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A New Pixel Level Image Fusion Method based on Genetic Algorithm

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Abstract

Background/Objectives: To propose a new fusion technique for combining optical and IR images and validate the proposed technique with the existing techniques using entropy as an evaluating measure. **Methods/Statistical Analysis:** In this paper we propose a new pixel level fusion method using Continuous Genetic Algorithm (CGA) using Heuristiccrossover for reproduction. **Findings:** Pixel level Fusion methods are computationally less complex and converge quickly. The proposed approach is applied on multispectral images which are used in applications like multispectral face recognition, Medical imaging, Remote Sensing etc. The proposed algorithm requires less memory space and has less computational complexity. **Conclusion/Improvements:** An increase in the entropy of the fused image indicates that there is an increase in the overall information content. The proposed technique is implemented on a set of visual and thermal images and an increase in the entropy value of the fused image is observed.

Keywords: Continuous Genetic Algorithm, Entropy, Heuristic Crossover, Image Fusion, Pixel Level Fusion

1. Introduction

With rapid advancements in technology it is now possible to obtain information from multiple sources. Several fusion algorithms have been proposed to fuse the information extracted from visible and LWIR face images[1]. The goal of image fusion is to integrate the information collected from different sensors and produce a fused image which contains more information than the individual images. Image fusion has been used in many application areas. In remote sensing and astronomy, multisensory fusion is used to achieve high spatial and spectral resolution. There are number of applications of image fusion in the field of medical imaging like simultaneous evaluation of CT, MRI, PET images.

Image fusion techniques can be classified into three Types. They are pixel based, feature based and based ondecision level. The common techniques which come under pixel level fusion are simple averaging method,select maxima and select minimum methods. These methods often result in the degradation of quality of image because they give equal weights to both images or select the maximum/minimum intensity values. The main objective of fusion is to obtain maximum amount of information from individual images. This can be done by giving appropriate weights to the individual images. Evolutionary methods such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are used in almost every application and every discipline of engineering in recent years[2]. Different research has been tried at different levels under some constraints to minimize the search space of GAs[3].The proposed approach uses the continuous genetic algorithm to calculate the weights of individual images so that maximum information can be extracted. This technique has been implemented on Visual and Infrared images which finds its application in military, security, and surveillance areas.

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2. Preprocessing Steps

Fusion requires some preprocessing steps like enhancement and registration.

1) The process of improving the quality of digitally stored image by manipulating it is called image enhancement. Enhancement of an image is application specific and includes the operations like noise removal, sharpening, smoothening, colour adjustments etc. If low contrast or poor visibility images are used for image fusion, then it leads to the degradation of image quality. So as preprocessing step of image fusion, linear or non-linear operations are applied to the image to improve the contrast.

2) In image processing the term registration refers to transformation of different sets of data into one coordinate system. Registration optimizes the parameters that describe a spatial transformation between source and reference image. For two images to be properly fused they have to be perfectly aligned. So before going for fusion, an appropriate transformation function has to be estimated and applied to the moving image (image that has to be aligned).

3. Proposed Approach

As mentioned earlier appropriate weights have to be assigned to input images to extract more information. In this approach entropy is taken as measure of information. The term entropy can be defined as measure of uncertainty or the average information contained in any message

$$E = -\sum_{i=0}^{l-1} Pi \log_2 Pi \tag{1}$$

where, l is the total number of grey levels and P_i is the probability of occurrence of each intensity value.

An increase in entropy of the fused image can be considered as overall increase in the amount of information. Hence the quality of the fused image can be assessed by observing the entropy fused data and original data.

In this paper the task of finding the finding the weights of input images to get maximum entropy is viewed as an optimization problem.

The optimization problem is the problem of finding the best solution among plausible solutions. The set of solutions may be continuous or discrete.If the solutions are continuous then the problem is called "continuous optimization problem". If the solutions are discrete then the problem called as"combinatorial optimization problem". There are many techniques to solve optimization problem. Here one of the efficient techniques known as continuous genetic algorithm is used to solve the optimization problem.

4. Continuous Genetic Algorithm (CGA)

GA is a searching technique used to solve the optimization problems. GA derives its basic idea from the evolutionary theory put forward by Charles Darwin. Simply stated, GA's enforce Darwinian survival of the fittest among a population of creatures. In every generation new set of individuals are created and only the fittest individuals will get a chance to contribute to the next generations. A new algorithm called CGA is proposed for the global optimization of multiminima functions[4]. Usually in GA's, solution is represented as binary strings. For this application it is more convenient to represent the solutions as real numbers, and it is known as continuous genetic algorithm. GA's has the advantage of requiring less storage and are faster than binary counter parts. Figure1 shows Basic flowchart of CGA.

The elements of the genetic algorithm are as follows:

4.1 Fitness Function and Variables

The function which has to be maximized or minimized is called as Fitness function or cost function. The value associated with the fitness function is called as fitness value or cost. Based on this criterion it will be decided whether a particular individual would contribute to the next generation or not. The variables or parameters on which the fitness function depends are stored in an array and is referred as chromosome.

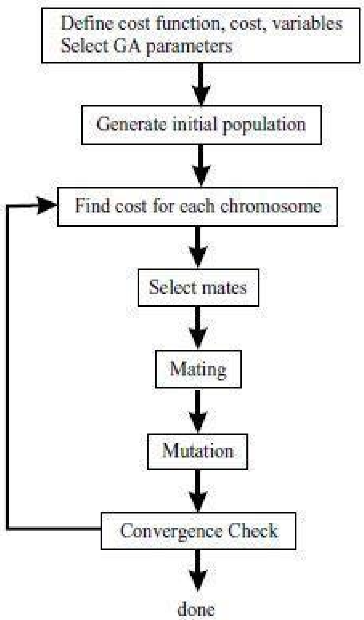


Figure 1. Basic flowchart of CGA.

Consider the fitness function F depends on variables V_1, V_2, V_3 ………V_n. Then an individual chromosome can be represented as

Chromosome = $[V_1\ V_2 V_3 \ldots V_n]$ (2)

Cost = f(chromosome) = $f(V_1, V_2, .., V_n)$ (3)

In this approach we consider entropy of the fused image as the cost function and variables associated with this cost function are weights of the individual images. As mentioned above this technique is implemented on visual and infrared images Let W_V and W_{IR} be the weights of visual and thermal images respectively then the cost function and chromosome is as follows:

Cost function=entropy (W_V*V+ W_{IR}*IR) (4)

where V-Visual image,

IR – Thermal image

Chromosome = $[W_V W_{IR}]$ (5)

4.2 Initial Population

To initiate the CGA process some initial population has to be selected. The initial population can be selected randomly. If the probable region of solutions is known, then the values within that region can also be considered as initial population. In case of Image fusion, since the weights of the individual images will be in the range of [0 1] a matrix of size Np x 2 containing random values between 0 to 1 is generated and this is said to be initial population.

where, Np is the number of chromosomes generated under initial population.

Each row of this matrix is considered as chromosome and its corresponding fitness value (Entropy of fused image) is calculated and then the matrix is sorted in descending order according to the fitness values.

4.3 Selection

Among the individuals generated as initial population only the fittest are selected to contribute to the next generation. In the matrix obtained above only the top 'Nk' elements are kept and the remaining are discarded.

4.4 Mating/Crossover

The performance of a genetic algorithm is dependent on the genetic operators, in general, and on the type of crossover operator, in particular[5]. Crossover is a basic operation done as a part of the GA. This operator is analogous to the"reproduction" or "Biological Crossover", upon which the genetic algorithm is based. During the evolution process by a GA, if the selected chromosomes are identical, some of the crossover operators have failed to create offspring that are different from their parents. In this process more than one solution of the present generation is taken and are made to produce the new generation solutions. The present generation solutions taken for crossover are called "Parents", the new solutions produced are called as "children". The performance of the GA is largely dependent on the type of crossover applied. During the process of evolution, if the selected parents are identical, some crossover operators fail to create a child which is different from the parents. Hence effective crossover in a GA is achieved through establishing the optimum relationship between crossover and search problem itself[5].

In such cases the process gets stuck at some particular value and final solution may not be obtained even after large number of iterations.

There are different types of crossovers. Some of them are as follows.

Let parent1 be mother chromosome and parent 2 be father chromosome.

Mother chromosome = $[V_{m1} V_{m2} V_{m3} \ldots V_{mn}]$ (6)

Father chromosome= [Vf1 Vf2Vf3.….Vfn] (7)

4.4.1 Uniform Crossover

The offsprings obtained afteruniform crossover are as follows

Child1= [V_{m1} V_{f2} V_{m3} V_{f4} V_{m5} V_{f6}……V_{fn}] (8)

Child2= [V_{f1} V_{m2} V_{f3} V_{m4} V_{f5} V_{m6}……V_{mn}] (9)

In uniform crossover the offspring do not exceed the limits set by the parent chromosomes, i.e maximum and minimum cost remains unchanged even after the cross over. This is more suitable when probable region of solutions is known.

4.4.2 Blending Method

In these techniques offspring isproduced by replacing the old variables with new variables. The new variables are obtained using

$V_{new}=\beta V_{mn}+(1-\beta)V_{fn}$ (10)

where, β is random number between 0 and 1.

Vmn is nth variable of mother chromosome.

V_{fn} is nth variable of father chromosome.

The new chromosome will be

Child1=[V_{m1} V_{m2} …..V_{new} … V_{mn}] (11)

Child2=[Vf1 Vf2 …...Vnew……Vfn] (12)

In this manner desired number of off springs can be produced either by changing values of β or by changing the combination of mother and father chromosomes. In this technique also, the values of children chromosomes do not exceed the values set by parent chromosomes, this is also suitable when probable region of solutions is known.

4.4.3 Heuristic Crossover

The two techniques mentionedabove fail to obtain values or search points beyond the limits of parents because of which the search will be limited to some region of values. Such techniques depend only on process of mutation to introduce new genetic material. In order to overcome this disadvantage a new type of crossover called as heuristic crossover was introduced.

In this type of crossover Offspring are allowed to exceed the boundaries of parents but they'll be still in the limits of variables.

Vnew1=Vmn – β[Vmn –Vfn] (13)

Vnew2 =Vfn+ β[Vmn –Vfn] (14)

For the process of image fusion heuristic crossover is used since the probable weights of individual images are not known.

WVnew = WVm+ β[WVm – Wfm] (15)

WIRnew = WIRf - β[WIRf– WIRf] (16)

Child =[$WV_{new}$$WIR_{new}$] (17)

Desired no of chromosomes can be produced for different values of β.

4.4.4 Mutation

The term mutation refers to alteration of one or more gene values in a chromosome from its initial state. This genetic operator is used to maintain genetic diversity and to avoid fast convergence of GA[6]. If the algorithm converges too quickly then it will lead to false maxima. This can be avoided by randomly introducing some changes into the present generation. The amount of mutation introduced can be measured using the parameter "Mutation Rate". Mutation Rate can be defined as the ratio of number of values changed in a given generation to the total number of values in a generation. The mutation rate can be adjusted according to the requirement. The mutation operator is applied only to the weak individuals i.e. chromosomes having lower fitness values.

4.4.5 Convergence Check

Chromosomes in the population with high fitness values have a high probability of being selected for combination with other chromosomes of high fitness[7]. All the above mentioned steps are iterated until the final solution (maximum entropy) is obtained. In order to determine whether a given solution is the global solution or not a convergence check is performed after every iteration. For each generation, all the chromosomes are evaluated, and the best individual is recorded[8]. The convergence time of GA depends upon many parameters like initial population, mutation rate, type of crossover etc. At some point of time the GA should stop. Hence a stopping condition or termination condition or stopping criteria is used. This stopping condition can be implemented in different ways.

a) A fixed number of iterations are set to the algorithm, i.e. the algorithm can be terminated when some fixed number of generations is produced.

In this case the convergence time can be calculated for a given initial population, mutation rate and the type of crossover. The cost obtained in the last iteration is considered as the global solution.

b) The GA can be stopped after some allocated time. The cost at the end of the allocated time is considered as the final solution.

c) The algorithm can be terminated if there is no significant improvement in the fitness values from the previous generations. In this case the convergence time cannot be calculated since one cannot determine at what point the improvement in the fitness values gets saturated.

d) If the approximate value of the global solution is known, then the algorithm can be terminated when the fitness value is close enough to the required solution. The convergence time cannot be calculated in this case.

e) The combinations of the above mentioned conditions can also be used as stopping criteria.

5. Evaluation Criteria

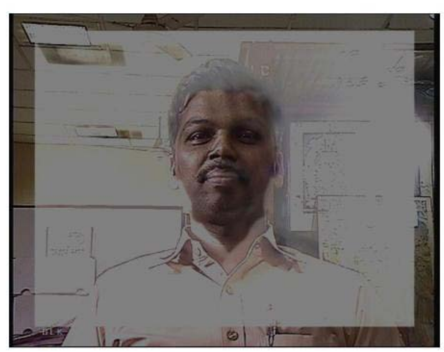
The most popular evaluating criterion is quality[9]. As mentioned earlier, The Fused image is then more suitable for human/ machine perception and for further image processing tasks such as segmentation, feature extraction and object recognition[10]. Lower value for the metric Root Mean Square Error, Relative Average Spectral Error, Normalized Absolute Error, Laplacian Mean Squared Error and higher value for spatial information implies the improved fused image[11]. The entropy is taken as the performance metric for the process of image fusion. An increase in the entropy of the fused image indicates that there is increase in the overall information content. The proposed technique is implemented on a set of visual and thermal images and an increase in the entropy value of the fused image is observed. Over the last decade, images fusion has found enormous applications in the area of remote sensing[12].

6. Results and Observations

It can be observed from Figures 2 and 3 that, the methods like simple average, select maximum, select minimum give a substandard quality image. When compared to other methods the proposed approach gives a better quality image. Tables 1 and 2 show the comparison of entropy values of all the methods and it is to be noted that the entropy of the fused image obtained by proposed approach has the highest value of the entropy, which is greater than that of input set of images as well as entropy values of the images obtained by other methods.

(a)

(b)



(c)

(d)

(e)

(f)

Figure 2. (a)Visual Image (b) Infrared Image (c)Fused Image using simpleaverage method (d) Fused image using select maxima method (e) Fused image using select minima method (f) Fused image using the proposedtechnique (based on genetic algorithm).

Table 1. Entropy values of Figure 2

Figure	Image	Entropy
2a	Visual Image	7.7414
2b	Thermal Image	6.1827
2c	Fused image using simple average method	4.0780
2d	Fused image using select maxima method	7.2100
2e	Fused image using select minima method	6.8555
2f	Fused image using the proposed approach	7.8469

(a)

(b)

(c)

(d)

(e)

(f)

Figure 3. (a) Visual Image (b) Infrared Image (c) Fused image using simple average method (d) Fused image using select maxima method (e) Fused image using select minima method (f) Fused image using the proposed technique (based on genetic algorithm).

Table 2. The entropy values of Figure 3

Figure	Image	Entropy
3a	Visual Image	7.7424
3b	Thermal Image	6.1115
3c	Fused image using simple average method	6.0806
3d	Fused image using select maxima method	7.5779
3e	Fused image using select minima method	6.1695
3f	Fused image using the proposed approach	7.8686

Table 3. The genetic algorithm used the following inputs

Number of Iterations	200
Number ofindividuals in initial population	150
Number of chromosomes kept after each generation	20
Number of chromosomes undergoing mutation	60

Table 4. The weights of visual and thermal images obtained using genetic algorithm

Figure	WV	WIR
Figure 2a &Figure 2b	0.8861	0.1558
Figure 3a &Figure 3b	0.9648	0.0965

As night vision images are blurred and clouded[16], It must be noted that weights for same set of input parameter, may not be the same after every execution, because random values have been introduced during every iteration, which vary from execution to execution.

7. Conclusion

As Infrared Imaging is a noncontact sampling and these images are unique for each object17, the proposed approach is applied on multispectral images which are used in applications like multispectral face recognition, Medical imaging, Remote Sensing etc. It can be seen from quantitative and visual results, GA based image fusion are better than the conventional techniques.

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