Mestrado em Engenharia Elétrica

Processamento de Imagem

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1. **Objetivo:** Pesquisar técnicas heurísticas para segmentação de imagens. Aplicações em processamento de imagens compreendendo:
   a. Lógica Fuzzy e Agrupamento
   b. Redes neurais
   c. Heurísticas de busca
   d. Aplicações
2. **Bibliografia:**
   a. The Image Processing Handbook – John Russ. IEEE Press
   b. Artigos diversos
3. **Metodologia**: aulas expositivas e trabalhos de implementação

Overview and Merits of Metaheuristic

- A metaheuristic is a set of algorithmic concepts that can be used to define heuristic methods applicable to a wide set of different problems.
- A metaheuristic can be seen as a general-purpose heuristic method designed to guide an underlying problem specific heuristic toward promising regions of the search space containing high-quality solutions.
- A metaheuristic therefore a general algorithmic framework, which can be applied to different optimization problems with relatively few modifications to make them, adapted to a specific problem.
- The use of metaheuristics has significantly increased the ability of finding very high-quality solutions to hard, practically relevant combinatorial optimization problems in a reasonable time.
- Meta-heuristics:
    - genetic algorithms (GA),
    - ant colony optimization (ACO)
    - tabu search
    - simulated annealing
- ACO and GA use multiple agents, each of which has its individual decision made based upon collective memory or knowledge.

Introduction to GA

- A genetic algorithm is an iterative procedure that involves a population of individuals,
- Individuals are represented by a finite string of symbols, known as the genome, encoding a possible solution in a given problem space
- The search space comprises all possible solutions to the problem at hand.
- Standard genetic algorithm

1 An initial population of individuals is generated at random or heuristically.
2 Every evolutionary step, known as a generation:
2.1 The individuals in the current population are decoded
2.2 Evaluated according to some predefined quality criterion, referred to as the fitness, or fitness function.
2.3 Individuals are selected according to their fitness to form a new population.
2.3.1 High-fitness individuals stand a better chance of 'reproducing', while low-fitness ones are more likely to disappear.
2.4 Then crossover is performed with the probability Pc between two selected individuals, called parents, by exchanging parts of their genomes to form two new individuals, called offspring.
2.5 The mutation operator is introduced to prevent premature convergence to local optima by randomly sampling new points in the search space, flipping bits at random carries it out; with some small probability Pm.

- Genetic algorithms are stochastic iterative processes that are not guaranteed to converge.
- The termination condition may be specified as some fixed maximal number of generations or as the attainment of an acceptable fitness level.

Overview of Ant Colony Optimization:

- The ant algorithm was first proposed by Marco Dorigo (1992) and has been receiving extensive attention due to its successful applications to many combinatorial optimization problems
- The ACO is based upon the behaviors of ants that they exhibit when looking for a path to the advantage of their colony.
- Real ants are capable of finding the shortest path from a food source to the nest without using visual cues.
- Ants are moving on a straight one that connects a food source to their nest is a pheromone trail.
- Pheromone is a volatile chemical substance lay down by ants while walking, and each ant probabilistically prefers to follow a direction rich in pheromone.
- This elementary behavior of real ants can be used to obtain optimum value from a population.
- Solutions of the problem are constructed within a stochastic iterative process, by adding solution components to partial solutions.
- Each individual ant constructs a part of the solution using an artificial pheromone, which reflects its experience accumulated while solving the problem, and heuristic information dependent on the problem.

Problem: Interpretation of mammograms

- Two different techniques are used for:
    - The first technique consists of a systematic search of each mammogram for visual patterns symptomatic of tumors.
        - a bright,
        - approximately circular blob with hazy boundary might indicate the presence of a circumscribed mass.
    - The second technique, the asymmetry approach, consists of a systematic comparison of corresponding regions in the left and right breast.
        - Significant structural asymmetries between the two regions can indicate the possible presence of a tumor.
        - Most researchers have focused on processing a single image to find abnormalities
        - Given a pair of identical-view mammograms of the left and right breast,
        - detect all structural asymmetries between corresponding positions in the left and right breast.
        - Significant asymmetries are taken as evidence for the possible presence of a tumor.

Methodology

Image Acquisition

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Median Filtering

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Border Detection using GA

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Nipple Identification using GA/ACO

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Alignment of Mammograms

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Generating Asymmetry Image

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Extracting Asymmetries and Classification

- Initially the mammogram images were enhanced by median filter to remove the high frequency components (i.e. noise) from the image.
    - The global appearance (brightness, contrast, etc.) of the two breasts may differ (variations in the recording procedure).
    - The pectoral muscle region is removed from the breast region
        - A histogram-based thresholding technique is used to separate the dark background region.
        - The local optimum in the histogram is selected as the threshold value.
        - The intensity values smaller than this threshold are changed to black (O), and the gray values greater than the threshold are changed to white (1).
        - The segmented foreground regions are processed using morphological operations
    - The mammogram images are normalized [0,255]

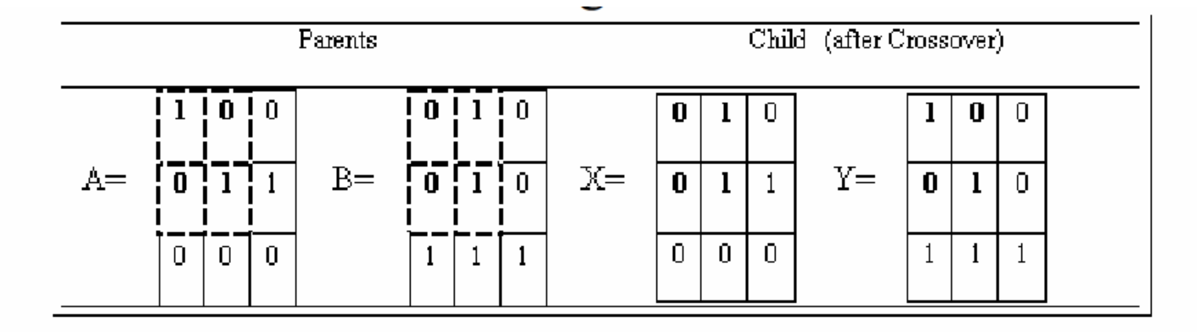
- The breast border and the nipple position of the mammogram are detected to find the deflection between both left and right mammograms.
    - Due to natural asymmetry, and due to the mammographic recording procedure, the shapes of the left and right breast do not match.
    - Defining corresponding positions in both breasts becomes therefore a nontrivial task.
- In border detection:
    - The mammogram image is converted into binary image [55].
    - From the binary image the border points are extracted and it is mapped with the original image.
    - The extracted border is enhanced using GA as follows:
        - From the extracted border, for each border points a 3x3-window size of neighborhood pixels (kernel) are taken as initial population for genetic algorithm.
        - The sum of intensity values of all the pixels in a kernel is considered as fitness values for the kernel.
        - The genetic operators like reproduction, crossover, and mutation are applied to the kernels.
        - The kernels from the final population has the enhanced border pixels, they are mapped with the original image.
- To find out the nipple position using GA/ACO.
    - The border points are considered as the population for both GA and ACO algorithms to identify the nipple position.
    - In GA:

    - The genetic operators, reproduction, crossover and mutation are applied on border points to generate the new population at each iteration.
    - The minimum value is calculated from the final population at final iteration.
    - This minimum value is compared with the intensity values of the border points.
    - The matching pixel is considered as the nipple position.
- In the case of ACO:
    - The ants start their search from a random border point with initial pheromone value.
    - Then the Maximizing A Posterior (MAP) function is evaluated for each ant,
    - The pheromone values are updated for each ant.
    - The global minimum value is calculated at the end of each iteration.
    - The border pixel, whose intensity value is equal to the global minimum value from the final iteration, is considered as the nipple position.
- The coordinate points of border points and nipple position of both left and right images are compared to find out the deflection between two images.
- Then the right image is aligned to correspond with the left image and both images are subtracted to extract the suspicious region.

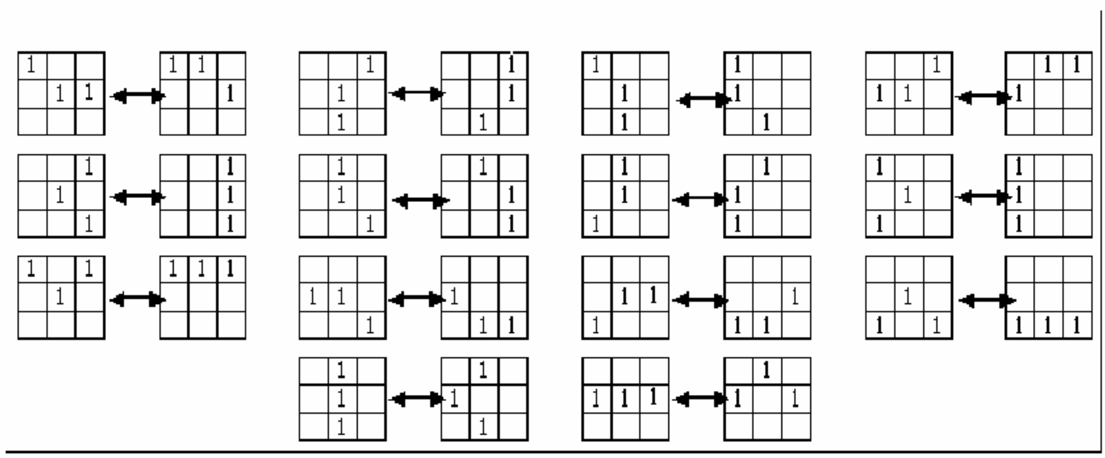
Detection of the breast border using Genetic Algorithm

- Border detectors normally represent edges in a binary image, where each pixel takes on either the intensity value zero for a non-border pixel or one for a border pixel.
- A kernel is defined as a neighborhood array of pixels with the size of 3 x 3 window instead of the conventional bit vector, or string
- The intensity values of the pixels in the kernel are summed and this sum is considered as fitness values.
- After the initial population is generated, genetic operators can be applied in this population to generate the new one.
- Selection operator obtains an individual for crossover.
    - Roulette wheel with slots weighted in proportion to kernel fitness values.
    - In this function, a random number multiplies the sum of the population fitness, called as stopping point.
    - The partial sum of the fitness value is accumulated in a real variable until it is greater than or equal to the stopping point.
    - The location where the iteration stops, the corresponding kernel is selected for crossover.

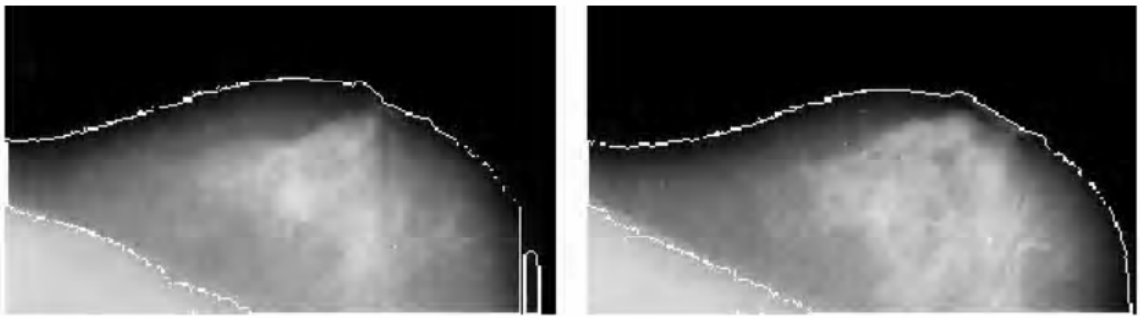
- The newly selected kernels are crossed over by exchanging the values in the window with the size of 2x2.



- Mutation is implemented flipping bits at random carries it out, with some small probability
  - The bit corresponding to the gene to be mutated is flipped or flopped, i.e., its value is changed from 0 to 1 or vice versa.
  - If a border configuration that matches one of the 28 configurations is found, the corresponding transformation is performed.
  - If the edge configuration at this site does not correspond to any of those, no change is made.



- The new kernels are stored as new population.
    - This procedure is performed until the size of the new population is equal to the initial population.
    - Then the old population is assigned with new population value and the same procedure is performed again to generate the next population.
    - Finally, the kernels in the latest population have the enhanced border points.
    - They can be mapped with the original image.



Algorithm: Detection of Breast Border using Genetic Algorithm

S_{ij} ← Original Image; B_{ij} ← Border image
[m n] ← size of B_{ij}
for each border pixel in B_{ij}
K ← kernel of the border pixel of size 3×3
F ← fitness value; sum of the intensity values of all the pixels in a kernel
Pop1 ← initial population contains K and F
end
repeat for N times
  for each string in Pop1
    k1, k2 ← select two kernels for reproduction.
For the selection of two kernels roulette wheel is implemented as follows:
(i) r = random() * sum_of_fitness
  [Hint: random() function returns a random number between 0 and 1]
(ii) partsum = 0, i=0, m → size of the population
(iii) p → contains the population strings
(iv) partsum = partsum + p(i)
(v) i = i + 1
(vi) if ((i <= m) and (partsum < r)) Goto Step: (iv) else return i
k3, k4 ← new kernels after crossover.
k5, k6 ← kernels after mutation, here a random bit in the kernel is flipped or flopped. In mutation, if a border configuration that matches one of the 28 configurations in Figure 5 is found, the corresponding transformation is performed.
Pop2(p) ← k5; p ← p+1; Pop2(p) ← k6;
end

Identification of Nipple Position using Genetic Algorithm

- The intensity values of the border pixels are considered as initial population for the genetic algorithm and converted as binary strings
- The border pixel, which generates the minimum value of the population, is considered as the nipple position.

Algorithm: Identification of Nipple Position using Genetic Algorithm

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S_{ij} ← Original Image; B_{ij} ← Border image;
[m n] ← size of B_{ij}
for each border pixel in B_{ij}
G← intensity of the border pixel from S, converted to binary string
F← fitness value; intensity values of the pixels
Pop1 ← initial population contains G
end
p ← 1
repeat for N times
  for each string in Pop1
    g1, g2 ← select two strings for reproduction.
For the selection of two strings roulette wheel is implemented as follows:
(i) r = random() * sum_of_fitness
  [Hint: random() function returns a random number between 0 and 1]
(ii) psum = 0, i=0, m → size of the population
(iii) p → contains the population strings
(iv) psum = psum + p(i)
(v) i = i + 1
(vi) if ((i <= m) and (psum < r)) Goto Step: (iv)
(vii)return i

g3, g4 ← new strings after cross over.
g5, g6 ← strings after mutation, here a random bit in the kernel is flipped or flopped.

Pop2(p) ← g5; p ← p+1; Pop2(p) ← g6;
end
min ← Min(Pop2); Pop1 ← Pop2;
pos ← where the B(i,j) = min;
end

Identification of Nipple Position using Ant Colony Optimization

- Individual ants are simple insects with limited memory and capable of performing simple actions.
- The collective behavior of ants provides intelligent solutions to problems such as finding the shortest paths from the nest to a food source.
- Ants foraging for food lay down quantities of a volatile chemical substance named pheromone, marking their path that it follows.
- Ants smell pheromone and decide to follow the path with a high probability and thereby reinforce it with a further quantity of pheromone.
- The probability that an ant chooses a path increases with the number of ants choosing the path at previous times and with the strength of the pheromone concentration laid on it

- Similar to GA, the breast is divided into three regions.
- The border pixels in the second region are extracted.
- For each kernel in the border pixel, calculate the posterior energy function value U(x).

$$U(x)=\{\Sigma[(y-\mu)^2 / (2*\sigma^2)]+\Sigma\log(\sigma)+\Sigma V(x)\}$$

  - where y is the intensity value of pixels in the kernel,
  - μ is the mean value of the kernel,
  - σ is the standard deviation of the kernel,
  - V is the potential function of the kernel, and
  - x is the label of the pixel.
  - If x1is equal to x2 in a kernel, then V (x) = β,
  - otherwise 0,
    - where β is visibility relative parameter ($\beta > 0$).
- The MAP probability estimate can be written as:
  - P(x/y) = exp (-U(x)),
- The challenge of finding the MAP estimate of the segmentation is search for the optimum label which minimizes the posterior energy function U(x).
- The goal of this method is to find out a pixel of the image on the border that maximizes the posterior energy function value.
- Initially assign the values for number of iterations (N), number of ants (K), initial pheromone value (T0), a constant value for pheromone update (p). [Hint: N=50, K10, T0=0.001 and p=O.9].

- Pheromone Initialization:
  - For each ant assign the initial pheromone value T0.
  - For each ant select a random pixel from the border pixels set which has not been selected previously.
    - A flag value is assigned for each pixel to know whether the pixels are selected or not.
    - Initially the flag value is assigned as 0, once the pixel is selected the flag is changed to 1.
  - For each ant a separate column for pheromone and flag values is allocated in the solution matrix.
- Local Pheromone Update:
  - Update the pheromone values for all the randomly selected pixels using the following equation:

$$T_{new} = (1 - \rho) * T_{old} + \rho * T_0 ,$$

    - where T_{old} and T_{new} are pheromone values,
    - and ρ is rate of pheromone evaporation parameter in local update, ranges from [0,1] i.e., $0 < p < 1$.
    - Calculate the posterior energy function value for all the selected pixels by the ants from the solution matrix.

- Global Pheromone Update:
  - Compare the posterior energy function value for all the selected pixels from each ants,
  - Select the maximum value from the set, which is known as 'Local Maximum' (Lmax) or 'Iterations best' solution.
  - This value is again compared with the 'Global Maximum' (Gmax).
  - If local maximum is greater than global maximum, then the global maximum is assigned with the current local maximum.
  - Then the ant, which generates this local maximum value, is selected and whose pheromone is updated using the following equation:

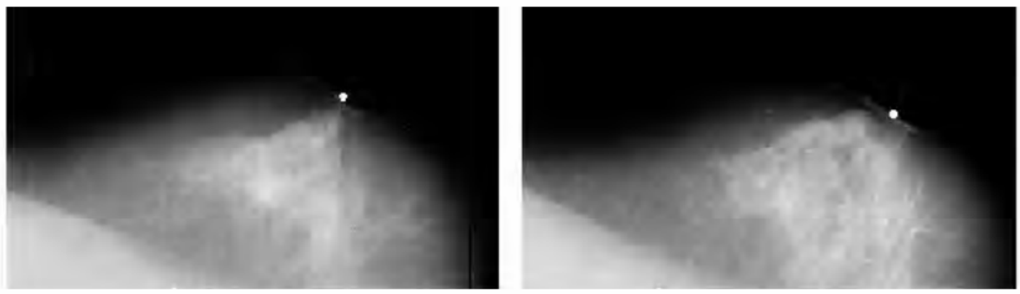
$$T_{new} = (1 - \alpha) * T_{old} + \alpha * \Delta T_{old},$$

    - where T_{old} and T_{new} are pheromone values
    - α is rate of pheromone evaporation parameter in global update called as track's relative importance, ranges from $0 < \alpha < 1$,
    - Δ is equal to (1/Gmax).
  - For the remaining ants their pheromone is updated as:

$$T_{new} = (1 - \alpha) * T_{old},$$

    - Δ is assumed as 0.
  - The pheromones are updated globally.
  - The ant, which generates the Gmax, is traced and the corresponding pixel and its co-ordinates are stored.
  - This procedure is repeated for all the image pixels.

- The entire procedure can be repeated for N number of times.
- At the final iteration, the co-ordinate of the image pixel that maximizes the posterior energy function value is considered as nipple position.
- Nipple position of a mammogram, detected by ant colony optimization algorithm.



- Comparative Study:
    - Maximum height method: 0-50 pixels of distance between the real position and the position obtained
    - The second derivative method: 0- 30 pixels.
    - The average intensity gradient method: the difference is reduced to 0-15 pixels.
    - The genetic algorithm approach has the difference of 0- 10 pixels.
    - The proposed ant colony optimization algorithm is 0-5 pixels.

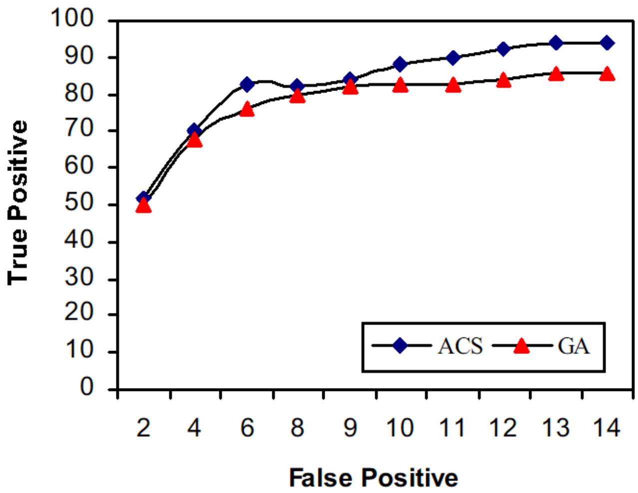
Algorithm: Identification of Nipple Position using Ant Colony Optimization:

M_{ij} ← Original Image
B_{ij} ← Border pixels
[m n] ← size of B_{ij}
for each border pixel in B_{ij}
G ← kernel of the border pixel of size 3×3 from M
U ← fitness value; the posterior energy U (x) is calculated.

$$U(x) = \{\Sigma[(y-\mu)^2/(2*\sigma^2)] + \Sigma \log(\sigma) + \Sigma V(x)\}$$

end
N ← 50 - Number of iterations
K ← 10 - Number of Ants
T_0 ← 0.001 - Initial pheromone value
ρ ← 0.9 - rate of pheromone evaporation parameter
S ← {U(x),T_0, flag} flag column mentions whether the pixels is selected by the ant or not.
Store the energy function values in S. Initialize all the pheromone values with T_0=0.001.
repeat for N times
for each pixel in M_{ij}
for each ant
g_i ← a random border pixel for each ant, which is not selected previously.
$T_{new} \leftarrow (1-\rho) * T_{old} + \rho * T_0$ for g_i
end
Lmax ← max($U_i(x)$)
if (Lmax < Gmax) then Gmax = Lmax
g ← Select the ant, whose solution is equal to local maximum
$T_{new} \leftarrow (1-\alpha) * T_{old} + \alpha * \Delta T_{old}$, only for g
end
Trace the ant that generates the Gmax, from the ant's position find out the co-ordinates of the border pixel from the solution matrix. Consider this co-ordinate as nipple position.
end

MIAS Category	No. of Image pairs	No. of Abnormalities
Normal	53	-
Circumscribed Masses	21	26
Spiculated Masses	19	19
Ill-defined Masses	14	15
Architectural Distortion	18	19
Asymmetry	14	14
Calcification	22	25
Total	161	118



Operating Points	1	2	3	4	5	6	7	8	9	10
Misc TP	86.0	88.0	92.6	92.6	86.0	86.0	79.3	79.3	88.0	86.0
Misc FP	1.6	9.0	2.7	3.9	5.7	5.2	6.5	8.2	1.6	9.0
Circ TP	64.8	88.2	78.5	93.3	94.3	93.3	94.2	94.2	74.8	93.2
Circ FP	2.0	8.9	3.2	5.0	6.9	5.9	6.8	7.9	2.0	8.9
Asym TP	65.1	78.4	79.4	90.7	86.5	87.5	88.5	81.4	67.1	81.4
Asym FP	2.0	8.9	3.2	5.1	6.7	6.1	7.1	8.0	2.0	8.9
Spic TP	47.6	74.6	64.3	89.3	82.0	85.0	85.0	77.6	51.6	76.6
Spic FP	2.2	10.2	3.7	5.6	6.9	6.9	8.0	9.4	2.2	10.2
Arch TP	38.5	74.4	63.6	75.4	77.4	77.4	84.4	78.4	41.5	68.4
Arch FP	2.0	9.3	3.4	4.5	5.6	6.3	3.4	7.9	2.0	9.3
Total TP	59.2	82.3	75.5	88.5	85.6	83.6	76.5	84.0	63.2	85.3
Total FP	2.0	9.2	3.3	4.8	5.9	6.9	3.3	8.2	2.0	9.2
Calc TP	14.0	32.0	22.0	28.0	29.0	46.0	25.0	30.0	8.0	34.0
Calc FP	2.5	9.5	3.8	5.2	6.5	7.9	3.8	8.7	2.5	9.5
Norm FP	2.1	9.4	3.6	5.1	6.6	7.6	3.6	8.5	2.1	9.4

IMG_Ageneticalgorithmforimage segmentation_00957019.pdf;

IMG_P1150527002.pdf;

IMG3_Robust image segmentation using genetic algorithm with a fuzzy measure .pdf) (6h)