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Compressing Face Images Using Genetic and Gray Wolf Meta-heuristic Algorithms Based on Variable Bit Allocation

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ABSTRACT

In image processing, compression plays an important role in monitoring, controlling, and securing the process. The spatial resolution is one of the most effective factors in improving the quality of an image; but, it increases the amount of storage memory required. Based on meta-heuristic algorithms, this article presents a compression model for face images with block division and variable bit allocation. Wavelet transform is used to reduce the dimensions of high spatial resolution face images. In order to identify important and similar areas of identical macroblocks, genetic algorithms and gray wolves are used. A bit rate allocation is calculated for each block to achieve the best recognition accuracy, average PSNR, and SSIM. The CIE and FEI databases have been used as case studies. The proposed method has been tested and compared with the accuracy of image recognition under uncompressed conditions and using the common SPIHT and JPEG coding methods. Recognition accuracy increased from 0.18% for 16×16 blocks to 1.97% for 32×32 blocks. Additionally, the gray wolf algorithm is much faster than the genetic algorithm in reaching the optimal answer. Depending on the application type of the problem, the genetic algorithm or the gray wolf may be preferred to achieve the maximum average PSNR or SSIM. At the bit rate of 0.9, the maximum average PSNR for the gray wolf algorithm is 34.92 and the maximum average SSIM for the genetic algorithm is 0.936. Simulation results indicate that the mentioned algorithms increase PSNR and SSIM by stabilizing or increasing recognition accuracy.

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1. INTRODUCTION

In general, the process of compression and recognition reduces the quality of the image by increasing the compression ratio. The study of block transform coding systems has been conducted in a variety of domains of discrete two-dimensional transformations. As a result, most coding systems in this regard rely on sinusoidal transformations (such as DFT or DCT) that provide more accurate and closer estimates of information packaging and computational complexity. Choosing a particular transform for a particular application depends on the amount of reconstruction error that can be tolerated and the computational resources available. The JPEG format uses a DCT conversion method that offers a good compromise between information packing capability and computational complexity. One of the challenges of facial recognition systems is maintaining the rate of image recognition. Today, due to the advancement of technology, most cameras are equipped with high resolution, which is usually expressed in megapixels. High spatial resolution, on the other hand, is one of the most important factors for increasing image quality, resulting in a larger storage volume. Reducing the resolution to a lower limit will decrease recognition accuracy, and the higher the resolution, the desired quality.

Many face recognition applications capture images with low resolution. Because face recognition methods are trained on high resolution face images, they perform poorly on low resolution images. Compression rates for lossy methods are much higher than those for lossless methods. The smaller the image size, the faster it can be compressed and transferred, and it requires less storage

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space. A point that is preferable to other aspects. Due to this, the proposed method, which allows simultaneous access to high compression rates while maintaining or improving the accuracy of image recognition, is suitable for the intended applications. However, these methods always result in distortions by destroying some of the primary data. At lower bit rates, the amount of distortion increases. The most important application of face images is in the recognition of people, and as such, the amount of distortion may be so high that it reduces the accuracy of recognition, it is important to provide a method that does not reduce the recognition rate.

Mobile phones and social networks have led to an increase in the production of digital content today. Recent advances in compression methods such as H.265 or HEVC have enabled CCTV images to be compressed and encoded in high quality [1]. As a general rule, the smaller the images, the faster they will be compressed and transmitted, and the less storage space they will require [2]. As the volume of information in circulation is so large, managing and optimizing these processes is of utmost importance. Therefore, it is very important to compress images. Images are usually compressed in such a way that some details are lost. When the removed details are noisy and do not contain important and real details of the face, the recognition percentage may even be increased. The primary objective of image compression is to reduce the number of bits necessary to display an image, since the transfer of images is a costly process [3]. Image compression begins with identifying data redundancy, and among the types of data redundancy, we can mention cryptographic redundancy [4], inter-pixel redundancy [5], and psychovisual redundancy [6]. The main objective of image compression algorithms is to reduce all types of image redundancy. As a result, the type of algorithm to use depends on how the image is to be used. Video surveillance systems place a high value on the compression of face images, and the images are always designed to consume the least amount of bandwidth possible. Therefore, infrastructure equipment should be considered much smaller, with lower energy consumption and lower costs.

By compressing facial images, in addition to removing redundancies, the distortion resulting from compression should not affect or even increase the recognition percentage of the system. Face images with a low degree of spatial resolution are compressed under conditions in which the distance between two eyes is approximately 90 pixels and the image dimensions are approximately 180-200 pixels. However, in this article, facial images with a high degree of spatial resolution have been evaluated, and, therefore, the conditions considered are for images larger than the approximate dimensions, usually 200××.

Finding compression methods that have minimal impact on image processing systems is an interesting area of research. Meta-heuristic algorithms have recently emerged with significant power in solving optimization problems [7]. The optimization of objective criteria in compression by examples of these algorithms has been investigated. However, the impact these improvements have on the compression of face recognition systems has received less attention.

In this article, a compression method is used to allocate the bit budget from meta-heuristic algorithms (genetics and gray wolf) for identifying valuable areas without reducing the recognition rate of facial images. An optimization problem can be solved in a variety of ways. A number of these methods [8, 9] are derived from natural processes. The genetic algorithms are under the search algorithms and instead of directly dealing with the values of the parameters of the problem, they operate on a coded representation of the set of parameters. To find solutions to the problem and optimize the objective function of the problem, they search a population of points in a search space without knowing the gradient information related to the objective function. A genetic algorithm is a type of evolutionary algorithm that uses biological methods such as inheritance and mutation. One of these algorithms, inspired by the genetics of living organisms, seeks to find an optimal state within a reasonable period of time [10]. The gradient of the objective function is used as a guide in most computational optimization methods. However, these methods often encounter difficulties if, for example, the objective function is discontinuous and its derivative cannot be calculated. Genetic algorithms are often beneficial to regression-based prediction methods [11]. It is, however, the aim of the discussion to identify a suitable answer among a variety of samples that will provide an optimal learning system that delivers high accuracy and significant speed. In this case, the topic is to identify the best learning system with a high level of accuracy and significant speed from a variety of samples. In this learning system, in fact, the loop process of accessing the optimal estimation of the bit rate of each of the blocks separately, is performed, provided that the recognition accuracy of images is equal to the condition without compression (the highest value of recognition accuracy) or even greater if it is possible.

Genetic algorithms are usually based on repetition, most of their parts are chosen at random, and they are considered to be meta-heuristic methods for discrete optimization. The popularity of meta-heuristic methods can be attributed to their flexibility, derivative-free mechanism, and ability to avoid getting stuck in local optima. These methods [12] are relatively simple and are founded on very simple concepts. This article also discusses the gray wolf algorithm, which is based on collective intelligence and the life of gray wolves [13]. In these animals, the leader, or alpha, makes decisions regarding areas such as attack and timing. According to this algorithm, the hunting method of this kind of animal involves tracking, chasing and approaching the prey. It involves following and encircling the prey until it stops moving, and then attacking it. In order to model wolf social behavior, a random population of solutions is generated, and the most appropriate is referred to as (α). As well as the second best solution, other solutions are known as wolves of packs (ω). As such, the gray wolf algorithm uses the following three answers to guide hunting (optimization).

Meta-heuristic algorithms are designed to find the optimal solution within a reasonable amount of time. A process can be optimized by improving it, as we know. Essentially, optimization involves adjusting inputs, the characteristics of a device, a mathematical process, or an experiment in order to achieve the minimum or maximum output [14]. To achieve a reasonable and good answer at the right time, instead of searching all the states, we use various meta-heuristic methods [15]. While working in a lossy environment, an image data compression algorithm [16] should preserve most of the data's features and be less complex in algorithmic terms. The general nature of these methods [17-19] usually begins with a set of variables and continues until the objective function reaches a minimum or maximum value. The image of a face is one of the most popular and widely used images. There is a growing importance of the issue of identity verification in surveillance systems [20], control systems [21] and security systems [22]. Most of these systems require a large database of face images of different people, especially when they are used in large, international and significant organizations. Meanwhile, the effectiveness of these systems is highly dependent on the correct identification of facial features and the correct detection of facial areas [23]. Some features of the face play an instrumental role in face recognition, and it is critical not to lose this information when compressing images. When compressing face images, it is a priority to maintain the quality of valuable features of the face at an appropriate level, particularly at low bit rates [24]. As part of the proposed method, it is automatically determined for each image to decompose the input image I(i,j) into several levels (L), and to use the approximate sub-image of each level as the basis for further processing. This means that after the implementation of the last decomposition step in the proposed method, the approximation sub-image is delivered to the segmentation block as the input image with low level resolution. In this research, A meta-heuristic algorithm (genetics and gray wolf) is responsible for allocating the bit budget in this research. In part 2, previous research on image compression methods, especially those for face images, is reviewed. In section 3, the proposed method will be described in detail, and its evaluation results will be compared to those obtained from several reference methods. In section 4, we discuss the conclusion.

2. RELATED WORKS

Most of the methods that have been proposed for image compression are general-purpose, which is an advantage since they can be applied to a wide variety of images. On the other hand, it is a negative point and does not take into account the content of the images. As a consequence, all-purpose methods are not able to optimally utilize the abundance of images within a limited set of categories (face, medical, text, etc.). The use of smart optimization methods can offer much better solutions to these problems. Meta-heuristic optimization methods and evolutionary algorithms are effective and constructive methods for solving feature selection problems. With approximate algorithms, it is possible to find effective (near-optimal) solutions to difficult optimization problems. A heuristic, a meta-heuristic, and a super-heuristic are examples of approximate algorithms. We present meta-heuristic algorithms to solve the problem of heuristic algorithms getting stuck in local optimal points and converge prematurely to them. Meta-heuristic algorithms can be classified according to a variety of factors:

I. Based on a single answer and the population as a whole
II. Natural and non-natural designs
III. Memory and non-memory
IV. Definite and probable
V. Algorithms based on collective intelligence.

The use of smart optimization methods can provide much better solutions to these problems. As a consequence, meta-heuristic optimization methods and evolutionary algorithms are effective and constructive methods for solving feature selection problems. Nowadays, it is possible to compress images using various classical or meta-heuristic algorithms, and in this regard, many experts have presented various ideas [25]. To learn algorithms and repeat the process, many calculations must be made in order to use these methods and different functions to approach learning, optimization, decision-making, etc. A learning system, however, must be able to find the optimal answer with high accuracy among various samples. Based on the proposed method, the loop process of accessing the optimal bit rate estimation for each of the blocks is based on the assumption that the accuracy of image recognition is equivalent to the discussed methods, or even higher if possible.

The number of compression methods for natural images and even text images is relatively small in comparison. As a result, no specific classification has been provided for these methods. One of the reasons for the low number of methods may be the lack of serious attention paid to the uniqueness of these images [26]. Face images are usually compressed using images with a low spatial resolution (usually images with a dimension of 200×200), and in most cases, the use of high resolution images has not been investigated. In relevant applications, there is a very limited amount of space allocated for storing face images [27]. Recent years have seen the introduction of intelligent and meta-heuristic methods for solving image compression problems. Unlike precise optimization methods, these algorithms look for points close to the global optimum, based on rules that govern natural phenomena. As a result of meta-heuristic methods, optimal solutions can be found at acceptable computational costs, but there is no guarantee that they will lead to the optimal solution, and the results are entirely random. Consequently, these methods are also known as imprecise methods [28], as random mechanisms have a significant impact on their structure. The most influential and widely used approaches include genetic algorithms [29], differential evolution algorithms [30], particle swarm algorithms [31], ant colony algorithms [32], honey bee algorithms [33], used in various industries today. Asiedu et al. [34] presented a face recognition algorithm based on wavelet transforms and compression coefficient values. Based on sparse representation (SRC), the classification method compares residual errors between test samples and reconstruction samples. The algorithm not only improves recognition and reliability, but it also reduces detection time to some extent [35]. A matrix of facial features is extracted and classified. Compared with reconstructed samples. The results using the ORL[1] and FERET [36] databases have shown that this method provides better recognition capability, accuracy, and recognition speed than traditional methods.

He and Chen [37] proposed a novel variable block size for a face image compression method (E2EFIC), whose parameters can be automatically optimized based on gradient feedback. Image compression uses a network (GAN). The metrics should be applied directly to the image compression scheme. This scheme has been demonstrated to be effective by showing a performance improvement of 71.71%, 48.28%, and 52.67% when compared with JPEG2000, WebP, and neural network encodings. This is under the same face accuracy measurement. To enhance face recognition in low-resolution images, a Generative Adversarial Network is employed by Shahbakhsh and Hassanpour [38]. The network considers image edges and reconstructs high-frequency details in order to preserve the structure of the face. Any face recognition method can benefit from the proposed technique for generating super-resolved features. In order to preserve the structure of the face, the proposed network considers image edges and recovers high-frequency details. Using the generated high resolution features, any face recognition method can be improved in terms of recognition accuracy.

Selimović et al. [39] performed content-aware compression by prioritizing the areas of the image that are more relevant to the interpretation of the image and compressing them at a higher bit, i.e. without loss or with less loss. Encodes information about the rest of the image. By examining multiple regions of interest (MS-ROI), a convolutional neural network (CNN) is able to locate different regions of interest within an image. It is expressed as a sensitivity map that characterizes the relevance of different regions of the image and provides a merit value for every pixel. As a result of this information, compression is guided. This method [40] examines the recognition of remote face recognition (FR) schemes within the framework of compact image recognition (CS). Using predictors such as autoencoder that provide compact measurements, error images can be obtained as the difference between original and predicted images. Subsampled measurements of the thin error image and part of the original image are then transmitted. At the destination end, the test image is reconstructed from the CS error image and the partial information. Following the reconstruction of the image, principal component analysis is used to extract significant features. The performance of the proposed method has been evaluated on both AR and ORL databases, with 93.99% accuracy for the former and 91.5% accuracy for the latter.

Asghari Beirami and Mokhtarzade [41] proposed a new method for FR called multiscale Gabor covariance-based ensemble Log-euclidean SVM (MGcov-ELSVM), which utilizes descriptors of Gabor magnitude and phase derived from multiscale face representations. MGcov-ELSVM begins by producing multiscale representations of faces. In the second stage, Gabor magnitude and phase features are derived from multiscale face images. The Gabor magnitude and phase features are then used to generate covariance descriptors. As a final step, log-Euclidean SVM classifiers are used to classify covariance descriptors, and a majority voting method is used to determine the recognition results. According to experimental results from two face databases, ORL and Yale, the MGcov-ELSVM outperforms some recent FR methods. Elad et al. [24] described compressing face images by changing the geometric shape to a standard form, dividing the resulting image into blocks, and then coding each block according to the vector quantization (VQ) method. The method has been used to exploit the excess of the same facial features in different individuals. This was done by converting images to standard form and

[1] https://paperswithcode.com/dataset/orl

using VQ in order to increase compression efficiency, particularly at low bit rates. One disadvantage of this method is the long training time for the VQ data culture. In addition, there is the relatively large external memory required to store this data culture in both the encoder and decoder. Another disadvantage of this method is the visual disruptions created by the block method and the separate coding of each block in the image. Al-Khafaji et al. [42] introduced a new mathematical iterative polynomial model to represent both coding bases. The model proposes an efficient hybrid way where coefficients are represented as lossless while residuals are presented as a lossy but with minimum loss, which ensures effective performance in terms of compression ratios and quality. Results show that while the technique has some limitations, the proposed system achieves equivalent compression ratios as the standard JPEG technique, but with superior quality for the same compression ratio.

Discrete Wavelet Transform (DWT) is used by Qiuyu and Suozhong [43] to encode the wavelet coefficients of the three areas of the face image. These coefficients are then coded according to the importance specified in the image quality. The embedded block coding algorithm with optimal shortening (EBCOT) is applied in this method. Facial recognition technology has advanced significantly over the past ten to fifteen years. Algorithms for recognizing and identifying faces can be applied. For face recognition, some researchers have used genetic algorithms [44]. In this algorithm, an optimal subset of the extracted features is sought. Sun and Yin [45] applied a genetic algorithm to select a 3D diagnosis. Liu and Wechsler [46] used an evolutionary tracking method based on a genetic algorithm to recognize faces.

In this plan, the axes defined in PCA space are rotated to determine the basis of the face. The existing methods do not provide satisfactory general classification, so a better feature selection and integration method is needed to improve the accuracy and precision of general classification. Even though evolutionary algorithms have powerful structures for classifying data and learning patterns, the difficulty of training and using a comprehensive network that includes all the desired features is another issue with these algorithms. This paper does not place a high priority on computational processing time. Based on genetic and gray wolf algorithms, this paper proposes assigning variable bits to each block of face images. It is important to pay attention to the recognition rate in addition to the process of compressing images and dividing the appropriate bit budget for each block. Although due to the nature of compression, the information and redundant details of the image are removed, the recognition percentage for the images should be calculated in a way that does not decrease from the recognition accuracy in uncompressed conditions or even increases if possible. In this way, if we can identify areas of the face image that are of low value and importance with the aid of genetic algorithms and gray wolves, fewer bits will be assigned to each block and redundant information will be removed. In contrast, we can assign a higher bit rate to high-value portions of face images (such as the eyes, nose, and mouth) that contain facial details. As a result, the face image is encoded using SPIHT, and after decoding and applying the wavelet transform, it is saved. All test images are subjected to the loop described above. To conclude, the recognition accuracy criterion was used to determine the appropriate choice of bit block rate using principal component analysis (PCA). According to the explanations provided, each method has its advantages and disadvantages and is used for different purposes and functions in different fields. We will next examine how to allocate a variable bit budget between image blocks using the algorithms used in the proposed method.

3. PROPOSED METHOD

A suitable bit budget is proposed in this paper article for the image blocks and a map of the importance of face images is provided. For this reason, an importance map is created for the valuable regions of the face images, which can be analyzed to determine the region of interest (ROI) and valuable regions. The areas of the face details can be assigned a higher priority and bit rate than other areas. The meta-heuristic algorithms of the proposed method take into account the objective function of recognition rate. This objective function seeks to find the bit string length (BSL) assigned to each block that does not reduce the recognition rate during compression. The highest recognition rate is recorded in the output as soon as the meta-heuristic algorithm has reached the termination condition (maximum repetition).

Because the input image is divided into equal-sized blocks, it is possible to remove redundancy and allocate fewer bits in some blocks with less critical information. Conversely, if a block contains facial image details that have more value and information (such as eyes, nose, and mouth), more bits should be allocated to that block. In the training database set, 70% of the images are included, while in the test database set, 30% of the images are randomly selected. In the section on dimension reduction, discrete wavelet transforms are used. Three modes with dimensions 16, 32, and 64 have been divided into blocks. As test steps, we have applied two meta-heuristic algorithms, one based on evolutionary structure (genetics) and the other based on collective intelligence (gray wolf). Algorithms described above are responsible for identifying valuable areas in the face and allocating the required amount of bits. These algorithms begin with a population of 10 and a number of generations.

We evaluated the results of the algorithms with the images in the test gallery set without compression, as well as compressed (JPEG) and SPIHT coding. In order to verify the termination condition, the classification department has been assigned the task of classifying and identifying the correctness of the images using principal component analysis. The process view of the proposed method is shown in Figure 1.

Final steps in the process are to evaluate and compare the results of the recognition test and the accuracy of image recognition for the set of compressed images. The following sections provide more information about the facade process.

3. 1. Facial Database The spatial resolution of face images is 1536×2048 (high), 480×640 (relatively high), and 150×200 (low). In the existing face image compression methods, images with a low spatial resolution (such that the distance between two eyes is about 90 pixels, and the image dimensions are 180-200 pixels) have been employed, high-resolution face images have not been examined. In most existing methods for compressing face images, images with a low spatial resolution (normal images with dimensions of approximately 200×200 pixels) are used. As the selected images in this paper require high spatial resolution analysis, CIE[1] and FEI[2] images are used. These databases present simulation results. In the CIE database, there are 300 color images (for 30 individuals) with dimensions of 2048×1536. Figure 2 illustrates examples of images from the CIE database.

In the FEI database, there are 2000 images (for 200 people) with dimensions of 640×480, and there are 100 images of males and females in color. Most of the faces in this photo are taken from FEI students and staff ranging in age from 19 to 40, and they all have distinctive hairstyles and cosmetics. Figure 3 shows FEI database images.

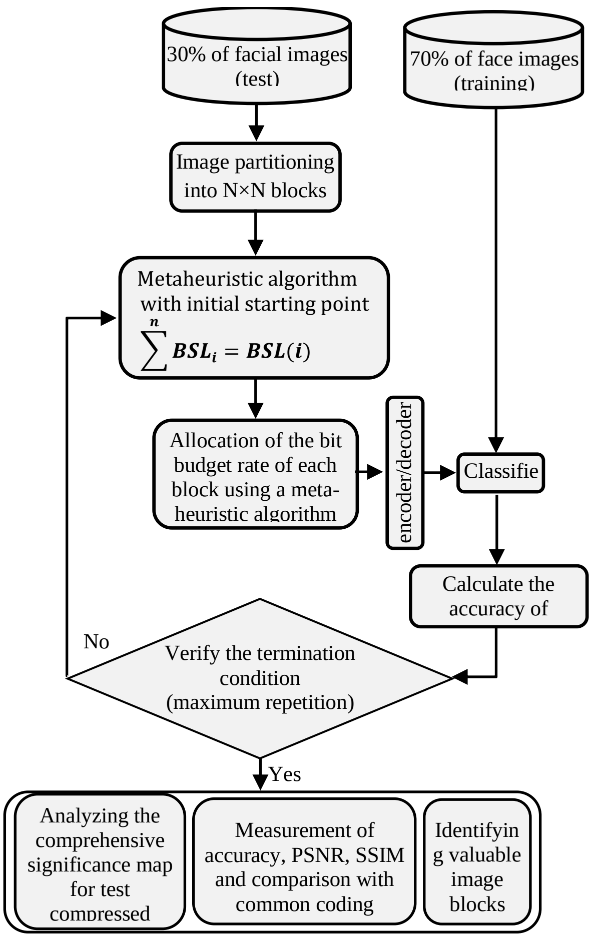

Figure 1. Compression process and recognition accuracy calculation

3. 2. Discrete Wavelet Transform This article proposes a method in which input images (high resolution) are received and reduced in dimensions using wavelet transforms. There are two purposes for which wavelet transforms are used. First, the high resolution images are reduced to the lowest possible level, and the horizontal, vertical, and diagonal details are left out, leaving only the approximate image of low resolution as a measurement criterion. For this reason, with one goal, image detail has been removed (compressed), and with another goal, the dimensions have been reduced so that the processing can be carried out at a faster rate.

Figure 2. Images of the CIE database [50]

Figure 3. Images of the FEI database [51]

[1] https://www.researchgate.net/figure/Example-images-of-CIE-database_fig3_343240268

[2] https://fei.edu.br/~cet/facedatabase.html

Based on the level reduction number selected for wavelet transformation, the output of this section consists of a series of images with a lower resolution and smaller dimensions than the original images. In other words, every time wavelet analysis is applied to an image, its dimensions are cut by a quarter. As an example, if a two-level wavelet decomposition is applied to an image, the approximate dimensions at the second level will be approximately one-sixteenth of the original dimensions. Thus, wavelet transforms are used to reduce dimensionality. The number of levels of decomposition in the proposed method is automatically determined for each image, and after the last decomposition step (L), the approximate sub-image is provided to the segmentation block as an input image with low-level resolution. In each level of wavelet decomposition, there are three subbands of details, called horizontal (D^d), vertical (D^V), and diagonal (D^h). EN is calculated by dividing the energy of each subband by the total number of pixels in that subband. The analysis of the input image continues automatically in the proposed method until a level where at least one of the subbands of that level of analysis meets the following condition, at which point parameter L equals the number of the analysis level (or, equivalently, the energy of at least one subband exceeds the threshold value T). The significant value will be determined by Equation (1). The parameter T is a threshold whose value is determined by a coefficient (α) of the energy normalized by the area of the input image.

$$E_N \geq T \tag{1}$$

The α parameter for each subband in each level and for the whole image is fixed at 0.1, which was selected empirically. Because the larger the value of α is chosen, the more compression we will achieve, but the amount of distortion will also increase. Additionally, larger values result in a reduction in the accuracy of detail subband estimation.

$$T = \frac{\alpha \times \sum_{i=1}^{M} \sum_{j=1}^{N} I(i.j)^2}{M \times N} \tag{2}$$

According to relation (2), M and N represent the dimensions of the input image. As a result of the proposed method, the larger the value of L, the greater the reduction in the dimensions of the input image. Therefore, the amount of compression will also increase. Figure 4 shows the output of horizontal, vertical, and diagonal levels, as well as the sub-image of the approximation of the fourth level (L=4).

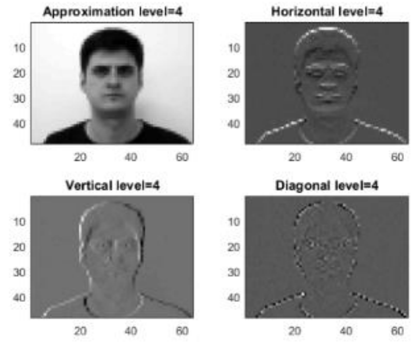

Figure 4. Approximate details of sub-images, horizontal, vertical, and diagonal decompositions up to the fourth level

3. 3. Image Block Division It is possible to divide an image into blocks both in a fixed and in a variable manner [47]. Monochrome images are segmented based on their brightness [48] and color images are segmented based on their color components [49]. On the other hand, image and texture edges are also useful features for segmentation [50]. As a result of the proposed method, it is possible to change the dimensions of the blocks uniformly. In the second step of the proposed method, these conditions have been specified. This is to facilitate the evaluation of results for image segmentation with 8×8, 16×16, 32×32, 64×64, and 128×128 blocks. At this stage, the output of the dimensionality reduction diagram block (low-resolution images) is segmented accordingly. In the proposed method, default values are provided for the three states of equal blocks due to a limited number of pages to present the results. We have therefore divided each image into equal blocks of 16×16, 32×32 and 64×64 dimensions and analyzed their results. Table 1 provides instructions for dividing the number of images into blocks.

In the next step of the proposed method, the values of the number of blocks will be the initial population members of our search space algorithm for bit budget allocation. As explained above, in the first step (reduction of dimensions by the wavelet transform method), the number of reduction levels determines the size of the output images (low-resolution images). If we choose the original input images from the CIE database, and we use the first step of the proposed method, we will obtain images with a scale of 64×48. Based on the default block size of 16 by 16, if the second step (block division section) is completed, 12 blocks will be created for the image.

3. 4. Bit Rate Per Block A meta-heuristic algorithm is designed so that a suitable bit budget is allocated to each block for each bit rate with a fixed bit string value. Meta-heuristic algorithms (genetics and gray wolf) have been applied to the investigated data to determine the appropriate bit budget for each block.

TABLE 1. Block division of images

Size of the image	64×48	128×96	256×192	512×384	1024×768	2048×1536
Blocks totaled	12	48	192	768	3072	12288

Using the meta-heuristic algorithms mentioned above, the proposed method extracts the most valuable and most effective features related to valuable face image blocks. If we can allocate a suitable bit budget rate to critical areas of the face, such as the eyes, nose, mouth, etc., then this is the most appropriate answer. There is no doubt that other areas, such as the background, will have less value, and therefore a shorter bit string length will be considered for them. Simply stated, genetic and gray wolf algorithms identify and allocate the desired bit rate for each image block. These meta-heuristic algorithms are used to determine the value between the blocks of an image.

The genetic algorithm does not require any special prerequisites in order to solve the problem. As a result of this feature, genetic algorithms have become powerful optimization tools. The genetic algorithm, like many stochastic methods, does not guarantee finding the optimal solution to a problem and only assists in finding a relatively good solution to the problem. In the proposed method, the search space is comprised of the number of image segmentation blocks. The proposed method considers a maximum of 10 primary populations for the statistical population. There are 70% of chromosomes in the population that are considered for crossover, and 30% for mutation. Genetic algorithm of the proposed method selects crossover and mutation coefficients of 3 and 2, respectively. The selection process is based on a roulette wheel. Upon reducing the dimensions and dividing the approximate image (the last level of decomposition), the number of blocks will equal the number of genes of the genetic algorithm. Since the total length of the bit string is fixed, it is important to note that after determining the values assigned to each gene, their sum equals the total length of the bit string.

For each block in the iteration loop, the algorithm determines the appropriate gene value and provides stopping conditions. Whenever the objective function requires a large number of computations, convergence is considered to be faster. In the proposed method, a stop condition is used to achieve the highest detection accuracy possible. Gray wolf algorithm were presented in 2014 based on the gray wolf's life [14]. A group's leader (α) determines how attacks and timing should be handled by these animals, which live in groups.

- Tracking, chasing, and approaching
- Following and surrounding the hunt
- Assaulting the prey

According to the proposed method based on the gray wolf algorithm, it is assumed that we have three viable solutions. However, we have no idea of the location of the prey in the initial search space. For 3D modeling, it is therefore necessary to first determine the points around the prey. It then moves toward the prey and attacks it. These relationships are used to determine the bait's location.

$$\vec{D} = \left|\vec{C} \cdot \overrightarrow{X_p}(t) - \vec{X}(t)\right| \tag{3}$$

$$\vec{X}(t+1) = \overrightarrow{X_p}(t) - \vec{A} \cdot \vec{D} \tag{4}$$

Here, t is the current iteration of the algorithm, $\vec{A}$ and $\vec{C}$ are the coefficient vectors, $(\overrightarrow{X_p})$ is the prey position vector, and $\vec{X}$ is the gray wolf position vector. As a result of the following relationship, we can also obtain the vectors $\vec{A}$ and $\vec{C}$.

$$\vec{A} = 2\,\vec{\alpha}\,\vec{r_1} - \vec{\alpha} \tag{5}$$

$$\vec{C} = 2\,\vec{r_2}$$

In the above relationship, $(\vec{r_1})$ and $(\vec{r_2})$ are random vectors in the interval [0 and 1]. An intelligent optimization algorithm makes a compromise between exploration and mining by adjusting its control parameters. An optimization algorithm with a large number of control parameters does not necessarily result in better performance. The fewer the parameters, the greater the possibility of adjusting these parameters to increase the speed of convergence and avoid becoming stuck in the local optimum. But the gray wolf optimization algorithm lacks any parameter control. During the optimization process, the parameter (α) is the only parameter that changes.

The parameter $\vec{\alpha}$ also decreases from 2 to zero during the algorithm execution process. To mathematically model the prey approaches, the value of a is reduced. It should be noted that the range of changes of A will also decrease with a. In other words, A is a random value in the interval [-2a, 2a], where a decreases from 2 to 1 during the steps of solving the iteration of the algorithm. For the random values of A in the interval [1,1], the next position of The search agent can be anywhere between the current position of the agent and the position of the prey. In the gray wolf algorithm, the position of the wolves is updated according to the position of a, β, and δ. Other solutions (called ω wolves) should change their positions to converge to the optimal solution, according to the following relations.

$$\overrightarrow{D_\alpha} = \left|\overrightarrow{C_1} \cdot \overrightarrow{X_\alpha} - \vec{X}\right| \tag{7}$$

$$\overrightarrow{D_\beta} = \left|\overrightarrow{C_2} \cdot \overrightarrow{X_\beta} - \vec{X}\right| \tag{8}$$

$$\overrightarrow{D_\delta} = \left|\overrightarrow{C_3} \cdot \overrightarrow{X_\delta} - \vec{X}\right| \tag{9}$$

$$\overrightarrow{X_1} = \overrightarrow{X_\alpha} - \overrightarrow{A_1}(\overrightarrow{D_\alpha}) \tag{10}$$

$$\overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{A_2}(\overrightarrow{D_\beta}) \tag{11}$$

$$\overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{A_3}(\overrightarrow{D_\delta}) \tag{12}$$

$$\vec{X}(t+1) = \frac{\vec{X_1} + \vec{X_2} + \vec{X_3}}{3} \tag{13}$$

The wolves may sometimes need to move apart in order to find prey, and they may not always congregate. A random value greater than 1 or less than -1 is used to model such phenomena. As a result, if |A|>1, the wolves will move away from the prey, whereas if |A|<1, the wolves will be forced to attack the prey. For example, if we have an image (low resolution) with dimensions of 64×48 and a total number of blocks of 12, and we want to compress it at a bit rate of BPP = 0.5, in this situation, the output data bit string length (BSL) will be equal to 1536 and the number of genes on each chromosome or the number of attacking wolves will be equal to 12. Consequently, the pattern of dividing these 1536 bits into 12 (genes/wolves) and selecting the optimal place to allocate the most appropriate bit budget to each block (in terms of the highest recognition accuracy across all images, and how to swap the values of genes/wolves) is the responsibility of the meta-heuristic algorithm (Genetics/Gray Wolf). It is very significant to pay attention to the fact that the number of genes of each chromosome or the number of invading wolves after combining does not increase more than the amount considered in the bit budget allocation (BSL=1536). A mutation process is used to increase or decrease each of the (genes/wolves) in the proposed method so that the budget amount does not change. Essentially, our method of comparing the accuracy of the recognition is based on the fact that the size of the total bit string of each block should equal the length of the output bit string if the same conditions apply as usual. Therefore, the fitting function used in meta-heuristic algorithms (genetics/gray wolf) of the proposed method is chosen in a way that converges at the same time to the highest recognition accuracy of all images, the highest average PSNR and the highest average SSIM. As a result, the condition of stopping the function and exiting the process loop is met.

3. 5. Coding/Decoding In compression processes, the most vital part, which happens to have the most computational complexity, is related to image encoding and decoding. In the proposed method of this article, SPIHT coding is used due to the production of integrated sequences, high encoding efficiency, and low computational complexity [51]. It is also possible to express one of the benefits of this type of coding in terms of the transmission process. The transmission is designed as a progressive transmission. It can be stopped at any time during the encoding process to achieve the highest image quality at the available bit rate. It was found by Xiang et al. [52], the way of coding in the proposed method is that the bit rate of each of the image blocks is determined by meta-heuristic algorithms (genetics and gray wolf) and then unique coding is done for each block through the implementation of the SPIHT coder and finally the output bit string for each block is generated. As we know, in compression methods, there is always some overhead, which is insignificant, because the number of pixels in the image is large. The compressor unit performs the functions of the reconstruction unit, as it is aware of the quality of the final image in advance. After reducing the dimensions of the input images using wavelet transformation, the approximate sub-image obtained at the end of the compression path is used as an independent face image in the next step. As a result, it is never necessary to encode in the SPIHT method the details of the suggested dimensionality reduction method. A block of the low-resolution image is received as input at a time. This input image, as we know, is the result of reducing the dimensions of the original image using the proposed method based on the wavelet transform. In fact, it is the last subband of the wavelet decomposition approximation. After the dimension reduction process and the search for budgeting for key blocks in the face image have been completed, the low-frequency coefficients of the image are sorted and coded using the SPIHT method. The approximate sub-image can be obtained from the photo wavelet transform method after obtaining the output bit string and the data values of the reduction levels and image dimensions in the image reconstruction section.

3. 6. Accuracy Measurement DCT conversion is one of the most popular compression methods (including JPEG), but it is not suitable due to problems such as hardware complexity and computational costs. In contrast, an algorithm such as JPEG-LS[1] does not suffer from the problem of hardware complexity to a certain extent, since it uses the correlation method between pixels, but it is not efficient at improving the compression speed of images. The use of appropriate color space conversion algorithms increases the speed and quality of compressed images in this regard [53]. Researchers have studied methods such as fractal coding to increase speed, which utilizes similarity in different areas of the image [54]. Principal component analysis is a method that has proven successful in the recognition of faces [55]. PCA is used in the proposed method to extract features for recognition. The advantages of this method include its simplicity of application and use, its positive effects on large databases, and its acceptable efficiency level. Many researchers have worked to improve it [56]. A number of studies have also focused on the problem of choosing the most appropriate eigenvectors. This is with the objective of increasing and improving PCA's efficiency by removing noise eigenvectors and reducing processing time. The PCA method is therefore used to remove

[1] https://jpeg.org/jpegls/

correlations in the data by imaging the data in a new space [57]. Based on the explanations provided, the secondary objective of this research is to develop an identification system based on principal component analysis (PCA). For each sample, we consider one vector or array of information or features. In order to obtain an average vector, we first average the vectors of all samples. According to Equation (14), an image containing n samples and b dimensions can be displayed as a vector variable.

$$X_i = [x_{i1}. x_{i2}. \dots . x_{in}]^T \quad i = 1.2. \dots . b \tag{14}$$

With relation (14) where the nth sample is included in the i-th band, the data is presented in the modified coordinate system with the vector variable resulting from relation (15).

$$Y_i = X_i - (\frac{1}{n}\sum_{k=1}^{n} x_{ik})[1]_{n1} \quad , \quad i = 1.2. \dots . b \tag{15}$$

The distance between each sample and the mean vector is then calculated, resulting in a matrix. Multiplying the obtained matrix by its transpose yields the covariance matrix.

$$C(i.j) = \frac{1}{n}\left(Y_i Y_j^T\right) \quad i = 1.2. \dots . b, \ j = 1.2. \dots . b \tag{16}$$

In the next step, we calculate the eigenvalues and eigenvectors of this matrix, and after calculating the eigenvalues, we sort them in descending order. Each eigenvalue has its own eigenvector, and the larger the value of an eigenvalue, the greater the differentiation in the data in that dimension. The proposed method uses 70% of the low-resolution facial images of each individual in the database as training images. Test images were evaluated on the remaining 30% of images (with low resolution). For the first experiment, the system is trained using seven random images of each person in the FEI database, which contains 280 images. For the purpose of this test, the remaining three images of each person in the database, which contains 120 images, are considered. In the first step of the proposed method, the size of the feature vector is determined by the number of reduction levels. In the second test, 300 images from the CIE database were examined. For this step, 210 images are used for training and 90 images for testing. In order to measure the accuracy of the recognition of the set of images, PCA transformation has been used to extract the features of the images. In a situation where we are trying to increase or maintain the accuracy of image recognition in comparison to conventional methods, the performance of the recognition system is acceptable. The process of creating the database for the proposed method is shown in Figure 5.

Therefore, meta-heuristic algorithms (genetics/gray wolf) will be used to achieve the research's sub-goal, which is to detect and identify the image recognition algorithm with the highest accuracy value based on PCA

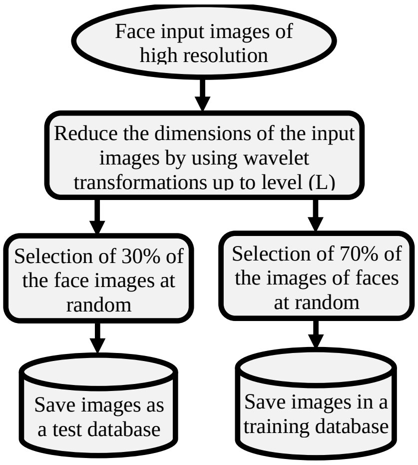

Figure 5. Training and test phases for creating the proposed method's database

transformation. The optimal vector proposed by the algorithm (genetics/gray wolf) for allocating the bit budget of each image block is determined when the efficiency and accuracy of the recognition of the test images are at their peak. Face recognition is based on the following recognition accuracy criteria (17):

$$Accuracy = \frac{\sum true\ positive + \sum true\ negative}{\sum total\ \ population} \tag{17}$$

The term (correct positive) refers to the number of images that belong to the positive category and have been properly classified. This refers to the number of images that are classified as negative by the classifier and have been correctly identified as such. It is significant to note that the denominator of the above fraction is the total number of images that have been verified.

4. TEST RESULTS

For a better comparison, the test results were reviewed and evaluated in two databases, CIE and FEI. Researchers compared uncompressed random test images and compressed images using SPIHT and JPEG coding methods as well as meta-heuristic genetics and gray wolf methods. The simulations have been performed in MATLAB R2016. The conditions have been selected in such a way that the performance of the algorithms in each of the different situations has been evaluated and compared, including the change in the bit rate, the change in the division of blocks, and the change in the reduction levels in the two databases. In the simulations, an Intel Core (TM) i5 processor with 2.4 GHz processing speed and 6 GHz RAM memory is used.

All three tests are conducted using FEI database images, the number of reduction levels is 4, 3, and 2, and the dimensions of the images after reduction are 48x64, 96×128, and 192×256, respectively. A second step involves examining the images from the CIE database, and determining that the reduction levels are 5, 4, and 3, and this subsequently leads to the same size images as those in the first step. The total number of blocks in each step is 12. For all three tests, the dimensions of dividing the blocks into the two stages are 16, 32, and 64, respectively. The bit value assigned to each block must be an integer, and the maximum value of the bit string (BSL) will be rounded to the lower integer value in each test. As a result of the changes in the dimensions of the block division, the compression ratios for each test will differ slightly, and the assumptions and parameters of both tests (two databases) summarized in Table 2. Tables 3, 4 and 5 present simulation results for the set of FEI database images based on the assumptions in Table 2.

We report the average values for PSNR, SSIM, and CR ratio in uncompressed and compressed conditions using SPIHT, JPEG coding methods, and genetic algorithms and gray wolf algorithms. In the context of image compression and recognition, it is critical to note that recognition efficiency does not necessarily decrease or remain constant at all bit rates; in other words, it may be slightly increased in some cases. As an example, in the third experiment, where the block division is 64, for a bit rate of 0.5, there is a relative increase in recognition efficiency. are illustrated below images. Figure 6 illustrates; the accuracy of image recognition in the division of 16, 32, and 64 blocks for bit rates ranging from 0.2 to 1 in the FEI database.

TABLE 2. assumes the parameters of the FEI and CIE databases

Database	The number of images in the database		The reduction levels (L)	Image dimensions after reduction	Size of the block	The block number
	Training	Test				
FEI	280	120	4	64×48	16×16	12
			3	128×96	32×32	
			2	256×192	64×64	
CIE	210	90	5	64×48	16×16	
			4	128×96	32×32	
			3	256×192	64×64	

TABLE 3. Recognition percentages for different bit rates in the FEI database

Bit Per Pixel	Conpration Ratio	Size of the block	Performance averages in recognition				
			Original	SPIHT	JPEG	GA	GWO
	40.0261	16×16	99.16	97.5	97.83	97.5	97.5
0.2	40.0098	32×32	97.5	98.33	98.96	99.16	98.33
	40.0016	64×64	99.16	99.16	98.33	99.16	99.16
0.3	26.684	16×16	97.5	97.5	97.5	97.5	97.5
	26.6696	32×32	100	99.16	97.5	99.16	100
	26.6678	64×64	98.33	98.33	98.33	99.16	99.16
	20.013	16×16	100	98.33	97.5	99.16	99.16
0.4	20.0008	32×32	98.33	97.5	97.5	100	98.16
	20.0008	64×64	99.16	98.33	97.3	9916	99.16
	16	16×16	98.33	97.5	97.5	98.33	98.33
0.5	16	32×32	99.16	99.16	97.5	99.16	99.16
	16	64×64	99.16	99.16	98.33	100	100
	13.3348	16×16	99.16	98.33	97.5	99.16	99.16
0.6	13.3348	32×32	100	100	97.5	100	100
	13.3334	64×64	97.5	97.5	98.33	98.33	98.33
	11.4307	16×16	98.33	98.33	96.66	99.16	99.16
0.7	11.4294	32×32	99.16	99.16	97.5	100	100
	11.4287	64×64	96.66	96.66	98.33	98.33	99.16
	10.0024	16×16	98.33	98.33	97.5	99.16	99.16
0.8	10.0004	32×32	99.16	98.33	97.5	99.16	99.16
	10.0002	64×64	98.33	98.33	97.5	98.33	99.16
	8.8915	16×16	97.5	97.5	97.5	99.16	100
0.9	8.889	32×32	99.16	99.16	96.66	100	99.16
	8.889	64×64	98.33	98.33	97.5	98.33	98.33
	8	16×16	97.5	98.33	97.5	98.33	99.16
1	8	32×32	99.16	98.33	97.5	99.16	99.16
	8	64×64	97.5	98.33	97.5	98.33	100

TABLE 4. Average PSNR values for different bit rates in the FEI database

Bit Per Pixel	Conpration Ratio	Size of the block	Performance of average PSNR (dB)				
			Original	SPIHT	JPEG	GA	GWO
	40.0261	16×16	22.92	17.92	17.09	15.17	16.09
0.2	40.0098	32×32	22.13	21.03	17.33	18.70	20.20
	40.0016	64×64	21.62	21.49	17.44	22.03	28.75
	26.684	16×16	22.69	19.37	17.24	15.50	16.64
0.3	26.6696	32×32	21.99	21.38	16.95	22.68	25.29
	26.6678	64×64	21.58	21.53	17.52	24.68	28.94
	20.013	16×16	23.04	20.53	17.18	19.71	21.69
0.4	20.0008	32×32	21.93	21.56	17.16	23.61	21.77
	20.0008	64×64	21.84	21.81	17.41	28.30	27.60
	16	16×16	22.35	20.85	17.03	18.45	20.83
0.5	16	32×32	22.44	22.22	17.33	24.15	23.26
	16	64×64	21.76	21.73	17.21	28.42	27.57
	13.3348	16×16	22.85	21.32	17.09	22.97	23.05
0.6	13.3948	32×32	22.10	21.92	17.56	27.75	30.02
	13.3334	64×64	21.67	21.67	17.43	24.84	28.18
0.7	11.4307	16×16	22.65	21.64	17.23	22.93	21.78

	11.4294	32×32	21.79	21.70	17.17	25.97	23.22
	11.4287	64×64	21.53	21.53	17.53	27.59	20.12
	10.0024	16×16	23.00	22.15	17.05	20.95	25.88
0.8	10.0004	32×32	22.04	21.97	17.03	26.52	25.67
	10.0002	64×64	21.73	21.71	17.37	27.58	25.19
	8.8915	16×16	22.51	21.92	17.23	21.88	23.14
0.9	8.889	32×32	22.74	22.65	17.29	23.88	29.66
	8.889	64×64	21.86	21.86	17.63	32.51	34.92
	8	16×16	22.60	22.16	16.97	20.71	20.79
1	8	32×32	22.10	22.03	17.10	24.34	26.43
	8	64×64	21.32	21.33	17.30	32.49	25.27

TABLE 5. Average SSIM values for different bit rates in the FEI database

Bit Per Pixel	Conpration Ratio	Size of the block	Performance of the SSIM on average				
			Original	SPIHT	JPEG	GA	GWO
	40.0261	16×16	0.787	0.428	0.581	0.529	0.447
0.2	40.0098	32×32	0.766	0.602	0.625	0.648	0.684
	40.0016	64×64	0.781	0.720	0.690	0.782	0.828
	26.684	16×16	0.774	0.489	0.582	0.498	0.529
0.3	26.6696	32×32	0.758	0.635	0.624	0.721	0.741
	26.6678	64×64	0.781	0.742	0.692	0.817	0.839
	20.013	16×16	0.784	0.542	0.587	0.633	0.649
0.4	20.0008	32×32	0.762	0.666	0.625	0.779	0.712
	20.0008	64×64	0.786	0.762	0.690	0.840	0.824
	16	16×16	0.770	0.580	0.576	0.594	0.669
0.5	16	32×32	0.774	0.701	0.631	0.787	0.748
	16	64×64	0.786	0.770	0.694	0.842	0.871
	13.3348	16×16	0.780	0.607	0.583	0.719	0.719
0.6	13.3348	32×32	0.769	0.709	0.632	0.819	0.852
	13.3334	64×64	0.786	0.777	0.691	0.861	0.865
	11.4307	16×16	0.769	0.629	0.585	0.736	0.721
0.7	11.4294	32×32	0.760	0.715	0.627	0.795	0.750
	11.4287	64×64	0.782	0.777	0.693	0.867	0.831
	10.0024	16×16	0.781	0.663	0.583	0.693	0.805
0.8	10.0004	32×32	0.764	0.729	0.625	0.798	0.812
	10.0002	64×64	0.784	0.780	0.693	0.862	0.827
	8.8915	16×16	0.776	0.676	0.580	0.750	0.751
0.9	8.889	32×32	0.780	0.751	0.630	0.816	0.861
	8.889	64×64	0.788	0.786	0.695	0.936	0.924
	8	16×16	0.774	0.689	0.577	0.724	0.682
1	8	32×32	0.768	0.745	0.629	0.786	0.881
	8	64×64	0.777	0.776	0.689	0.911	0.880

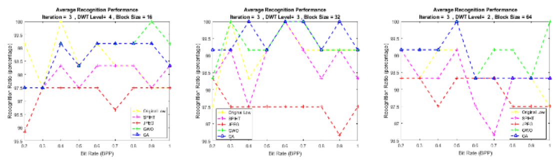

Figure 6. Accuracy of image recognition in the division of 16, 32, and 64 blocks for bit rates ranging from 0.2 to 1 in the FEI database

Figure 7 shows the average PSNR for images in 16, 32, and 64 block divisions for bit rate values between 0.2 and 1.

Figure 8 shows the average SSIM images with bit rates ranging from 0.2 to 1 in the FEI database divided into 16, 32, and 64 blocks.

Using the test image set of the FEI database as an example, the results of the image importance map calculated by dividing the 64×64 blocks (the third test from the first stage) at each of the bit rates from 0.2 to 1 are illustrated in Figure 9.

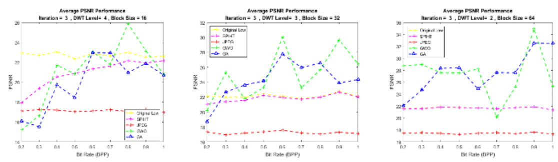

Figure 7. Average PSNR for images in 16, 32, and 64 block divisions for bit rate values between 0.2 and 1

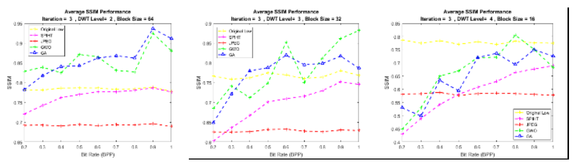

Figure 8. Average SSIM of images with bit rates ranging from 0.2 to 1 in the FEI database

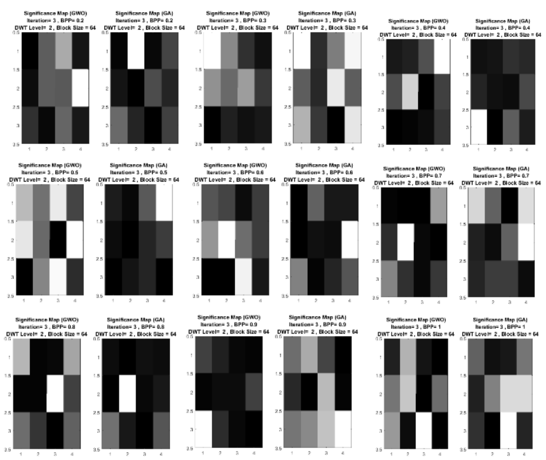

Figure 9. illustrates the importance of image compression in genetic and gray wolf methods for bit rate values ranging from 0.2 to 1 in the FEI database

Figure 10, for example, shows the amount of total processing time for genetic and gray wolf meta-heuristic algorithms with 16, 32, and 64 block allocations for bit rates ranging from 0.2 to 1.

Based on the CIE database, simulation results related to accuracy, average PSNR, and SSIM parameters are presented in Figures 11, 12, and 13.

As shown in Figure 14, the total amount of processing computing time for genetic and gray wolf meta-heuristic algorithms is calculated by dividing bit rate values from 0.5 to 1 into 16, 32, and 64 blocks.

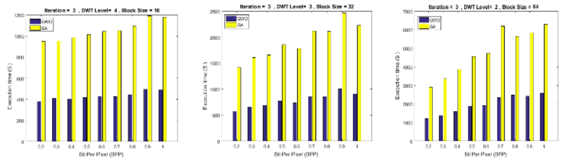

Figure 10. Comparison of execution times for genetic and gray wolf methods with block allocations of 16, 32, and 64 in the FEI database for bit rates 0.2 to 1

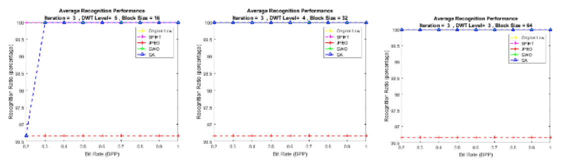

Figure 11. shows the accuracy of image recognition in the CIE database based on the division of 16, 32, and 64 blocks

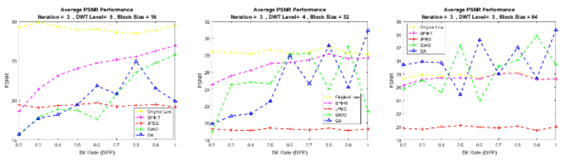

Figure 12. Average PSNR of images for bit rates ranging from 0.2 to 1 for images divided by 16, 32, and 64 blocks

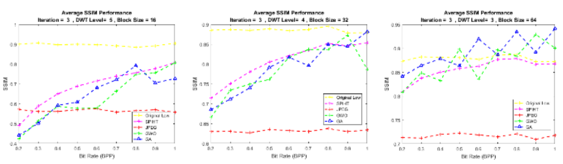

Figure 13. Average SSIM of images for bit rates between 0.2 and 1 for 16 blocks, 32 blocks, and 64 blocks

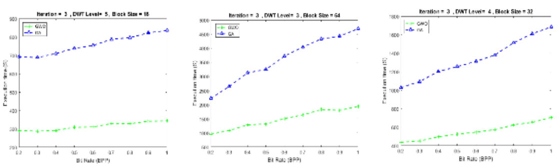

Figure 14. Comparison of execution times for genetic and gray wolf methods with 16, 32, and 64 blocks allocated for bit rates of 0.2 to 1 in CIE database

The meta-heuristic algorithm of genetics and gray wolf is used in this article to identify significant blocks and assign appropriate bits to each block. As a result, the coefficients of the image blocks have been encoded with the SPIHT method. The accuracy criterion has been evaluated to determine the accuracy of image recognition and the effectiveness of the proposed method. It is used in conjunction with learning and testing images obtained from a principal component analysis (PCA) process. Based on a comparison of the accuracy of the test images at different bit rates with JPEG methods, SPIHT will be the final method for testing the proposed method. When comparing the proposed method with the SPIHT coding curve and evaluating its recognition efficiency in accordance with the bit rate criterion, it is apparent that it can maintain significant and effective features in recognition. In Table (6), we present the percentage of recognition rate and the performance efficiency of the proposed method compared with the without compression method (Original) and the compression methods (SPIHT and JPEG).

The results shown in the graphs related to accuracy recognition (Table 6) indicate that at some bit rates, the accuracy value of face image recognition will be higher than without image compression. As stated in the abstract, we are looking for a method in which compression does not decrease the recognition rate compared to the original conditions (without compression) and even increases it.

As evidence of this claim, a bit rate of 0.7 is obtained for all three block modes of 16, 32, and 64 bits. By using meta-heuristic algorithms (genetics and gray wolf), the proposed method has significantly improved SSIM and PSNR over SPIHT and JPEG. According to the structure of the meta-heuristic algorithms that follow the search in the problem space, part of the time will be allocated for the calculations of the iterative loops until the objective function is reached. Therefore, in a new approach to reach the final goal, meta-heuristic algorithms can be used as a way to reduce the amount of time spent on computing. In the following research, the authors will focus on reducing computing time by using meta-heuristic algorithms and comparing them. On the other hand, based on this idea, future research could be done

TABLE 6. values of image recognition accuracy in meta-heuristic algorithms for blocks 16, 32 and 64 in terms of percentage

Method name	Original			SPIHT			JPEG		
Dimensions of blocks	64×64	32×32	16×16	64×64	32×32	16×16	64×64	32×32	16×16
GA	0.56	0.46	0.18	0.56	0.74	0.64	0.84	1.97	1.16
GWO	0.93	0.16	0.37	0.93	0.44	0.83	1.21	1.67	1.35

on variable image segmentation based on a quad tree similar to the H.265 method. Additionally, a new approach to development and future activities can be proposed and evaluated using deep learning methods.

5. CONCLUSION

When presenting the latest image compression algorithms, it has always been a priority to eliminate coding redundancy (shortest length for fewer code words), spatial or temporal redundancy, and irrelevant information caused by the data being removed by the human eye. On the other hand, the pace of upgrading equipment and updating capabilities within existing systems is continuously increasing. Therefore, there is a need for algorithms capable of providing high quality and efficient performance in the field of image compression. Since high resolution is an essential component of increasing quality, this article proposes the use of meta-heuristic algorithms to compress images with high resolution based on dimension reduction and bit budget allocation for dividing image blocks in wavelet transformation by using a method derived from dimension reduction.

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Persian Abstract

چکیده

فشرده‌سازی نقش مهمی در نظارت، کنترل و امنیت پردازش تصویر دارد. وضوح مکانی یکی از موثرترین عوامل در بهبود کیفیت تصویر است، اما میزان حافظه ذخیره سازی مورد نیاز را افزایش می دهد. این مقاله بر اساس الگوریتم‌های فراابتکاری، یک مدل فشرده‌سازی برای تصاویر چهره با تقسیم بلوک و تخصیص بیت متغیر ارائه می‌کند. تبدیل موجک برای کاهش ابعاد تصاویر چهره با وضوح فضایی بالا استفاده می شود. به منظور شناسایی مناطق مهم و مشابه ماکروبلاک های یکسان، از الگوریتم های ژنتیک و گرگ های خاکستری استفاده می شود. یک تخصیص نرخ بیت برای هر بلوک برای دستیابی به بهترین دقت تشخیص، میانگین PSNR و SSIM محاسبه می شود. پایگاه‌های اطلاعاتی CIE و FEI به عنوان مطالعات موردی استفاده شده‌اند. روش پیشنهادی با دقت تشخیص تصویر در شرایط فشرده نشده و با استفاده از روش‌های رایج کدگذاری SPIHT و JPEG آزمایش و مقایسه شده است. دقت تشخیص از ۰/۱۸ درصد برای بلوک های ۱۶×۱۶ به ۱/۹۷ درصد برای بلوک‌های ۳۲×۳۲ افزایش یافته است. علاوه بر این، الگوریتم گرگ خاکستری در رسیدن به پاسخ بهینه بسیار سریعتر از الگوریتم ژنتیک است. بسته به نوع کاربرد مشکل، الگوریتم ژنتیک یا گرگ خاکستری ممکن است برای دستیابی به حداکثر میانگین PSNR یا SSIM ترجیح داده شود. ماکزیمم متوسط PSNR برای الگوریتم گرگ خاکستری برابر ۳٤/۹۲ و ماکزیمم متوسط SSIM برای الگوریتم ژنتیک برابر ۰/۹۳٦ در نرخ بیت ۰/۹ بدست آمده است. نتایج شبیه‌سازی نشان می‌دهد که الگوریتم‌های مذکور با تثبیت یا افزایش دقت تشخیص، PSNR و SSIM را افزایش می‌دهند.