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A Novel Lossless Image Compression Technique Based on Firefly Optimization Algorithm

[1]Abdulrahman Alturki and [2]Abdulrahman A. Alrobaian
[1]Department of Electrical Engineering, College of Engineering, Qassim University, Buraydah, Saudi Arabia
[2]Department of Mechanical Engineering, College of Engineering, Qassim University, Buraydah, Saudi Arabia

Abstract: Image compression still remains a hot research topic due to the generation of massive amount data which needs to be stored or transmitted. Numerous approaches have been presented for image compression to represent the images in a compacted form with no repeated or unrelated pixels. Presently, evolutionary algorithms become more popular to solve the real world problems in an efficient manner. In this study, Firefly (FF) optimization algorithm based on Discrete Cosine Transformation (DCT) is introduced to determine the best fitness value for all DCT block. When the fitness values are computed for DCT blocks, compression process takes place. To enhance the overall compression performance, image warping process is also used as a preprocessing step. However, Space Invariant Feature Transform (SIFT) matching procedure is employed to validate the difference between reference and reconstructed image. A detailed comparison study is performed between the proposed Firefly (FF) algorithm and existing Pollination Based Optimization (PBO) using a set of benchmark images. The proposed method is successfully applied and the experimental analysis prove that the presented FF method is found to be better than previous methods in terms of various performance measures like Compression Ratio (CR), Compression Time (CT), Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE) and Structural Similarity Index (SSIM).

Key words: Image compression, lossless, SIFT, MSA, pixels, validate

INTRODUCTION

Due to the growth of internet and high-end electronic devices, large amount of data is being generated at each and every second. It creates a major demand of storing or transmitting data at a reasonable amount of time and space. To effectively utilize the available computational resources to store or transmit data, data compression techniques are introduced to save communication bandwidth and memory (Bookstein and Storer, 1992). Particularly, image compression techniques are useful to compress images by the avoidance of unwanted and repetitive pixels. In the recent days, the field of image compression gains more attention and more researches are carried out in this field. Pixels are considered as the basic element of an image where the reduction in number of pixels reduces the image size effectively (Rehman *et al*., 2014). Image compression techniques are broadly classified to lossless and lossy image compression techniques (Drost and Bourbakis, 2011). In lossless compression, the image quality is retained where the decompressed image is same as the applied original image (Holtz, 1993). Satellite imaging, medical imaging and several quality sensitive applications follow lossless compression. At the same time, some kinds of applications like browsing, social media allow loss of information to a particular level. In this case, lossy image compression is usually recommended. Next, based on the process of compression, image compression techniques are classified to predictive and transform based coding techniques. Predictive coding techniques identify the future values based on the present pixels and the differences in pixel values are encoded. Contrastingly, transform coding techniques converts the image to an intermediate representation and the transformed values are compressed by any other coding techniques. On comparing the effectiveness of the predictive and transform coding techniques, predictive coding performs worse and transform coding is found to be efficient. But to enhance the efficiency of transform coding technique, image warping procedure can be employed as a pre-processing step. Image warping is defined as the process of digital manipulation of an image in a way that the shapes portrayed in the image have been

Corresponding Author: Abdulrahman S. Alturki, Department of Electrical Engineering, College of Engineering, Qassim University, Qassim, Buraydah, Saudi Arabia

significantly distorted (Heikkila and Silven, 1997). This step decreases the distortion in the images and thereby increases the compression performance. Image warping is a geometric transformation technique which maps every individual position in an image plane to positions in another plane. It is useful in several image analysis applications, intends to register an image with a map or alignment of two or more images. Scale Invariant Feature Transform (SIFT) technique is introduced to assess the level of matching between the original and the reconstructed images. SIFT algorithm is commonly used for image matching or detection, to identify local features in images.

The key points of SIFT are initially identified from the reference image and stored in a database. After decompression, the key points stored in the database are compared with the key points identified in the reconstructed image. When more number of key points is perfectly matched it implies the better quality of the decompressed image.

The contribution of the study is summarized here. This study introduces Firefly (FF) algorithm to compute the DCT coefficients of an image in an optimized manner. Then, the computed AC and DC coefficients are encoded by RLE and Huffman coding, respectively. In addition, the proposed method incorporates image warping process and SIFTS matching procedure to improve the overall compression performance and reconstructed image quality. The results of the presented FF algorithm is evaluated using a set of 10 benchmark images and the obtained values are compared with existing Pollination Based Optimization (PBO) method in terms of MSE, PSNR, SSIM, CR and CT, respectively.

Literature review: Least-Square (LS) based adaptive prediction method for lossless compression of natural images is adapted by Li and Orchard (2011). The results imply the proposed method outperformed because of the nature of edge-directed property that allows the predictor to adjust well from smooth regions to edge areas. By Aiazzi *et al.* (2002), a differential pulse code modulation technique adaptable for lossless and near-lossless compression is proposed of monochrome still images. It uses a classified linear-regression prediction proceeded by context-based arithmetic coding of the output residuals. This method performs well than JPEG-LS interms of bit rate, particularly for medical images. Deever and Hemami (2003) introduced a projection-based method to decrease first-order entropy of transform coefficients and improves compression results of IWT. To minimize the encoding time of fractal images, particle swarm optimization algorithm is developed by Muruganandham and Banu (2010). By Horng and Jiang (2011), Honey Bee Mating Optimization (HBMO) algorithm is employed to build the codebooks of vector quantization. The HBMO method achieved better codebooks with lesser distortion levels. Similarly, by Horng (2012), FF algorithm is also used to build the codebooks efficiently. By Ukrit and Suresh (2013), the presented technique integrates super-spatial structure prediction with interframe coding to attain better CR. To enhance the CR, a new method called head code compression is presented. The performance of this method for medical images attains 25% more compression than previous works. By Paul and Bandyopadhyay, (2014), a histogram based image compression method is introduced on the basis of multi-level image thresholding.

Wu (2014) presented a Genetic Algorithm (GA) based on DWT to eliminate the limitation of high computational time of fractal encoder. A lossless image compression method is developed by the integration of IWT with a prediction step by Fouad (2015). Mohammed Ismail also, reduced the fractal image encoding time by the use of Cuckoo Inspired Fast Search (CIFS) technique (Omari and Yaichi, 2015). CIFS technique makes use of vectors of range blocks which are arranged by the level of resemblance and coordinate distance, respectively. Kaur *et al.* (2015) introduced a lossless image compression technique for compressing significant parts by the extraction of a region of interest in DICOM images. Then, Huffman coding is used to compress the extracted region and GA, further enhances the compression performance. Ismail *et al.* (2018) exploited the relativity between fractional numbers and their respective quotient representation. Every individual sub-image is mapped to a fractional number by RGB representation and then decreased to an effective quotient. Jindal and Kaur (2016) introduced Pollination Based Optimization (PBO) algorithm in image compression based on the fitness value of a DCT block of image data.

MATERIALS AND METHODS

The lossless image compression algorithm: The proposed method operates on three stages: image warping process, computation of DCT using FF algorithm and SIFT matching. At the beginning, the image needs to compressed is loaded and is divided to 8×8 blocks of sub images. Then, SIFT matching process extracts the key points from the image and archived it in a database. The sub images are initially undergoes image warping process. Image warping is a pre-processing technique used to reduce image distortion, so that, the compression

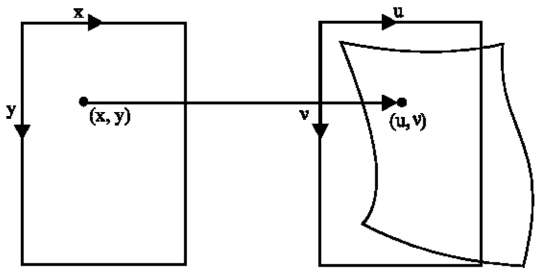

Fig. 1: Notation of image warping

performance can be maximized. Then, the warped image is compressed using FF algorithm based on DCT. The coefficients of DCT are encoded by RLE and Huffman coding technique. During decompression, the reverse operation takes place with RLE decoding, Huffman decoding, IDCT and image warping. Once, the image is reconstructed in the decompression process, SIFT matching finds key points in this image and a comparison is made with the key points in the database to identify the reconstructed image quality.

Pre-processing: Before compressing an image, some pre-processing techniques are employed to facilitate the image compression process. Here, image warping technique is used to eliminate optical distortions produced by camera or viewing perspectives (Tang and Suen, 1993). Image warping is a geometric transformation technique which maps every individual position in an image plane to positions in another plane (Brown, 1992). It is useful in several image analysis applications, intends to register an image with a map or alignment of two or more images. The selection of wrap is done by a compromise between smooth distortion and one which attains a better match. Smoothness is verified by the assumption of a parametric form for the wrap or limiting it by differential equations. Matching is indicated by points to be brought into alignment by local measures of image correlation or by the coincidence of edges. A warping is defined as a pair of 2D functions, u(x, y) and v(x, y) which maps a position (x, y) in one image to position (u, v) in another image where x and y represents the column and row numbers, respectively as shown in Fig. 1 and 2.

FF algorithm: The overall process of the presented FF algorithm is given in Fig. 2. In the year 2007 and 2008, Yang (2009) introduced a metaheuristic algorithm named FF algorithm, based on the flashing patterns and behavior of FFs. The FF algorithm follows three rules; FFs are unisex.

Attractiveness is based on the brightness of the flashlights; the lesser bright FF will be attracted towards

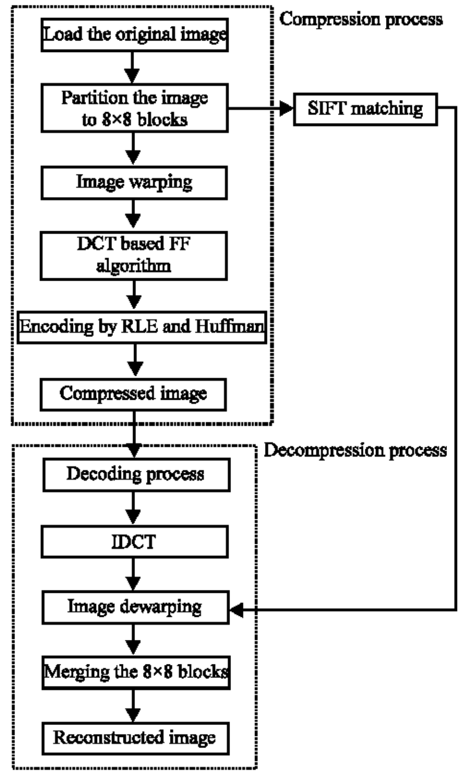

Fig. 2: Overall process of the proposed algorithm

the brighter FF. Since, the FF attractiveness is a monotonically decreasing function of the distance to the selected FF, e.g., the exponential function Eq. 1 and 2:

$$r_{ij} = \left\| x_i - x_j \right\| \tag{1}$$

$$\beta = \beta_0 e^{-\gamma r_{ij}} \tag{2}$$

Where:

β_0 = The attractiveness at $r_{ij} = 0$
γ = The light absorption coefficient at the source

The movement of a FF i is attracted to other FF j and is calculated Eq. 3 and 4:

$$x_{i,k} \leftarrow (1-\beta) x_{i,k} + \beta x_{j,k} + u_{i,k} \tag{3}$$

$$u_{i,k} = \propto \left(r \text{ and } 1 - \frac{1}{2} \right) \tag{4}$$

The specific FF xi with maximum fitness will moves in a random manner based on Eq. 5-7:

$$x_{i,k} \leftarrow (1-\beta) \tag{5}$$

$$x_i \max_{,k} \leftarrow x_i^{+} \max_{,k} u_i \max_{,k} \quad (6)$$

$$u_i \max_{,k} = \propto \left(r \text{ and } 2\text{-}\frac{1}{2} \right) \quad (7)$$

where are r and ≈U(0, 1) r and 2≈(0, 1) random numbers attained from uniform distribution. The brightness of the FF is computed by the landscape of the objective function.

Scale Invariant Feature Transform (SIFT) matching: SIFT algorithm is commonly used for image matching or detection to identify local features in images (24). For any object in the reference image, interesting points (key points) on the object are identified to give feature description about the object. The description obtained from the reference image can be employed to determine the object when intends to identify the object in a test image which holds several objects. Here, the key points of SIFT are initially identified from the reference image and stored in a database. Then the compression and decompression process takes place. Once, the image is reconstructed, the object in the reconstructed images are discovered by the individual comparison of every feature from this image with the database to compute candidate matching features by the use of the euclidian distance between the feature vectors. Using the complete set of matches, a subset of key points which agrees on the object its position, scaling and orientation in the reconstructed image are determined to extract the good matches. At last, the possibility of a certain set of features denotes the presence of objects. When an object passes all these criteria it can be identified as correct with high confidence.

RESULTS AND DISCUSSION

The highlights of the presented FF algorithm is verified by applying a collection of 10 benchmark images from (25) dataset. The proposed method is successfully applied and the experimental analysis prove that the proposed method is found to be superior than existing methods in terms of various performance measures like CR, CT, MSE, PSNR and SSIM. The comparison results of proposed and PBO method is tabulated in Table 1. Figure 3-7 illustrates the compared results of proposed and exiting methods. Figure 3 provides the obtained results of proposed method interms of CR. From Fig. 3, it is clear that the CR of the FF algorithm is significantly better than the existing method. FF algorithm obtained a better CR of 0.277 for some of the images which is much

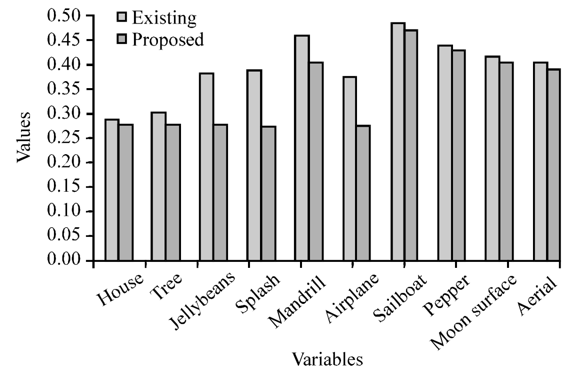

Fig. 3: Performance analysis of two methods in terms of CR

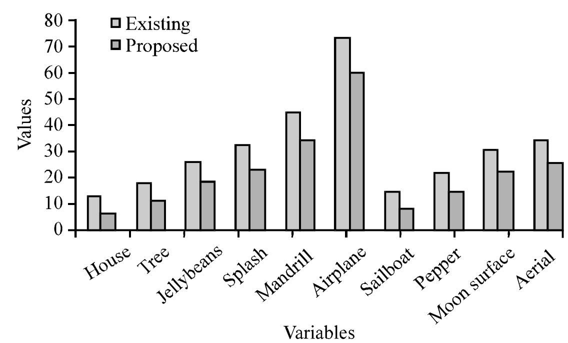

Fig. 4: Performance analysis of two methods in terms of CT

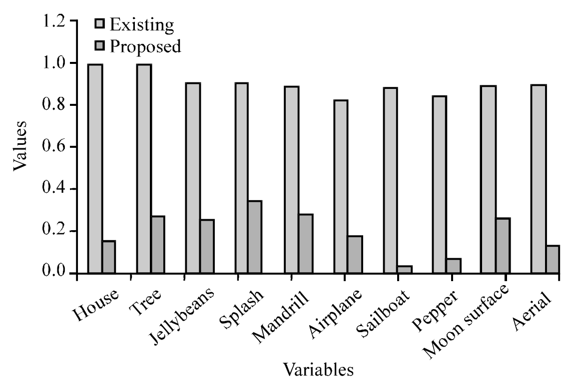

Fig. 5: Performance analysis of two methods in terms of MSE

lower than the PBO method. In terms of CT, Fig. 4 illustrates the results of proposed and compared methods. From this Fig. 4, it is clearly shown that the CT of proposed method is much lower than the PBO method. The proposed method attains a minimum CT of 6.76 and maximum CT of 59.71 sec, respectively. Likewise, the PBO

Table 1: Comparison results of proposed method and PBO method interms of various metrics

Image dataset	CR Existing	CR Proposed	MSE Existing	MSE Proposed	PSNR Existing	PSNR Proposed	SSIM Existing	SSIM Proposed	CT (sec) Existing	CT (sec) Proposed
House	0.29	0.278	0.993	0.151	48.19	64.55	0.69	0.98	13	6.76
Tree	0.303	0.277	0.977	0.267	48.33	59.60	0.68	0.96	18	11.14
Jellybeans	0.383	0.277	0.898	0.25	49.07	60.17	0.74	0.98	26.09	18.23
Splash	0.389	0.277	0.896	0.342	49.08	57.45	0.61	0.90	31.8	23.23
Mandrill	0.461	0.402	0.888	0.283	49.16	59.10	0.75	0.96	44.6	34.44
Airplane	0.372	0.277	0.813	0.175	49.93	63.27	0.65	0.98	73.44	59.71
Sailboat	0.483	0.471	0.877	0.022	49.27	81.28	0.72	0.99	14.67	8.22
Peppers	0.439	0.427	0.833	0.063	49.72	72.14	0.64	0.99	21.99	14.64
Moon surface	0.416	0.404	0.885	0.259	49.19	59.86	0.67	0.95	30.9	22.44
Aerial	0.402	0.39	0.89	0.127	49.14	66.05	0.66	0.98	34.33	25.45

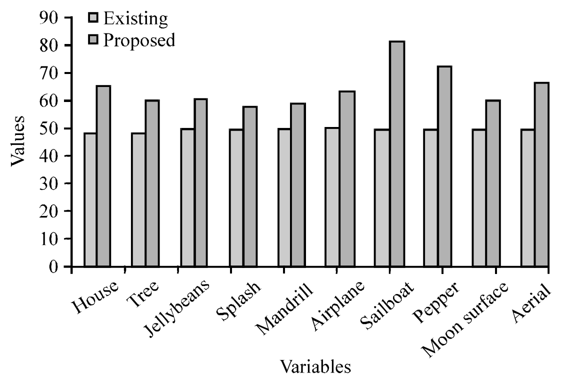

Fig. 6: Performance analysis of two methods in terms of PSNR

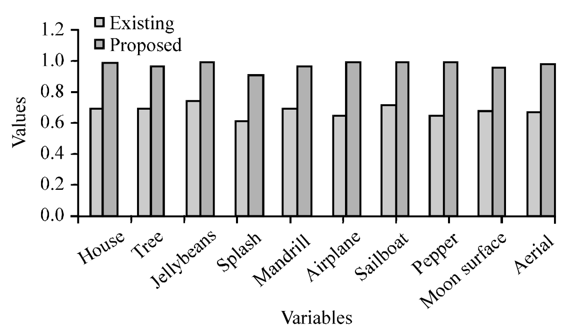

Fig. 7: Comparison of various methods in terms of SSIM

method obtained a minimum CT of 13 sec and maximum CT of 73.44 sec, respectively. Next, Fig. 5 shows the attained values of proposed method on the basis of MSE. The lower values of MSE achieved by proposed method imply better compression performance. Similarly, the higher value of MSE by the existing PBO method denotes worse compression performance. Then, the results of proposed and existing methods in terms of PSNR are depicted in Fig. 6. The PBO method resulted to a PSNR of 49.93 which is very low when compared to the proposed method value of 81.28. Finally, Fig. 7 illustrates the SSIM values of proposed and PBO methods. Since, SSIM indicates the level of resemblance between applied and decompressed images. The proposed method produces SSIM values closer to 1 for all the images which represents the better level of resemblance than PBO method.

CONCLUSION

This study has proposed a novel lossless image compression technique using FF algorithm which is one of the popular metaheuristic algorithms found in the literature. FF algorithm is inspired from the flashing patterns and behaviors of FFs. Image warping and SIFT matching process is also incorporated to FF algorithm to enhanced the efficiency of the proposed method. The results of the proposed method is evaluated using a set of 10 benchmark images and the obtained values are compared with existing Pollination Based Optimization (PBO) method in terms of various performance metrics such as MSE, PSNR, SSIM, CR and CT, respectively. All of the obtained results ensured that the proposed method is superior to PBO method in terms of several performance measures.

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