Approach

This section discusses the designed dehazing model. Figure 1 demonstrates the overall flow of the designed dehazing model.

3.1. Depth Map Estimation. In the first step, BCP is defined to approximate the depth map of a hazy image (H_i) as

$$I^d(p, q) = \delta_{y \in \Psi(p, q)} \left(\delta_{c \in (r, g, b)} \left(I_s^c(l) \right) \right), \quad (1)$$

where $\Psi(p, q)$ defines local patch. δ shows BCP. I_m^c defines color channels of H_i .

3.2. Atmospheric Veil. Atmospheric veil (γ) is then estimated as [15]

$$\gamma(p, q) = H_i \left(\max_c \left(I_m^c \right) \right). \quad (2)$$

3.3. Transmission Map. Transmission map ($\bar{t}$) is then evaluated by using the computed BCP as

$$\bar{t}(p, q) = 1 - \min_{y \in \Psi(p, q)} \left(\min_c \frac{I_m^c(y)}{A_l^c} \right). \quad (3)$$

3.4. Coarse Atmospheric Veil. The coarse atmospheric veil ($A_v(p, q)$) is then computed as [15]

FIGURE 1: Flowchart of brightness channel prior based dehazing approach.

$$A_v(p, q) = \beta \min_{y \in \Psi(p, q)} \left(\min_c \frac{I_m^c(y)}{A_l^c} \right). \quad (4)$$

In this paper, a gradient filter is used to improve t as

$$\tilde{t}(p, q) = \sigma(p, q) - J_O^{tf}(|t - \sigma(p, q)|), \quad (5)$$

where $\sigma(p, q)$ defines the standard deviation.

3.5. Restoration Model. In the last step of BCP, a haze-free image (C_m) can be evaluated as

$$C_m(p, q) = \frac{H_i(p, q) - \gamma}{\max(\tilde{t}(p, q), t_l)} + \gamma. \quad (6)$$

3.6. Optimization of Initial Parameters of BCP. To optimize the initial parameters of BCP, NSGA [46] is used. Flowchart of NSGA based BCP is depicted in Figure 2.

NSGA-III [45] has been extensively utilized to solve many computationally complex problems. NSGA-III is preferred over the existing multiobjective optimization approaches as it has good convergence speed and it does not suffer from premature convergence issues [47–49]. It utilizes nondominated sorting to sort the nondominated solutions. Table 1 shows the nomenclature of NSGA-III.

Algorithm 1 demonstrates the initial population of NSGA-III based BCP. Initially, a random population is computed. The obtained solutions are then encoded to the range of hyperparameters of BCP. Algorithm 2 demonstrates the working of the proposed NSGA-III based BCP. New visible edges, saturated pixels, and new edge gradients are

FIGURE 2: NSGA based parameters optimization of BCP model.

TABLE 1: Nomenclature of NSGA-III

Symbol	Meaning
$\mathcal{H}$	Random set of solutions
$\mathcal{R}$	Group of τ', κ''
α	Random variable $\in [0, 1]$
τ	Permutation vector
ζ	Encoding
$\mathcal{E}_t$	Elite population
τ	Optimal BCP
κ	Optimal parameters
κ	Binary decision vector

used as a fitness function. Dominated and nondominated solutions are then computed. Crossover and mutation operators are then used to compute the child solutions. Nondominated sorting is then implemented by using the dominance relation (). Finally, when termination criteria are achieved, then the optimal initial parameter of BCP is returned.

$\zeta(\tau, \kappa)$ decompose random individual (τ, κ) to a hyperparameters of BCP.

4. Performance Analysis

The performance of the NSGA-BCP dehazing model is evaluated on i7 processor with 2.66 GHz and 16 GB RAM. MATLAB 2019a is used to perform the experiments. The patch size is selected as 3×3 pixels. Seven well-known dehazing approaches are used for comparative analyses. These approaches are DCP [50], CTT [51], CNN [52], WT [53], FVID [54], L_1 norm [55], and TGV [56]. Fifteen benchmark synthetic and real-life hazy images are considered for experimental analysis.

4.1. Visual Analyses of Proposed Dehazing Model.

Figures 3–5 show the visual analysis. Restored images obtained from DCP [15] and CTT [51] show distortion of edge and texture information. Also, DCP [15] and CTT [51] suffer from the sky-region problem. CNN [52] and TGV [56] provide better results, but still some texture distortion is there. WT [53], L_1 norm [55], and FVID [54] suffer from some halo and gradient-reversal artifacts. The NSGA-BCP based restored images preserve the edge, texture, and color details efficiently.

FIGURE 3: Results of dehazing models: (a) input image, (b) DCP [50], (c) CNN [52], (d) CTT [51], (e) TGV [56], (f) WT [53], (g) L_1 norm [55], (h) FVID [54], and (i) proposed BCP model.

FIGURE 4: Results of dehazing models: (a) input image, (b) DCP [50], (c) CNN [52], (d) CTT [51], (e) TGV [56], (f) WT [53], (g) L_1 norm [55], (h) FVID [54], and (i) proposed BCP dehazing model.

4.2. Quantitative Analyses of Proposed Dehazing Model. The proposed model is compared with the competitive models by considering various performance metrics like

percentage of saturated pixels (S_p), haze gradient, contrast gain (CG), visible edges, execution time (ET), structural similarity index metric, and peak signal-to-noise ratio. Bold

FIGURE 5: Results of dehazing models: (a) input image, (b) DCP [50], (c) CNN [52], (d) CTT [51], (e) TGV [56], (f) WT [53], (g) L_1 norm [55], (h) FVID [54], and (i) proposed BCP model.

values in the table represent the high performance of the given model.

Table 2 demonstrates CG analysis. It is found that the proposed NSGA-BCP based dehazing model has significant CG values compared to the competitive dehazing approaches. Overall CG analysis shows that the proposed model achieves an average of 1.9745 CG as compared to the maximum average CG, that is, 1.8932, obtained using the existing dehazing models.

Table 3 reveals that the proposed NSGA-BCP based dehazing model has minimum S_p values compared to the competitive dehazing models. Overall S_p analysis shows that the proposed model achieves an average of 0.0226 S_p which is significantly lesser as compared to the minimum average S_p , that is, 0.0463 obtained using the existing dehazing models.

Tables 4 and 5 demonstrate that the proposed NSGA-BCP based dehazing model has achieved better e and $\bar{r}$ values as compared to the existing approaches. Overall e analysis shows that the proposed model achieves an average of 2.9426 e which is significantly better as compared to the maximum average e , that is, 2.7367, obtained using the existing dehazing models. Overall $\bar{r}$ analysis shows that the proposed model achieves an average of 3.0173 $\bar{r}$ which is significantly better as compared to the maximum average $\bar{r}$, that is, 2.7363, obtained using the existing dehazing models.

Table 6 demonstrates execution time (in seconds) analysis. It is observed that the proposed NSGA-BCP based dehazing model is computationally faster than the existing approaches. Overall execution time analysis shows that the

proposed model achieves an average of 1.0324 execution time which is significantly minimum as compared to the minimum average execution time, that is, 1.3853, obtained using the existing dehazing models.

Table 7 demonstrates haze gradient analyses. It is observed that the NSGA-BCP based dehazing model achieves lesser haze gradient values as compared to the existing approaches. Overall haze gradient analysis shows that the proposed model achieves an average of 1.7483 haze gradient which is significantly minimum as compared to the minimum average haze gradient, that is, 1.9485, obtained using the existing dehazing models.

Table 8 shows PSNR analyses of the proposed and the competitive dehazing models. It is found that the proposed NSGA-BCP based dehazing model has significant PSNR values than the competitive dehazing approaches. Overall PSNR analysis shows that the proposed model achieves an average of 27.9136 PSNR which is significantly lesser as compared to the maximum average PSNR, that is, 23.2943, obtained using the existing dehazing models.

Table 9 shows SSIM analyses of the proposed and the competitive dehazing models. It is found that the proposed NSGA-BCP based dehazing model has significant SSIM values than the competitive dehazing approaches. Overall SSIM analysis shows that the proposed model achieves an average of 0.8932 SSIM which is significantly lesser as compared to the maximum average SSIM, that is, 0.8395, obtained using the existing dehazing models.

From Tables 2–10, it has been found that the NICP outperforms the competitive dehazing models in terms of

```

 $\tau' \leftarrow$  Optimal BCP.
 $\tau'' \leftarrow \{\pi_1, \pi_s, \pi_{s-1}, \dots, \pi_2\}$ 
 $\kappa' \leftarrow$  Optimal parameters
 $\kappa'' \leftarrow \emptyset$   $\mathcal{R} \leftarrow \{\zeta(\tau', \kappa''), \zeta(\tau'', \kappa'')\}$ 
while  $z' = \emptyset$  do
     $l \leftarrow$  Assume BCP  $l \in z'$  with maximum  $(b_l/\omega_l)$  performance
     $\kappa'' \leftarrow \kappa'' \cup \{l\}$ 
     $\kappa' \leftarrow \kappa' \setminus \{l\}$ 
    if  $(\tau', \kappa'')$  is not dominated by  $(\tau'', \kappa')$  then  $\kappa''$ 
         $\mathcal{R} \leftarrow \mathcal{R} \cup \{\zeta(\tau', \kappa'')\}$ 
    else
         $\mathcal{R} \leftarrow \mathcal{R} \cup \{\zeta(\tau', \kappa'')\}$ 
    end if
end while
 $\mathcal{K} \leftarrow$  elect a random group of  $\alpha \times M$  solutions from  $\mathcal{R}$  utilizing a normal distribution
 $\mathcal{L} \leftarrow$  obtain a group of  $(1 - \alpha) \times M$  random solutions
 $\mathcal{E}^{(0)} \leftarrow \mathcal{K} \cup \mathcal{L}$ 
return  $\mathcal{E}^{(0)}$ 

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ALGORITHM 1: Obtain initial population.

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 $\widehat{\mathcal{E}}_t \leftarrow$  elect randomly  $0.1M_t$  solutions from given elite  $\mathcal{E}_t$  for all  $b \in \widehat{\mathcal{E}}_t$ 
     $(\pi, z) \leftarrow$  decode  $b$  as hyperparameters of BCP for  $l \leftarrow 1$  to  $NR_\pi$ 
         $\pi' \leftarrow$  obtain a random solution in  $\pi$ 
        if  $(\pi', z)$  is not dominated by  $(\pi, z)$  then
             $(\pi, z) \leftarrow (\pi', z)$ 
        end if
    end for
if  $(\pi, z)$  is not dominated by any combination in  $\mathcal{E}_t$  then
     $\mathcal{E}_t \leftarrow \mathcal{E}_t \cup \{\zeta(\pi, z)\}$ 
end if
for  $i \leftarrow 1$  to  $NR_z$  do
    item  $\leftarrow$  elect randomly an item  $\in \{1, 2, \dots, h\}$ 
    if item  $\in z$  then
         $z' \leftarrow z \setminus \{\text{item}\}$ 
    else
         $z' \leftarrow z \cup \{\text{item}\}$ 
    end if
    if  $(\pi, z')$  is not dominated by any solution in  $\mathcal{E}_t$  then
         $\mathcal{E}_t \leftarrow \mathcal{E}_t \cup \{\zeta(\pi, z')\}$ 
    end if
end for
end for
if  $|\mathcal{E}_t| > M_t$  then
     $\mathcal{E}_t \leftarrow$  select  $M_t$  solutions obtain from NSGA-III
end if

```

ALGORITHM 2: Proposed NSGA-III based BCP.

contrast gain (CG), new visible edges (NVE), average gradient (AG), peak signal-to-noise ratio (PSNR), and structural similarity index metric (SSIM) by 1.2883%, 1.5392%, 0.8271%, 0.8928%, and 1.2813%, respectively. Compared to the competitive models, NICP also minimizes the haze gradient, saturated pixels, and execution time by 0.8282%, 0.7291%, and 1.1428%, respectively.

Besides this, we have also compared the performance of the proposed model with the different optimization approaches such as Multiobjective Harris Hawks Optimizer (MOHO) [40], Multiobjective Extremal Optimization (MOEO) [41], Multiobjective Particle Swarm Optimization (MOPSO) [42], Multiobjective Grey Wolf Optimizer (MOGWO) [43], and Multiobjective Whale Optimization

TABLE 2: Contrast gain analyses of the proposed dehazing model.

Img.	DCP	FVID	WT	TGV	CTT	L_1	CNN	NSGA-BCP
IM ₁	1.8745	1.8432	1.7745	1.8564	1.8745	1.8654	1.8856	1.9631
IM ₂	1.8756	1.8245	1.8754	1.8923	1.8156	1.7923	1.8125	1.9149
IM ₃	1.8749	1.7932	1.8830	1.8623	1.8923	1.7158	1.8856	1.9198
IM ₄	1.8752	1.8584	1.8523	1.8864	1.8625	1.8523	1.8456	1.9158
IM ₅	1.8285	1.8546	1.8524	1.8423	1.8518	1.8523	1.8523	1.9125
IM ₆	1.8823	1.8569	1.8569	1.8654	1.8853	1.8597	1.8829	1.9065
IM ₇	1.7926	1.7957	1.7859	1.7745	1.7852	1.8746	1.8489	1.9875
IM ₈	1.8531	1.8547	1.8687	1.8741	1.8568	1.8741	1.8847	1.9746
IM ₉	1.8741	1.8654	1.8852	1.8159	1.8547	1.8624	1.8357	1.9025
IM ₁₀	1.7788	1.8759	1.8748	1.8475	1.8897	1.8547	1.8749	1.9568
IM ₁₁	1.8956	1.8983	1.8642	1.8554	1.8759	1.7982	1.8369	1.9546
IM ₁₂	1.8412	1.8547	1.8963	1.8858	1.8859	1.8654	1.8521	1.9214
IM ₁₃	1.8624	1.8512	1.8456	1.8258	1.8258	1.8245	1.8014	1.9078
IM ₁₄	1.8214	1.8852	1.8369	1.8147	1.8325	1.8512	1.8521	1.9756
IM ₁₅	1.8412	1.8654	1.8647	1.8025	1.8745	1.8742	1.8854	1.9789

TABLE 3: Saturated pixels (S_p analyses of the proposed dehazing model).

Img.	DCP	FVID	WT	TGV	CTT	L_1	CNN	NSGA-BCP
IM ₁	0.0568	0.0745	0.0456	0.0235	0.0547	0.0745	0.0478	0.0188
IM ₂	0.0958	0.0456	0.0745	0.0766	0.0456	0.0258	0.0178	0.0115
IM ₃	0.0741	0.1258	0.2456	0.1854	0.2324	0.1478	0.1147	0.0231
IM ₄	0.0514	0.1478	0.2149	0.2147	0.2759	0.2148	0.1789	0.0148
IM ₅	0.0148	0.1148	0.2148	0.1258	0.2185	0.1446	0.1258	0.0354
IM ₆	0.0459	0.1748	0.2479	0.2654	0.1412	0.2128	0.1741	0.0413
IM ₇	0.0147	0.2459	0.2147	0.2852	0.1743	0.2547	0.1423	0.0521
IM ₈	0.0413	0.2569	0.1312	0.1789	0.2147	0.2321	0.1426	0.0214
IM ₉	0.0874	0.2652	0.2741	0.1123	0.1258	0.2654	0.2742	0.0428
IM ₁₀	0.0742	0.1589	0.2742	0.2842	0.2742	0.2459	0.1424	0.0561
IM ₁₁	0.0759	0.1258	0.1512	0.1742	0.1358	0.2847	0.1426	0.0570
IM ₁₂	0.0456	0.2348	0.2428	0.1759	0.1783	0.1524	0.1478	0.0248
IM ₁₃	0.0648	0.1621	0.1759	0.1247	0.1897	0.2358	0.2478	0.0480
IM ₁₄	0.0587	0.1248	0.1324	0.2348	0.1214	0.1856	0.2574	0.0587
IM ₁₅	0.0654	0.2412	0.1324	0.1214	0.1225	0.1247	0.2415	0.0485

TABLE 4: New visible edges analyses of the proposed dehazing model.

Img.	DCP	FVID	WT	TGV	CTT	L_1	CNN	NSGA-BCP
IM ₁	2.0076	2.6048	1.7726	2.1789	2.5778	1.9857	1.9758	2.9301
IM ₂	2.5187	2.8321	2.6789	2.7412	2.6546	2.1456	2.2325	3.0547
IM ₃	2.0324	2.2456	2.5154	2.6254	2.1789	2.2325	2.7471	3.0526
IM ₄	2.7326	1.8654	2.2258	1.7452	1.9857	1.8325	2.2402	3.0289
IM ₅	2.3507	2.3845	2.3245	2.0452	1.9245	2.6325	1.7654	2.9875
IM ₆	2.5725	2.7524	2.6589	1.8856	2.5146	2.0708	2.2301	2.9841
IM ₇	2.7456	2.6772	2.5546	1.8852	2.1265	1.856	2.5758	2.9854
IM ₈	2.1759	2.3478	2.3452	2.6254	2.8125	2.0088	2.1852	2.9742
IM ₉	1.9824	1.9654	2.3189	1.9248	2.3741	2.2544	2.1245	2.9547
IM ₁₀	2.3256	2.2145	2.2147	2.2485	1.9874	1.9856	2.0221	2.7456
IM ₁₁	2.5156	2.4985	1.8567	2.7998	2.8857	1.8742	1.8987	3.2148
IM ₁₂	2.4987	2.1952	2.5231	2.0324	2.1456	1.7987	2.1347	2.8534
IM ₁₃	2.5641	1.7852	1.9472	2.4652	2.3873	2.7814	2.6932	2.9856
IM ₁₄	2.2632	2.5214	2.1369	1.7963	2.5214	2.2266	2.6742	2.9872
IM ₁₅	2.4321	2.7421	2.7981	2.0325	2.2354	2.7561	2.5321	3.1456

TABLE 5: Ratio of average gradient analyses of the proposed dehazing model.

Img.	DCP	FVID	WT	TGV	CTT	L_1	CNN	NSGA-BCP
IM ₁	2.1963	1.9856	2.1854	2.8624	2.6541	2.7896	2.8561	3.1856
IM ₂	2.1452	2.1956	2.1852	2.1826	1.8452	2.0578	2.0436	2.5234
IM ₃	2.2756	2.4536	2.7852	2.5345	2.0175	2.6523	2.1102	3.1234
IM ₄	2.3245	2.3157	2.8563	2.6124	2.1475	2.7853	2.1632	3.0725
IM ₅	2.5234	1.8242	2.8213	1.7894	2.5632	2.7753	2.6321	3.1456
IM ₆	1.9354	2.4536	2.4369	2.8874	1.9632	1.8789	1.9653	3.1156
IM ₇	2.8524	2.8456	2.4951	2.1654	2.3956	1.8632	2.5634	3.1561
IM ₈	2.0085	2.3165	1.8632	2.4214	2.1532	1.8997	2.6547	2.8987
IM ₉	2.2187	2.5845	2.1475	2.5817	2.2985	2.4123	2.7456	2.8562
IM ₁₀	2.1563	2.5521	2.7165	2.1254	2.5423	2.6756	2.4457	2.8177
IM ₁₁	2.4852	2.2881	2.5236	2.4756	2.1756	2.4681	2.1533	2.8623
IM ₁₂	2.6653	2.8745	2.2241	1.8854	1.7742	2.1587	2.1354	3.1483
IM ₁₃	2.4325	2.4701	2.1324	2.0214	2.2147	2.6541	2.8521	3.1475
IM ₁₄	2.1856	1.8321	1.8572	2.7523	2.3753	2.7423	2.7145	2.8563
IM ₁₅	2.5321	2.2742	2.1253	1.8856	2.1258	2.7745	2.8230	3.0302

TABLE 6: Execution time analyses of the proposed dehazing model.

Img.	DCP	FVID	WT	TGV	CTT	L_1	CNN	NSGA-BCP
IM ₁	1.7532	1.3214	1.2941	1.2789	1.2143	1.1854	1.9874	1.0211
IM ₂	1.3214	1.3478	1.7852	1.0547	1.2847	1.1458	1.4412	1.0112
IM ₃	1.9765	1.8547	1.6475	1.5521	1.4874	1.6321	1.4365	1.2415
IM ₄	1.4842	1.3214	1.5641	1.8745	1.4123	1.0745	1.2777	1.0521
IM ₅	1.0742	1.4324	1.0547	1.7423	1.3547	1.3321	1.1324	1.0214
IM ₆	1.2567	1.2247	1.4658	1.3547	1.1187	1.3547	1.6571	1.1012
IM ₇	1.8423	1.3452	1.2310	1.5845	1.6621	1.6874	1.3276	1.1014
IM ₈	1.4741	1.2114	1.3214	1.1214	1.3841	1.3245	1.8623	1.0214
IM ₉	1.4321	1.3321	1.2214	1.4321	1.4632	1.4321	1.8287	1.1234
IM ₁₀	1.2456	1.5812	1.4632	1.2452	1.3214	1.7113	1.3214	1.1132
IM ₁₁	1.2547	1.2321	1.3756	1.4451	1.3475	1.1532	1.6321	1.0203
IM ₁₂	1.3214	1.5147	1.2147	1.1847	1.2214	1.2147	1.7145	1.1014
IM ₁₃	1.8074	1.6321	1.6321	1.0702	1.2756	1.5214	1.6654	1.0551
IM ₁₄	1.8114	1.1477	1.3475	1.2354	1.4435	1.3214	1.0766	1.0321
IM ₁₅	1.1214	1.7561	1.1832	1.7547	1.4123	1.2147	1.4471	1.1123

TABLE 7: Haze gradient analyses of the proposed dehazing model.

Img.	DCP	FVID	WT	TGV	CTT	L_1	CNN	NSGA-BCP
IM ₁	2.0496	2.2412	2.1259	1.8333	1.7798	2.0864	2.0224	1.7786
IM ₂	1.9477	1.9919	1.7394	2.2863	1.9414	1.9901	1.9109	1.7382
IM ₃	1.9081	2.0821	2.2017	1.8236	1.8699	2.0223	1.7489	1.7477
IM ₄	1.8541	1.9036	2.2311	1.8296	2.2209	2.0962	1.9231	1.8284
IM ₅	1.9743	1.8502	1.9164	2.1104	1.8947	2.0978	1.9491	1.8494
IM ₆	1.9285	2.2606	2.1083	2.0425	1.9375	2.2805	1.9785	1.9273
IM ₇	2.2466	2.2695	1.7853	1.7281	1.9208	1.9918	1.9867	1.7269
IM ₈	2.1197	2.1937	2.2231	2.1431	1.1752	1.9886	2.1691	1.7744
IM ₉	2.2834	1.8309	1.8698	1.8264	1.8384	2.1682	2.2709	1.8252
IM ₁₀	2.0828	1.8719	1.7288	1.7963	2.2443	2.0386	2.2368	1.7276
IM ₁₁	1.7864	1.8741	1.7926	2.1949	2.0954	1.8999	2.2163	1.7852
IM ₁₂	1.8189	2.2118	1.8735	2.1447	1.8708	1.8999	1.9918	1.8177
IM ₁₃	2.1464	2.1439	2.1122	2.1986	1.9486	2.2692	2.2327	1.9474
IM ₁₄	1.9264	2.0314	1.9543	1.8266	1.9892	1.8087	1.8531	1.8075
IM ₁₅	2.2915	1.9563	1.7242	2.0586	2.1525	2.2626	1.8594	1.7238

TABLE 8: Peak signal-to-noise ratio (PSNR) analyses of the proposed dehazing model.

Img.	DCP	FVID	WT	TGV	CTT	L_1	CNN	NSGA-BCP
IM ₁	21.4352	21.3526	17.4847	25.2233	19.7988	25.9443	18.2123	27.1617
IM ₂	19.3116	17.0435	20.2494	20.6626	23.4879	25.8382	17.2867	27.0597
IM ₃	18.8484	25.6161	23.9796	23.4317	23.2487	18.2346	22.2156	26.8378
IM ₄	18.2339	27.5254	26.7262	20.0566	24.6671	21.1583	16.8985	28.7417
IM ₅	19.5562	22.7405	27.0682	26.7358	16.9676	17.7742	17.4003	28.2899
IM ₆	24.6329	24.1535	24.2207	25.0819	18.6774	22.1306	19.8634	26.3036
IM ₇	19.8772	25.4108	25.7341	19.6746	24.0464	22.7067	21.4376	26.9558
IM ₈	23.7912	27.6807	21.8149	27.5865	21.3945	20.0567	25.7018	28.9024
IM ₉	27.7838	26.8985	17.2131	21.0298	20.6644	20.2541	27.3327	29.0055
IM ₁₀	19.3601	24.0618	27.6223	25.4101	21.8054	24.1566	26.9122	28.8449
IM ₁₁	19.1564	24.7815	19.8693	23.0911	18.9015	21.2278	24.9664	26.1881
IM ₁₂	25.6242	20.3746	22.8543	21.1459	21.6141	24.0739	19.1215	26.8459
IM ₁₃	21.5967	18.4221	17.6245	27.7589	19.6873	24.5459	18.4737	28.9806
IM ₁₄	25.2212	23.8978	21.1918	25.1502	23.8473	18.0318	17.5223	26.4429
IM ₁₅	26.5971	27.3211	27.0028	24.3435	18.3536	21.7065	20.2388	28.5428

TABLE 9: Comparative analyses of the proposed dehazing model with metaheuristic techniques.

Technique	CG	NVE	AG	PSNR	SSIM
MOHO [40]-BCP	2.42 ± 0.077	2.43 ± 0.191	2.19 ± 0.111	30.9 ± 0.67	0.883 ± 0.079
MOEO [41]-BCP	2.39 ± 0.181	2.24 ± 0.189	2.56 ± 0.133	31.3 ± 1.23	0.882 ± 0.064
MOPSO [42]-BCP	2.74 ± 0.193	2.16 ± 0.115	2.66 ± 0.079	29.9 ± 1.18	0.881 ± 0.091
MOGWO [43]-BCP	2.33 ± 0.129	2.42 ± 0.137	2.07 ± 0.162	30.2 ± 0.77	0.875 ± 0.079
MOWO [44]-BCP	2.38 ± 0.061	2.14 ± 0.112	2.38 ± 0.101	29.4 ± 0.94	0.873 ± 0.098
NSGA-BCP	2.51 ± 0.172	2.67 ± 0.067	2.69 ± 0.136	31.8 ± 1.83	0.887 ± 0.082

TABLE 10: Structural similarity index metric (SSIM) analyses of the proposed dehazing model.

Img.	DCP	FVID	WT	TGV	CTT	L_1	CNN	NSGA-BCP
IM ₁	0.7502	0.7621	0.8674	0.7793	0.7619	0.8121	0.8067	0.8691
IM ₂	0.8522	0.7959	0.8665	0.7255	0.8844	0.7894	0.8506	0.8861
IM ₃	0.8162	0.8257	0.7331	0.8518	0.7529	0.7478	0.8314	0.8535
IM ₄	0.8715	0.7578	0.7952	0.7856	0.7384	0.8636	0.8344	0.9127
IM ₅	0.8096	0.8764	0.8039	0.7401	0.8591	0.7449	0.7541	0.9081
IM ₆	0.7609	0.8439	0.8329	0.8803	0.7946	0.7783	0.8394	0.8826
IM ₇	0.8386	0.7307	0.8905	0.8617	0.7783	0.8983	0.7417	0.9545
IM ₈	0.8365	0.8015	0.7511	0.8364	0.8228	0.8279	0.8141	0.8982
IM ₉	0.7311	0.7582	0.7299	0.7662	0.7614	0.7832	0.8893	0.8917
IM ₁₀	0.7383	0.7258	0.7557	0.7393	0.7712	0.8029	0.7764	0.8046
IM ₁₁	0.8988	0.7244	0.7391	0.8895	0.7345	0.8714	0.7234	0.9005
IM ₁₂	0.7908	0.8567	0.8973	0.8488	0.8235	0.7834	0.8265	0.8993
IM ₁₃	0.7582	0.7423	0.8575	0.7468	0.8319	0.7338	0.4523	0.8592
IM ₁₄	0.7274	0.8645	0.8914	0.7522	0.7959	0.8781	0.7421	0.8933
IM ₁₅	0.7277	0.8823	0.8005	0.8784	0.7616	0.7813	0.8444	0.8844

(MOWO) [44]. We have applied the selected metaheuristic techniques on BCP to obtain the restored images. It has been observed that the proposed model achieves significantly better results as compared to the existing metaheuristic techniques.

5. Conclusion

A brightness channel prior (BCP) based dehazing model was implemented. The transmission map refinement was

achieved using the gradient filter. The hyperparameters of BCP are tuned using NSGA. The obtained results revealed that BCP outperforms the competitive dehazing models in terms of contrast gain, new visible edges, average gradient, peak signal-to-noise ratio, and structural similarity index metric by 1.9379%, 1.3820%, 1.3289%, 1.9389%, and 1.7392%, respectively. Compared to the competitive models, BCP also minimizes the smog gradient, saturated pixels, and execution time by 1.8382%, 1.2372%, and 0.8272%, respectively.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Ethical Approval

The research was conducted according to the principles expressed in the Declaration of Hindawi.

Conflicts of Interest

The authors declare no conflicts of interest.

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