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Hyperbolic tangent sigmoid as a transformation function for image contrast enhancement

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***Abstract*—Contrast enhancement is critical for investigating and highlighting important hidden features in a computer vision system. Continuous functions, such as incomplete beta or sigmoid functions, have traditionally been used for histogram equalization. However, histogram equalization cannot uniformly enhance the local contrast of an image, which is its main limitation. In this study, we investigate a contrast enhancement method based on a hyperbolic tangent sigmoid whose parameters can be optimized by metaheuristics. In our study, we investigated the performance of three popular metaheuristics when coupling the proposed hyperbolic tangent sigmoid to find the optimal pixel values that can intensify features of low-contrast images. The proposed method is studied on a public domain image dataset and evaluated using standard performance indicators. Preliminary results show that the proposed hyperbolic tangent sigmoid can improve image contrast and quickly adapt to other metaheuristics.**

***Index Terms*—Sigmoid functions, metaheuristics, image contrast enhancement.**

I. Introduction

Digital image processing techniques are employed to analyze objects, shapes, and patterns in various research areas. However, factors such as lack of luminosity, brightness, and other elements can compromise the results' accuracy and reliability, directly affecting the image quality [1]. Therefore, it is necessary to apply image contrast enhancement (ICE) techniques to deal with such drawbacks. The contrast can be defined as the differences between the high- and low-intensity levels present in the image.

We can find diverse proposals to enhance image contrast in the specialized literature. One of the most commonly used techniques is histogram equalization (HE), which can be applied to color and grayscale images [2]–[8]. Other examples of methods are those based on fuzzy rules [2], [9], [10]. Although the above techniques allow for the redistribution of image pixels considering their statistical characteristics throughout the entire intensity scale, they exhibit approaches that lead to a sub-optimal redistribution of pixel data in the presence of noise or irrelevant sets of pixels in the image [11]. Other strategies adopted for image contrast enhancement are transformations based on continuous functions. In this sense, the use of the incomplete Beta function and sigmoid functions have also been employed [2], [12]–[20].

On the other hand, the problem of contrast enhancement has been addressed with metaheuristic algorithms [1], [21], such as evolutionary algorithms that aim to obtain the optimal solution by defining a fitness function and iteratively improving it to achieve better contrast quality in the image. Kannan et al. [2] proposed an enhancement image contrast methodology using a fuzzy rule-based method and a modified logistic sigmoid function. This method shows a significant contrast improvement and is helpful in sports image processing. The modified logistic sigmoid function has the advantage of being flexible, as the contrast factor can be adjusted until satisfactory results are achieved. Kim-Ngan et al. [22] proposed a method that employs a configurable logistic sigmoid function and the differential evolution algorithm. The adopted evolutionary algorithm is employed to identify the parameters in the logistic sigmoid function and maximize the contrast measure by identifying the optimal threshold and contrast factor for each color plane of the image. Chen et al. [1] proposed an enhancement image contrast method using an artificial bee colony (ABC) algorithm. The approach optimizes the incomplete Beta function [12] in order to generate new pixel intensities to improve the original image. Khan et al. [21] proposed another method to improve the contrast of grayscale images. The image contrast enhancement is performed based on an optimization algorithm called political optimizer (PO) inspired by the multi-phased process of politics. In this approach, the incomplete Beta function is optimized to improve the contrast of grayscale images. Luque-Chang et al. [11] proposed an approach based on agents called ABICE for image contrast enhancement. Regardless, studies based on hyperbolic tangent sigmoid, the topic investigated in this paper, have been less investigated. In this regard, Garg et al. [23] used a static hyperbolic tangent sigmoid to improve the contrast of digital images. An inverse hyperbolic tangent sigmoid function was also used in [24] to enhance image contrast. In both approaches, the hyperbolic tangent function was not optimized to enhance

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image contrast.

This paper presents a transformation function based on the hyperbolic tangent sigmoid with adaptive parameters for contrast enhancement. The proposed transformation function is coupled and evaluated in a Genetic Algorithm (GA), a Differential Evolution (DE) algorithm, and a Particle Swarm Optimizer (PSO). The above algorithms are widely recognized and employed in the field of global optimization. The experimental study presented in this paper indicates the viability of incorporating, in an easy way, the proposed hyperbolic tangent sigmoid function into bioinspired metaheuristics. A series of experiments are conducted to evaluate the adopted algorithms over a set of color images adopting standard quality indicators of digital images.

The presented paper is organized as follows. Section II introduces the general background to understand this study, including quality indicators related to images. Section III describes the proposed transformation function and how to use it within evolutionary approaches. Section IV presents the experimental study carried out in this investigation. Section V exposes an analysis of results that includes a comparative study of performance between the algorithms adopted in our experimental study. Finally, in Section VI, we provide our conclusions and some possible paths for future investigations.

II. General Background

A. Contrast

The contrast of an image can be understood as the intensity levels present in the pixels, which determine the image's appearance. It refers to the disparity between light and dark tones in the image. High contrast implies a noticeable difference between the tones, resulting in a striking and dramatic image. On the other hand, low contrast indicates a more minor difference and a smoother image. In summary, contrast relates to the ability to perceive subtle details and variations in pixel intensity in an image.

1) Sum Edge Intensity (SEI): Since the edges of an image are areas with abrupt intensity transitions between adjacent regions, the Sum of Edge Intensity (SEI) calculation involves summing the intensity disparities between neighboring pixels along the detected edges. This calculation is performed after applying edge detection algorithms such as Sobel or Canny. A value is obtained by computing the intensity disparities along the edges, representing the total intensity change in those edges. The image contrast is directly proportional to the SEI value. The higher the SEI value, the greater the image contrast, indicating a more significant presence of details and features in the image.

2) Count of Edge Pixels (CEP): The pixel edge count involves identifying and counting the pixels that form the edges in an image, providing a quantitative measure of the number of edges present. This is achieved using edge detection techniques such as convolution operators (e.g., Sobel or Roberts), thresholding algorithms, or more advanced methods like the Canny algorithm. A higher count of pixel edges indicates greater edges and intensity transitions in the image, which can be associated with a higher presence of features and details. Furthermore, the pixel edge count can also be used as a metric to evaluate the quality and sharpness of an image.

3) Entropy of Image (EI): Entropy is used to assess the distribution of intensity levels in an image. If the entropy value is high, it indicates a more significant variation in intensity levels and, therefore, higher contrast. The entropy of an enhanced image is calculated as follows.

$$EI = \begin{cases} -\sum_{j=0}^{255} h_j log_2(h_j) & \text{if } h_j \neq 0 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

B. Quality indicators in images

To evaluate the quality of the enhanced images, it is necessary to employ some metrics. Most metrics used for this purpose compare the original image with the processed image. The comparison is made based on the different parameters described in this section.

1) Peak Signal-to-noise ratio (PSNR) [25]: The PSNR is a commonly used metric that compares the two images regarding the pixel´s information. The PSNR is defined as:

$$PSNR = 20 \log \frac{255}{RSME} \quad (2)$$

such that:

$$RMSE = \sqrt{\frac{1}{Ro \times Co} \sum_{i=1}^{Ro} \sum_{j=1}^{Co} (I_o(i,j) - I_e(i,j))} \quad (3)$$

where, Ro and Co define the size of the image, I_o is the original image, and I_e is the enhanced image.

2) Structural Similarity Index Measure (SSIM) [25]: The SSIM is a metric that evaluates the similarity between a reference image and another compared image. It measures the quality of the image by comparing three main components: luminance, contrast, and structure. The SSIM is defined in Eq. (4).

$$SSIM = \frac{(2\mu I_o \mu I_e + C_1)(2\sigma I_o I_e + C_2)}{(\mu^2 I_o + \mu^2 I_s) + C_1)(\sigma^2 I_o r + \sigma_(I_e)^2 + C_2)} \quad (4)$$

such that:

$$\sigma_{(I_o I_e)} = \frac{1}{Co - 1} \sum_{i=1}^{Co} (I_{o_i} + \mu_{I_o})(I_e + \mu_{I_e}) \quad (5)$$

3) Relative Enhancement Contrast (REC) [26]: The REC measures the difference of contrast between the original image and the enhanced one. The REC is a ratio of the contrast of the original image and the enhanced output. The REC is computed as follows:

$$REC = \frac{C_{I_o}}{C_{Ie}} \quad (6)$$

In Eq. (6), C_{I_o} is computed using Eq. 7 and C_{I_e} is computed in the same way.

$$C_{I_o} = 20\log\left[\frac{1}{Ro \times Co}\left(\sum_{i=1}^{Ro}\sum_{j=1}^{Co} {I_o}^2(i,j)\right) - \left(\sum_{i=1}^{Ro}\sum_{j=1}^{Co} I_o(i,j)\right)^2\right] \tag{7}$$

III. Proposed Approach

This section introduces the proposed transformation function based on the hyperbolic tangent sigmoid for contrast enhancement and the fitness function adopted in our experimental study.

A. Transformation function

In the specialized literature, a transformation function is often used to modify the original intensity of each pixel of a low-contrast image. Some methods apply a piecewise linear transformation function for this purpose [27], [28]. In essence, the parameters in these transform functions are optimized to better contrast the underlying image over the one to which it is applied. Once the transformation function is applied, the transformed pixels can become more remarkable than the number of intensity levels allowed or, if applicable, become negative. To solve this problem, the piecewise curve must be replaced with a continuous curve. This paper presents a transformation function based on a hyperbolic tangent sigmoid with adaptive parameters for contrast enhancement.

The known hyperbolic tangent function is defined by:

$$f(x) = \tanh(x) = \frac{\sinh(x)}{\cosh(x)} = \frac{e^x - e^{-x}}{e^x + e^x} \tag{8}$$

Hyperbolic tangent function has a domain in $x \in [-\infty, \infty]$ and codomain $(-1, 1)$ as shown in Fig. 1(a).

An adaptive hyperbolic tangent function with scaling parameter α and translation parameter β can be defined by modifying the above Eq. (8) as follows.

$$f(x) = \tanh\left(\frac{x-\beta}{\alpha}\right) \tag{9}$$

where $\alpha > 0$ and $\beta \in \mathbb{R}$.

In the above function, the scaling parameter α shall accentuate the concave and convex parts of the sigmoid, while the translation parameter β shall control the position of the inflection point in the sigmoid. Figs. 1(b) and 1(c) illustrate hyperbolic tangent sigmoid functions for different α and β values.

Considering an image with Λ intensity levels, the hyperbolic tangent sigmoid as enhanced contrast function is formulated by:

$$f(x) = \frac{\Delta}{2}\tanh\left(\frac{x-\beta}{\alpha}\right) + \frac{\Delta}{2} \tag{10}$$

where x denotes the pixel intensity, $\alpha > 0$ and $\beta \in [0, \Lambda]$. Parameters α and β must be optimized for a better-enhanced contrast image.

In this study, the proposed method employs the above transformation function to define the new pixel values of the concerned image. On the other hand, the search space was restricted to $\alpha \in [10, 50]$ and $\beta \in \left[\frac{1}{3}\Delta, \frac{2}{3}\Delta\right]$.

B. Fitness function

The proposed method utilizes a fitness function to measure enhanced image quality. The literature shows that researchers rely on different image-related factors to evaluate the quality of enhanced images using optimization algorithms. In this investigation, the following common image aspects are considered to define the fitness function[1].

1) The sum edge intensity (SEI) levels of pixels,
2) The count of edge pixels (CEP), and
3) The entropy of image (EI).

The above indicators are considered to define the following fitness functions.

$$F(I_E) = \log(\log(SEI)) \times CEP \times EI \tag{11}$$

where I_E is the image obtained after optimizing the α and β parameters in Eq. (10). In this way, any other bioinspired metaheuristic can adopt the above fitness function.

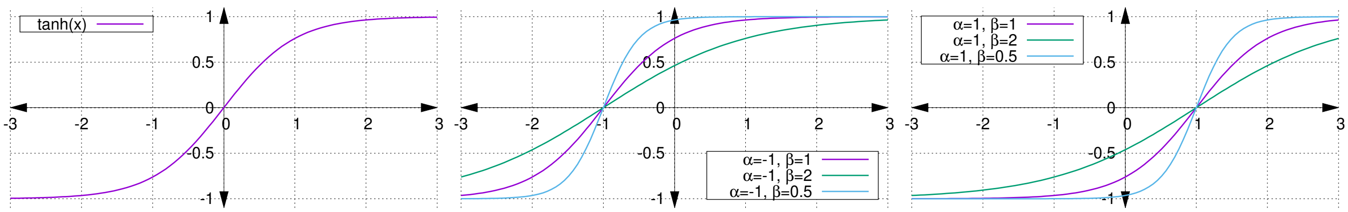
In the following, we investigate the performance of the proposed transformation function and its benefits for enhancing contrast in digital images.

IV. Experimental Study

This section presents the performed experiments along with the visual and numerical outcomes achieved by the three adopted algorithms, i.e., Differential Evolution (DE), Genetic Algorithm (GA), and Particle Swarm Optimizer (PSO).

1) Experimental setup: In this experimental study, we evaluate the proposed transformation function using 10 color images from the Kodak dataset [29] with a resolution of 756×512 pixels. Additionally, three performance indicators were taken into account to evaluate the adopted algorithms: Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and Relative Enhancement Contrast (REC). These indicators allow for analyzing the quality of the enhanced images and are suitable for comparison with other studies related to contrast enhancement of images. As we consider a real encoding, the GA adopted SBX and PBM operators [30]. Besides, the survival selection mechanism adopted by the GA was the well-known $(\mu + \lambda)$ selection scheme. GA was evaluated using a crossover probability $P_c = 0.9$ and a mutation probability $P_m = 0.5$. DE algorithm was performed with a differential weight $F = 0.9$ and a crossover probability $C_r = 0.5$. PSO algorithm was executed using acceleration coefficients $c_1 = 1.7$ and $c_2 = 1.7$, while the inertia weight $w = 0.7289$. For all algorithms, the population size was $N = 100$, and the maximum number of iterations was $G_{max} = 500$.

[1]An explanation of such indicators is presented in Section II-B.



(a) (b) (c)

Fig. 1. Hyperbolic tangent sigmoid functions for: (a) $\tanh(x)$; (b) $\tanh(\frac{x-\alpha}{\beta})$ for $\alpha = -1$ and $\beta = 2, 1, 0.5$, respectively; (c) $\tanh(\frac{x-\alpha}{\beta})$ for $\alpha = 1$ and $\beta = 2, 1, 0.5$, respectively.

2) Performance evaluation: The performance of three bioinspired algorithms using the hyperbolic tangent sigmoid was thoroughly compared, as detailed in Table I. The table shows the average and standard deviation in parentheses. The results correspond to 30 independent runs of each algorithm on the 10 images from the Kodak dataset.

For each performance indicator, the algorithm that achieved the best average value for each image is highlighted in **boldface**. The visual results of the three contrast enhancement methods are visually presented in Fig. 2. Notably, the different algorithms significantly enhance the contrast and illumination of the original images, indicating the excellent performance of the proposed hyperbolic tangent function in conjunction with the three adopted metaheuristics, i.e., the DE, GA, and PSO algorithms.

In the subsequent section, we delve into a comprehensive discussion of the noteworthy results obtained from the experimentation.

V. Analysis of Results

The results emanating from the three adopted algorithms are analyzed, considering three indicators used to measure contrast enhancement. In the following, a discussion of each performance indicator is presented.

A. Peak Signal-to-Noise Ratio in DE, GA, and PSO

As observed in Table I, the PSNR values obtained in the images after applying the contrast enhancement function indicate that the PSO algorithm exhibited better efficiency in most images from the Kodak dataset compared to the DE and GA algorithms. Fig. 2 illustrates the contrast enhancement in five adopted images. As can be seen, the images in Fig. 2 show slight differences in the contrast improvement achieved by each algorithm. The enhanced images compared to the original images allow a better appreciation of the contrast enhancement result obtained with the proposed hyperbolic sigmoid tangent.

B. Structural Similarity Index Measure

Analyzing the results obtained with the SSIM indicator, it can be observed how the DE, GA, and PSO algorithms proportionally enhance the images in terms of structure and details. In Table I, it is noticeable that 99% of the SSIM values are above 0.75, indicating a high structural similarity between the compared images and suggesting that the images improved by the DE, GA, and PSO algorithms are pretty similar to the original images in terms of structure and details. However, it is worth noting that PSO achieved more images with more structural similarity among the three algorithms.

This observation is also visually appreciated when analyzing the images in Fig. 2, where the differences between the enhanced images obtained by the algorithms are very subtle but easily distinguishable compared to the original image.

C. Relative Enhancement Contrast in DE, GA, and PSO

Regarding the REC indicator, the results range between 0.935 and 1.056. These results indicate that the contrast enhancement algorithms have had a positive impact on the images, improving their overall contrast. In fact, the REC indicator better evaluates the contrast improvement in the adopted images. After analyzing the REC indicator for each algorithm, the results in Table I show that both the DE and PSO algorithms outperformed the GA by generating a greater number of images with a higher contrast enhancement. Both algorithms share the same number of images with outstanding results. Visually, we can also observe in Fig. 2 the contrast enhancement results obtained with the three algorithms. Once again, we can clearly see the difference between the original and enhanced images, with improved features in the enhanced images.

VI. Conclusions and Future Work

This paper introduces a technique to enhance image contrast based on a hyperbolic tangent sigmoid function coupled with the DE, GA, and PSO algorithms. The proposed methodology focuses on improving the intensity of each pixel in low-contrast images. In this way, bioinspired metaheuristics can optimize the parameters of the introduced sigmoid function to deal with low-contrast images. Therefore, the contrast-enhancing method can be adaptable to the luminosity of a particular image to enhance its contrast. While the proposed transformation function was initially applied to just three state-of-the-art metaheuristics, its potential utility can also be broadened to encompass other evolutionary approaches. The experimental study's findings indicate the effectiveness of the hyperbolic tangent-based sigmoid function for enhancing image contrast. Notably, the PSO algorithm outperforms DE and GA in achieving the best results. Furthermore, these algorithms demonstrate competitive performance in terms of Peak Signal-to-Noise Ratio (PSNR) compared to some established methods in the

TABLE I

STATISTICAL COMPARISON OF THE PSNR, SSIM, AND REC INDICATORS OBTAINED BY THE DE, GA, AND PSO ALGORITHMS. THE BEST AVERAGE VALUES FOR EACH IMAGE ARE INDICATED IN BOLDFACE, WHILE THE STANDARD DEVIATION VALUES ARE SHOWN IN PARENTHESES.

	DE			GA			PSO		
Image	**PSNR**	**SSIM**	**REC**	**PSNR**	**SSIM**	**REC**	**PSNR**	**SSIM**	**REC**
Kd1	14.8139 (0.000516)	0.794176 (0.000003)	**0.954260** (0.000004)	14.8137 (0.000000)	0.794176 (0.000000)	0.954259 (0.000000)	**14.8143** (0.000105)	**0.794323** (0.000028)	0.954249 (0.000002)
Kd2	14.4403 (0.008144)	0.888743 (0.000520)	0.9701648 (0.000838)	14.4510 (0.000098)	0.889278 (0.000576)	0.969811 (0.000159)	**14.4861** (0.065356)	**0.890102** (0.001724)	**0.971044** (0.002851)
Kd3	15.8970 (0.013693)	0.854513 (0.000106)	0.957570 (0.000126)	15.8996 (0.000098)	0.854521 (0.000002)	**0.957598** (0.000001)	**15.9002** (0.000286)	**0.854617** (0.000044)	0.957587 (0.000005)
Kd4	15.3739 (0.049316)	0.827909 (0.000860)	**0.963123** (0.000694)	15.3577 (0.0000)	0.828191 (0.000000)	0.962896 (0.000000)	**15.3583** (0.000114)	**0.828362** (0.000032)	0.962882 (0.000003)
Kd5	14.9143 (0.000300)	0.804523 (0.000009)	0.935853 (0.000001)	14.9143 (0.000286)	0.804524 (0.000009)	0.935853 (0.000001)	**15.0235** (0.146186)	**0.806814** (0.002865)	**0.936985** (0.001619)
Kd6	**15.0559** (0.000000)	0.669947 (0.000000)	1.056249 (0.000000)	15.0558 (0.000032)	0.669932 (0.000012)	1.056237 (0.000009)	15.0558 (0.000004)	**0.669956** (0.000002)	**1.056260** 0.000002
Kd7	13.9996 (0.030972)	0.832300 (0.000812)	0.945118 (0.000187)	14.1470 (0.080074)	0.838182 (0.003746)	0.945653 (0.000420)	**14.2036** (0.061943)	**0.841485** (0.002289)	**0.945663** (0.000380)
Kd8	17.6903 (0.000000)	0.809575 (0.000000)	0.990722 (0.000000)	17.7049 (0.006662)	0.809931 (0.000162)	0.990830 (0.000049)	**17.7078** (0.000000)	**0.810003** (0.000000)	**0.990852** (0.000000)
Kd9	**18.3645** (0.039306)	0.824856 (0.001695)	**0.998641** (0.001720)	18.2913 (0.080103)	0.829576 (0.004189)	0.994894 0.003576	18.2400 (0.055507)	**0.832768** (0.001921)	0.992361 (0.002056)
Kd10	17.2968 (0.078092)	0.827815 (0.000707)	0.979380 (0.000777)	**17.5074** (0.132986)	0.829832 (0.001348)	**0.981433** (0.001287)	17.4751 (0.057300)	**0.833646** (0.001897)	0.979710 (0.001332)

literature. The versatility of the proposed technique allows its application in various domains such as medicine, industry, pattern recognition, etc., where improving image contrast is essential.

In our future endeavors, we plan to explore novel transformation functions that have the potential to enhance image contrast further. Additionally, we recognize the significance of addressing the challenges posed by local optima, which can be attributed to the current properties of the image luminosity. To overcome this, we intend to incorporate more robust and powerful bioinspired metaheuristics. By combining these two research directions, we aim to achieve even more notable results in contrast enhancement. These paths represent exciting and promising avenues for future investigations, allowing us to push the boundaries of image processing and contribute to advancing image quality improvement techniques.

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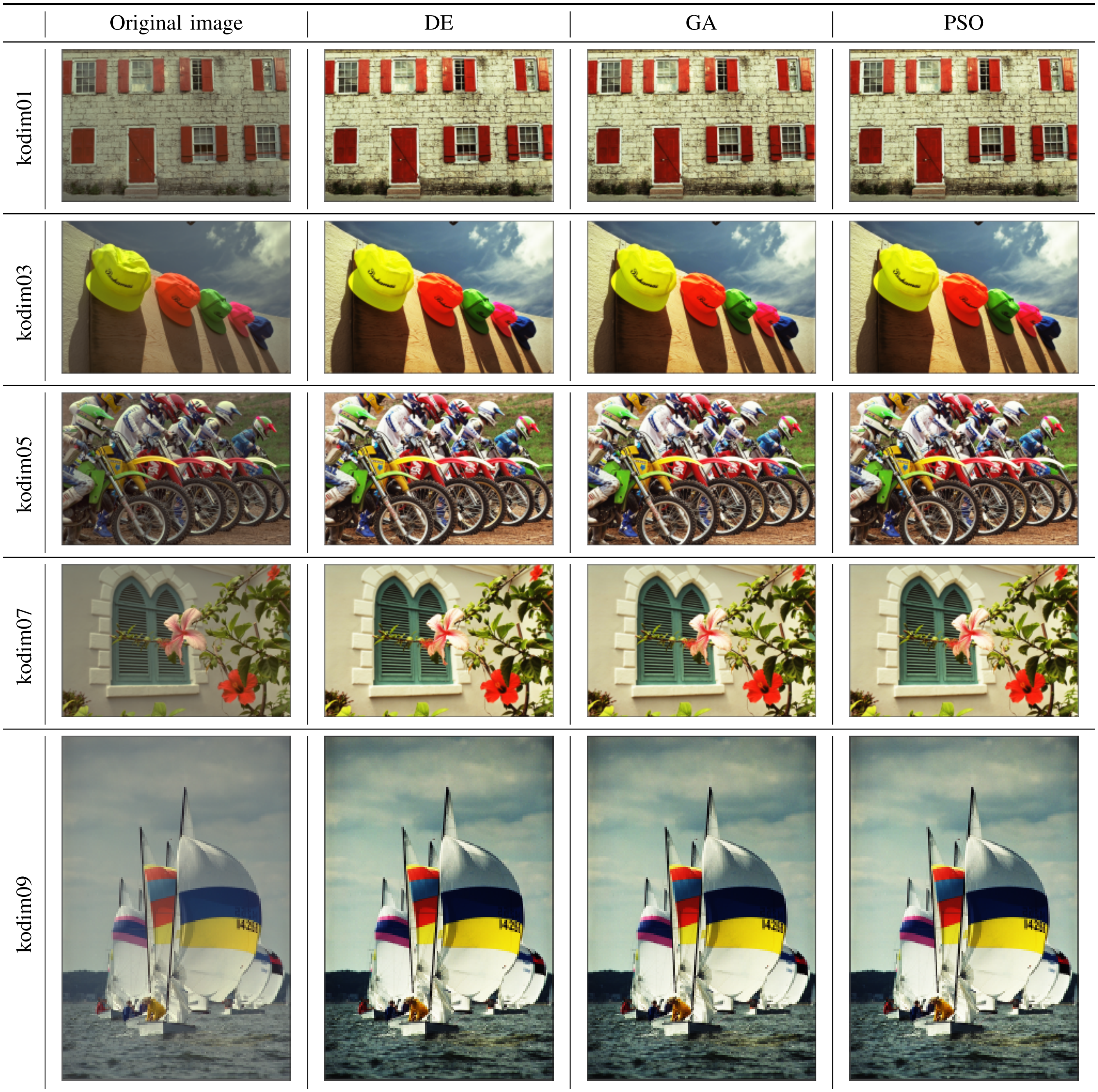

Fig. 2. Enhanced images obtained by DE, GA, and PSO algorithms on the benchmark images kodim01, kodim03, kodim05, kodim07, and kodim09.

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