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A Comparative Study on Search Heuristic Techniques with Genetic Algorithm in Segmentation of Medical Resonance Imaging

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Abstract- Brain tumors are very common fatality in current scenario of health care society. Image segmentation is used to extract the abnormal tumor portion in brain. Tumor is an atypical mass of tissue in which cells grow and multiply uncontrollably, apparently unregulated by system that control cells. Several techniques have been developed for detection of tumor in brain using MRI. Here we use image segmentation technique and Genetic Algorithm (GA) to detect brain tumor. Genetic Algorithm (GA) is a search heuristic that resemble the process of natural evolution. This search heuristic is routinely used to achieve useful solutions to optimization and search problems. Genetic algorithms are part of the larger class of Evolutionary Algorithms, which develop solutions to optimization problems using techniques inspired by natural evolution such as inheritance, selection, mutation and crossover.

Keywords- Genetic Algorithm (GA), Magnetic Resonance Imaging (MRI), Evolutionary Algorithms (EA)

I. INTRODUTION

A. Image Segmentation

Image segmentation is the method of splitting a digital image into several regions or set of pixels. This splitting can be done by various image segmentation methodologies. To be useful, these techniques must typically be combined with a domain's precise knowledge in order to effectively solve the domain's segmentation problems. This is usually used to identify other relevant information in digital images. In other words the aim of image segmentation is to group pixels into preeminent image regions, i.e., regions analogous to individual surfaces, objects, or natural parts of objects. The outcome of image segmentation consists of a set of regions whose merger forms the intact image.

Brain tumor: A tumor (also called a neoplasm or lesion) is anomalous tissue that grows by uncontrolled cell division. Normal cells grow in a controlled way as new cells replace old or damaged ones. For reasons not fully understood, tumor cells reproduce uncontrollably. Brain tumors are titled after the cell type from which they grow. They may be primary (starting in the brain) or secondary (expand to the brain from another area). Treatment options vary depending on the tumor type, size and location; either the tumor has spread; and the age and medical health of the person. Treatment options may be focus on relieving symptoms. Of the more than 120 types of brain tumors, many can be successfully treated [16].

Brain tumor Segmentation: Brain tumor is a more dangerous and life-threatening disease because of its invasive and infiltrate character in the limited space of the cranial cavity. Brain tumor is curable and treatable if it is diagnosed in earliest stages of disease. Analysis of brain tumor is done by specialist called neurologist. Brain tumor segmentation partitions a portion into mutually special and collapsed regions such that each region of interest is spatially contiguous and the pixels within the region are equal with respect to a predefined criterion. The automatic segmentation has great potential in clinical medicine by granting freedom to the physicians from the burden of manual labeling; whereas only a quantitative measurement allows to track and modeling accurately the disease. MR is generally more sensitive in detecting brain abnormalities during the initial stages of disease, and is superior in early detection of cases of cerebral infarction, brain tumors, or infections [8].

B. Genetic Algorithm

Genetic algorithms resides the part of the larger class of Evolutionary Algorithms (EA), which generates solutions to optimization problems using methods stimulated by natural evolution such as inheritance, selection, mutation, and crossover.

- GAs is inspired by Darwin's Theory about Evolution "Survival Of Fittest".
- GAs is adaptive heuristic search based on the evolutionary ideas of natural selection and genetics.
- GAs is intelligent exploitation of random search used in optimization problem.
- GAs is randomized, but exploits historical information to direct the search into the region of better performance within the search space.
- Genetic algorithms discover application in bioinformatics, phylogenetic, computational science, engineering, economics, chemistry, manufacturing, mathematics, physics and other fields [3].

Algorithm is a programming technique who forms its basis from the biological evolution [1].

Genetic Algorithm is fundamentally used as a problem solving strategy in order to provide with an optimal solution. They are the most excellent way to determine the problem for which little is known. They will perform strong in any search space because they form a very common algorithm. The only thing to be known is what the particular situation are where the solution performs very well and a genetic algorithm will generate a high quality solution. Genetic algorithms use the principles of selection and evolution to produce several solutions to a given problem [11].

- *Individual* – Any possible solution
- *Population* – Group of all individuals
- *Search Space* – All possible solutions to the problem
- *Chromosome* – Blueprint for an individual
- *Trait* – Possible aspect of an individual
- *Allele* – Possible settings for a trait
- *Locus* – The position of a gene on the chromosome
- *Genome* – Collection of all chromosomes for an individual

II. BASIC FUNCTIONALITY OF GENETIC ALGORITHM

A. Selection

There are many various techniques which a genetic algorithm can be used to select the individuals to be copied over into the next generation.

- *Elitist selection*: The fittest members of every generation are guaranteed to be selected.
- *Fitness-proportionate selection*: More fit entities are more likely selected, but it is not certain that they will be always selected.
- *Roulette-wheel selection*: It is fitness-proportionate selection in which the possibility of an individual's being selected is proportional to the amount by which its fitness is higher or lower than its competitor's fitness.
- *Scaling selection*: As the average fitness of the population rises, the strength of the selective pressure increases with it and the fitness function becomes more recognizable. This technique can be helpful in making the best selection later on when all individuals have relatively high fitness and only small changes in fitness distinguish one from another.
- *Tournament selection*: Subgroups of individuals are preferred from the larger population and members of each subgroup challenge against each other. Only one individual from each of the subgroup is chosen to reproduce.

B. Crossover

Once the individuals have been preferred the next thing is to produce the offspring [2]. The most common solution for this is something named as crossover and also there are many different kinds of crossover, the most common kind of crossover is single point crossover. In single point crossover, chooses a locus at which you swap the remaining alleles from one parent to the other. This is very complicated and is best understood visually.

The children take one portion of the chromosome from each of the parent. The point at which the chromosome is to be broken totally relies upon the randomly selected crossover point. This particular method is called as single point crossover because only one crossover point occurs. It is the case that sometime only child 1 or child 2 is created, but most of time both offspring are generated and put into the new population. Crossover does not always occur, but frequently, based on a set probability, no crossover will occur and the parents are copied directly to the new population. The probability that the crossover will arise is usually 60% to 70%.

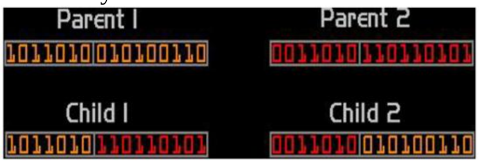

Fig 1: Crossover

C. Mutation

After completion of selection and crossover, one can earn new population full of individuals. Some of them are directly copied and others are produced by crossover. To assure that the individuals are not all exactly the same, one can be allowed for a small possible of mutation. Then one can loop through all the alleles of all the individuals. If that allele is preferred for mutation, one can either change it by a small amount or replace it with a new value [3]. The probability of mutation is mostly between 1 and 2 tenths of a percent. Mutation is shown below.

Fig 2: Mutation

Mutation is simpler. One can just change the selected alleles based on what one feels is necessary and then can move on. Mutation is important to provide genetic diversity within the population.

- *[Selection]* Select two parent chromosomes from population accordance to their fitness (if fitness is better, the bigger chance to be selected).
- *[Crossover]* With a crossover possibility cross over the parents to form a new offspring (children). If no crossover was performed, then offspring will be an exact copy of parents.
- *[Mutation]* With a mutation possibility mutate new offspring at each locus (position in chromosome).
- *[Accepting]* Place new offspring (child) in a new population.

III. OUTLINE OF THE BASIC GENETIC ALGORITHM

- *[Start]* Generate 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.

IV. COMPARISON WITH OTHER PROBLEM SOLVING TECHNIQUES

This section covers the three aspects of GAs. First of all it describes the different issues and challenges that are faced by the GA [4]. Then it elaborates the difference between the GA and Heuristic Search. Finally provides the detailed comparison of GA with the various search techniques such as the Hill Climbing and Simulation Annealing.

A. Issues related to the Genetic Algorithm are

1. Certain optimization problems (they are called variant problems) cannot be solved by means of genetic algorithms. Main reason behind it is poorly known fitness functions which generate bad chromosome blocks in spite of the fact that only good chromosome blocks cross-over.
2. There is no absolute assurance that a genetic algorithm will find a global optimum. It occurs very often when the populations have a lot of subjects.
3. In case of Clinical decision support system GA faces lack of transparency that is used for the decision support systems making it undesirable for physicians. While using genetic algorithms, the main challenge is in defining the fitness criteria. In order to use a genetic algorithm here, many components are to be considered such as multiple drugs, symptoms; treatment therapy and so on should be available in order to solve a problem.
4. In case of research study which has found the possibility of automating parameter selection for an EEG-based P300-driven Brain-Computer Interface (BCI) Genetic Algorithm requires lengthy execution times which display it infeasible for online utilization. The GA method was then replaces by the less execution time-intensive N-fold Cross-Validation (NFCV) for the meta-optimization of feature extraction and pre-processing parameters using Fisher's Linear Discriminant Analysis (FLDA).
5. GA also faces scalability issues of exchanging building blocks.
6. Like various artificial intelligence techniques, the genetic algorithm cannot always assure constant optimization response times. Also, the difference between the shortest and the longest optimization response time is much larger than with conventional gradient methods. This genetic algorithm property limits the genetic algorithms use in real time applications.
7. Genetic algorithm applications in controls which are performed in real time are limited because of random solutions and convergence. It means that the entire population is improving, but this cannot be said for an individual within this population. Therefore, it is very unreasonable to use genetic algorithms for on-line controls in real systems without testing them first on a simulation model.

Table 1 Comparison between Genetic Algorithm and Heuristic Search

Genetic Algorithm	Heuristic Search
1) Genetic Algorithm are typically applied to problems that require only the location of a vertex that satisfies the search	1) Heuristic search often require the construction of a path through the graph.
2) A problem addressed by Genetic Algorithm does not specify a starting space or/and goal state.	2) A problem addressed by Heuristic Search often specify a starting space or/and goal state.
3) Genetic Algorithm is often applied to problems that do not specify how an acceptable solution can be recognized.	3) Heuristic Search is often applied to problems that do specify how an acceptable solution can be recognized.
4) The graph searched via heuristic algorithm does not determine predefined connectivity.	4) The graphs searched via heuristic algorithms often have some predefined connectivity determined.
5) Genetic Algorithm navigates on several graphs.	5) State space search algorithm tends to navigate on a single graph.

Table 2 Comparison of Genetic Algorithm with Hill Climbing and Simulating Annealing

Parameters	Genetic Algorithm	Hill Climbing	Simulated Annealing
Functionality	Genetic Algorithm belong to a family of computational models are inspired by evolution. These algorithms will encode a potential solution to a specific problem on a simple chromosome like data structure and apply recombination operators to these structures as to preserve critical information.	Hill Climbing is a mathematical optimization technique which belongs to the family of local search. It is an iterative algorithm that always starts with an arbitrary solution to a problem, and then it attempts to find a better solution by incrementally changing a single element of the solution.	Simulated annealing (SA) is a generic probabilistic meta heuristic for the global optimization problem of locating a good approximation to the global optimum of a given function in a large search space.
Performance	Genetic Algorithm are faster than the hill climbing as it implements implicit parallelism wherein each new string is completely independent of the previous one, so each new string is given independently to the new schema region.	Moves in space of string by single bit mutation from an original string, so that each new sample has all but one of the same bits as the previous sample.	Simulating Annealing performance is slower as compared to Genetic algorithm.
Representation	Bit-String representation is critical	Move Set design is critical	Move Set design is critical
Multi-dimensional solving	Supports the multi-dimensional approach	Does not support the multi-dimensional approach	Does not support Multi-dimensional approach
Technique preferred	Global Optimum	Local Optimum	Global optimum
Distribution of population is diverse and large	GA makes a large, useful and structured jump even after partial convergence.	Hill Climbing is not good as compared to GA when the distribution of population is diverse and large.	Simulating Annealing is not so good as compared to GA.
Least diverse population	GA does not gain benefit in least diverse population.	Hill climbing search operate fruitfully produces good result.	Simulating Annealing does not gain benefit in least diverse population
Search via Sampling i.e. Blind search.	GAs achieves much of their breadth by ignoring information except that concerning payoff.	Rely heavily on such information and in problem where the necessary information is not available or difficult to obtain, these technique breaks down.	Simulating Annealing too rely heavily on such information.
Search Mechanism	GA performs a multi-directional search by maintaining a population of potential solution and encourages information exchange between these directions.	HC uses a iterative improvement technique, which can be applied to a single point in the search space	Simulating Annealing is used when the search space is discrete.
Examples	Acoustics, Aerospace engineering, Astronomy, Astrophysics, Chemistry, Electrical engineering, Financial markets, Game playing, Geophysics, Material engineering.	The travelling salesman problem, circuit design, the eight-queen problem.	Simulated annealing is often used for engineering design applications such as determining the physical layout of components on a chip.

V. ADVANTAGES OF GENETIC ALGORITHM

- GAs locates a population of points in parallel, not as a single point.
- GAs does not require derivative information or auxiliary knowledge, but only the objective function is needed and corresponding fitness levels influence the directions of search.
- GAs does not use deterministic ones, but uses probabilistic transition rules.
- GAs always works on an encoding of the parameter set rather than the parameter set itself (except in which real-valued individuals are used). Therefore, an increase in sensor density by a factor of *k* improves the SNR at a sensor by *10 log k db*.

VI. APPLICATIONS OF GENETIC ALGORITHM

Nearly everyone can gain benefits from Genetic Algorithms, once one can encode solutions of a given problem to chromosomes in GA, and compare the relative performance (fitness) of solutions. An effective Genetic Algorithm representation and meaningful fitness evaluation are the keys of the success in GA applications. The appeal of Genetic Algorithms comes from their simplicity and elegance as robust search algorithms as well as from their power to discover good solutions rapidly for difficult high-dimensional problems. GAs is useful and efficient when

- The search space is complex, large, or poorly understood
- Domain knowledge is expert knowledge is difficult to encode to narrow the search space
- No mathematical analysis is available
- Traditional search methods fail

The advantage of the GAs is the ease with which it can handle arbitrary kinds of constraints and objectives; all such things can be handled as weighted components of the fitness function, making it easy to adapt the GA scheduler to the particular requirements of a very wide range of possible overall objectives.

GAs has been used for problem-solving and modeling. GAs is applied to many scientific, engineering problems, in business and entertainment, including:

- *Optimization*: GAs have been used in a different optimization tasks which also includes numerical optimization and combinatorial optimization problems such as circuit design, traveling salesman problem (TSP), job shop scheduling and video & sound quality optimization.
- *Automatic Programming*: GAs has been used to develop computer programs for specific tasks and to design other computational structures such as cellular automata and sorting networks.
- *Machine and robot learning*: GAs has been used for many machine-learning applications, including classification and protein structure prediction. GAs have been used to design neural networks, to derive the rules for learning classifier systems or symbolic production systems and to design and control robots.
- *Economic models*: GAs also has been used to model processes of innovation, the emergence of economic markets and the development of bidding strategies.
- *Immune system models*: GAs has been used to model various aspects of the natural immune system, which will also include somatic mutation during an individual’s lifetime and the analysis of multi-gene families during evolutionary time.
- *Ecological models*: GAs have been used to model ecological development such as host-parasite co-evolutions, biological arms races, symbiosis and resource flow in ecologies.
- *Population genetics models*: GAs has been used to study questions in population genetics, such as “under what conditions will a gene for recombination be evolutionarily viable?”
- *Interactions between evolution and learning*: GAs has been used to study how individual learning and species evolution affect one another.
- *Models of social systems*: GAs is used to study evolutionary aspects of social systems, such as the evolution of cooperation, the evolution of communication, and trail-following behavior in ants.

VII. CONCLUSION

Genetic algorithms are emerging as an independent discipline. Genetic Algorithms are a family of computational models inspired by evolution. These Genetic Algorithms encode a potential solution to a specific problem on a simple chromosome like data structure and implement recombination operators to these structures as to preserve critical information. Genetic Algorithms are very easy to implement to a wide range of problems starting from optimization problems like the traveling salesperson problem up to scheduling, inductive concept learning, and layout problems. The results can be either good or poor on some problems. The algorithm is very slow if only mutation is used. To keep it faster Crossover is the best solution which makes the algorithm much faster.

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