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Image Enhancement Using Hybrid Particle Swarm Optimization and Krill Herd Algorithm

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Abstract. Image enhancement, which aims to improve the contrast and information quality of images, is one of the crucial phases in image processing techniques. Due to insufficient enhancement and the mean shift problem of conventional image enhancement techniques, new artificial intelligence-based image enhancement approaches have become an inevitable need in image processing. This paper proposes a new hybrid method using particle swarm optimization (PSO) and krill herd algorithm (KHA) for image enhancement (PSOKHA). The suggested PSOKHA method is employed to search for the optimum parameters of the transfer function to produce new pixel intensities for the enhanced images. To evaluate the effectiveness of the suggested algorithm, its performance is compared with six latest successful enhancement techniques: PSO, KHA, histogram equalization (HE), screened Poisson equation (SPE), brightness preserving dynamic fuzzy histogram equalization (BPDFHE), and adaptive gamma correction weighted distribution (AGCWD). The experiments are carried out in three diverse test images including a medical image, a satellite image, and a handwritten image. Results demonstrate that the suggested strategy can produce better enhanced images in terms of several measurement criteria such as contrast, PSNR, entropy, and structure similarity index (SSIM).

Keywords: Image enhancement, particle swarm optimization (PSO), krill herd algorithm (KHA), SNPR

1 Introduction

Image enhancement is a mathematical method that improves the quality of a given image by contrast stretching, removal of the noise, and magnification of pixels. Image enhancement can facilitate image interpretation both for a human observer and for machine recognition. Therefore, it plays an important role in many fields such as medical image analysis, human vision, fault detection, remote sensing, and so on [1]. Image enhancement techniques are divided into two groups: spatial domain and frequency domain techniques. Methods in the spatial domain are performed on pixel values itself while the approaches in frequency domains use transformations like Fourier or Wavelet Transform of the image [2]. Contrast stretching (often called contrast enhancement) is

one of the most common and useful spatial image enhancement methods. The contrast stretching approach improves the contrast level of a given image by expanding the range of the pixel intensity values utilizing a linear transformation (mapping) function [3].

Besides of widely used Histogram equalization based methods for image enhancement [4], recently several evolutionary algorithms have been employed to increase the quality of images such as genetic algorithm [5], particle swarm optimization [6], artificial bee colony [7], firefly algorithm [8], cuckoo search algorithm [9], and so on. Although there are many approaches to enhance the contrast of the images, most of them lead to abnormality in the natural-looking of the images. So enhancement of the image in a different area is still a challenging task [2].

In this study, a new hybrid approach based on particle swarm optimization and krill herd algorithm (PSOKHA) is proposed for image enhancement. Due to the simplicity and excellent performance of the krill herd algorithm (KHA), it has been utilized in various domains. However, some times the KHA may get stuck into some local optima leading to its modifications in terms of hybridizations with other metaheuristics [10]. For an improved performance of the KHA, the particle swarm optimization (PSO) algorithm is utilized at the first stage to enhance the original image. Then the enhanced image is fed to KHA to increase the contrast of the image further. The evaluation on enhanced images reveals that the proposed PSOKHA shows better performance than six latest successful enhancement techniques: PSO [6], KHA [11], histogram equalization (HE) [12], screened Poisson equation (SPE) [13], brightness preserving dynamic fuzzy histogram equalization (BPDFHE) [14], and adaptive gamma correction weighted distribution (AGCWD) [15].

The rest of the paper is organized as follows. In section 2, an image enhancement transformation and fitness functions are described. An overview of the KHA, PSO, and the details of the proposed PSOKHA are provided in section 3. Section 4 presents experimental results, and the paper ends with a conclusion in section 5.

2 Problem Formulation

In the spatial domain, a transformation function is used to improve the image contrast by changing the intensity value of each pixel in the original image to a new value [2]. The transformation function can be defined as:

$$G(i, j) = T[F(i, j)] \quad (1)$$

where $G(i, j)$ and $F(i, j)$ are the intensity values of the $(i, j)^{th}$ pixel in the enhanced and original image, respectively. The transformation T in Eq. (1) can be expressed as

$$T[F(i, j)] = \frac{k * M}{(\sigma(i, j) + b)} * [F(i, j) - c * \mu(i, j)] + \mu(i, j)^a \quad (2)$$

where a , c , b , and k are the unknown constants, M is the global mean, $\mu(i, j)$ is local mean, and $\sigma(i, j)$ is local standard deviation of the entire input image. The M , $\mu(i, j)$, and $\sigma(i, j)$ can be formulated as follows:

$$M = \frac{1}{H \times V} \sum_{x=0}^{n-1} \sum_{y=0}^{n-1} (F(x, y)) \quad (3)$$

$$\mu(i, j) = \frac{1}{n \times n} \sum_{x=0}^{n-1} \sum_{y=0}^{n-1} [F(x, y)] \quad (4)$$

$$\sigma(i, j) = \left[\frac{1}{n \times n} \sum_{x=0}^{n-1} \sum_{y=0}^{n-1} [F(x, y) - \mu(i, j)]^2 \right]^{0.5} \quad (5)$$

where $H \times V$ is the total number of pixels in the input image, and a user-defined window of size $n \times n$ is used for local information extraction. The enhanced image is obtained using the transformation function with a, b, c , and k parameters. In our problem, the a, b, c and k are the variables that should be optimized. After obtaining the enhanced image, its quality is evaluated using a fitness function defined as follow:

$$\Theta(I_e) = \frac{\log(\log(E(I_{s(e)})) \times ne(I_e) \times H(I_e))}{H \times V} \quad (6)$$

where I_e is the enhanced image obtained by using transformation function, $I_{s(e)}$ is the image obtained by applying the Sobel edge detector operator to I_e , and $E(I_{s(e)})$ is sum of the edge pixel values in $I_{s(e)}$. The $ne(I_e)$ refers to the total number of edge pixels of the enhanced image, and $H(I_e)$ represents the entropy value of the enhanced image, which is calculated by using Eq. (7).

$$H(I_e) = \sum_{i=0}^{255} (h_i \log_2(h_i)) \quad (7)$$

where h_i is the probability of occurrence of i^{th} intensity level in I_e .

3 Proposed PSOKHA method

Gandomi and Alavi proposed the Krill herd algorithm (KHA) as a new nature-inspired search optimization algorithm for solving global optimization function [16]. The idea of the algorithm is to allocate krill individuals to inspect the search space to find feasible solutions, based on the herding behavior of the krill. The fitness function in KHA for each krill individual is measured by the highest density of the herd and shortest distance of each krill's position from food. The position of the krill individuals in the population are updated according to three basic motions, which are (i) movement of other krill individuals, (ii) location of food, and (iii) random diffusion. The movement of krill individuals can be formulated as a Lagrangian model as follows:

$$\frac{dx_i}{dt} = N_i + F_i + D_i \quad (8)$$

where N_i is related to the motion included by other krill individuals, F_i is related to new foraging motion and D_i is the physical diffusion of the i th krill individual. More detailed information about the KHA can be found in [10].

Particle Swarm Optimization (PSO) is one of the most commonly used metaheuristic algorithms that inspired by the concept of swarm intelligence in some animals such as flocks of birds or school of fish. The PSO has been successfully applied in numerous

application domains. Its modified versions and its hybrid with other algorithms have been vastly investigated in the literature. Birds are considered as particles with position and velocity in the algorithm. Particles keep flying in the search space to find the optimal position (solution), while the movement of each particle in the search space influenced by the optimal position of itself and its colleagues. A more detailed explanation of the steps of the PSO can be found in [17].

The proposed approach (PSOKHA) utilizes the combined attributes of PSO and KHA for efficiently enhancing the quality of images. The proposed PSOKHA is utilized to find the best set of values for a, b, c and k parameters of the transformation function that maximize the fitness function. The proposed PSOKHA involves the following steps:

1. A random population is of size N is initialized and a maximum number of iteration is fixed to a predefined value for both PSO and KHA separately. Each individual solution in both algorithms consists of four random values with specific ranges for a, b, c , and k parameters.
2. In the first step, PSO is utilized to enhance the original image. Using a, b, c and k values in the transformation function, each individual creates a new image. The quality of each image is determined by a fitness function. The individuals will be updated at each iteration to find optimal values for a, b, c , and k that produce higher fitness value.
3. After the terminate condition of the PSO is met, an enhanced image with new pixel intensities is obtained. This enhanced image is fed to the KHA for further enhancement. The step 2 is repeated for the KHA, and the best image with the highest fitness value is reported.

4 Experimental Results and Discussion

To compare the enhanced quality and optimization capabilities of the proposed enhancement algorithm, the performance evaluation has been conducted using the latest state-of-the-art enhancement algorithms. For a fair comparison of the results, the optimization algorithms (PSO, KHA, and the PSOKHA) were initialized with a constant population size of 35 and were run for a fixed number of iterations (100). The boundary limits for the optimized parameters are set to be $a \in [0, 1.5]$, $b \in [0, 0.5]$, $c \in [0, 1]$ and $k \in [0.5, 1.5]$. The proposed algorithm was tested on three satellite, medical and hand-written images to demonstrate the robustness of the proposed PSOKHA algorithm. Several metrics such as contrast, peak signal-to-noise ratio (PSNR), entropy, and structure similarity index (SSIM) were considered for quantification of enhancement efficiency of an algorithm. Tables 1, 2, 3, and 4 summarise the results achieved by comparing all of the above-mentioned metric values for the six various enhancement algorithms that have been evaluated using the given images. In each case, the best outcome is bolded and the second-best outcomes are underlined. The evaluation of the above-mentioned metric values for all the compared methods demonstrate that the proposed method outperforms the others. The PSNR values acquired for all comparative images show that using the suggested procedure, the quality of the processed image is well enhanced

considering the original image. The SSIM, which is a highly appropriate metric for evaluating the performance of an algorithm, shows that the proposed PSOKHA has great superiority over the other methods for all images. A high entropy value means that the improved image preserves all the information in the original image. The PSOKHA outperforms all the state-of-the-art algorithms in terms of entropy. Moreover, the contrast metric obtained from the gray-level co-occurrence matrix (GLCM) demonstrates the comparative performance of the PSOKHA against other algorithms.

Table 1. Comparison of PSNR for experimental images.

image	PSO	KHA	HE	SPE	BPDFHE	AGCWD	Proposed
Satellite	14.12	16.43	12.796	18.12	<u>24.78</u>	13.81	31.77
medical	18.83	18.77	16.35	12.22	29.98	14.34	<u>27.19</u>
Handwritten	13.9	20.05	10.53	21.01	<u>27.98</u>	16.08	29.90

Table 2. Comparison of SSIM for experimental images.

image	PSO	KHA	HE	SPE	BPDFHE	AGCWD	Proposed
Satellite	0.575	0.598	0.799	<u>0.923</u>	0.906	0.866	0.982
medical	0.435	0.699	0.826	0.530	<u>0.975</u>	0.893	0.978
Handwritten	0.456	0.874	0.405	0.898	0.894	<u>0.966</u>	0.972

Table 3. Comparison of entropy for experimental images.

image	PSO	KHA	HE	SPE	BPDFHE	AGCWD	Proposed
Satellite	<u>7.52</u>	7.59	5.59	6.33	6.66	6.80	7.23
medical	7.59	<u>7.62</u>	5.74	6.56	7.32	7.25	7.63
Handwritten	6.92	6.49	5.32	6.50	5.83	6.00	<u>6.74</u>

Table 4. Comparison of Contrast for experimental images.

image	PSO	KHA	HE	SPE	BPDFHE	AGCWD	Proposed
Satellite	3.98	<u>2.800</u>	1.240	1.257	1.020	1.069	1.297
medical	2.63	0.400	0.173	<u>0.473</u>	0.163	0.180	0.184
Handwritten	1.24	0.620	<u>0.680</u>	0.610	0.353	0.366	0.466

Fig. 1 demonstrates how our proposed method performs on three test images. This figure also shows the difference between the reference image histogram and the enhanced image. Histograms of all the enhanced images are much flatter than the original images (referring to a more uniform intensity distribution). The subjective evaluation of the images produced with all six enhancement algorithms is shown in Fig. 2. It indicates that the proposed PSOKHA algorithm not only enhances any minor detail in the image effectively but also maintains the average intensity of the images. The results also emphasize the robustness of the proposed algorithm, which makes it applicable to images from different domains.

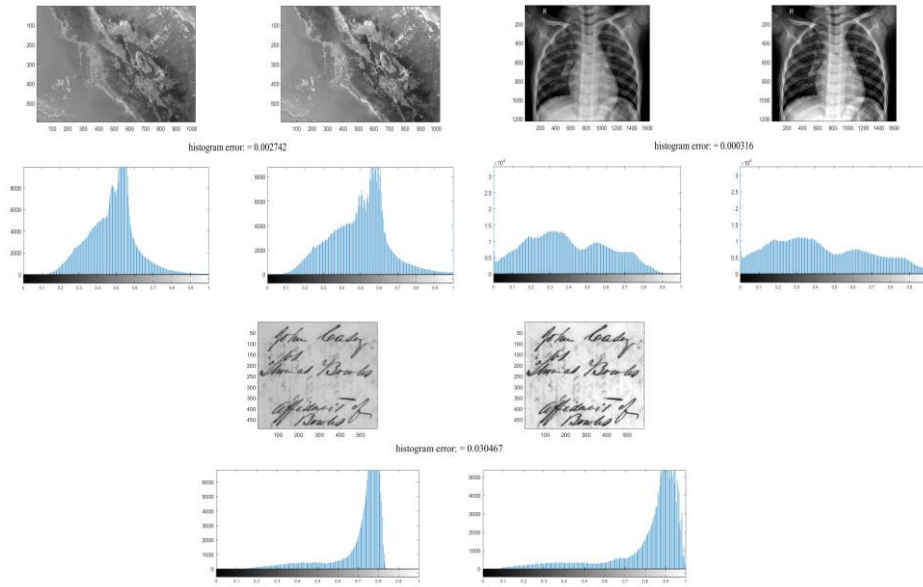
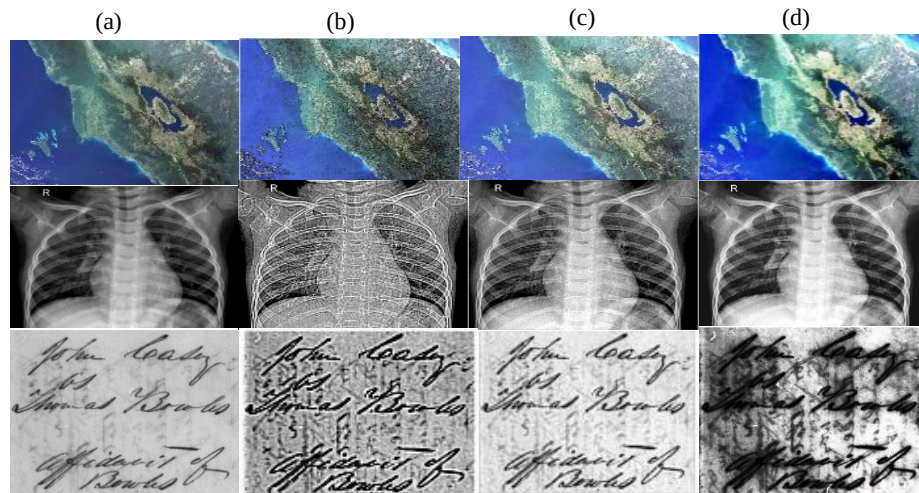


Fig. 1. Results of the proposed PSOKHA enhancement technique: (left) original image and its histogram, (right) the enhanced image and its histogram.



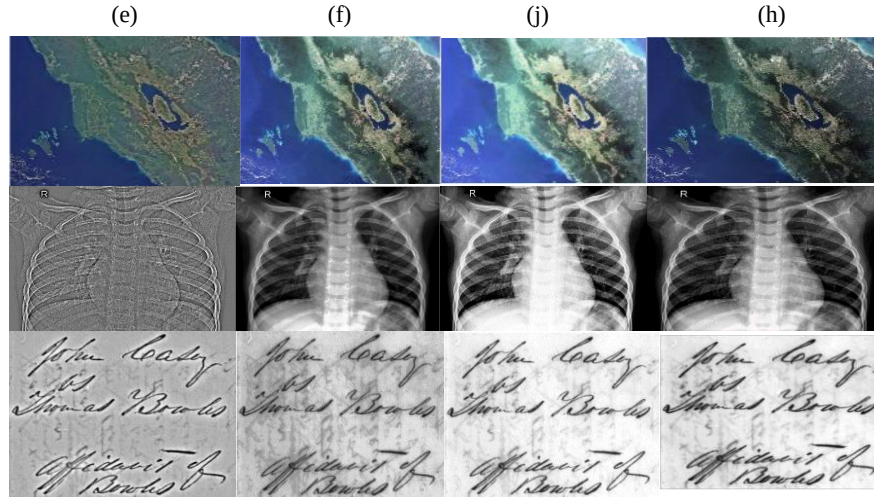


Fig. 2. Enhancement results of Images: (a) original, (b) PSO, (c) KHA, (d) HE, (e) SPE, (f) BPDFHE, (j) AGCWD, and (h) proposed PSOKHA.

5 Conclusion

In this paper, a new hybrid of two metaheuristic algorithms, namely particle swarm optimization (PSO) and krill herd algorithm (KHA) has been proposed for gray level image enhancement. The performance of the PSOKHA is evaluated on three different gray images: a medical image, a satellite image, and a handwritten image. The enhanced images obtained by the proposed method are compared with six states of art contrast enhancement techniques: PSO, KHA, HE, SPE, BPDFHE, and AGCWD. The computed performance metrics reveal that the proposed PSOKHA outperforms other approaches in all cases. Therefore, it can be concluded that the proposed PSOKHA possesses the potential for enhancing images, and can make images more visible by adjusting their contrast. As future work, the usefulness of the proposed method can be investigated in solving other related domains of image processing such as segmentation and noise reduction.

References

1. Gogna, A., Tayal, A.: Comparative analysis of evolutionary algorithms for image enhancement. *Int. J. Metaheuristics*, 2, 80 (2012). <https://doi.org/10.1504/ijmheur.2012.048219>.
2. Dhabal, S., Saha, D.K.: Image Enhancement Using Differential Evolution Based Whale Optimization Algorithm. In: *Advances in Intelligent Systems and Computing*, pp. 619–628. Springer Verlag (2020). https://doi.org/10.1007/978-981-13-7403-6_54.

3. Suresh, S., Lal, S.: Modified differential evolution algorithm for contrast and brightness enhancement of satellite images. *Appl. Soft Comput. J.* 61, 622–641 (2017). <https://doi.org/10.1016/j.asoc.2017.08.019>.
4. Nithyananda, C.R., Ramachandra, A.C., Preethi: Review on Histogram Equalization based Image Enhancement Techniques. In: *International Conference on Electrical, Electronics, and Optimization Techniques, ICEEOT 2016*. pp. 2512–2517. Institute of Electrical and Electronics Engineers Inc. (2016). <https://doi.org/10.1109/ICEEOT.2016.7755145>.
5. Hashemi, S., Kiani, S., Noroozi, N., Moghaddam, M.E.: An image contrast enhancement method based on genetic algorithm. *Pattern Recognit. Lett.* 31, 1816–1824 (2010). <https://doi.org/10.1016/j.patrec.2009.12.006>.
6. Gorai, A., Ghosh, A.: Gray-level image enhancement by particle swarm optimization. In: *2009 World Congress on Nature and Biologically Inspired Computing, NABIC 2009 - Proceedings*. pp. 72–77 (2009). <https://doi.org/10.1109/NABIC.2009.5393603>.
7. Chen, J., Yu, W., Tian, J., Chen, L., Zhou, Z.: Image contrast enhancement using an artificial bee colony algorithm. *Swarm Evol. Comput.* 38, 287–294 (2018). <https://doi.org/10.1016/j.swevo.2017.09.002>.
8. Dhal, K.G., Iqbal Quraishi, M., Das, S.: Development of firefly algorithm via chaotic sequence and population diversity to enhance the image contrast. *Nat. Comput.* 15, 307–318 (2016). <https://doi.org/10.1007/s11047-015-9496-3>.
9. Agrawal, S., Panda, R.: An efficient algorithm for gray level image enhancement using cuckoo search. In: *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. pp. 82–89 (2012). https://doi.org/10.1007/978-3-642-35380-2_11.
10. Bolaji, A.L., Al-Betar, M.A., Awadallah, M.A., Khader, A.T., Abualigah, L.M.: A comprehensive review: Krill Herd algorithm (KH) and its applications, (2016). <https://doi.org/10.1016/j.asoc.2016.08.041>.
11. Kandhway, P., Bhandari, A.K., Singh, A.: A novel reformed histogram equalization based medical image contrast enhancement using krill herd optimization. *Biomed. Signal Process. Control.* 56, 101677 (2020). <https://doi.org/10.1016/j.bspc.2019.101677>.
12. Kim, H.-J., Lee, J.-M., Lee, J.-A., Oh, S.-G., Kim, W.-Y.: Contrast Enhancement Using Adaptively Modified Histogram Equalization. Presented at the (2006). https://doi.org/10.1007/11949534_116.
13. Morel, J.-M., Petro, A.-B., Sbert, C.: Screened Poisson Equation for Image Contrast Enhancement. *Image Process. Line.* 4, 16–29 (2014). <https://doi.org/10.5201/ipol.2014.84>.
14. Sheet, D., Garud, H., Suveer, A., Mahadevappa, M., Chatterjee, J.: Brightness preserving dynamic fuzzy histogram equalization. *IEEE Trans. Consum. Electron.* 56, 2475–2480 (2010). <https://doi.org/10.1109/TCE.2010.5681130>.
15. Huang, S.C., Cheng, F.C., Chiu, Y.S.: Efficient contrast enhancement using adaptive gamma correction with weighting distribution. *IEEE Trans. Image Process.* 22, 1032–1041 (2013). <https://doi.org/10.1109/TIP.2012.2226047>.
16. Gandomi, A.H., Alavi, A.H.: Krill herd: A new bio-inspired optimization algorithm. *Commun. Nonlinear Sci. Numer. Simul.* 17, 4831–4845 (2012). <https://doi.org/10.1016/j.cnsns.2012.05.010>.
17. Yang, X.S., Karamanoglu, M.: Swarm Intelligence and Bio-Inspired Computation: An Overview. In: *Swarm Intelligence and Bio-Inspired Computation*. pp. 3–23. Elsevier Inc. (2013). <https://doi.org/10.1016/B978-0-12-405163-8.00001-6>.