Applied Soft Computing Journal 73 (2018) 1039–1052

Contents lists available at ScienceDirect

Applied Soft Computing Journal

journal homepage: www.elsevier.com/locate/asoc

Evolutionary multiobjective multiple description wavelet based image coding in the presence of mixed noise in images

Huseyin Kusetogullari [a,*], Amir Yavariabdi [b]

[a] Department of Computer Science and Engineering, Blekinge Institute of Technology, Karlskrona, 37141, Sweden
[b] Department of Mechatronic Engineering, KTO Karatay University, Konya, Turkey

HIGHLIGHTS

- A multiobjective optimization algorithm (MOEA) has been adapted to optimize two different objective functions and find Pareto solutions.
- The MOEA is integrated with Dual-Tree Complex Wavelet Transform (DT-CWT) to provide effective multimedia communication in lossy networks.
- The DT-CWT is used to obtain the subbands or set of coefficients which are used as a search space in the optimization problem.
- One fitness function is designed to generate optimal multiple description coding (MDCs) or descriptions and the second one is used to obtain optimal parameter values for denoising filter to reduce mixed noise on descriptions.
- Proposed adaptive MDC system can be applied to the corrupted mixed noisy image (e.g. Gaussian and Impulse noise).

GRAPHICAL ABSTRACT

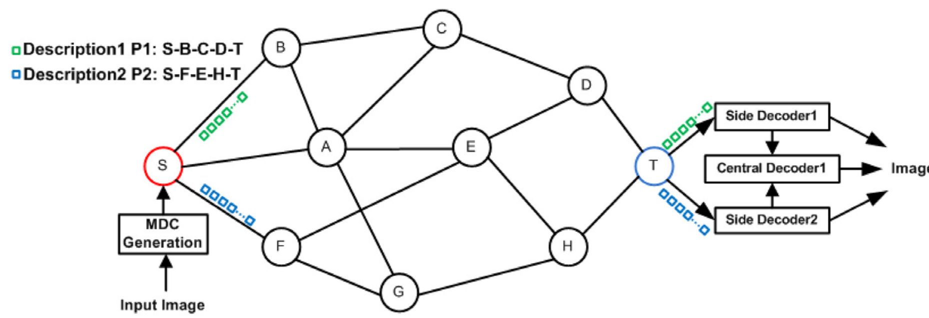


Fig. 1 Multimedia Transmission

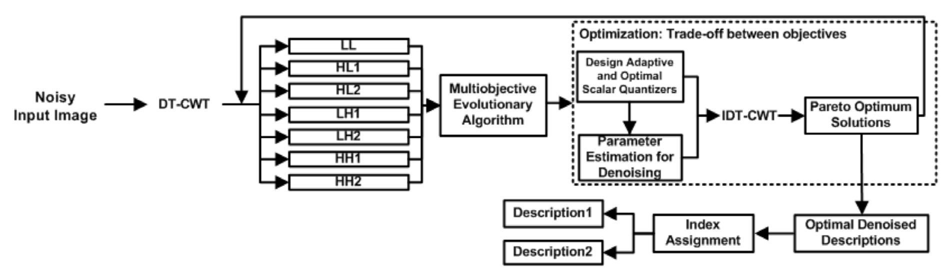


Fig. 2 MDC Generation

ARTICLE INFO

Article history:
Received 13 December 2016
Received in revised form 8 July 2018
Accepted 6 October 2018
Available online 10 October 2018

Keywords:
Adaptive and optimal quantizer design
Mixed Gaussian impulse noise reduction
Multiple description coding (MDC) for multimedia communication

ABSTRACT

In this paper, a novel method for generation of multiple description (MD) wavelet based image coding is proposed by using Multi-Objective Evolutionary Algorithms (MOEAs). Complexity of the multimedia transmission problem has been increased for MD coders if an input image is affected by any type of noise. In this case, it is necessary to solve two different problems which are designing the optimal side quantizers and estimating optimal parameters of the denoising filter. Existing MD coding (MDC) generation methods are capable of solving only one problem which is to design side quantizers from the given noise-free image but they can fail reducing any type of noise on the descriptions if they applied to the given noisy image and this will cause bad quality of multimedia transmission in networks. Proposed method is used to overcome these difficulties to provide effective multimedia transmission in lossy networks. To achieve it, Dual Tree-Complex Wavelet Transform (DT-CWT) is first applied to the noisy image to obtain the subbands or set

* Corresponding author.
E-mail addresses: hku@bth.se (H. Kusetogullari), amir.yavariabdi@gmail.com (A. Yavariabdi).

https://doi.org/10.1016/j.asoc.2018.10.015

Multi-objective formulation and optimization
Wavelets

of coefficients which are used as a search space in the optimization problem. After that, two different objective functions are simultaneously employed in the MOEA to find pareto optimal solutions with the minimum costs by evolving the initial individuals through generations. Thus, optimal quantizers are created for MDCs generation and obtained optimum parameters are used in the image filter to remove the mixed Gaussian impulse noise on the descriptions effectively. The results demonstrate that proposed method is robust to the mixed Gaussian impulse noise, and offers a significant improvement of optimal side quantizers for balanced MDCs generation at different bitrates.

1. Introduction

In the last decades, effective multimedia transmission has become a challenging problem in the lossy communication networks. In order to deliver good quality of multimedia source data, various multimedia transmission schemes such as progressive transmission, multiple description coding (MDC), unequal error protection (UEP) transmission scheme etc. have been proposed [1]. The multimedia transmission schemes have been applied to an input image in the server node to create different descriptions in such a way that bitrate and quality of reconstructed image increase when descriptions are received at the destination node [1]. Amongst many schemes, MDC has become an efficient approach to transmit the multimedia source data through the network channels/paths in the lossy networks [1,2]. The main purpose of using MDC is to split the information from a given source image into the MDs. After that they are transmitted through multipath in the communication networks and there should be a certain amount of common information correlation between the descriptions [1,2].

1.1. Survey of MDC methods

MDC is one of the promising solutions for image delivery over lossy networks. Most of MDC schemes are designed to create MDs from a given noise-free image and MDs should be equally important in terms of quality and bitrate for the advanced performance of multimedia communication. However, producing equally important or balanced MDs is a very challenging problem and many MDC schemes have been presented to solve it. For instance, Vaishampayan [3] proposed MDC generation scheme by using uniform MD Scalar Quantization (MDSQ). The purpose of this method is to design scalar quantizers to create different descriptions from the given noise-free input image. Samuelsson et al. [4] combined Gaussian mixture models (GMMs) with the scalar quantizers to generate MDCs. According to the parameters of the GMM, the method combines MDC scalar quantizers, yielding a source-optimized vector MDC system. In [5], the pairwise correlating transform to generate multiple correlated descriptions in the framework of standard DCT-based image coding is presented. In this work, coefficients are quantized by using scalar quantizers to create two side descriptions. Servetto et al. [6] proposed a MDC method by using Discrete Wavelet Transform (DWT) combined with the uniform scalar quantization technique. The method successfully creates equally important MDs from the obtained sub-bands of the decomposed noise free input image. However, generating MDCs using uniform quantization technique is not an effective approach, since each subband has different information content of the input image. In [7] and [8], different wavelet based MDC methods have been used to create descriptions. MDC versions of many popular image coding techniques were also examined, such as SPIHT [9], subband coding [10], vector quantization [11], and subsampling [12]. However, the main problem in those methods is to design optimal quantizers for the MDC generation so that it is necessary to apply an optimization method to design optimal quantizers. In [13], Genetic Algorithm (GA) combined with wavelet transformation technique is proposed and it is applied to design optimal subband uniform quantizers. The method single objective function to optimize the problem for designing uniform quantizers and creates descriptions sequentially. Liu et al. [14] proposed sampling-based image coding scheme to achieve competitive coding efficiency at lower encoder computational complexity. The method first generates compact image representation of the input image. Thus, a polyphase down-sampled version of the image is created using local random binary convolution kernel with down-sampling method. The results demonstrate that the proposed scheme provides promising results at low bit-rates. In another work [15], an adaptive multiple description depth image coding scheme based on wavelet sub-band coefficients is proposed to create MDCs of the image. The method uses DWT to create subbands and the low frequency and high frequency subbands are separately encoded using optimized multiple description lattice quantization and embedded block coding, respectively. However, using two different encoding methods increase the complexity of decoding at the receiver side. Also, the method uses DWT which suffers from some drawbacks discussed in [16]. Another multiple description image coding scheme is proposed in [17] which uses 2D dual-tree transform and the enhanced x-tree encoding method. However, optimal MDCs are not generated as the method does not use any optimization strategy. Zong et al. [18] proposed perceptual multiple description coding with randomly offset quantizers which partitions the image into M subsets, and then obtaining M descriptions. The method uses non-optimal step sizes which are applied in DCT to generate the descriptions. In [19], a multiple description vector quantizer (VQ) method is proposed to produce MDCs. The method has been developed based on the self-organizing map (SOM) and MDSQ. Furthermore, different MDC methods have been proposed and applied in different image transmission problems such as encrypted image transmission [20] and airborne image transmission [21].

The common problem in the state-of-the-art methods is that they are sensitive to noise and vulnerable to complicated scenarios with existence of noise in the input images. These methods are mostly used to create MDCs from noise-free images, but the quality of MDC transmission highly depends on the quality of the input image which may be corrupted by various noises, particularly Gaussian and impulse noises. In order to transmit high quality MDs, it is essential to remove the noise from descriptions while keeping the desired image features such as edges, textures and details of images. To resolve it, one type of approach is to use MDC coders with the denoising filters, sequentially. Many image denoising methods have been proposed to remove Gaussian and impulse noise separately or together. However, they may remove high frequency features from the images, especially when they are corrupted with the high level of noise(s) [22–24]. Another drawback in some of MDC methods is that DWT or DCT is used as the transformation domain which cannot represent sufficient orientations of the images. For instance, DWT suffers from multiple weaknesses which are discussed in [16]. Another problem of MDC methods is to generate descriptions of the input image sequentially which is time consuming and not effective process. In this case, MDC methods must be executed more than one time to generate multiple descriptions [1,3,4,6,11,13,25]. Furthermore, many MDC methods cannot provide optimal solution for the description generation.

1.2. Contribution

To address the above-mentioned drawbacks, we propose a new optimization approach using MOEA to provide trade-off between objectives for achieving a satisfactory solution to the problem. The main contributions of this work are to:
(1) develop a new optimization-based denoising algorithm for mixed Gaussian and impulse noise reduction;
(2) adapt MOEA for effective multimedia transmission in the lossy networks;
(3) use DT-CWT to preserve high frequency components in descriptions;
(4) find optimal pareto solutions for simultaneously designing optimal quantizers and to obtain optimal parameters of denoising filter
(5) generate good quality of descriptions for efficient multimedia transmission.

To achieve these, two different objective functions have been proposed and used in the MOEA to generate optimal quality MDCs at different bitrates. The first objective function is used to design the adaptive optimum quantizers for MDC generation. The second objective function is used to find optimal parameters for designing filter to remove the mixed Gaussian impulse noise on descriptions. Unlike the other search based algorithms (e.g. GA), the MOEA provides pareto optimal solutions at each iteration. Thus, it optimizes more than one objective function simultaneously and it is employed to provide an optimal trade-off between the objective functions which may preserve more important contents in obtained descriptions. The MOEA performs on a single-level decomposition of an input image produced by DT-CWT and the performance of the proposed method is examined in terms of generating optimal quality of MDCs. Simulation results demonstrate an improvement in the objective measure of peak signal to noise ratio (PSNR). Numerical experiments, on standard test images with the mixed Gaussian impulse noise, illustrate the effectiveness and efficiency of our approach comparing to the state-of-the-art.

The rest of this paper is organized as follows. In Section 2, multimedia transmission in lossy networks is provided. In Section 3, a brief description of using DT-CWT is given. Section 4 presents the proposed wavelet based adaptive MDC generation method using MOEA. Results and discussions will be provided in Section 5. The paper will be concluded in Section 6.

2. MDC for multimedia transmission

Multiple description coding (MDC) has been proposed as an efficient multimedia transmission approach to increase the robustness of image and video transmission in lossy networks such as Internet and wireless network. Most of MDC generation schemes create equally important or balanced multiple descriptions from the same source signal [1]. For instance, Fig. 1 shows a small communication network model involving 10 nodes connected with 16 indirect links. In the multimedia communication, it is required to create MDCs based on the network link capacities because achievable bitrates of MDCs depend on the network link capacities and the generated descriptions are transmitted through the multipath in the lossy networks [1]. Let the server node (S) have two balanced and independent MDCs (e.g. Description1 and Description2) to send to the receiver node (T). Two MDCs are split into the packets to transmit over two independent paths P1 (S–B–C–D–T) and P2 (S–F–E–H–T), respectively. Let us suppose that there are three decoders (side and central decoders) at the receiver as shown in Fig. 1. Side decoder employs on a single description if one description is received (MDC1 or MDC2) at the receiver node. On the other hand, central decoder is employed on two different descriptions if both MDCs are received and the best quality of image is obtained if both MDCs are reached at the destination node. As a result, increasing number of descriptions received at the receiver node will raise the quality of image at the receiver side.

3. Wavelet transformation for MDC generation

The wavelet transformation methods have been widely used to resolve many image processing problems. For instance, they are used in denoising [26], edge detection [27], feature extraction [28], speech recognition [29], biomedical imaging [30], image compression and image resolution segmentation [31,32] and others [33,34]. Besides this, many MDC generation schemes have been using DWT to create the MDCs [6,13]. However, DWT has several weaknesses such as lack of shift invariance and phase information and limited directionality. As an alternative to DWT, complex-valued wavelet transforms have been proposed to overcome these difficulties [35]. One of the well-established complex-valued wavelet transformation methods is DT-CWT, which is used in this work to create spatial domain of image into the frequency domain.

The purpose of using DT-CWT is to generate the real and imaginary parts of the transform in parallel decomposition trees by applying low pass and high pass filters to an image [35]. Two parallel decomposition trees are used for the columns of the input image and other two parallel trees for the rows in a quad-tree structure with 4:1 redundancy. After that, the four quad-tree components of each DT-CWT coefficient are combined by using arithmetic sum and difference operations to yield a pair of complex coefficients [35]. Fig. 2 illustrates the obtained real and imaginary parts of decomposition with the degree of directionality of the CWT, e.g. $\theta = \{\pm 15, \pm 45, \pm 75\}$. Unlike the other transformation methods, applying one level decomposition of DT-CWT to the input image provides one complex-valued low-pass subband, LL and six complex-valued high-pass subbands, two HL, two LH, and two HH. Let M involve all subbands or coefficients of the decomposition of an input image and inverse DT-CWT (IDT-CWT) of M reconstructs the original input image. The coefficient matrix M is used as a search space in the proposed method to create the optimal quantizers and to design the filter to remove the noise on the descriptions.

4. Proposed adaptive MDC generation method

The purpose of using MDC generation methods is to generate descriptions by using quantizers which include the reconstruction and decision values [3]. Many description generation methods have been using uniform quantizers and noise-free input images to create MDCs. However, this is a difficult task, not robust to noise, and time-consuming process. Besides this, in sequential MDC generation methods, it is required to know the reconstruction and decision values of the first quantizer to design the second quantizer for two balanced MDCs generation. In order to create the third quantizer, it is necessary to know the details of the first two quantizers and so on. For instance, Khelil et al. [13] proposed sequential GA based MDC generation method to optimize single objective function for designing optimal uniform quantizers. It applied to the sub-bands of the decomposed input image obtained by discrete wavelet transform (DWT) and results demonstrate that the method finds optimum uniform quantizer values in the given sub-bands. The optimization approach to find the global optimum results in the sub-bands is not very efficient because the proposed optimization approach attempts to find the optimum values in the restricted intervals of the quantizers.

Complexity of the MDC coder problem has been raised significantly if an input image is affected by any type of noise such as Gaussian or/and impulsive noise(s). In this case, MDC coder has to take two different problems into account which are designing the optimal side quantizers and removing noise on descriptions. One way of solution is to first use denoising image filter to the noisy image and then apply any MDC generation scheme to create MDCs. However, applying these methods sequentially will cause loss of detail information (e.g. edge, line, sharpening of image details)

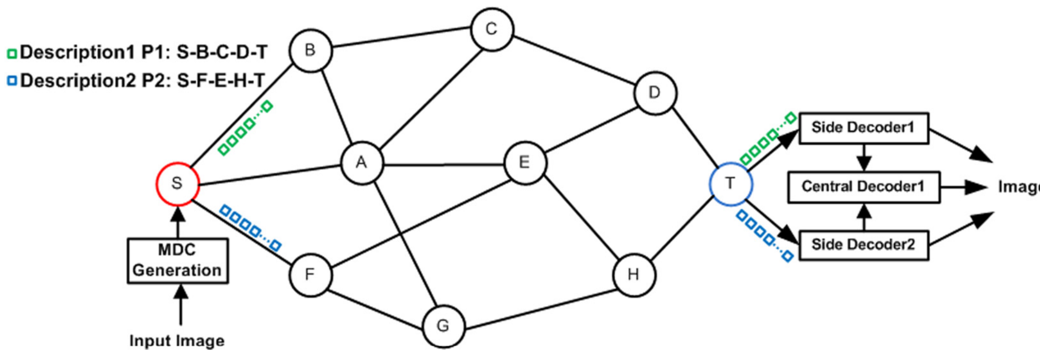


Fig. 1. A small communication network model for MDCs transmission through multipath.

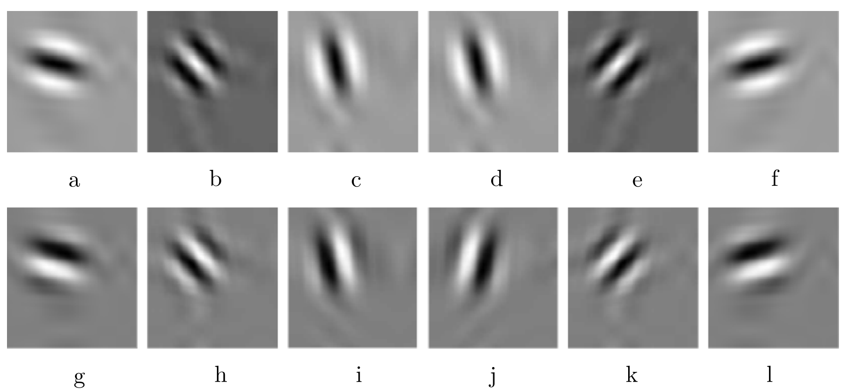


Fig. 2. The real and imaginary parts of the 2-D DT-CWT with the six degree of directionality: (a) real, −15°; (b) real, −45°; (c) real, −75°; (d) real, 75°; (e) real, 45°; (f) real, 15°; (g) imaginary −15°; (h) imaginary, −45°; (i) imaginary, −75°; (j) imaginary, 75°; (k) imaginary, 45°; (l) imaginary, 15°.

on the noisy images. As a result, the quality of image may twice be lowered because denoising causes blurring of high and low frequency components of the input image and MDC coder also decreases the quality of the resulting denoised image because of quantizers. Therefore, it is necessary to provide trade-off between two different problems and essential to design a new adaptive MDC generation scheme and a denoising filter to solve this challenging problem. In this work, to achieve this, MOEA has been used to solve these two problems and provide trade-off between them.

The proposed method is used to obtain optimal parameters to design the denoising filter to remove the mixed Gaussian impulse noise and create optimal and adaptive quantizers simultaneously which can be uniform or non-uniform to generate descriptions at different target bitrates. To achieve this, noisy input image is first transformed from the spatial domain into the frequency domain by using the DT-CWT. By applying the wavelet transformation technique, six different subbands or set of coefficients are obtained and each of them has different signal energy weight in the overall transformed image. After that, MOEA employs on the set of coefficients by iteratively minimizing two different fitness functions to design the optimal quantizers and reduce the mixed noise on descriptions. Thus, optimum decision and representation values into the quantizers are evaluated to generate balanced descriptions and parameters of the image filter are estimated simultaneously. As a result, the proposed method generates optimal quality MDCs, efficiently. Note that, bitrate and distortion value of each description is same and generated descriptions are transmitted through the multipath in the lossy networks. At the destination node, acceptable quality of image is received if only one description received and one side decoder is used in this case. On the other hand, better quality of image is obtained if more than one description received and the central decoder is used at the receiver side. In general, a block diagram of the proposed method is shown in Fig. 3.

4.1. Optimization approach using multi-objective evolutionary algorithm

Unlike the other search space based algorithms, MOEA optimizes more than one objective function simultaneously [36–41]. By applying MOEA to a multi-objective optimization problem, more than one equally important solution or pareto solutions can be obtained in each iteration. Many optimization problems have multiple objectives and constraints to bring promising solution for the optimization problems. A multi-objective optimization problem (MOP) is formulated as:

$$minimize \quad F(x) = (f_1(x) \quad f_2(x) \ldots \quad f_n(x))^T \tag{1}$$

where $F(x)$ has n objective functions and $x = [x_1, x_2, \ldots, x_m]$ is the vector of decision variables. One way of solution for multi-objective optimization problem is to transform it into the single optimization function. There are different techniques to obtain the single objective function from many objective functions. For instance, weighted sum of the objective functions and Euclidean norm have been mostly used in different multi-objective optimization problems to obtain the single objective function [42]. After that, a single objective search space based algorithm such as GA is employed to find the optimum result. However, improvement of one objective may cause deterioration for another objective when the algorithm performs finding the best optimum result. According to Deb et al. [36], it is shown that conversion of multi-objective in a single optimization problem does not give efficient result in terms of accuracy. MOEAs have been very popular in solving MO problems and they are proposed and developed mostly based on the EAs, particularly GA (description of the GA is provided in [42]). Also, they have been applied to resolve different problems such as face recognition [43], image segmentation [44] and change detection in satellite images [45]. The two goals of a MOEA are — 1)

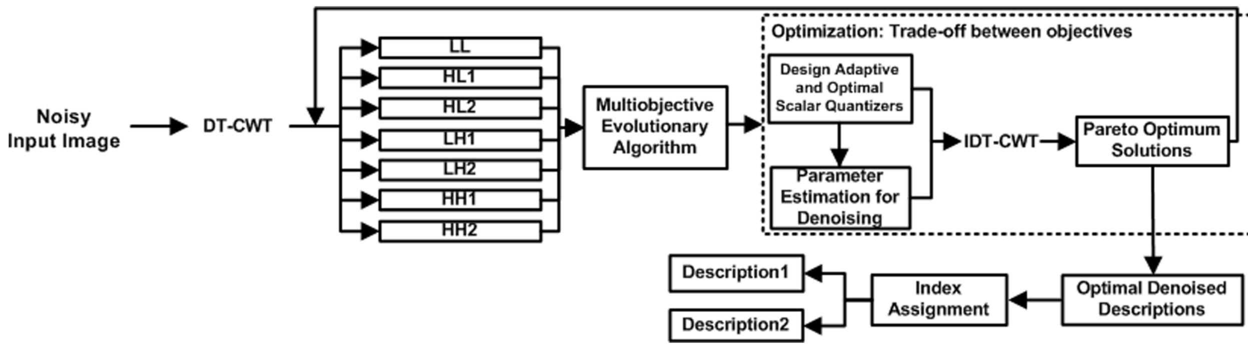


Fig. 3. Block diagram of the proposed method.

to find a set of solutions as close as possible to the Pareto Front, 2) to find a well distributed set of solutions [40]. To achieve these goals, several MOEAs have been proposed [36,39]. For instance, Schaffer et al. [38] proposed one of the first MO method which is called Vector Evaluated Genetic Algorithm (VEGA) to solve MO problems. The method uses number of sub-populations and, at each generation a number of sub-populations was generated by performing proportional selection according to each objective function. By using VEGA method, it is hard to produce Pareto-optimal solutions effectively. Fonseca et al. proposed a MOGA method which uses different ranking scheme to obtain Pareto-optimal solutions. The method is easy to implement but it is highly depending on an appropriate selection of the sharing factor. The Non-dominated Sorting Genetic Algorithm (NSGA) has been proposed by Srinivas et al. which is explained in [46]. In the NSGA, the population is first ranked on the basis of nondomination before selection technique is performed. Thus, all the nondominated individuals are categorized in one group. NSGA is an effective method which can solve any number of objectives [46] in both maximization and minimization problems. Besides of these methods, other MOEAs have been proposed to resolve different MO problems [40,47,48]. The common problem of these methods is that they cannot effectively find Pareto-optimal solutions to resolve MO problems. The elitist nondominated sorting genetic algorithm (NSGA-II) has been proposed [36] that uses the non-dominated sorting (NDS) scheme and a crowding measure to rank individual designs. The method is an effective method to produce and obtain Pareto-optimal solutions. In this paper, NSGA-II has been used to resolve the MO-MDC generation problem. There are several reasons to use NSGA-II for solving the corresponding problem. It is an efficient and robust algorithm as well as effective approach for finding Pareto-optimal solutions when there are multiple objectives in a problem. In addition, it is proved that NSGA-II provides more promising results than the other MOEA approaches such as the strength Pareto evolutionary algorithm (SPEA-2) [48].

Previously proposed MDC scheme methods use a single objective function for the MDC generation scheme, and due to the noise in the given input image, they fail removing noise on the MDCs. In order to solve this challenging problem, denoising filter can be used after the MDC scheme method. However, using this solution approach is not effective. In this work, NSGA-II is adopted to split the information from a given noisy source image into the optimal quality MDs. The steps of the evolutionary multiobjective optimization using NSGA-II are given in details below:

(1) The generation number g, population size K, crossover rate p_c and mutation rate p_m are initialized.
(2) Population initialization is an important step in the algorithm because the performance and efficiency of a search space algorithm depend on the representation scheme of a chromosome in the population. Fig. 4 shows a chromosome to produce one single description, a chromosome is represented with the decision and reconstruction values d_1, r_1, d_2, r_2, d_3, r_3...,d_n. In the proposed method, restricted ranges of real numbers are used to initialize the chromosomes where each one is randomly chosen between the real number $[\Lambda_{min}, \Lambda_{max}] \varepsilon R$, where Λ_{min} is the lowest and Λ_{max} is the greatest coefficient value in the decomposed sub-band of the input image.

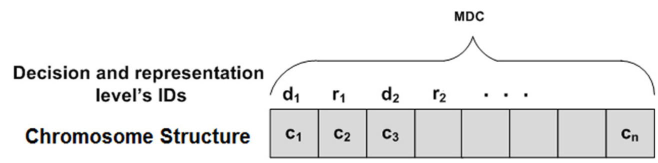


Fig. 4. Illustration of a chromosome which is used to create one description.

(3) There are two fitness functions f_1 and f_2 as defined in Eqs. (2) and (6). The former equation aims to maximize the quality of MDCs by finding the optimal decision and reconstruction values whereas the latter one aims to maximize the noise reduction by finding optimal parameters.
(4) Tournament selection strategy is used in the NSGA-II algorithm to select two parents from the population P. After that, genetic operators are applied to the selected parents (individuals or chromosomes) to create new individuals or offspring, as shown in Fig. 5. Crossover and mutation operators are the well known genetic operators which are also used in the algorithm, respectively. Crossover operates on two chromosomes and creates offspring by combining segments of both chromosomes. Thus, there is a transfer of genes between the parents which leads to find better result. Mutation operator follows the crossover operator and produces random changes of genes in various offspring to avoid getting stuck in a local optimum.
(5) Obtained new individuals are added in the new population Q. Then, both the current P and the new population Q are joined; the resulting population, Z, is ordered according to a ranking procedure and a density estimator known as crowding distance. Finally, the population P is updated with the best individuals in Z and the population P is used for the next generation creation in the next iteration.
(6) These steps are repeated until the termination condition is satisfied.
(7) There are two different outputs which are a set of Descriptions or MDCs and a set of Parameters for the denoising filter.

Fitness Function: The proposed multi-objective functions are employed in the MOEA to create d descriptions. Let the input image I and ith generated description d_i be of size $H \times W$ pixels, and consist of one spectral band at bitrate R. In the problem, two objective functions are used to obtain adaptive quantizers and optimal filter simultaneously. In order to create optimum and balanced descriptions of an image, one fitness cost function is used to obtain optimum decision and reconstruction values for each chromosome when another is used to estimate optimal parameters for image filter design to remove mixed Gaussian impulse noise on the descriptions. The method minimizes two objective functions f_1 and f_2 by estimating the average distortion of k descriptions at the server node to transmit good quality of image in the lossy network. The first fitness cost function f_1 between the noisy image and the generated d_i descriptions, i.e.

minimize $F = [f_1 \;\; f_2]$

$$f_1 = \frac{1}{k}\sum_{i=1}^{k}\sqrt{\frac{1}{HxW}\sum_{\forall x,y}\big(I(x,y) - d_i(x,y)\big)^2} \qquad (2)$$
$$for \quad R^i = R^{(i+1)}, i = 1, 2, \ldots, m$$

Each description rate R is defined as:

$$R = -\sum_{\forall j} p(a_j)log(p(a_j))(\text{bit per pixel}) \qquad (3)$$

where x, y denote the pixel coordinates of the noisy image I and $p(a_j)$ is the probability of the pixel intensity d_i, which is estimated from the normalized histogram. The first objective function f_1 computes the average root mean square error between the k different generated descriptions at different bitrates and noisy input image at each iteration in the MOEA. Thus, using the first fitness function provides to design multi optimal quantizers to produce descriptions at different bitrates. Note that, lower average root mean square error provides higher quality of descriptions of the input image at different bitrates so the MOEA minimizes the fitness function f_1. However, the generated descriptions still contain noise so that it is necessary to reduce or remove it. To achieve this, the second objective function f_2 which estimates optimal parameters of denoising filter is explained with further details in the following subsection.

4.2. Parameter estimation and optimization for image denoising

Image denoising is one of the most important tasks in the image processing applications such as image segmentation, multimedia communication, image feature extraction, image registration, storage and image retrieval. The presence of noise in the images will lead to serious impacts to resolve such problems. Besides this, it affects the quality of image as the Peak Signal to Noise Ratio (PSNR) of the images is reduced and it is necessary to improve it before performing image analysis tasks. The major challenge in designing the image filter for images is to remove the noise efficiently without removing the details of information such as edges, lines etc. [49].

Different models have been proposed for image denoising including ROF model [50], total variation model (TVM) [49], bias model (BM) [51], graphical model (GM) [52] and multiplicative noise model (MNM) [53]. They are shown as great approaches for removal of a variety of noise like Gaussian noise, salt-and-pepper noise, uniform noise, Rayleigh noise, exponential noise, Gamma noise and poison noise. However, they have ability to remove one noise type on the images and the parameters used in the models are not optimal. In this paper, we have used a denoising filter which combines the bilateral filter (BF) [54] and noise removal algorithm [55] to remove the mixed Gaussian noise and impulse noise (salt-and-pepper noise) on the images [56]. However, it is necessary to use optimal parameters in the noise reduction filter to remove the noise efficiently. Therefore, the proposed method is used to optimize parameters to design effective image filter.

Fitness Function: In the proposed method, parameters are estimated from the descriptions which are generated based on the first fitness function f_1 at each iteration. Thus, different parameter values can be obtained at each iteration and optimum parameters can be achieved to design the image filter. Thus, the second fitness function f_2 is used to estimate and update the parameter values of denoising method which will be used to decrease the effect of the noise on the descriptions. To achieve it, the fitness function f_2 computes the mean absolute error between the k denoised descriptions and noisy input image. Note that, lower the mean absolute error provides higher quality of descriptions so it is necessary to minimize the fitness function f_2. As a result, important details such as edge and features of the input image are better preserved in the descriptions by optimizing two different fitness functions simultaneously using the MOEA which provides trade-off between the two fitness functions. Let d_i and $\hat{d}_i$ be the ith description and denoised description, respectively. Assuming that the pixels of a local processing block δ of size $(2r_i + 1) \times (2r_i + 1)$ are denoted as $s_1, \ldots, s_\ell, \ldots, s_N$ where s_ℓ is in the center, $\hat{d}_i(x, y)$ is the output and N is the number of pixels of the block δ. The image denoising which reduces mixed Gaussian impulse noise can be defined as [56]:

$$\hat{d}_i(x,y) = \frac{\sum_{j=1}^{N} w_j.s_j}{\sum_{j=1}^{N} w_j}$$
$$w_j = \alpha(d_i(x,y); \mu_i, \sigma_i)\left(\frac{1}{\beta}\sum_{k=1}^{\beta}(s_\ell - s_k)\right) \qquad (4)$$

where β denotes the number of nearest neighbors in a small window W size of 3×3, $\alpha(I(x, y); \mu_i, \sigma_i)$ is the Gaussian curve membership function of the ith description, μ_i, σ_i and r_i are the parameters of ith description which are mathematically described as

$$\alpha(d_i(x,y); \mu_i, \sigma_i) = \exp\left(\frac{-1}{2}\Big(\frac{d_i(x,y) - \mu_i}{\sigma_i}\Big)^2\right)$$
$$\mu_i = \frac{1}{H \times W}\sum_{x=1}^{H}\sum_{y=1}^{W} d_i(x,y)$$
$$\sigma_i = \sqrt{\frac{1}{H \times W}\sum_{x=1}^{H}\sum_{y=1}^{W}\big(d_i(x,y) - \mu_i\big)^2} \qquad (5)$$
$$r_i = \frac{\mu_i}{\sigma_i}, \quad \beta = \frac{\mu_i}{\sigma_i}$$

As a result, there will be k different parameters of μ, σ, r and β based on the generated descriptions. Thus, k different filters can be designed by using these parameters. In order to optimize the parameters, the second fitness function f_2 is defined as:

$$f_2 = \frac{1}{k}\sum_{i=1}^{k}\frac{1}{H \times W}\sum_{\forall x,y}|\big(d_i(x,y) - \hat{d}_i(x,y)\big)| \qquad (6)$$

By minimizing the second fitness function, we can reduce the mixed Gaussian impulse noise while preserving the image details on the descriptions. After that, descriptions are transmitted through the lossy networks.

5. Validation and experimental results

The experiments presented in this section aim to maximize the quality of image data receiving at the client nodes in the lossy networks. Besides this, the performance of the proposed method is examined in generating MDCs in terms of quality estimation with different achievable bitrates and discussed with respect to its robustness to the mixed Gaussian noise and impulse noise (salt-and-pepper) in images. The proposed method is the combination of Multi-Objective Evolutionary Algorithm and Dual Tree-Complex Wavelet Transform (MOEA–DTCWT) and it is compared with the

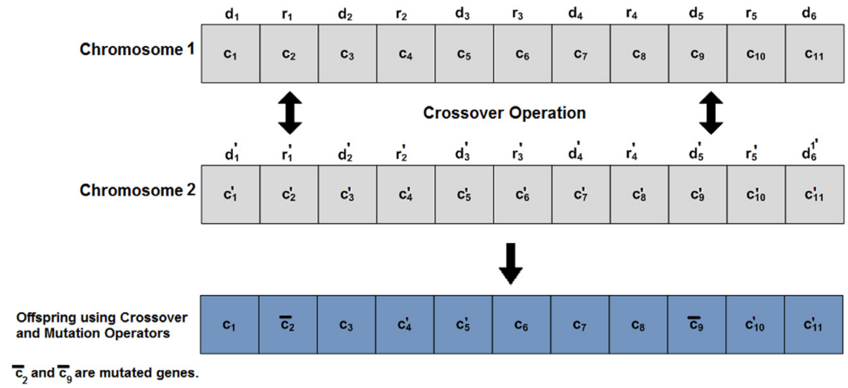


Fig. 5. Illustration of genetic operators on two different chromosomes.

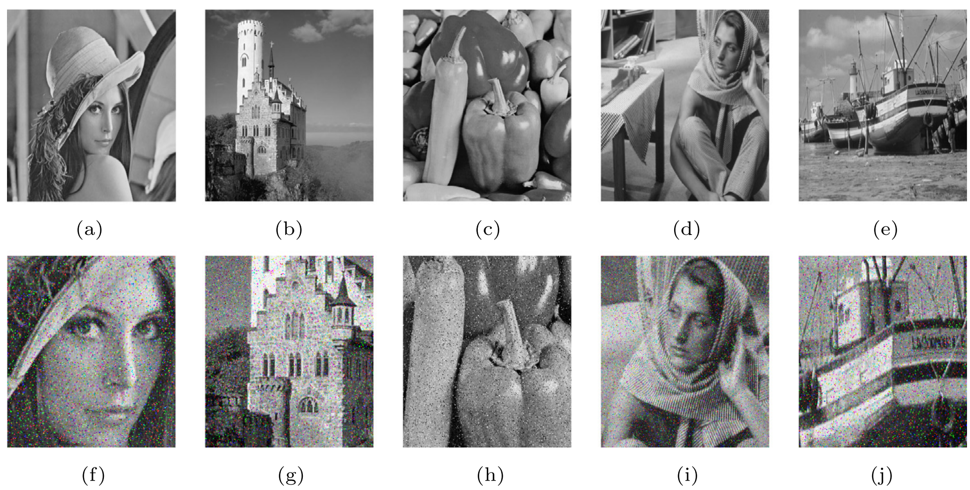


Fig. 6. Test Images: (a) Lena, (b) Castle, (c) Pepper, (d) Barbara, (e) Boat and (f)–(j) Illustration of part of test images corrupted by the Gaussian noise of zero mean and standard deviation $\sigma = 0.06$, and impulse noise $p = 0.06$. Signal-to-Noise Ratio (SNR) results of corrupted test images (f)–(j) are 10.8326 dB, 11.8904 dB, 11.4062 dB, 11.3160 dB, and 11.2992 dB, respectively.

Table 1
Parameters of the MOEA.

Parameter	Value
Population size (P)	150
P_m	0.1
P_c	0.8
Number of generations	200

other MDC generation methods which are Multiple Description Wavelet Based Image Coding (MD-DWT) [6], Multiple Description Scalar Quantization (MDSQ) [3] and Genetic Algorithm Discrete Wavelet Transform based MDC generation (GA-DWT) [13]. In this work, five different one spectral band images which are LENA, CASTLE, PEPPER, BARBARA and BOAT with the resolution of 512×512, have been used as test images which are shown in Fig. 6. Table 1 lists the parameters used for the MOEA and they are selected empirically.

5.1. Robustness of the MDC generation methods to the mixed gaussian impulse noise

In order to verify the robustness of the proposed method to the mixed Gaussian impulse noise, we used two different noise types which are Gaussian noise of zero mean and standard deviation σ and salt-and-pepper noise p. In this experiment, we consider the standard deviation σ of the zero-mean Gaussian varies from 0.02 to 0.1 with increment of 0.02 and salt-and-pepper noise varies from 0.02 to 0.1 with increment of 0.02. Besides this, total added noise τ is estimated by using $\tau = \sigma + p$ and both Gaussian noise and salt-and-pepper noise are added to the five different test images to understand and analyze the robustness performance of the proposed method over existing methods. As shown in Fig. 6, it is obvious that adding noise to the whole image will cause a major distortion in the context of the images and noise dominates most of pixels in the images such as edges, lines, and other features.

In this experiment, the implemented algorithms have been used to generate two side descriptions from the given noisy images. Each method was simulated 10 times to create two balanced MDCs at the bitrate $R = 1.0$ bpp and it was performed on the coefficients of the three different noisy images 1-level decomposed by the DT-CWT. In order to understand and analyze the results clearly, the mean of 10 *PSNR* measurements is used, which each of PSNRs is estimated by $PSNR = 10 \log \frac{255^2}{MSE}$ where MSE is the mean squared error between the original image and the generated description. The estimated PSNR results are shown in Fig. 7(a), (b), (c), (d) and (e) for different test images, respectively. The results are obtained by applying different additive noise values on the input images. Note that the noise level τ varies from 0.04 to 0.2 with step 0.04. In Fig. 7, it is clearly seen that the highest quality of description is obtained by using the proposed method and the lowest quality is estimated by using the MD-DWT method [3]. Moreover, comparison between measurements obtained with the proposed method shows that the least obtained PSNR, which is

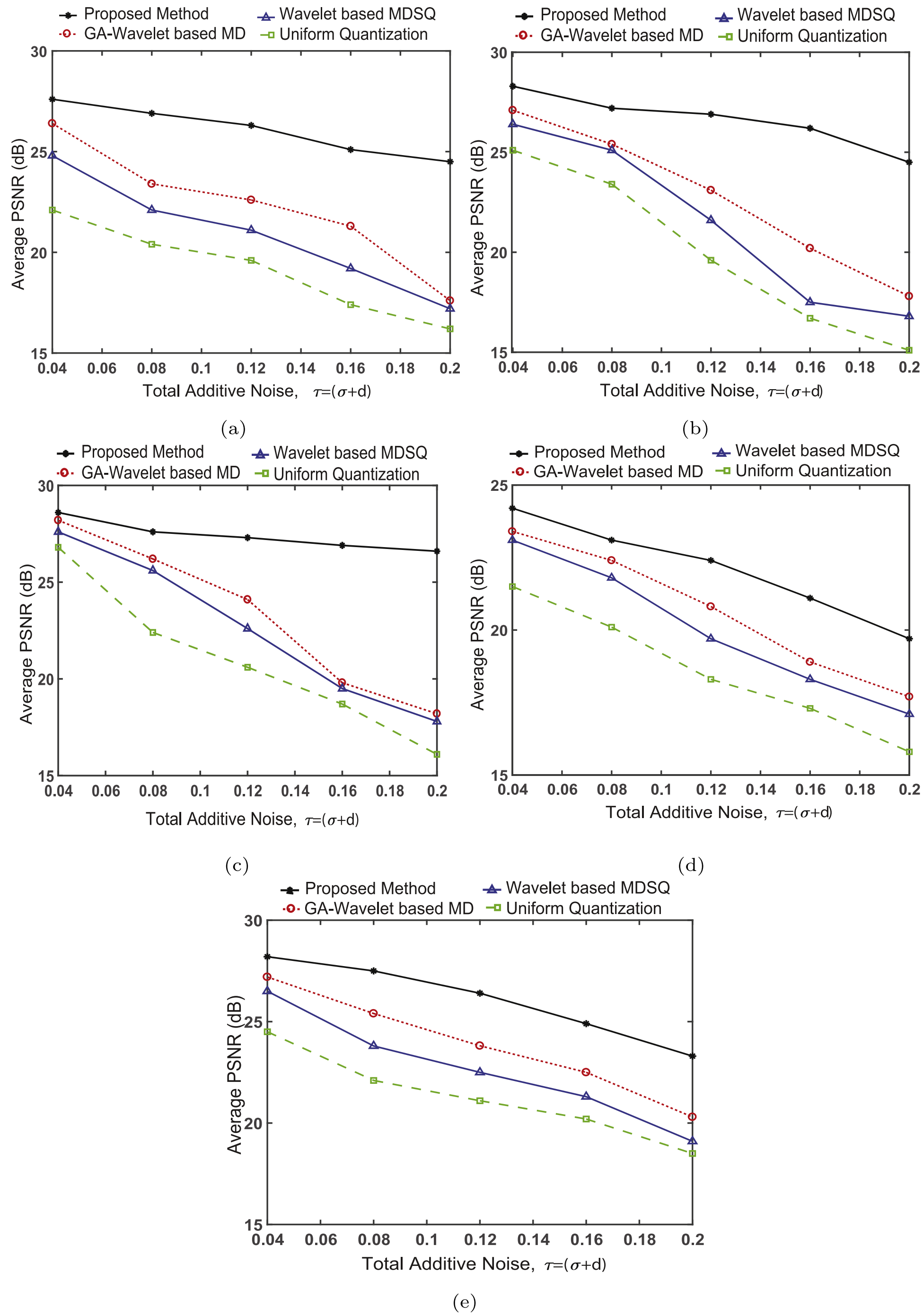


Fig. 7. The robustness performance analysis of the MDC generation methods to the mixed Gaussian impulse noise. (a) Lena Image, (b) Castle Image, (c) Pepper Image, (d) Barbara, (e) Boat.

19.7 dB, belongs to the BARBARA image with the highest level of noise ($\tau = 0.2$). However, even for the worst-case scenario, we can see that the proposed method has significant performance improvement in terms of PSNR when compared with GA-DWT with 17.7 dB, MDSQ with 17.1 dB, and MD-DWT with 15.8 dB. Thus, the proposed method creates the highest quality of one side description at the difference levels of noise and overcomes the problems of noise artifacts on the input images. However, other MDC generation methods suffer from noise artifacts and they are unable to remove noise on descriptions which cause low quality of MDC creation. Consequently, the proposed method is robust to mixed Gaussian impulse noise and it provides the greatest performance to generate a side description with the lowest average distortion at target-bitrate. Moreover, beside from the effect of noise on the results of compared methods, another reason that MD-DWT and MDSQ provide the worst results is due to the fact that they are not using any optimization approach to design quantizers. On the other hand, GA-DWT and the proposed method show that using optimization techniques improve the performance of MDC generation methods.

5.2. Performance comparison of the MDC generation methods

In the second experiment, five standard test images, which are shown in Fig. 6(f)–(j), are used to compare the proposed method

Fig. 8. MDC generation using Lena and Castle test images. (a) Part of original Image, (b) Noisy Image corrupted by the Gaussian noise of zero mean and $\sigma = 0.06$, and impulse noise $p = 0.06$, (c), (d), (e) Proposed Method, (f), (g), (h) GA-DWT [13], (i), (j), (k) MD-DWT [6], (l), (m), (n) MDSQ [3].

with the other MDC generation methods. The implemented methods have been applied to generate two side quantizers. In the proposed method, we generate two descriptions by minimizing the distortion and finding optimal parameters of image denoising. In contrast, the other compared methods generate the descriptions without applying any denoising method. Each implemented method was executed 20 times at total noise $\tau = 0.12$ to create two optimal side quantizers for two balanced MDC generation and obtained results are shown in Fig. 9(a)–(e) with different bitrates which vary from 0.4 to 2.2 bpp. Fig. 8 shows that the higher the bitrate, the better the description quality is, which simply leads to the higher PSNRs. For instance, Fig. 9(a) illustrates the PSNR results for one side description obtained from noisy LENA image. In the proposed method, the PSNR values vary from 26 dB to 36.2 dB, whereas the PSNR values in the MDSQ, MD-DWT, and GA-DWT vary from 20 dB, 20.8 dB, and 22 dB to 28.2 dB, 29.4 dB, and 30.1 dB, respectively. From Fig. 9 it is obvious that increasing the bitrate does not significantly improve the quality of the descriptions generated by the state-of-the-art methods. On the other hand, the proposed method remarkably improves the PSNR values because it provides the trade-off between noise reduction and preserving image features. Fig. 8 illustrates the side and central descriptions of part of Lena and Castle images, respectively. The methods are used to create two side descriptions of input noisy images of LENA (see the first and second columns of Fig. 8) and CASTLE (see the fourth and fifth columns of Fig. 8). Their central descriptions which are the combination of two side descriptions are illustrated in the third and sixth columns. Based on the qualitative results, it is obvious that the compared MDC generation methods cannot design optimal quantizers and cannot be successful to reduce any type of noise. These will simply cause low quality of description generation. As seen in Fig. 8, the GA-DWT [13] provides the higher performance than the MDSQ and MD-DWT methods as it designs optimal quantizers. However, this method provides lower performance than the proposed method because it uses only one single objective function without considering noises on the input images to create MDCs. The proposed method MOEA–DTCWT appears to be the most resistant to noise, thereby reducing the distortion as well as preserving the detailed information of descriptions generated. Besides this, the proposed method achieves the highest performance among all the compared methods even if the noise level increases on the input images.

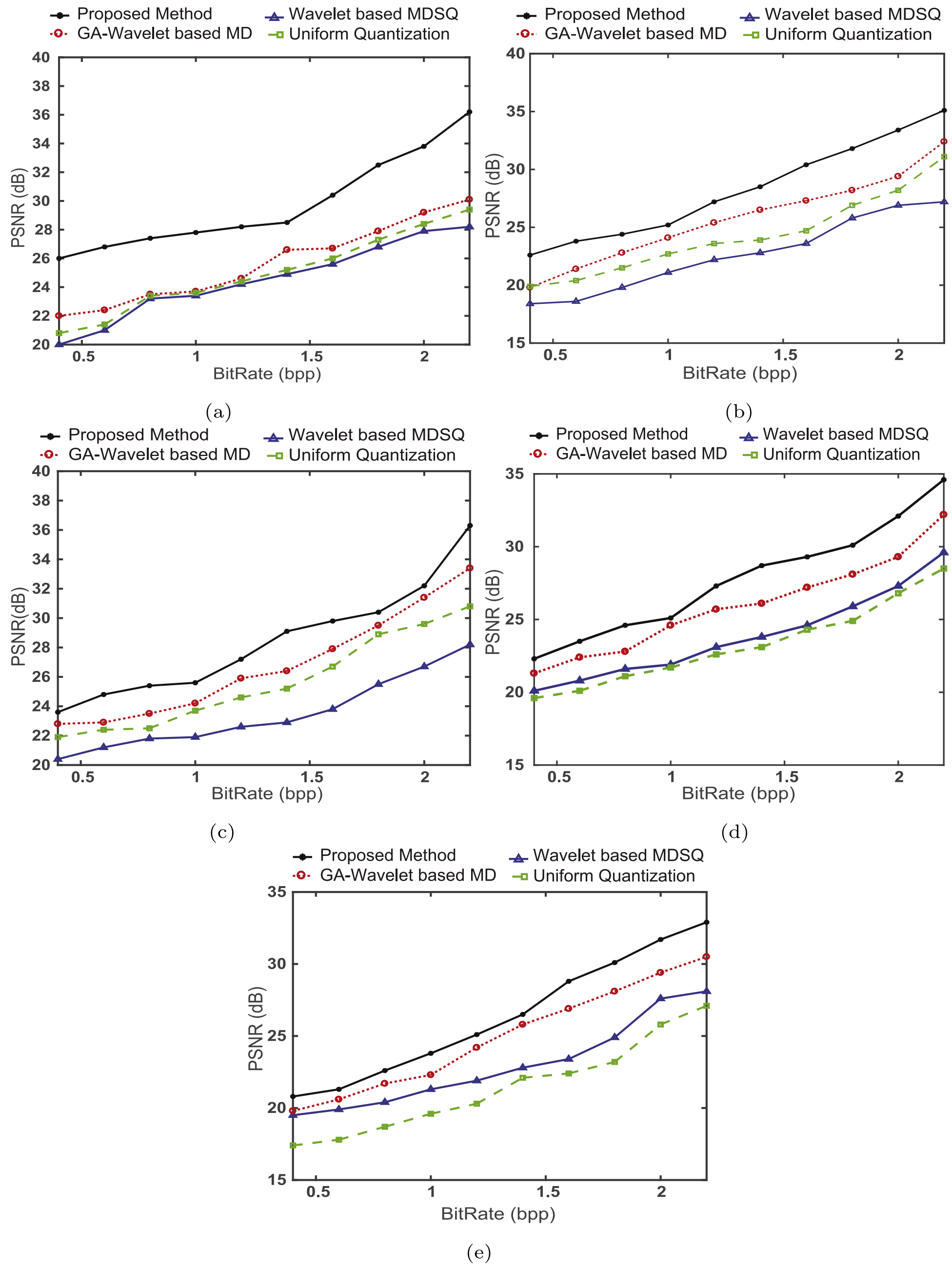


Fig. 9. Average quantitative results at different bitrates. Average PSNR results for; (a) Lena, (b) Castle, (c) Pepper, (d) Barbara, (e) Boat.

Table 2
Comparison of execution time (seconds) of the algorithms for the Lena image.

Method	Two MDCs	Five MDCs	Twelve MDCs
Proposed method	8.82	8.91	8.96
GA-DWT [13]	9.53	28.16	56.89
MD-DWT [6]	4.86	9.55	22.58
MDSQ [3]	3.18	9.16	19.14

Table 3
Comparison of execution time (seconds) of the algorithms for the Castle image.

Method	Two MDCs	Five MDCs	Twelve MDCs
Proposed method	9.63	9.76	9.88
GA-DWT [13]	10.12	32.12	63.11
MD-DWT [6]	3.94	12.23	25.18
MDSQ [3]	3.77	10.08	23.04

Tables 2–4 illustrate the comparison of the CPU time required to execute the algorithms to find optimal MDCs for three test images (LENA, CASTLE and PEPPER). The implemented algorithms have been used to produce two, five and twelve descriptions for each test image, respectively. For generation of two MDCs in terms of execution time, the proposed method is faster than GA-DWT but slower than MD-DWT and MDSQ. On the other hand, for generation of five and twelve MDCs, the proposed method provides the best execution time compared to the other algorithms. For instance, it takes 4.91 and 4.96 s for execution for Lena image to generate five and twelve descriptions, respectively. As a result, from this perspective, the proposed method requires less execution time to generate five and twelve MDCs. The proposed method requires less execution time because it finds pareto optimal solutions and

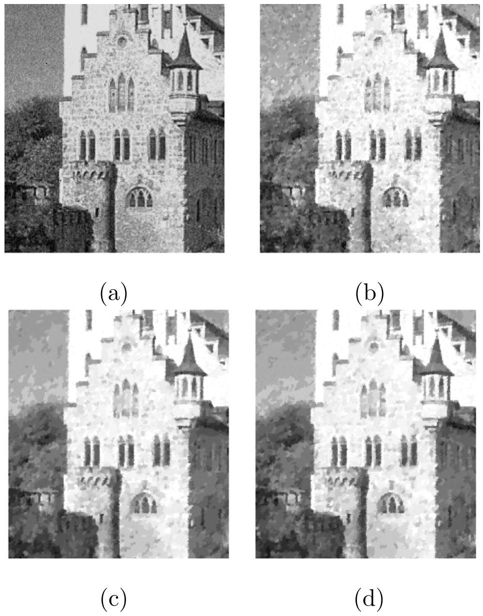


Fig. 10. MDC generation using noisy Castle test image shown in Fig. 6(g). (a) Proposed Method, (b) TV denoising method with GA-DWT [13], (c) TV denoising method with MD-DWT [6], (d) TV denoising method with MDSQ [3].

Table 4
Comparison of execution time (seconds) of the algorithms for the Pepper image.

Method	Two MDCs	Five MDCs	Twelve MDCs
Proposed method	9.79	9.86	9.92
GA-DWT [13]	6.12	28.12	58.15
MD-DWT [6]	3.23	10.23	23.45
MDSQ [3]	3.96	11.12	19.17

design quantizers simultaneously to create many optimal MDCs. However, other MDC generation methods sequentially design the quantizers, which are high time-consuming and not effective process for MDC generation.

5.3. Effects of denoising method on descriptions

In order to understand the effects of denoising method on descriptions, we compare the proposed method with the conventional approach in terms of producing optimal quality of MDCs. In the conventional approach, it is first necessary to reduce or remove the noise on the input image and then MDC generation methods are applied to the denoised image to create the descriptions. In this experiment, a Total Variation denoising method (TV) proposed by Chambolle et al. [57] is first applied to the noisy image and then the state-of-the-art MDC generations methods are applied to the resulting denoised image. Note that in this experiment, the descriptions are created with the bitrate $R = 1$ bpp.

Figs. 10 and 11(a)–(d) illustrate the side descriptions generated by using the proposed method, TV-GA-DWT, TV-MD-DWT and TV-MDSQ, respectively. According to the qualitative results, it is seen that although the TV-based denoising approach reduces noise, it causes undesired artifacts such as blurring, visuality loss of some edge(s) and feature(s) etc. on the descriptions generated. Moreover, Table 5 shows the quantitative results of one description and the compared MDC generation methods with TV-based denoising approach give the lower PSNR results than the proposed method. From the both quantitative and qualitative results, we can conclude that applying denoising method to the noisy input images improves slightly the performance of the MDC generation methods, but they are not able to preserve detailed information on descriptions. This is due to the fact that using of two different methods (e.g. TV and MDSQ) sequentially causes more loss of detail information as non-optimal quantizers are used to create MDCs from the image which includes undesired artifacts. Although the compared methods are used with the denoising method, the proposed method provides the best PSNR results with 27.8 dB, 25.2 dB, and 25.6 dB and TV-MDSQ provides the least PSNR results with 24.76 dB, 22.92 dB, 23.48 dB for LENA, CASTLE, and PEPPER images, respectively.

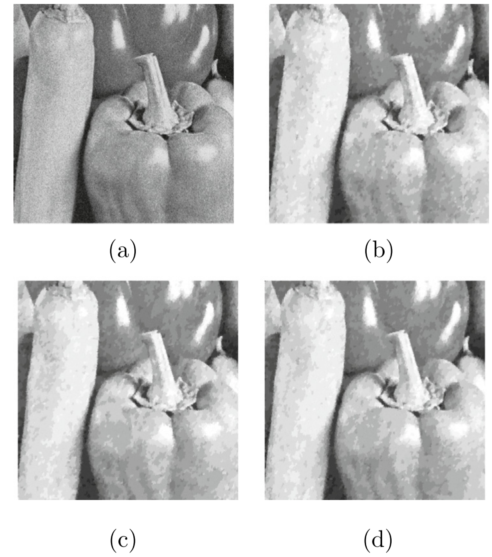


Fig. 11. MDC generation using noisy Pepper test image shown in Fig. 6(h). (a) Proposed Method, (b) TV denoising method with GA-DWT [13], (c) TV denoising method with MD-DWT [6], (d) TV denoising method with MDSQ [3].

Table 5
Quality of one description with PSNR results.

Method	LENA	CASTLE	PEPPER
Proposed method	27.8	25.2	25.6
TV-GA-DWT [13]	26.25	24.72	24.85
TV-MD-DWT [6]	25.71	23.81	24.52
TV-MDSQ [3]	24.76	22.92	23.48

The purpose of the next experiment is to evaluate the performance of the GA and MD methods with the DT-CWT. To achieve the results, the TV denoising technique is first applied to the noisy test images and then the GA or MD with DT-CWT is applied to generate MDCs. In this experiment, two different noisy test images have been used which are Lena and Castle images corrupted by different τ values. Based on the PSNR results in Fig. 12, the proposed method provides the best performance comparing to the TV-GA-DTCWT and TV-MD-DTCWT. The main reason is that the proposed method optimizes the parameter values for designing image filter as well as optimizing quantizers to generate good quality of MDCs. Furthermore, the TV-GA-DTCWT and TV-MD-DTCWT provide better PSNR results as compared to the TV-GA-DWT and TV-MD-DWT, respectively. This is due to fact that TV-GA-DWT and TV-MD-DWT are using DWT which has disadvantages such as lack of shift invariance, limited directionality when extended to higher dimensions and lack of phase information.

5.4. Quality analysis of receiving MDCs

In this experimental setup, three test images (see Fig. 6(f)–(h)) are firstly denoised and then transmitted from a server to a client node in the lossy network. The performance of the proposed

Table 6
Average rankings of the MDC generation schemes using the non-parametric statistical procedure.

Method	Friedman	Friedman aligned	Quade
Proposed method	1.33	9.66	1.24
GA-DWT [13]	1.66	10.33	1.75
MD-DWT [6]	3.11	27.11	3.02
MDSQ [3]	4.00	33.11	4.0
Statistics	33.15	7.26	25.42
p-value	1.25×10^{-6}	0.1206	2.44×10^{-9}

method MOEA–DTCWT is evaluated against TV-GA-DWT, TV-MD-DWT, and TV-MDSQ in terms of quality estimation of receiving image at the client node. Notably the received descriptions are decoded at the destination node. The main goal of this experiments is to understand whether increasing number of descriptions can improve the quality of received image as some of the MDC packets can be lost in the lossy networks because of several reasons such as: (1) delayed packet dropping and (2) congestion may occur over lossy transmission networks. Fig. 13 denotes the comparison results between the average PSNR and the number of descriptions received. In order to estimate the average quantitative results, the algorithms generate different number of descriptions (i.e. 2, 3, 5, 8, and 12) at bitrate $R = 0.25$ bpp and the average PSNR is estimated as follows:

$$\overline{PSNR} = \frac{1}{mn_1n_2} \sum_{k=1}^{m} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} PSNR^{k,i}(R_j) \tag{7}$$

where m is the number of descriptions with n_2 different bitrates and n_1 is the number of times that MDCs are generated which is 10 times in this experiment. Fig. 13 shows that increasing the descriptions from 2 to 5 sharply increases the quality of received images in all methods. However, increasing number of descriptions from 5 to 8 cannot always improve the performance except for the proposed method (see Fig. 13(a)). From Fig. 13 it is obvious that in all methods, increasing the number of descriptions to 12 always decreases the quality of received images as combining more MDCs degrades important features of reconstructed images due to the existence of noise. Thus, it causes distortion and the results prove that using denoising methods cannot remove the noise on MDCs completely but using proposed approach provides more promising results than the TV-GA-DWT, TV-MD-DWT and TV-MDSQ. Amongst the compared MDC generation methods, using MOEA–DTCWT provides the most effective multimedia communication in terms of delivering good quality of images even if only two MDCs are successfully received at the client.

5.5. Comparison of MDC generation methods using non-parametric tests

In this subsection, non-parametric test results are shown and examined for comparing the proposed method MOEA–DTCWT with the existing MDC generation methods [58,59]. In order to achieve the test results in Table 6, Friedman, Friedman Aligned and Quade non-parametric tests are applied to the average of all results showing in Figs. 7, 9 and 12. The purpose of using Friedman, Friedman Aligned and Quade non-parametric tests is to determine whether there are significant differences among the algorithms considered over given set of data. These tests obtain the ranks of the algorithms for each individual data set, i.e., the best performing algorithm receives the rank of 1, the second best rank 2, etc.

Table 6 depicts the average ranks computed using Friedman, Friedman Aligned and Quade non-parametric tests. Based on the results, proposed method MOEA–DTCWT is the best performing algorithm of the comparison, with the average rank of 1.33, 9.66, and 1.24 for the Friedman, Friedman Aligned, and Quade tests, respectively. This shows that proposed method provides great performance to design quantizers for MDCs generation and proves the improvement of the MOEA–DTCWT over the rest of MDC generation methods. The p-values computed through the statistics of each of the tests considered (1.25×10^{-6}, 0.1206, 2.44×10^{-9}). The Iman Davenport statistic and p-value are computed 84.57 and 1.51×10^{-16}, respectively.

5.6. Discussion

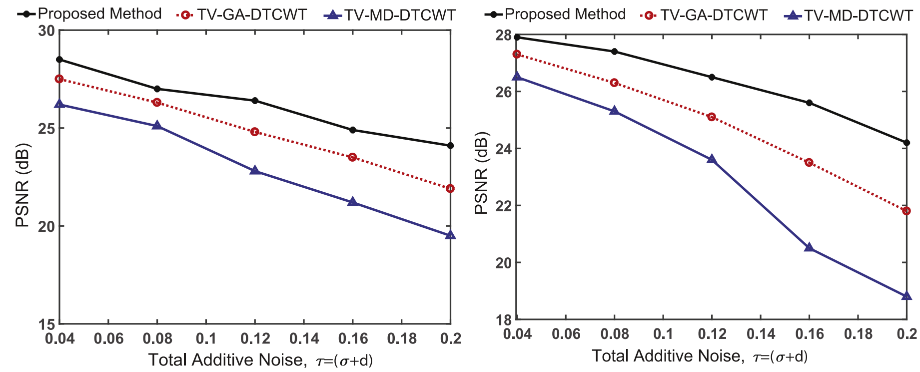
In this paper, an MDC generation method using MOEA with the DT-CWT is proposed for effective multimedia transmission. Five different test images have been used to understand and analyze the performance of the proposed method. According to the results, it is shown that the proposed method finds the optimal reconstruction and decision values to design different and optimal quantizers to generate MDCs at different bitrates. Also, it obtains optimal parameter values in image denoising to reduce the mixed Gaussian impulse noise in the descriptions. Moreover, the proposed method provides the best PSNR results of the generated MDCs comparing to the other MDC generation methods if the input image is corrupted by the mixed Gaussian impulse noise. Besides of this, the proposed method requires less execution time comparing to the other MDC methods to generate five and twelve MDCs. Furthermore, non-parametric test results using Friedman, Friedman Aligned and Quade non-parametric tests are provided and examined for comparing the proposed method MOEA–DTCWT with the other MDC generation methods. Based on the statistical results, the proposed method is the best performing algorithm amongst the MDC generation methods.

6. Conclusion

In this paper, we have presented a novel MDC generation method which is robust to the mixed Gaussian impulse noise. The method uses dual-tree wavelet based image coding with the Multi-objective Evolutionary Algorithms (MOEAs) for effective multimedia transmission in lossy networks. The purpose of the proposed method is to optimize two different objective functions for designing image filter with optimal parameters and creating optimal and adaptive side quantizers. Thus, the method reduces the mixed Gaussian impulse noise and produces optimal quality MDCs which are then transmitting through lossy networks. To achieve it, Dual-Tree Complex Wavelet Transform (DT-CWT) is first applied to the noise input image to produce the sub-bands or set of coefficients. After that, MOEA is used to provide trade-off between reducing noise and generating good quality MDCs by finding optimal parameters of image denoising and by obtaining the decision and reconstruction values in the set of coefficients for designing optimal and adaptive quantizers. Simulation results illustrate that MOEA performs well to optimize two objective functions simultaneously for optimal description generation comparing to the existing MDC generation methods. Consequently, proposed multi-objective MDC generation method is robust to mixed Gaussian impulse noise and, designs optimal and adaptive side quantizers to create MDCs with good quality for effective multimedia transmission over lossy networks.

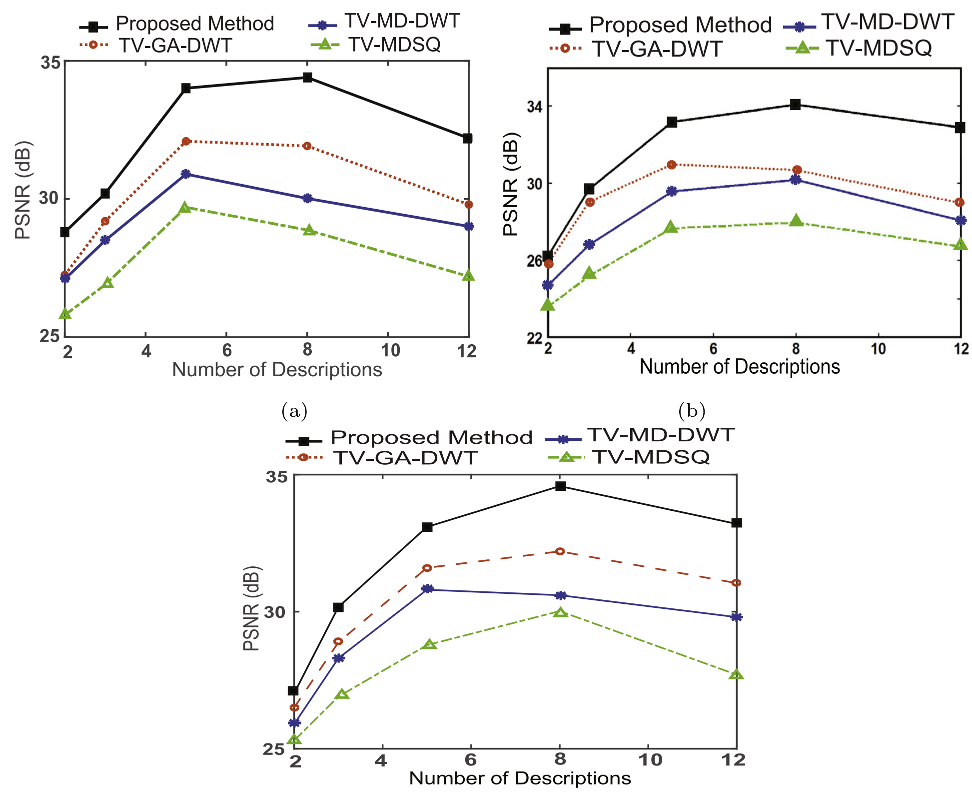
Acknowledgments

Huseyin Kusetogullari is funded by the research project Scalable resource efficient systems for big data analytics by the Knowledge Foundation (grant: 20140032) in Sweden. We thank the Associated Editor Prof. Mengjie Zhang, Editor-in-Chief Prof. Mario Köppen and anonymous reviewers for their constructive comments, which helped us to improve the manuscript.



(a) (b)

Fig. 12. Quantitative results estimated based on different τ values. (a) PSNR results for Lena Image, (b) PSNR results for Castle Image.



(a) (b)

(c)

Fig. 13. Average quantitative results estimated based on number of description received. (a) Average PSNR results for Lena Image, (b) Average PSNR results for Castle Image, (c) Average PSNR results for Pepper Image.

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