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Removal of Impulse Noise Using Fuzzy Genetic Algorithm

S.Ravisankar[1] , S.Sabari Guru Rajaa[2] , S.S.Sriram Prasath[3]

Department of Electronics and Communication Engineering, K.L.N College of Engineering, Pottapalyam, Tamilnadu, India.

Department of Electronics and Communication Engineering, K.L.N College of Engineering, Pottapalyam, Tamilnadu, India.

Department of Electronics and Communication Engineering, K.L.N College of Engineering, Pottapalyam, Tamilnadu, India.

ABSTRACT:- Digital image processing plays a key role in medical diagnosis. Medical images are obtained and analyzed to determine the presence or absence of abnormalities such as tumor, which is vital in understanding the type and magnitude of a disease. Unfortunately, medical images are susceptible to impulse noise during acquisition, storage and transmission. Hence, image de-noising is a primary precursor for medical image analysis tasks. Noise removal can be done much more efficiently by a combination of image filters or a composite filter, than by a single image filter. Determining the appropriate filter combination is a difficult task. In this paper, we propose a technique that uses Fuzzy Genetic Algorithm to find the optimal composite filters for removing all types of impulse noise from medical images.

Here, a Fuzzy Rule Base is used to adaptively change the crossover probability of the Genetic Algorithm used to determine the optimal composite filters. We use Genetic Algorithm (GA) to determine composite filters that remove different levels of impulse noise from an image. In this method, the GA considers a set of possible filter combinations of a particular length, selects the best combinations among them according to a fitness value assigned to each combination based on a fitness function, and applies genetic operators such as crossover and mutation on the selected combinations to create the next generation of composite filters.

We expect that the results of simulations on a set of standard test images for a wide range of noise corruption levels will show that the proposed method output performs standard procedures for impulse noise removal both visually and in terms of performance measures such as PSNR, IQI and Tenengrad values.

I.INTRODUCTION

Image denoising refers to the recovery of a digital image that has been contaminated by additive white Gaussian noise (AWGN).

Many scientific data are contaminated with noise, either because of the data acquisition process, or because of naturally occurring phenomena. A first pre-processing step in analyzing such data is denoising, that is, estimating the unknown signal of interest from the available noisy data. There are several different approaches to denoise images.

The AWGN channel is a good model for many satellite and deep space communication links. Since Wideband Gaussian noise comes from many natural sources, such as the thermal vibrations of atoms in conductors (referred to as thermal noise or Johnson-Nyquist noise), shot noise, black body radiation from the earth and other warm objects, and from celestial sources such as the Sun. It also produces simple and tractable mathematical models.

Methods Of Denoising

Spatial filters have long been used as the traditional means of removing noise from images and signals. These filters usually smooth the data to reduce the noise, but, in the process, also blur the data.

A different class of methods exploits the decomposition of the data into the wavelet basis and shrinks the wavelet coefficients in order to denoise the data .While this is typically done using the more memory efficient decimated wavelet transforms, it is well known that the use of non-decimated transforms minimizes the artifacts in the demised data .

Our work on denoising complements the existing literature. These techniques use wavelets to transform the data into a different basis, where "large" coefficients correspond to the signal, and "small" ones represent mostly noise. The demised data is obtained by inverse-transforming the suitably threshold, coefficients.

Our implementation lets one calculate and apply thresholds either globally, in a level-dependent manner, or in a sub band-dependent manner. Finally, we wanted to compare and contrast these wavelet-based techniques with the more traditional approaches based on spatial filters.

II. GENETIC ALGORITHM

Genetic Algorithm (GA) is a global optimization algorithm derived from evolution and natural selection. Basically, an optimization problem looks really simple. One knows the form of all possible solutions corresponding to a specific question. The set of all the solutions that meet this form constitute the search space. The problem consists in finding out the solution that fits the best, i.e. the one with the most payoffs, from all the possible solutions. If it's possible to quickly enumerate all the solutions, the problem does not raise much difficulty. But, when the search space becomes large, enumeration is soon no longer feasible simply because it would take far too much time. In this it's needed to use a specific technique to find the optimal solution. Genetic Algorithms provides one of these methods. Practically they all work in a similar way, adapting the simple genetics to algorithmic mechanisms.

Once the reproduction and the fitness function have been properly defined, a Genetic Algorithm is evolved according to the same basic structure. It starts by generating an initial population of chromosomes. This first population must offer a wide diversity of genetic materials. Generally, the initial population is generated randomly. Then, the genetic algorithm loops over an iteration process to make the population evolve. Each iteration consists of the following steps:

2.1 SELECTION: The first step consists in selecting individuals for reproduction. This selection is done randomly with a probability depending on the relative fitness of the individuals so that best ones are often chosen for reproduction than poor ones.

2.2 REPRODUCTION: In the second step, offspring are bred by the selected individuals. For generating new chromosomes, the algorithm can use both recombination and mutation.

2.3 EVALUATION: Then the fitness of the new chromosomes is evaluated.

2.4 REPLACEMENT: During the last step, individuals from the old population are killed and replaced by the new ones. The algorithm is stopped when the population converges toward the optimal solution.

The basic genetic algorithm is as follows:

- [start] Genetic random population of n chromosomes (suitable solutions for the problem)

[Fitness] Evaluate the fitness f(x) of each chromosome x in the population

[New population] Create a new population by repeating following steps until the New population is complete

[selection] select two parent chromosomes from a population according to their fitness (the better fitness, the bigger chance to get selected).

[crossover] with a crossover probability, cross over the parents to form new offspring (children). If no crossover was performed, offspring is the exact copy of parents.

[Mutation]With a mutation probability, mutate new offspring at each locus (position in chromosome)

[Accepting] Place new offspring in the new population.

[Replace] Use new generated population for a further sum of the algorithm.

[Test] If the end condition is satisfied, stop, and return the best solution in current population.

[Loop] Go to step2 for fitness evaluation.

2.5 KEY ELEMENTS

The two distinct elements in the GA are individuals and populations. An individual is a single solution while the population is the set of individuals currently involved in the search process.

2.5.1 Individuals

An individual is a single solution. Individual groups together two forms of solutions as given below:

1. The chromosome, which is the raw 'genetic' information (genotype) that the GA deals.

2. The phenotype, which is the expressive of the chromosome in the terms of the model.

A chromosome is subdivided into genes. A gene is the GA's representation of a single factor for a control factor. Each factor in the solution set corresponds to gene in the chromosome. A chromosome should in some way contain information about solution that it represents

2.5.2 Genes

Genes are the basic "instructions" for building a Generic Algorithms. A chromosome is a sequence of genes. Genes may describe a possible solution to a problem, without actually being the solution. A gene is a bit string of arbitrary lengths

Fitness

The fitness of an individual in a genetic algorithm is the value of an objective function for its phenotype. For calculating fitness, the chromosome has to be first decoded and the objective function has to be evaluated. The fitness not only indicates how good the solution is, but also corresponds to how close the chromosome is to the optimal one.

2.5.3 Encoding: Encoding is a process of representing individual genes. The process can be performed using bits, numbers, trees, arrays, lists or any other objects

Types: Binary Encoding, Octal Encoding, Hexadecimal Encoding, Permutation Encoding (Real Number Coding), Value Encoding, Tree Encoding

2.5.4Breeding: The breeding process is the heart of the genetic algorithm. It is in this process, the search process creates new and hopefully fitter individuals.

The breeding cycle consists of three steps:

a. Selecting parents.

b. Crossing the parents to create new individuals (offspring or children).

c. Replacing old individuals in the population with *the new ones.*

2.5.5 Selection: Selection is the process of choosing two parents from the population for crossing. After deciding on an encoding, the next step is to decide how to perform selection i.e., how to choose individuals in the population that will create offspring for the next generation and how many offspring each will create.

Types: Roulette Wheel Selection, Random Selection Rank Selection, Tournament Selection Boltzmann Selection, Elitism

The first best chromosome or the few best chromosomes are copied to the new population. The rest is done in a classical way. Such individuals can be lost if they are not selected to reproduce or if crossover or mutation destroys them. This significantly improves the GA's performance.

2.5.6 *Crossover (Recombination)*

Crossover is the process of taking two parent solutions and producing from them a child. After the selection (reproduction) process, the population is enriched with better individuals. Reproduction makes clones of good strings but does not create new ones. Crossover operator is applied to the mating pool with the hope that it creates a better offspring.

Crossover is a recombination operator that proceeds in three steps:

i. The reproduction operator selects at random a pair of two individual strings for the mating.

ii. A cross site is selected at random along the string length.

iii. Finally, the position values are swapped between the two strings following the cross site.

Types: Single Point Crossover, Two Point Crossover, Multi-Point Crossover (N-Point crossover) Uniform Crossover, and Three Parent Crossover

2.5.7Crossover Probability

The basic parameter in crossover technique is the crossover probability (Pc).

Crossover probability is a parameter to describe how often crossover will be performed. If there is no crossover, offspring are exact copies of parents. If there is crossover, offspring are made from parts of both parent's chromosome. If crossover probability is 100%, then all offspring are made by crossover. If it is 0%, whole new generation is made from exact copies of chromosomes from old population

2.5.8 Mutation

After crossover, the strings are subjected to mutation. Mutation prevents the algorithm to be trapped in a local minimum. Mutation plays the role of recovering the lost genetic materials as well as for randomly disturbing genetic information. Mutation is viewed as a background operator to maintain genetic diversity in the population. It introduces new genetic structures in the population by randomly modifying some of its building blocks.

2.5.8.1 Mutation Probability

The important parameter in the mutation technique is the mutation probability (Pm). The mutation probability decides how often parts of chromosome will be mutated. If there is no mutation, offspring are generated immediately after crossover (or directly copied) without any change. If mutation is performed, one or more parts of a chromosome are changed. If mutation probability is 100%, whole chromosome is changed, if it is 0%, nothing is changed. Mutation generally prevents the GA from falling into local extremes.

2.5.9 Search Termination (Convergence Criteria) In short, the various stopping condition are listed as follows:

- Maximum generations–The genetic algorithm stops when the specified number of generation's has evolved.
- Elapsed time–The genetic process will end when a specified time has elapsed.

Note: If the maximum number of generation has been reached before the specified time has elapsed, the process will end.

• No change in fitness–The genetic process will end if there is no change to the population's best fitness for a specified number of generations.

Note: If the maximum number of generation has been reached before the specified number of generation with no changes has been reached, the process will end.

• Stall generations–The algorithm stops if there is no improvement in the objective function for a sequence of consecutive generations of length Stall generations.

• Stall time limit–The algorithm stops if there is no improvement in the objective function during an interval of time in seconds equal to stall time limit.

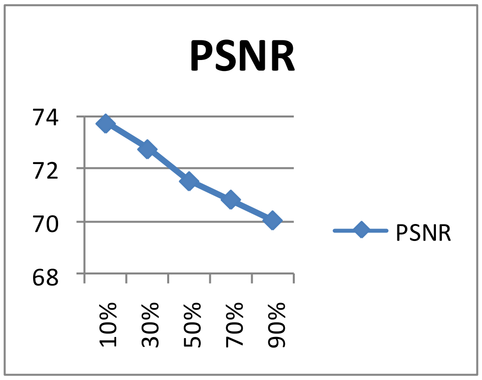
The termination or convergence criterion finally brings the search to a halt.

III. FUZZY ALGORITHM

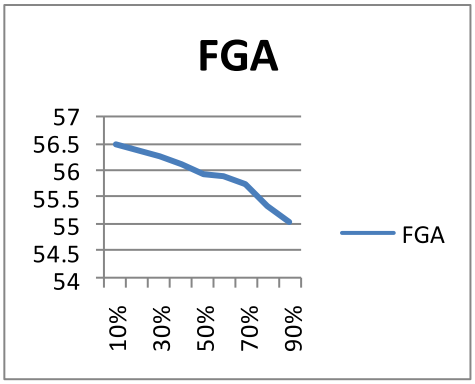
Fuzzy Logic is basically a multivalve logic that allows intermediate values to be defined between conventional evaluations like yes/no, true/false, black/white, etc. Notions like rather warm or pretty cold can be formulated mathematically and processed by computers. In this way an attempt is made to apply a more human-like way of thinking in the programming of computers.

3.1.FUZZY LOGIC ALGORITHM

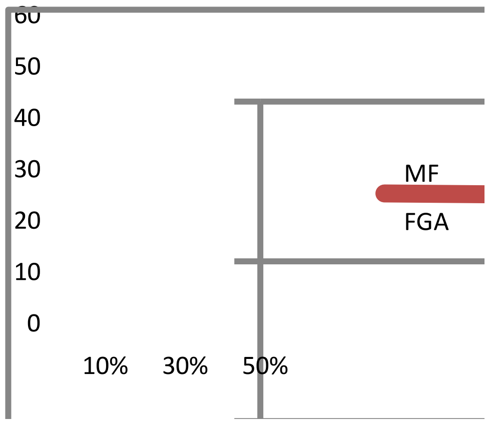
1. Define the linguistic variables and terms (initialization)
2. Construct the membership functions (initialization)
3. Construct the rule base (initialization)
4.Convert crisp input data to fuzzy values using the membership functions (fuzzification)
5. Evaluate the rules in the rule base (inference)
6. Combine the results of each rule (inference)
7. Convert the output data to non-fuzzy values (defuzzification)



S. N O	NOISE LEVEL	MF	WMF	FGA
1	10	19.008	18.11	54.2762
2	30	18.307	16.81	54.1705
3	50	16.426	14.86	53.7985
4	70	11.485	12.47	53.3760
5	90	6.3801	9.097	52.6734



IV.EXPERIMENTAL RESULTS



Comparison of PSNR values of Median filter and FGA.

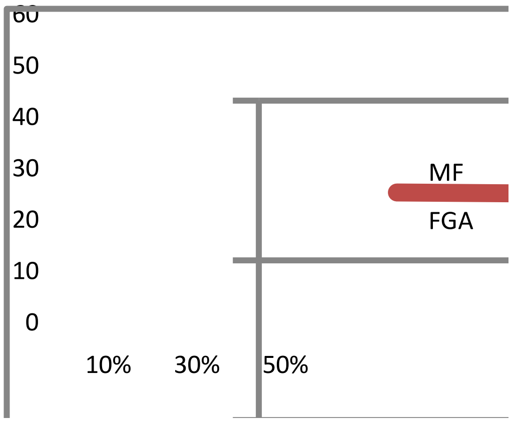


Fig.Comparison of PSNR Values For Various Noise Levels

V. CONCLUSION

In this project we have developed an algorithm called FUZZY GENETIC ALGORITHM to remove impulse noises in the medical images. The simulation shows that the FGA have better performance than the most commonly used filters like Median filter (MF), Weighted median filter (WMF), Standard median filter (SMF) and Adaptive median filter (AMF).

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