An Optimization Problem for Evaluation of Image Segmentation Methods

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Abstract: ***Image segmenting is one of the most important steps in movie and image processing and the machine vision applications. The evaluating methods of image segmenting that recently introduced. In this paper, we proposed a new formulation for the evaluation of image segmentation methods. In this strategy using probabilistic model that utilize the information of pixels (mean and variance) in each region to balance the under-segmentation and over-segmentation. Using this mechanism dynamically set the correlation of pixels in the each region using a probabilistic model, then the evaluation of image segmentation methods introduce for an optimization problem. For solving this problem (evaluation of image segmentation methods) use the novel Imperialist Competitive Algorithm (ICA) that was recently introduced has a good performance in some optimization problems. In this paper a new Imperialist Competitive Algorithm is using chaotic map (CICA2) is proposed. In the proposed algorithm, the chaotic map is used to adapt the radius of colonies movement towards imperialist's position to enhance the escaping capability from a local optima trap. Some famous benchmarks used to test proposed metric performance. Simulation results show this strategy can improve the performance of the unsupervised evaluation segmentation significantly.***

Keywords*:* Image segmentation, Imperialist Competitive Algorithm, Segmentation Evaluation.

1. Introduction

Image segmentation is used to partition an image into separate regions for analysis and understanding image. Different methods have been introduced for segmenting image. There are two main approaches in image segmentation: region segmentation and boundary detection.

We consider region-based image segmentation methods, because it has better results for texture images but there is no appropriate scale for evaluating these algorithms yet. The most usual evaluating method is the visual one in which the user visually observes different segmenting method at hand. Being time-consuming and gaining different results by users is disadvantages of this method.

In supervised method, different segmented images are compared and evaluated with a ground truth image which has been made by the experts or different users. This method is the best method because of its high evaluating precision. Up to now most researches has been one on the supervised methods.

In spite of their simplicity and low cost this method don't have a proper efficiency because of miscue resulted from user improper choosing and spending a long time to examine different existing segmenting methods and also the need of having the main segmented image of the intended image at hand.

Unsupervised method does not require comparison with a manually- segmented reference image, has received little attention. The key advantage of unsupervised segmentation evaluation ability to evaluate segmentations independently of a manually-segmented reference images. This metric is good for processing real-time systems.

The evaluating unsupervised which are given up to now, are base on the features of the image in locality area and the number of areas and the number of pixels in each region. In this paper, we examine a new scales for evaluating segmenting with and unsupervised methods.

In this paper, we formulated the evaluation of image segmentation methods for an optimization problem. For solving this problem used ICA algorithm.

So far, different evolutionary algorithms have been proposed for optimization which among them, we can point to a search algorithms were initially proposed by Holland, his colleagues and his students at the University of Michigan. These search algorithms which are based on nature and mimic the mechanism of natural selection were known as Genetic Algorithms (GAs) [1,2]. Particle Swarm Optimization algorithm proposed by Kennedy and Eberhart [3,4], in 1995. Simulated Annealing [5] and Cultural Evolutionary algorithm (CE), developed by Reynalds and Jin [5], in the early 1990s etc. The ant colony optimization algorithm (ACO), is a probabilistic technique for solving computational problems that can be reduced to finding good paths through graphs. This algorithm is a member of ant colony algorithms family, in swarm intelligence methods. Initially proposed by Marco Dorigo in 1992 in his PhD thesis [6][7] , the first algorithm was aiming to search for an optimal path in a graph, based on the behavior of ants seeking a path between their colony and a source of food. Differential evolution (DE) is an optimization algorithm. The DE method is originally due to Storn and Price [8][9] and works on multidimensional real-valued functions which are not necessarily continuous or differentiable.

Recently, a new algorithm [10], in 2007, which has inspired not natural phenomenon, but of course from a socio-human from phenomenon. This algorithm has looked at imperialism process as a stage of human's socio-political evolution. The Imperialist Competitive Algorithm makes relation between humans and social sciences on one hand, and technical and mathematical sciences on the other hand, having a completely new viewpoint about the optimization topic. In the ICA algorithm, the colonies move towards the imperialist country with a random radius of movement. In

[11] CICA algorithm has been proposed that improved performance of ICA algorithm by the chaotic maps are used to adapt the angle of colonies movement towards imperialist's position to enhance the escaping capability from a local optima trap. The ICA algorithm is used for Neural Network Learning based on Chaotic Imperialist Competitive Algorithm [12].

In this paper, we have proposed a new formulation for the evaluation of image segmentation methods that solved with Imperialist Competitive Algorithm.

We introduce in this paper a study of unsupervised evaluation criteria that enable the quantification of the quality of an image segmentation result. This evaluation metric computes some statistics for each region in a segmentation result. Suggested scales engage in evaluation methods of segmenting by extracting image features in spatial domain. This method evaluate by evolutionary algorithm (ICA). These methods compare considering the segmented images and the main image. For this comparative study, we use two database composed of 200 images segmented. We will explain the suggested methods afterwards.

This article is organized as follows: In Section 2, provides an introduction of the unsupervised evaluation criteria and highlight the most relevant ones and related work. In section 3, we introduced the Imperialist Competitive Algorithm (ICA). In section 4, described proposed algorithm and definition of chaotic radius in the movement of colonies toward the imperialist. In section 5, we present unsupervised evaluation methods and optimization problem. In Section 6, comparing results and show role correlation metric and our evaluation finally, in Section 7 we present a summary of our work and provide pointers to further work.

2. Related Work

Unsupervised method does not require comparison with a manually-segmented reference image, has received little attention and it is quantitative and objective. Supervised evaluation methods, evaluate segmentation algorithms by comparing the resulting segmented image against a manually segmented reference image, which is often referred to as ground-truth.

The degree of similarity between the human and machine segmented images determines the quality of the segmented image. One benefit of supervised methods over unsupervised methods is that the direct comparison between a segmented image and a reference image is believed to provide a finer resolution of evaluation. Unsupervised method also known as stand-alone evaluation methods or empirical goodness methods [13].

Table 1. Classification of evaluation methods.

Class	Details
Analytic methods	Methods attempt to characterize an algorithm itself in terms of principles, requirements, complexity etc.
Empirical goodness methods	Computing a "goodness" metric on the segmented image without a priori knowledge [14].
Empirical discrepancy methods	A measure of discrepancy between the segmented image output by an algorithm [15].
Region Differencing	Computing the degree of overlap of the cluster associated with each pixel in one segmentation [16][17][18].
Boundary matching	Matching boundaries between the segmentations, and computing some summary statistic of match quality [16][19][20].
Information-based	Formulate the problem as that of evaluating an affinity function that gives the probability of two pixels belonging to the same segment [16][21][22][23].

Unsupervised methods instead evaluate a segmented image based on how well it matches a set of features of segmented images as idealistic by humans.

For solving these problem we need to use unsupervised methods so unsupervised evaluation suitable for online segmentation in real-time systems, where a wide variety of images, whose contents are not known beforehand, need to be processed. We for evaluation segmented image need to original image and some of segmented images.

There are two major problems with segmentation: under-segmentation and over-segmentation [24][25] are shown in Figure1. We need to minimize the under- or over-segmentation as much as possible.

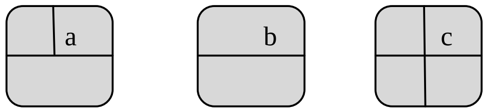

Figure 1. a) A ground truth image. b) Under-segmented image. c) Over-segmented image.

In the case of under-segmentation, full segmentation has not been achieved, i.e. there are two or more regions that appear as one. In the case of over-segmentation, a region that would be ideally present as one part is now, split into two or more parts. These problems, though important, are not easy to resolve.

Recently a large number of unsupervised evaluation methods have been proposed. Without any a priori knowledge, most of evaluation criteria compute some statistics on each region or class in the segmentation result.

We consider region-based image segmentation methods. Most of these methods consider factors such as region uniformity, inter-region heterogeneity, region contrast, line contrast, line connectivity, texture, and shape measures [26].

An evaluation methods has been proposed by Liu and Yang (1994) [27], that it is compute the average squared color error of the segments, penalizing over-segmentation by weighting proportional to the square root of the number of segments. It requires no user-defined parameters and is independent of the contents and type of image. The evaluation function:

$$F(x) = \sqrt{N}\,\sum_{j=1}^{N}\frac{e_j^2}{S_j} \qquad (1)$$

Where N is the number of segments, S_j is the number of pixels in segment j, and e_j^2 is the squared color error of region j. The F evaluation function has a very strong bias towards under-segmentation (segmentations with very few regions) and penalizing over-segmentation by weighting proportional to the square root of the number of segments. This metric is independent of the type of image. F is bias towards under-segmentation, so An evaluation methods has been proposed by Borsotti et al.(1998), that extended F by penalizing segmentations that have many small regions of the same size. Borsotti improved upon Liu and Yang's method, and improved F' by decreasing the bias towards both over-segmentation and under-segmentation. Proposing a modified quantitative evaluation (*Q*) [28], where

$$Q(I) = \frac{\sqrt{N}}{1000.S_I}\sum_{j=1}^{N}\left[\frac{e_j^2}{1+\log S_j} + \left(\frac{N(S_j)}{S_j}\right)^2\right] \qquad (2)$$

The variance e_j^2 was given more influence in *Q* by dividing by the logarithm of the region size, and *Q* is penalized strongly by $\frac{N(Sj)}{Sj}$ when there are a large number of segments. So *Q* is the less biased towards both under segmentation and over-segmentation.

More recently, Zhang *et al*.(2004), proposed the evaluation function E, an information theoretic and the minimum description length principle (MDL). This segmentation evaluation function instead of using squared color error they use region entropy as its measure of intra-region uniformity that measures the entropy of pixel intensities within each region [29]. To prevent a bias towards over-segmentation, they define the *layout entropy* of the object features of all pixels in image where any two pixels in the same region have the same object feature. Pal and Bhandari also proposed an entropy-based segmentation evaluation measure for intra-region uniformity based on the second-order local entropy. Weszka and Rosenfeld proposed such a criterion with thresholding that measures the effect of noise to evaluate some threshold images. Based on the same idea of intra-region uniformity, Levine and Nazif also defined criterion LEV1 that computes the uniformity of a region characteristic based on the variance of this characteristic. Complementary to the intra-region uniformity, Levine and Nazif defined a disparity measurement between two regions to evaluate the dissimilarity of regions in a segmentation result. We compare our proposed method against the evaluation functions of F, E and Q .

3. Introduction of Imperialist Competitive Algorithm (ICA)

In this section, we introduce ICA algorithm and chaos theory.

3.1. Imperialist Competitive Algorithm (ICA)

Imperialist Competitive Algorithm (ICA) is a new evolutionary algorithm in the Evolutionary Computation field based on the human's socio-political evolution. The algorithm starts with an initial random population called countries. Some of the best countries in the population selected to be the imperialists and the rest form the colonies of these imperialists. In an N dimensional optimization problem, a country is a $1 \times N$ array. This array defined as below

$$country = [p_1, p_2, \dots, p_N] \qquad (3)$$

The cost of a country is found by evaluating the cost function *f* at the variables $(p_1, p_2, p_3, \dots, p_N)$. Then

$$c_i = f(country_i) = f(p_{i1}, p_{i2}, \dots, p_{iN}) \qquad (4)$$

The algorithm starts with *N* initial countries and the N_{imp} best of them (countries with minimum cost) chosen as the imperialists. The remaining countries are colonies that each belong to an empire. The initial colonies belong to imperialists in convenience with their powers. To distribute the colonies among imperialists proportionally, the normalized cost of an imperialist is defined as follow

$$C_n = max_i\, c_i - c_n \qquad (5)$$

Where, $cost_n$ is the cost of *n*th imperialist and C_n is its normalized cost. Each imperialist that has more cost value, will have less normalized cost value. Having the normalized cost, the power of each imperialist is computed as below and based on that the colonies distributed among the imperialist countries.

$$p_n = \left|\frac{C_n}{\sum_{i=1}^{N_{imp}} C_i}\right| \qquad (6)$$

On the other hand, the normalized power of an imperialist is assessed by its colonies. Then, the initial number of colonies of an empire will be

$$NC_n = rand\{p_n.(N_{col})\} \qquad (7)$$

Where, NC_n is initial number of colonies of *n*th empire and N_{col} is the number of all colonies.

To distribute the colonies among imperialist, NC_n of the colonies is selected randomly and assigned to their imperialist. The imperialist countries absorb the colonies towards themselves using the absorption policy. The absorption policy shown in Fig.2, makes the main core of this algorithm and causes the countries move towards to their minimum optima. The imperialists absorb these colonies towards themselves with respect to their power that described in (8). The total power of each imperialist is determined by the power of its both parts, the empire power plus percents of its average colonies power.

$$TC_n = cost(imperialist_n) + \xi mean\{cost(colonies\ of\ empire_n)\} \qquad (8)$$

Where TC_n is the total cost of the *n*th empire and ξ is a positive number which is considered to be less than one.

$$x \sim U(0, \beta \times d) \qquad (9)$$

In the absorption policy, the colony moves towards the imperialist by *x* unit. The direction of movement is the vector from colony to imperialist, as shown in Fig.2, in this figure, the distance between the imperialist and colony shown by d and *x* is a random variable with uniform distribution. Where β is greater than 1 and is near to 2. So, a proper choice can be $\beta = 2$. In our implementation γ is $\pi/4\ (Rad)$ respectively.

$$\theta \sim U(-\gamma, \gamma) \tag{10}$$

In ICA algorithm, to search different points around the imperialist, a random amount of deviation is added to the direction of colony movement towards the imperialist. In Fig. 2, this deflection angle is shown as θ, which is chosen randomly and with an uniform distribution. While moving toward the imperialist countries, a colony may reach to a better position, so the colony position changes according to position of the imperialist.

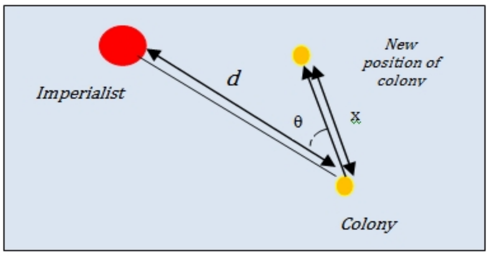

Figure2. Moving colonies toward their imperialist

In this algorithm, the imperialistic competition has an important role. During the imperialistic competition, the weak empires will lose their power and their colonies. To model this competition, firstly we compute the probability of possessing all the colonies by each empire considering the total cost of empire.

$$NTC_n = max_i\{TC_i\} - TC_n \tag{11}$$

Where, TC_n is the total cost of nth empire and NTC_n is the normalized total cost of nth empire. Having the normalized total cost, the possession probability of each empire is computed as below

$$p_{p_n} = \left| \frac{NTC_n}{\sum_{i=1}^{N_{imp}} NTC_i} \right| \tag{12}$$

after a while all the empires except the most powerful one will collapse and all the colonies will be under the control of this unique empire.

4. Proposed Algorithm

In this paper, we have proposed a new Imperialist Competitive Algorithm using the chaos theory (Chaotic Imperialist Competitive Algorithm CICA2). The primary ICA algorithm uses a local search mechanism as like as many evolutionary algorithms. Therefore, the primary ICA may fall into local minimum trap during the search process and it is possible to get far from the global optimum. To solve this problem we increased the exploration ability of the ICA algorithm, using a chaotic behavior in the colony movement towards the imperialist's position. So it is intended to improve the global convergence of the ICA and to prevent it to stick on a local solution.

4.1. Definition of chaotic radius in the movement of colonies towards the imperialist

In this paper, to enhance the global exploration capability, the chaotic maps are incorporated into ICA to enhance the ability of escaping from a local optimum.

The radius of movement is changed in a chaotic way during the search process. Adding this chaotic behavior in the imperialist algorithm absorption policy we make the conditions proper for the algorithm to escape from local peaks. Chaos variables are usually generated by the some well-known chaotic maps [30],[31]. Eq.(13), shows the mentioned chaotic maps for adjusting x parameter (radius of colonies movement towards the imperialist's position) in the proposed algorithm.

$$x_{n+1} = a x_n (1 - x_n) \tag{13}$$

Where, a is a control parameter. x is a chaotic variable in kth iteration which belongs to interval of (0,1). During the search process, no value of x is repeated. The CICA algorithm is summarized in Fig.3.

(1) Initialize the empires and their colonies positions randomly.
(2) Compute the adaptive x (colonies movement radius towards the imperialist's position) using the probabilistic model.
(3) Compute the total cost of all empires (Related to the power of both the imperialist and its colonies).
(4) Pick the weakest colony (colonies) from the weakest empire and give it (them) to the empire that has the most likelihood to possess it (Imperialistic competition).
(5) Eliminate the powerless empires.
(6) If there is just one empire, then stop else continue.
(7) Check the termination conditions.

Figure3. The CICA2 algorithm.

5. Unsupervised Image Segmentation and CICA2 algorithm

As mentioned before in algorithms the evaluations are bias towards the under-segmentation or over-segmentation. At first, we compute correlation and then present a new metric for evaluation of segmented images.
In this method, we extract the statistical information about the image from the each region to provide an adaptive evaluation. We proposed a probabilistic model [32]-[35], to decrease error of evaluation. The probabilistic model *P(x)* that we use here is a Gaussian distribution model. The joint probability distribution of pixels given by the product of the marginal probabilities of the countries:

$$p(intensity) = \prod_{i=1}^{n} N(intensity_i; \mu_i, \sigma_i) \tag{14}$$

Where

$$N(intensity_i; \mu_i, \sigma_i) = \frac{1}{\sqrt{2\pi}\sigma_i} e^{\frac{1}{2}\left(\frac{intensity_i - \mu_i}{\sigma_i}\right)^2} \tag{15}$$

The average, μ, and the standard deviation, σ, for the pixels of each region is approximated as below:

$$\hat{\mu}_i = \overline{intensity_i} = \frac{1}{M} \sum_{t=1}^{M} intensity_{t,i} \tag{16}$$

$$\hat{\sigma}_i = \sqrt{\frac{1}{M}\sum_{t=1}^{M}(Country_{t,i} - \overline{Country_i})^2} \quad (17)$$

Using this probabilistic model, the density of pixels is computed in each region. If the pixels density in the current region is more than the previous region, then with 75% the previous correlation of the evaluation of the pixels will be decrease and with 25% the mentioned correlation will be increase.

$$corr_i = 0.75(corr_{i-1} + \alpha) + 0.25(corr_{i-1} - \alpha) \quad (18)$$

$corr_i$, is the current correlation of pixel. $corr_{i-1}$, is the correlation of previous region and α is the constant value of decreasing and increasing the correlation of evaluation. The value of α is 0.5.

Otherwise, if the pixels density in the current region is less than the previous region, then with 75% the previous correlation of the evaluation of the pixels will be increased and with 25% the mentioned correlation will be decreased.

$$corr_i = 0.25(corr_{i-1} + \alpha) + 0.75(corr_{i-1} - \alpha) \quad (19)$$

If the pixels density in the current region is more than the previous region, it means that may be the pixels are in a good region. In Eq. (18), depending on the density of the pixels distribution, we set the correlation of region so that each pixel can escape from the dense area with 25% and with 75% the pixel is in its region with a decreasing correlation.

1. Reading segmented image.
2. Computing pixel density of each region in (14),(15).
3. Correlation in (18),(19).
4. Mean and variance each region in (16),(17).

Figure 4. A sequence from formulating the evaluation of Image Segmentation Methods for an optimization problem.

In Eq. (19), if the pixels density in the current region is less than the previous region, each pixel with possibility of 25% is in its region with a decreasing correlation and with 75% the pixel is in its region with an increasing correlation. This way, provides a more efficient evaluation in all over the image.

A good segmentation evaluation should maximize the uniformity of pixels within each segmented region, and minimize the uniformity across the regions. We propose a new function for evaluation of image segmentation for this function we need region-based segmentation. We compute variances of the R, G and B (variances color for image segmented in K-means) pixels of the region.

$$var(R_j) = \frac{1}{8*N}\left(2var^2_{R(R_j)} + 2var^2_{G(R_j)} + 2var^2_{B(R_j)}\right) \quad (20)$$

$var(R_j)$ is variances intensity of pixels in region R_j that you see in Eq. (20), and N is number of regions.

$$var(R_i) = \frac{1}{4}\left(var^2_{R(R_i)}\right) \quad (21)$$

Where in the Eq.(21). Means of region R_i original image is $\mu(R_i)$ and means of region R_i in gray-level segmented image is $\mu'(R_i)$.

$$Fitness - function = min\,(var(R_i) - corr_i) \quad (22)$$

We formulated the Evaluation of Image Segmentation Methods for an optimization problem and solved this problem with ICA algorithms. This method has a good precision for evaluating segmented image. This fitness function computes *derivation* of regions in segmented image. This Algorithm is show in Fig.5. This fitness function and ICA algorithm evaluate image segmentation algorithms. In this paper, ICA algorithm used for minimization the problem. We test this metric and is show result in next section.

(1) Eq.(21) is cost function.
(1) Initialize the empires and their colonies positions randomly.
(2) Compute the total cost of all empires (Related to the power of both the imperialist and its colonies).
(4) Pick the weakest colony (colonies) from the weakest empire and give it (them) to the empire that has the most likelihood to possess it (Imperialistic competition).
(5) Eliminate the powerless empires.
(6) If there is just one empire, then stop else continue.
(7) Check the termination conditions.

Figure 5. The CICA2 algorithm for evaluation of image segmentation methods.

6. Experimental Result

We empirically studied the evaluation methods F, Q, E and CICA2 algorithm on the segmentation results from two different segmentation algorithms, the Edge Detection and Image Segmentation (EDISON). It developed by the Robust Image Understanding Laboratory at Rutgers University. We used EDISON to generate images that vary in the number of regions in the segmentation to see how the evaluation methods are affected by the number of regions. The second segmentation algorithm is canny that is available in Berkeley dataset. We use these two segmentation methods to do a preliminary study on the effectiveness of these quantitative evaluation methods on different segmentation parameterizations and segmentation techniques. We use two dataset Berkeley with 1000 images and 1200 images, for computing error in evaluation.

In this section, we analyze the previously presented unsupervised evaluation criteria. We describe experimental results to evaluate CICA2 algorithm and results from four evaluation methods are examined and compared. We compute the effectiveness of F, Q, E and CICA2 based on their accuracy with evaluations provided by a small group of human evaluators. In our first set of experiments, we vary the total number of regions in the segmentation (using EDISON to generate the segmentations) to study the sensitivity of these an objective evaluation methods to the number of regions in the segmentation.

With an increase in the number of regions, the segmented images clearly look better to the observer, since more details are preserved. However, more regions do not necessarily make a better segmentation, since over-segmentation can occur and it is a problem for evaluations.

The proposed algorithm is a good algorithm for evaluation of segmented image because this method has a controller for under-segmentation and over-segmentation. The *corr* has important role in evaluation so error of evaluation is the less.

The effectiveness is described by accuracy, which is defined as the percentage of the number of times the evaluation measure correctly matches human evaluation result divided by the total number of comparisons in the experiment. We compute the effectiveness of F, Q, E and CICA2 algorithm based on their accuracy with evaluations provided on four dataset that is shown in Table.2.

Table 2: Accuracy (%) of the evaluation measures

Accuracy (%)	F	Q	E	CICA2 algorithm
1)Image Segmentation (EDISON)	%73.3	%76.22	%74.81	**%80.09**
2)Berkeley dataset (canny)	%64.3	%68.22	%63.81	**%75.85**
3)1200 images-Berkeley	%71.01	%73.35	%75.50	**%84.63**
4)1000 images-Berkeley	%62.43	%68.6	%71.32	**%83.43**

The results, given in Table 2, once again demonstrate the bias of many of the evaluation methods towards under-segmentation. F and E, achieve low accuracy in this experiment. On the other hand, those measures that are more balanced or less biased towards under-segmentation, i.e. Q and CICA2 algorithm, achieve higher accuracy. Overall, CICA2 algorithm performs best here.

We evaluate an image with four unsupervised evaluation and can see that CICA2 algorithm is better than F. and CICA2 algorithm no sensitive to under-segmentation and over-segmentation. It computes correlation and pixel density for each region and control error of under-segmentation and over-segmentation in evaluation.

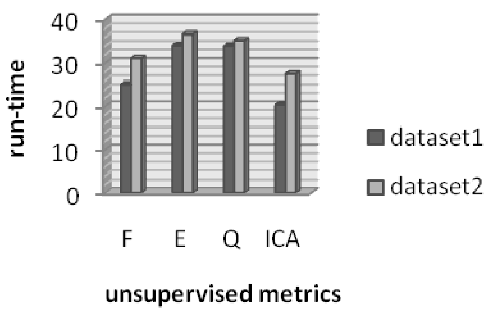

Figure 6. Run-time for four metrics for evaluation 100 image (second).

In Fig.6, we are shown that run-time for evaluation 100 images in CICA2 algorithm is better than E, F and Q.

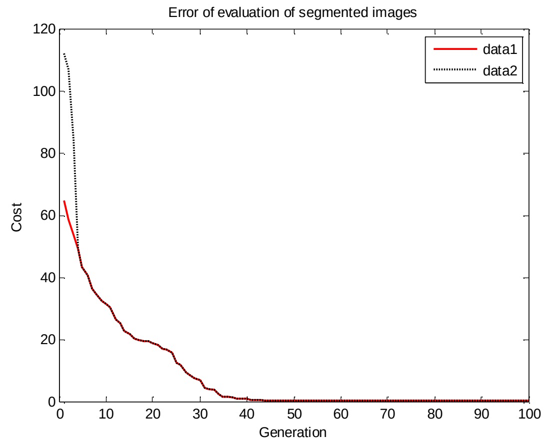

Figure 7. Cost of evaluation of segmented images datasets 3,4.

In Fig.7, we are shown that error for evaluation 100 images in CICA2 algorithm is near the zero.

7. Conclusion And Future Work

In this paper, we present an optimization method that objectively evaluate image segmentation. In this paper, we proposed a new formulation for the evaluation of image segmentation methods. In this paper using probabilistic model that utilize the information of pixels (mean and variance) in each region to balance the under-segmentation and over-segmentation. Using this mechanism dynamically set the correlation of pixels in the each region using a probabilistic model, then the evaluation of image segmentation methods introduce for an optimization problem. We first present four segmentation evaluation methodologies, and discuss the advantages and shortcomings of each type of unsupervised evaluation, among others. Subjective and supervised evaluations have their disadvantages. For example tedious to produce and can vary widely from one human to another and time-consuming. Unsupervised segmentation evaluation methods offer the unique advantage that they are purely objective and do not require a manually-segmented reference image and those embedded in real-time systems. We have demonstrated via our preliminary experiments that our unsupervised segmentation evaluation measure, CICA2 algorithm, improves upon previously defined evaluation measures in several ways. In particular, F has a very strong bias towards images with very few regions and thus do not perform well. Q outperforms F but still disagrees with our human evaluators more often than E did. The correlation and density in each region are important components in obtaining our results. Coding evaluation problem and present a new cost function and solving a optimization problem is interesting directions for future research.

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