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Evolutionary Computing and Second generation Wavelet Transform optimization: Current State of the Art

By S.Nagaraja Rao , Dr. M.N.Giriprasad

Abstract- The Evolutionary Computation techniques are exposed to number of domains to achieve optimization. One of those domains is second generation wavelet transformations for image compression. Various types of Lifting Schemes are being introduced in recent literature. Since the growth in Lifting Schemes is in an incremental way and new types of Lifting Schemes are appearing continually. In this context, developing flexible and adaptive optimization approaches is a severe challenge. Evolutionary Computing based lifting scheme optimization techniques are a valuable technology to achieve better results in image compression. However, despite the variety of such methods described in the literature in recent years, security tools incorporating anomaly detection functionalities are just starting to appear, and several important problems remain to be solved. In this paper, we present a review of the most well-known EC approaches for optimizing Secondary level Wavelet transformations.

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Evolutionary Computing and Second generation Wavelet Transform optimization: Current State of the Art

S.Nagaraja Rao^a, Dr. M.N.Giriprasad^Ω

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45

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I. INTRODUCTION

Wavelets are used by several image processing applications, including JPEG2000 [14] and fingerprint compression, [15]. Discrete wavelet transforms (DWTs) can enormously reduce the number of bits required for representation by reproducing an image's energy into a set of several lower-resolution trend sub-images. Techniques like "Quantization (approximating a signal with a smaller number of bits)" and "Thresholding (setting all but the largest transform values to zero)" may bring about an extra compression. But the drawback with both these techniques is that they cause irrevocable information loss, since the mean squared error (MSE) of restored images increases proportionately. The only solution to this problem would

be implementing "Evolutionary computation (EC)". EC is the technique which uses fitness-based selection and genetics-inspired operators to evolve remedies to a combinatorial optimization mission.

But the observed thing is that very few researchers have applied this technique to the wavelet domain. Grasemann and Mikkulainen[16] proposed a methodology for synthesizing new ideal reconstruction wavelets from an existing wavelet filter by combining a genetic algorithm (GA) with a lifting scheme. This method has improved presentation for certain classes of images.³ But nevertheless, this genetic algorithm inflicts none of the mathematical properties required of wavelets, such as conservation of energy.

II. EVOLUTIONARY COMPUTATION (EC)

A representation plan of action is chosen by the researcher to define the set of solutions that form the explored space for the algorithm. To form an initial population a number of individual solutions have been designed. Until a remarkable solution is found this satisfies a predefined conclusion criterion these following steps have been repeated iteratively. Each individual is estimates by a fitness function which is specific to the problem being solved; a number of individuals are picked to be parents based on their fitness values. New individuals, or offspring, are produced from those parents using reproduction operators and the fitness values of those offspring are regulated. Finally, the survivors are selected from the old population and the offspring to form the new population of the later generation.

A selection method is concerned for determining which and how many parents are to be selected, how many offspring are to be generated, and which individuals will have to sustain into the later generation. Many different selection methods have been suggested in the literature but differ in complexity. The thing to be noted is that most selection methods make certain that the population of each generation is the identical size.

a) Genetic algorithms and programming

Genetic algorithm has become the most approved technique in evolutionary computation research. Fixed-length bit string is the representation

^{About^a} - S.Nagaraja Rao, Professor of Electronics & Communication Engineering, G.Pullaiah College of Engineering & Technology, Kurnool, A.P., India

Ph: +91-9440328621, E-mail ID: suryakari2k1@yahoo.com

^{About^Ω} - Dr. M.N.GiriPrasad, Professor & Head, Dept. of Electronics & Communication Engineering, J.N.T.U.College of Engineering, Pulivandula, Kadapa, A.P., India, Ph: +91-9440566628, E-mailID: mahendran_gp@rediffmail.com

used in the traditional genetic algorithm. Each position in the string is assumed to represent a particular feature of an individual, and the value stored in that location represents how that characteristic is expressed in the result. Usually, the string is "evaluated as a collection of structural features of a solution that have tiny or no interactions" [1]. The analogy may be drawn directly to genes in biological organisms. Each gene indicates an entity that is structurally independent of other genes.

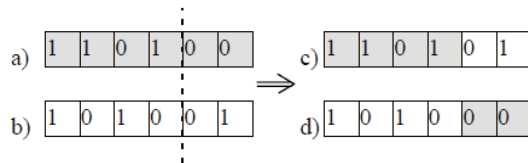


Fig 1: Bit-String Crossover of Parents a & b to form Offspring c & d

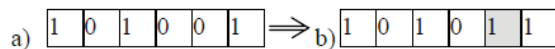


Fig 2: Bit-Flipping Mutation of Parent a to form Offspring b

Bit-string crossover is the main reproduction operator used in which two strings are used as parents and in between these two strings new individuals are formed by swapping a sub-sequence (see Figure 1). Bit-flipping mutation is an additional favoured operator in which a single bit in the string is flipped to create a new offspring string (see Figure 2). Several such variety of operators have also been evolved, but are used less frequently (e.g., inversion, in which a subsequence in the bit string is reversed). A chief difference may be made between the various operators is that they may or may not introduce any new information into the population. Crossover, for example, does not while mutation does. All operators are also prevailed to handle the string in a manner stable with the structural explication of genes. For example, two genes at the same location on two strings may be swapped between parents, but they are not merged based on their values. Traditionally, individuals are chosen to be parents probably supported on their fitness values, and the offspring that are produced replace the parents. For example, if N parents are chosen, then N offspring are generated, which replace the parents in the later generation.

"Genetic programming" is a popular technique that has been swiftly increasing. A variable-Sized tree of functions and values is the representation that is used in standard genetic program. Each leaf in the tree is a label from an available set of value labels and an each internal node in the tree is label from an available set of function labels.

The entire tree corresponds to a single function that may be evaluated. Typically, the tree is accessed in a leftmost depth-first manner and the leaf is accessed

as the proportional value. A function is evaluated using as arguments for the consequence of the evaluation of its children. Genetic algorithms and genetic programming are indistinguishable in most except that the reproduction operators are outfitted to a tree representation. Sub-tree crossover is the most frequently used operator, in which an entire sub-tree is swapped between two parents as shown in figure 3. In a standard genetic program, all values and functions are assumed to return the same type despite the fact that the functions may vary in the number of arguments they take. This closure principle [2] allows any sub-tree to be considered structurally on par with any other sub-tree, and ensures that operators such as sub-tree crossover will always produce legal offspring.

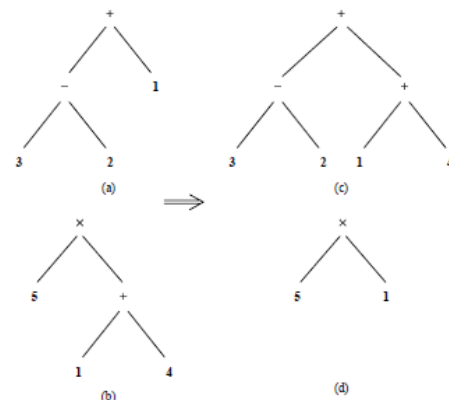


Fig 3: Subtree Crossover of Parents a & b to form Offspring c & d

b) Strategic Evolutionary Programming Strategies

In evolutionary strategies, the representation used is a fixed-length real-valued vector. As with the bit strings of genetic algorithms, each position in the vector corresponds to a feature of the individual.

However, the features are considered to be behavioral rather than structural. "Consequently, arbitrary non-linear interactions between features during evaluation are expected which forces a more holistic approach to evolving solutions" [1].

To create a new offspring the main reproduction operator used in evolutionary strategies is that the "Gaussian mutation", in which a random value from a Gaussian distribution is joined to each element of an individual's vector [Fig 4]. Another operator that is used is intermediate recombination, in which the vectors of two parents are averaged together, element by element, to form a new offspring [Fig 5]. The effects of these operators have bounced the behavioral as opposed to structural interpretation of the representation since knowledge of the values of vector elements is used to derive new vector elements.

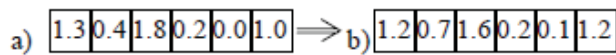


Fig 4: Gaussian Mutation of Parent a to form Offspring b

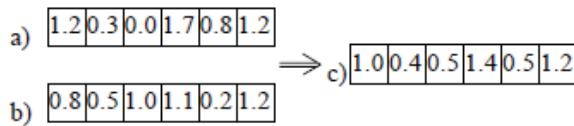


Fig 5: Intermediate Recombination of Parents a & b to form Offspring c

The selection of parents to form offspring is less constrained than it is in genetic algorithms and genetic programming. For instance, it is easy to average vectors from many individuals to form a single offspring due to the nature of the representation. In a typical evolutionary strategy, N parents are chosen uniformly randomly (i.e., not based upon fitness), more than N offspring are generated through the use of recombination, and then N survivors are chosen deterministically. The survivors are chosen either from the best N offspring (i.e., no parents survive) or produce the best N parents and offspring [3].

c) Evolutionary Programming

The representations used in evolutionary programming are typically tailored to the problem domain [3]. Fixed-length real-valued vector is one of the representation that is commonly used. The major difference between evolutionary programming and the preceding approaches is that there will be no exchange of material between individuals in the population made. Thus, only mutation operators are used. For real-valued vector representations, evolutionary programming is very similar to evolutionary strategies without recombination. The intension of a typical selection method is to select all the individuals in the population to be the N parents, to mutate each parent to form N offspring, and to probabilistically select, based upon fitness, N survivors from the total 2N individuals to produce the next generation.

d) Evolutionary Algorithms

Evolutionary algorithms (EA) are adaptive methods, which are used to solve, search and optimization problems, basing on the genetic processes of biological organisms. Charles Darwin in The Origin of Species first clearly stated that "over many generations, natural populations evolve according to the principles of natural selection and survival of the fittest". By mimicking this process, evolutionary algorithms are capable of evolving solutions to real world problems, if they have been suitably encoded [4]. These are generally grouped under the term Evolutionary Algorithms or Evolutionary Computation, we also spot the domains of genetic algorithms [5,6], evolution strategies [7], evolutionary programming [8], genetic

programming [2] and learning classifier systems. They all share a common conceptual base of pretending the evolution of individual structures via processes of selection, mutation, and reproduction. The processes depend on the recognized performance of the individual structures.

EA's deal with parameters of finite length, which are coded using a finite alphabet, rather than directly manipulating the parameters themselves. This means that the search is unconstrained neither by the continuity of the function under examination, nor the existence of a derivative function. Figure 6 represents the functional block diagram of a Genetic Algorithm (GA) and the various aspects are conversed below. It is assumed that a potential solution to a problem may be represented as a set of parameters. These parameters (known as genes) are joined together to create a string of values (known as a chromosome). A gene (also referred to a attribute, nature or detector) refers to a specific attribute that is encoded in the chromosome. The particular values that the genes can take are called its alleles. The position of the gene in the chromosome is its locus. Encoding issues deal with representing a solution in a chromosome and unfortunately, not atleast one technique works good for all troubles.

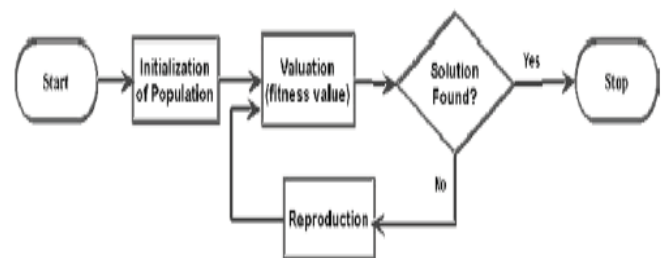


Fig 6: The functional block diagram of a genetic algorithm

There is a requirement for a fitness function that need to be devised for each problem to be solved. Given a particular chromosome, the fitness function returns a single numerical fitness or figure of merit, which determines the ability of the individual, which that chromosome indicates. Reproduction is the next critical attribute of GA's where two individuals selected from the population are allowed to mate to produce offspring, which will comprise the later generation. Having selected two parents, their chromosomes are recombined, typically using the mechanisms of crossover and mutation.

There are different ways in which crossover can be implemented. In a single point crossover two chromosome strings are cut at some randomly selected position, to produce two 'head' and two 'tail' segments. The tail segments are then swapped over to produce two new full-length chromosomes. Crossover is not generally applied to all pairs of individuals selected for mating. Another genetic operation is "Mutation", which

is an asexual operation that only operates on one individual. It randomly alters each gene with a small probability. The traditional view is that crossover is most desirable of the two techniques for rapidly exploring a search space. Mutation supplies a small amount of random search, and helps to ensure that no point in the search space has a zero probability of being examined. If the GA has been correctly implemented, the population will evolve over successive generations so that the fitness of the best and the average individual in each generation increases towards the global optimum. Selection is the survival of the fittest within GA's. It determines which individuals are to be survived to the later generation. Now coming to the selection phase it consists of three parts. The first part deals with the determination of the individual's fitness by the fitness function. A fitness function must be devised for each problem; given a particular chromosome, the fitness function returns a single numerical fitness value, which is proportional to the ability, or utility, of the individual represented by that chromosome. For many problems, deciding upon the fitness function is very straightforward. For example, for a function optimization search; the fitness is simply the value of the function. Ideally, the fitness function should be smooth and regular so that chromosomes with reasonable fitness are close in the search space, to chromosomes with slightly better fitness but it is not always possible to construct such ideal fitness functions. The second part involves converting the fitness function into an expected value followed by the last part where the expected value is then converted to a discrete number of offspring. Some of the commonly used selection techniques are 'Roulette wheel' and 'Stochastic universal sampling'. Genetic programming applies the GA concept to the generation of computer programs also. Evolution programming uses mutations to evolve populations. Evolution strategies incorporate many features of the GA but uses only real-valued parameters in place of binary-valued parameters. Learning classifier systems use GAs in machine learning to evolve populations of condition/action rules.

III. EVOLUTION FOR OPTIMIZATION

Evolutionary Computation (EC) [12] is a subfield of Artificial Intelligence (AI) which comprises of a sequence of biologically inspired search and optimization algorithms that progress iteratively better and better solutions. It involves methods inspired by biological evolution mechanisms such as reproduction, mutation, recombination, natural selection, and sustaining of the fittest. An Evolution Strategy (ES) [13] is one of the basic algorithms among Evolutionary Algorithms (EAs) that make use of a population of candidate solutions and bio-inspired operators to explore for a aimed solution. ES's are basically used for

optimization of real-valued vectors. The algorithm operators are iteratively applied within a loop, where each run is said to be a generation (g), until a termination criterion is met. Variation is skilled by the so-called mutation operator. For real-valued search spaces, mutation is ordinarily performed by adding a normally (Gaussian) distributed random value to every component that is under variation. Algorithm 1 shows pseudo code description of a typical ES. One of the particular characteristics of ESs is that the individual step sizes of the variation operator for each coordinate (or correlations between coordinates) is presided by self adaptation (or by covariance matrix adaptation (CMAES) [14]). This self-adaptation of the step size σ , also known as mutation strength (i.e., standard deviation of the normal distribution), implies that σ is also included in the chromosomes, undergoing variation and selection itself (coevolving along with the solutions). The recognized versions of the ES are denoted by $(\mu/\rho, \lambda)$ -ES and $(\mu/\rho + \lambda)$ -ES, where μ indicates the number of parents (parent population, $P\mu$), $\rho \leq \mu$ the mixing number (i.e., the number of parents involved in the procreation of an offspring), and λ the number of offspring (offspring population, $P\lambda$). The parents are deterministically chosen from the set of either the offspring, referred to as comma selection ($\mu < \lambda$), or both the parents and offspring, referred to as plus selection. This selection is based on the ranking of the individuals' fitness (F) choosing the μ best individuals out of the whole pool of candidates. Once selected, ρ out of the μ parents (R) are recombined to produce an offspring individual (rl) using intermediate recombination, where the parameters of the selected parents are averaged or randomly chosen if distinct recombination is used. Each ES individual $a := (y, s)$ consists of the object parameter vector y to be optimized and a set of strategy parameters s which evolve along with the solution (and are therefore being adapted themselves). This is a particular characteristic of ES called "self adaptation". For a general description of the $(\mu/\rho + \lambda)$ -ES, see [13].

```

(1)  $g \leftarrow 0$ 
(2) Initialize  $P_{\mu}^{(g)} \leftarrow \{(y_m, s_m), m = 1, \dots, \mu\}$ 
(3) Evaluate  $P_{\mu}^{(g)}$ 
(4) while not_termination_condition do
(5)   for all  $l \in \lambda$  do
(6)      $\mathcal{R} \leftarrow$  Draw  $\rho$  parents from  $P_{\mu}^{(g)}$ 
(7)      $r_l \leftarrow$  recombine ( $\mathcal{R}$ )
(8)      $(\tilde{y}_l, \tilde{s}_l) \leftarrow$  mutate ( $r_l$ )
(9)      $\mathcal{F}_l \leftarrow$  evaluate ( $\tilde{y}_l$ )
(10)  end for
(11)   $P_{\lambda}^{(g)} \leftarrow \{(y_l, s_l), l = 1, \dots, \lambda\}$ 
(12)   $P_{\mu}^{(g+1)} \leftarrow$  selection ( $P_{\lambda}^{(g)}, P_{\mu}^{(g)}, \mu, \dagger$ )
(13)   $g \leftarrow g + 1$ 
(14) end while

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Algorithm 1: $(\mu/\rho +, \lambda)$ -ES.

IV. ADAPTING WAVELETS BASED ON EC

Research on adaptive wavelets has been taking place during the last two decades. At first, dictionary-based approaches were used for the task. Coifman and Wickerhauser [9] select the best source from a set of predefined functions, modulated waveforms known as atoms, such as wavelet packets. Mallat and Zhang Matching Pursuit algorithm [10] uses a dictionary of Gabor functions by consecutive scalings, translations, and modulations of a Gaussian window function. It performs a search in the dictionary in order to find the best alike element (maximum inner product of the atom element with the signal). Later, the signal is decayed with this atom which leaves a residual vector of the signal. This algorithm is iteratively utilized over the residual up to n elements. The Matching Pursuit algorithm is capable to decompose a signal into a fixed, predefined number of atoms with arbitrary time-frequency windows. This gives a chance for a better level of adaptation than wavelet packets. These dictionary-based technologies do not generate new wavelets but just select the best blend of atoms to decompose the signal. In some cases, these methods were connected with EA for adaptive dictionary methods [11].

When the LS was put forward, new methods of building adaptive wavelets arose. One significant result is the one by Claypoole et al. [12] which used LS to adapt the prediction stage to lessen a data-based error criterion, so that this stage gets adapted to the signal formation. The revised stage is not adapted, so it is still used to protect wanted characteristics of the wavelet transform. The other area that is concentrated to bring the best reconstruction achievable without any

overhead cost was suggested by Piella and Heijmans [13] that makes the update filter utilize local gradient data to adjust itself to the signal. In this research, a very remarkable analysis of the state of the art on the topic is covered. These succinct remarks on the present literature proposals explain the tendency in the research community which has importantly involved the adaptation of the transform to the local properties of the signal on the fly. This suggests an extra computational work to find out the singularities of the signal and, later, use the suggested transform. In addition, a lot of work has been brought to light on adaptive threshold techniques for data compression.

The work being reported on in this paper discusses about finding a complete new set of filters adapted to a given signal type which is equal to changing the whole wavelet transform itself. so, the general lifting framework still applies. This has the benefit of keeping the computational difficulty of the transform at a minimum (as defined by the LS) not being overloaded with additional filtering features to adapt to these local changes in the signal (as the transform is being performed).

Therefore, the review of the state of the art discussed in this section will concentrate on bio-inspired methodologies for the automatic design of new wavelets (or even the optimization of existing ones). This means that the classical meaning of adaptive lifting (as mentioned above) does not apply in this work. Adaptive, within the possibility of this work, refers to the adaptability of the system as a whole. As a result, this system does not adapt at run time to the signal being analyzed, but, in contrast, it is optimized before to the system operation (i.e., during a calibration routine or in a post fabrication adjustment phase).

V. CURRENT STATE OF THE ART IN THE USE OF EC FOR DESIGNING IMAGE TRANSFORMS

Britny Herzog et al[17] proposed a satellite image compression technique in "Bio-Inspired Intelligent Satellite Image Compression". This paper demonstrates the technical feasibility of using evolutionary and bio-inspired optimization, for transmission of image data among unmanned aerial vehicles (UAVs) across band-width limited channels and to identify new coding and transform algorithms for optimized satellite data(e.g., image) communication (SATCOM). This research will optimize sets of transform defining filter coefficients optimized for satellite image processing. It seeks to develop new image compression algorithms that outperform the current state-of-the-art techniques for satellite image compression. The traditional wavelet algorithm currently employed in state-of-the-art signal processing systems replaces the optimized image compression algorithms.

Optimized transformers are compared with traditional wavelet-based transforms to determine the reduction in the number of bits required for robust transmission of satellite-captured images across narrow band width channels. Higher SATCOM capacity can be obtained without incurring costly hardware modifications by simply replacing the existing wavelet filter coefficients with optimized compression algorithms without altering the underlying transform algorithm. The project aims at identifying and evaluating two independent sets of satellite images which are used to develop and evaluate image compression algorithms. Next, these image sets are used to evaluate the performance of wavelet-based and optimized compression algorithms which can be the basis of comparison. Finally, a new methodology for optimizing image compression algorithms is to be devised, by exploiting the mathematical structure of wavelet-based compression techniques while leveraging the flexibility of bio-inspired optimization algorithms which enables the development of increasingly powerful satellite-based image algorithms that outperform the current state-of-the-art compression techniques. Modern signals and image processing applications often require the transmission of copious amounts of data over narrow band width channels and these require significant compression of data. Shannon's information entropy model places a theoretical limit on the possible rate of lossless compression for a given signal. Wavelets provide the basis of signal transformation in a wide range of signal processing tasks, such as image compression. Wavelets transform continuous or discrete time domain signals into a time frequency domain and they provide desirable properties for signal compression tasks. Wavelets conserve energy and redistribute the bulk of that energy to the "first trend" sub-signal. Quantization is the most common source of distortion in lossy image compression systems and it refers to the process of mapping each of the possible values of a given sampled signal y onto a smaller range of values $Q(y)$. For many applications, quantization is the most significant source of distortion in digital images. The drawback is that, in critical applications of wavelets of military, security or medical imaging tasks, there is degradation in amount of quantization error which results in loss of information. This research aims at minimizing the loss of information at a given quantization level with the goal of improving image quality at a stated level of lossy compression required by a given signal processing application. The methodology includes collection of two independent sets of satellite images from a diverse range of subjects. Having obtained two robust image sets, the performance of various image compression techniques over each image at various levels of quantization noise is established. The quality of performance of the image

compression algorithms over the entire image sets will be compared to one another using appropriate statistical hypothesis tests.

Observation: The use of bio-inspired optimization algorithms such as genetic algorithms to optimize a single set of coefficients defining either the forward or the inverse transform. Filters obtained under the proposed approach will more closely adhere to the properties of wavelets. The anticipated results include development of two robust satellite image sets, demonstration of evolutionary and bio-inspired techniques, robust methodology for image compression optimization and a novel approach for filters optimization.

In [18], the authors Yohei Katsuyama and Kaoru Arakawa discussed a new type of digital filter for removing impulsive noise from color images using interactive evolutionary computing. This new technique overcomes the drawback of median-type filters, which apart from reducing noise makes the image blurred. The method adopted by authors first detect image pixels on which impulsive noise is added on each RGB channel and interpolates the noisy signal component with some sort of weighted sum of the noiseless signal values around the pixels. Previously, the methods proposed by Taguchi et al. & Kerre et al. Used to cause less blur to image provided the noisy signals are correctly detected or else the performance gets highly degraded. The new filter discussed in this paper uses the interpolation technique proposed by Taguchi et al. In filtering phase, but the detection of noisy pixels is judged by a rule concerning the degree of peculiarity of the signals value and the relations among RGB colour components.

The phase of interpolation and then detection of noisy impulsive signal detection is described by the author in four phases as:-

Interpolation technique using colour correlation:

The interpolation technique expresses every image with colour component red(R), green (G), blue (B). Various variables are utilised by the author to use this technique on every pixel denoted by the matrix variables (i,j) . The concepts of probability and mean distribution are applied over the contaminated component defined as $x(i,j)$ by the relation:

$X(i,j) = S(i,j)$; probability $1-p$ & $h(i,j)$; probability p .

Where $h_c(i,j)$ denotes the noisy signal value on the channel c .

Rule to Detect Noisy RGB Components: For detecting the noisy signals precisely, authors employed two techniques, which are (1) analysis of the difference between the input pixel value and median of its nearby value, if the modulus of difference is large image is considered as noisy and (2) analysis of the dependency of image signals among RGB components, the degree

of correlation among RGB components of each signal is expressed with spatially adaptive neighbourhoods (SANs).

Noise detection using spatial adaptive neighbourhood (SAN):

For the noise detection using this technique firstly, the noisy pixels containing impulsive noise on at least one of the RGB channels is detected and then for a particular colour 'c' for a set of pixels (i,j) in the neighbourhood of (i₀,j₀) on a window sized $W_{SAN} \times W_{SAN}$ is checked for two conditions, which are (i)

$$|x(i,j) - x(i_0,j_0)| \leq \delta \quad \text{-----}(1)$$

where δ is a certain threshold.

(ii) any two pixels in SAN are spatially connected.

This particular set is operated under the union and intersection transformation and the number of elements in these sets are denoted by some variable say $\&J$ and $|J$. The value ΔJ is calculated as

$$\Delta J = (|J - \&J|) / \&J \quad \text{-----}(2)$$

The noisy signals are detected by the fact that when impulsive noise is added to each colour component randomly, the correlation becomes small and the SANs for RGB components become less overlapped.

A rule comes from this detection is quoted as:

Rule 1: If $(|J - \&J| \leq P\& \text{ or } \Delta J \geq P\Delta)$, noise is added to the pixel.

Noise detection using Peculiarity of Signal Value: This method of detection is adopted as Rule 1 suffers from two drawbacks, as:-

It is effective on the basis of assumption that the RGB color components are always correlated.

It can judge the noisiness of the pixel (i, j), but it cannot determine which channel is noisy.

Hence, based on the peculiarity a second rule is defined which is opted if the rule 1 fails to overcome its drawbacks.

Rule 2:- If $|x_c(i,j) - m_c(i,j)| \geq Q$, noise is added to the pixel (i,j), otherwise not.

Optimization of Colour Image Noise reduction with IEC:

The interpolation technique seems for removing the impulsive noise, but the parameters $P\&$, $P\Delta$ and Q is difficult to set such multiple parameters efficiently. The author apart from using quantitative criterions of some known training image data implies human subjective criteria which are significant for output image quality. In the application of IEC, each parameter are coded as a binary number and concatenated to make one sequence. The sequence is encoded as binary digit which hypothetically is correlated to the genetic algorithm. In this strategy first a set of M individuals are picked up to make a population and then image processing is done M times using M set of parameters $P\&$, $P\Delta$ and Q corresponding to M individuals. Lastly,

the user observes the M output images and select S satisfactory ones according to his/her taste and subjective criteria.

Observations: Hence, the techniques of interpolation described in the paper in combination of the IEC finds an optimized blend for the reduction of noise as well as maintaining the quality of output image.

The research paper "The Best Fingerprint Compression Standard Yet" proposed by Brendan Babb et al [19] describes how a genetic algorithm can outperform the 9/7 wavelet for fingerprint compression and reconstruction subject to quantization error. Genetic algorithm is used to evolve wavelet and scaling numbers for each level of a multi-resolution analysis (MRA) transform. It was demonstrated that four-level MRA transforms evolved at one quantization level actually perform across a range of quantization levels. This unexpected result provides users with a range of options: they may choose to use the evolved transforms at higher levels of quantization, without sacrificing the quality of reconstructed fingerprint images; or they may select the particular quantization level that results in the highest fidelity fingerprint images. This flexibility establishes evolved transforms as the best fingerprint compression standard yet. Modern fingerprint compression and reconstruction standards, such as those used by the US Federal Bureau of investigation (FBI), are based upon the 9/7 discrete wavelet transform. The evolved transforms also improve upon wavelets optimized by a genetic algorithm via the lifting scheme, and thus establish a new state-of-the-art in this important application area.

The discrete wavelet transforms are described by four sets of floating-point coefficients out of which $h_1(\text{Lo_D})$ and $g_1(\text{Hi_D})$ are the wavelet and scaling numbers for the forward discrete wavelet (decomposing) transform (DWT) while the other two i.e. $h_2(\text{Lo_R})$ dimensional DWT of a discrete input image \mathbf{f} with M rows and N columns is computed by first applying the one-dimensional (1D) sub-band transform defined by the coefficients from sets h_1 and g_1 to the columns of \mathbf{f} , and then applying the same transform to the rows of the resulting signal. A 2D DWT-1 is performed by applying the 1D DWT-1 defined by sets h_2 and g_2 first to the rows and then to the columns of a previously compressed signal.

Using the multi-resolution analysis (MRA) scheme, a one level DWT may be repeated as many as $k \leq \log_2 \{\min(M,N)\}$ times. The trend sub-image will typically be much larger than any of the fluctuation sub-images. A one-level DWT-1 is applied k times to reconstruct an approximation of the original M -by- N signal \mathbf{f} . Quantization i.e., the process of approximating a given signal using a relatively small number of bits, allows digital images to be more easily compressed.

Quantization is essential for rapid transmission, processing and effective storage of massive data sets.

De-quantization step $Q^{-1}(q)$ produces an image y' that differs from the original image y according to a distortion measure p . Quantization is the most significant source of distortion in digital images in many applications. The drawback is that the performance of wavelets degrades in proportion to the amount of quantization error; for critical applications of wavelets to military, security, or medical imaging tasks, such error may be unacceptable. A total of four universities have investigated the possibility of using genetic algorithms (GAs). This paper summarizes state-of-the-art advances in fingerprint compression and re-constructive via evolved MRA transforms. The GAs used for this research was characterized by certain features like each GA run utilized a specific quantization level, the initial population consisted of M candidate solutions, test population consisted of a set of 80 fingerprint images, to name a few.

Observations: Under the improved error reduction, the primary goal of this project was to demonstrate that a GA could evolve a different set of coefficients for each level of an MRA transform that outperformed the 9/7 wavelet used by the FBI fingerprint compression standard. An equally significant result is that MRA transforms optimized for a selected quantization level performed even better than the 9/7 wavelet when both were subsequently tested at higher quantization levels. The evolved transforms are capable of greater compression than the 9/7 wavelet, without sacrificing the quality of the reconstructed image.

Tae-min Jung et al[20] proposed a research paper "Mobile Interface for Adaptive Image Refinement using Interactive Evolutionary Computing" on a new image refinement interface in mobile devices, since we cannot use the interfaces like Photoshop and Gimp, due to low computing power and small memory of mobiles phones. The proposed interface is based on IEC (interactive evolutionary computing).

We will conduct two experiments to show the feasibility of our new interface among which the first one will show how we will refine different images, and second will show how easy and convenient is to use new interface.

IEC helps us to generate user filters dynamically. This type of system provides an interface of twelve candidate images from which user can choose the most appropriate image. This system can also make same functions without pre knowledge of user about the system. The filters which are used in IEC are of three types which are algebraic filter, parametric filter and structured filters.

Algebraic filter uses input pixels information to generate an arbitrary mathematical function relation between input and output. A parametric filter uses parametric function to optimize their parameter.

Structured filters uses algebraic or parametric filter to generate output.

Image filters actually uses mathematical functions to signals for refining an image. The IEC combines many predefined filters to refine an image.

We can also use brightness filter and contrast filter for image processing and by using them we can also process analog image along with digital image. And also by the use of gamma curve and color operation filter we can change the moods of image.

Evolutionary image filter can be done by genetic algorithm which is used for performing some of the natural evaluation mechanism like mutation, crossover and survival of the fittest to optimization and machine learning.

Except fitness evaluation the IEC works on the same principle as of EC (evolutionary computing), as in IEC user has to evaluate fitness of each individual. Therefore, IEC can also be used to solve problems like graphic design, music composition and vision.

To optimize the parameters the use of IGA (interactive genetic algorithm) which is a kind of IEC takes place. So firstly, selection of k random individual takes place. By decoding process, the selected individuals are matched to a pre-defined image filter. First candidate images are generated through these filters. The next generation population is determined by the best candidate selected by user. Optimal solution is generated by GA through manufacture of chromosomes. This chromosomes use 64 bits to encode parameter of filters for brightness, contrast, gamma and color as each parameter need 8 bits for encoding. Parameters in chromosome are matched to pre-defined filters. The initial filters are combined with pre-defined filters such as brightness, color, gamma curve and contrast operation. The combined filters are faster than four different filters because of only one time retouching. It covers the low performance of mobile devices.

Next, user has to evaluate an image refined by filters; results of evaluation must be applied to the fitness of evaluation. Here two problems can occurs which can be first, human fatigue and next is, interface in mobile devices. These problems can be sorted out by using relative fitness evaluation which requires selection of the best refined pictures only one at the time of regeneration.

Relative fitness value is distance between filters, which is used to calculate similarity between a best refined image and other image, by this way the best image will survive during the process. It also offer simple inter face that require just one click on the best image.

Last thing is about settings of genetic algorithm for that we can use one point crossover and mutation. For that firstly, two individuals are selected as parents

and they generate their children through crossover and finally apply mutation. We can also apply elitism to find optimal solution fast. And filters for image refinement are generated. This process is repeated until we get the best retouched image.

The interface will display nine images from which one is parent image and others are the candidate image. We will consider the display size and ratio of image. Each one of them will represent the different moods from other image. User can compare different images with the original one. Instead of providing the external buttons for image evaluation we can provide eight clickable candidate images around the original image. The user can click the best image preference from the eight parent images. The system will retain the previous selected image to provide backup for the worst image than the previous one.

Observations: The proposed method is a novel which is proved by the subjective test. It has performed better than the other methods in SUS test. This method can be expanded in many ways i.e. by using other filter such as blur, sharpen and distort, thus the user can get high quality image in mobile devices.

Kaoru Arakawa and Kohei Nomoto[21] proposed model for removing random noise in images, a combination of several non-linear digital filters. A powerful tool for noise reduction of images contains multiple filter parameters which are difficult to be optimized. Image signals are non-stationary. Various kinds of non-linear filters have been proposed to reduce the noise reduction. A non-linear filter in which the parameters are optimized by interactive evolutionary computing (IEC) is proposed in this paper. A cascade nonlinear filter system and a conditional median filter is proposed, in which the parameters are determined by IEC. This thesis provides us with a method to optimize the nonlinear filter not quantitatively is proposed using IEC. When the noise is not small enough, a cascade of multiple ϵ -filters is effective for reducing the noise while keeping the abruptness of the signal. When the noise is larger, the cascade ϵ -filters is not powerful enough. The conditional medium filter puts out the median value in the filter window, if the input signal is contaminated with noise. This filter is especially effective for removing large-amplitude impulsive noise without degrading signal component. Moreover, image quality is evaluated not only by quantity, but also by subjective assessment by human. Thus, such subjective optimization is considered to be a powerful tool for image denoising. Moreover, the statistical characteristics of image signal and noise are usually not known. Computer simulations in image processing show the high performance of this system. Here the parameters are set at random in the initial stage, but in order to get the satisfactory result faster, a method to set initial values at appropriate ones can be considered.

Observations: A simple crossover and mutation are adopted in this paper, but the methods for generation change can be improved.

In [22] Michael R. Peterson, Gary B. Lamont, Frank Moore, and Brendan Babb employed genetic algorithms (GAs) to evolve image transforms that reduce quantization error in reconstructed signals and images. Defense research deals with image and signal processing. Wavelets form a standard methodology for signal compression algorithms. The discrete wavelet transform (DWT) redistributes energy in a signal by transforming a time signal into time-frequency domain. In a multi-resolution analysis (MRA), the DWT may be recursively applied a number of times to maximize the energy redistribution of the original image. The GA successfully improves image reconstruction both when evolving a single filter for all MRA levels and when evolving unique filters for each level of MRA wavelet decomposition. The resulting filters, evolved with one or more training images are no longer wavelets because they violate mathematical constraints. This paper focuses on evolving reconstruction filters to improve image quality in the presence of quantization error. The experiments in this paper are performed in two iterations. The GA employs an image quality measure as a fitness function to assess the performance of potential image transform filters. Wang's Universal Image Quality Index (UQI) and mean squared error (MSE) are the two image quality measures. Mean squared error (MSE) provides a simple statistical measure to estimate the error of one image as an approximation of another. Experiments evaluating recombination operators employ MSE during fitness evaluation. Authors employ the GA described using Matlab's Genetic Algorithm and Direct Search Toolbox. The initial GA population is created using a random initialization of each gene value in the range $[-1, 1]$ at each filter coefficient position. GA always uses the original db4 wavelet decomposition filter. These experiments compared the well-known non-uniform, Gaussian, and Cauchy mutation operators, as well as a local operator designed specifically for the evolution of image transform filters. The non-uniform mutation operator was described by Michalewicz. Gaussian mutation will be employed as the mutation operator in the present experiments comparing and evaluating various recombination operators. Experiments compare the performance of real-coded GAs (RCGAs) using recombination operators. The blend crossover (BLX), which provides an acceptable performance, creates a child within a hypercube connecting two parents. The simulated binary crossover (SBX) provides self-adaptive search for RCGAs. FR and SBX operators provide the best performance under the global search conditions. The parent normal crossover (PNX) operator creates new genes from parent genes using a Gaussian distribution scale but fails to identify acceptable

reconstruction filters. Experiments assess the GA performance using only Gaussian mutation, with no crossover. The uniform crossover operator provides better performance though it fails to match the performance of the SBX, BLX, and operators.

Observations: The next step in this research will be to evaluate additional advanced crossover operators for real-valued recombination, such as the “unimodal normal distribution crossover” (UNDX) or the parent-centric crossover (PCX). GA is aid in the development of defense system algorithms.

The other considerable proposals are, Jones et. al [23] use genetic programming to define and evolve a lifting-based wavelet scheme and classifier for one-dimensional signal classification. Grasmann and Mikkulainen [24] use a GA to control the design of a lifting-based wavelet for signal compression. Moore [25] describes a real-coded GA to replace DWT filter coefficients for the reconstruction. Voight et. al [26] presented the fuzzy recombination (FR) operator which provide a tradeoffs between exploitation and exploration in the search space. Bruckmann et. al [27] employ a binary GA to evolve subband structures for wavelet packet based image compression. Rani and Renganathan [28] configure a self organizing map (SOM) with a GA that, taken with a wavelet-based filter, provides robust image texture classification.

VI. CONCLUSIONS

In this paper, we emphasized the utilities of Evolutionary Computation techniques in various domains to achieve optimization. The optimization of second generation wavelet transformations used for image compression has been explored and various types of Lifting Schemes were introduced in recent literature. It is concluded that Evolutionary Computing based lifting scheme optimization techniques are a valuable technology to achieve better results in image compression. In this paper, we presented a review of the most well-known EC approaches for optimizing Secondary level Wavelet transformations.

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