An Efficient Implementaionof Hybridsegmentation Based OnOtsus And Particle Swarm Optimization Technique

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ABSTRACT:*Digital Image segmentation is one of unique task in the field of digital image processing. It is the practice ofsplitting a digital image into its constituent objects.Otsu computes a global threshold by uncomplainingthe actuality of two classes, foreground and background pixels,and select the threshold that diminishes the interclass varianceof the threshold black and white pixels.Translating a gray scale image to binarize is a common imageprocessing task.This paper gives an outline of image segmentationtechniques based on Particle Swarm Optimization (PSO)based clustering techniques. PSO is one of the modern andemerging digital image segmentation techniques inspiredfrom the nature.*

KEYWORDS*-Particle Swarm Optimization (PSO), PSO Clustering, gbest, pbes*t.

I. INTRODUCTION

Image segmentation is a completely significant concern amongdigital image processing [1][2][3]. The reason wesegmentimage is regularly for further image compressionor definitely for image popularity. In some situation,image segmentation is apprehensive for a designated varietyof an image but not the entire image. When we areinteresting in recognizing a few part of the image, weuse image segmentation that's like this.Different from the outline above, in this paper wedevelop a simple set of rules of image segmentation forthe whole image. The reason we would really like to developa new segmentation algorithm is that we need to make ahigher and extra handy surroundings for us tocompress the unique image after we phase it. Forthis reason, the target of the new algorithm must suita few qualities.There are benefits and drawbacks for all of thealgorithms currently themselves. In this paper wesuggest a new hybrid method. We conglomerate the characteristicsof them and develop a novel algorithm with a simpleconcept. And we will demonstration that the new algorithm canachieve the three goals listed above which is fast withgood shape matching and virtuous connectivity of itssegmenting results.

Region growing segmentation is an method toscrutinize the neighboring pixels of the initial “seedpoints” and govern if the pixels are added to the seedpoint or not. The procedure is iterated as same as dataclustering.In the meantime the regions are grown on the basis of thethreshold, the image data is vital for us. Forinstance, getting to identify the histogram of the imagewould support us a lot subsequently we can proceeds it as a reference topick the threshold.

The K-mean algorithm technique is the furthermost prominentpartitional clustering algorithms [5]. When using themethod, we have to decide the numbers of cluster beforeperforming the segmentation. According to the numberof classes, we have to minimize some criteria of eachcluster. K-means is a very fast algorithm which canclassify the main database by parallel dealing theprocess with different initial points though it causes theinitial problem.However, there is one critical disadvantage inK-means which is the main reason we would not like tochoose it for our “compression-oriented” segmentation.

Liu et. al. [6] presented a PSO based fuzzy cluster for sonar image segmentation. This amalgamation tends to harvestrobust searching and high speed convergence ability. In adding, the fuzzy measure and fuzzy integral are also premeditatedto compute the fitness. In the meantime the possibilistic c-means (PCM) algorithm is very sensitive to initialization and parameters.

Jing et. al. [7] offered an methodology to fit clusters which are adjacent to one another. The t-Particle Swarm Optimization (tPSO) is used to solve the complex computation as well as initial parameter sensitivity problem in order to get accuratesegmentation. It is shown that the proposed algorithm is less prejudiced by the noise points and produce bettersegmentation results.

Zhang et. al. [8] exemplified how PCM can be integrated with PSO and provides a noteworthyenhancement on theefficiency of the segmentation. The PCM is more accurate as related to FCM, as it incapacitates the relative membershipproblem of FCM in image segmentation. The mahalonolis distance is used with PCM algorithm, since it enhances theperformance of the clustering algorithm. The PSO is used to optimize the initial clustering centers.

Hilbert Transform for Edge Detection

There is another method for edge detection that uses the Hilbert transform (HLT). The HLT is

$$g_H(\tau) = h(x) * g(x), \quad \text{where } h(x) = \frac{1}{\pi x}$$

……………………. (1)

and * means convolution. Alternatively,

$$G_H(f) = H(f)G(f) \quad \text{………… (2)}$$

where$G(f) = FT[g(x)]$ (FT means the Fouriertransform), $G_H(f) = FT[g_H(x)]$, and

$$H(f) = -j\,\mathrm{sgn}(f) \quad \text{,……………(3)}$$

where the sign function is defined as

$$\mathrm{sgn}(f) = 1 \text{ when } f > 0,$$
$$\mathrm{sgn}(f) = -1 \text{ when } f < 0,$$
$$\mathrm{sgn}(0) = 0$$

……(4)

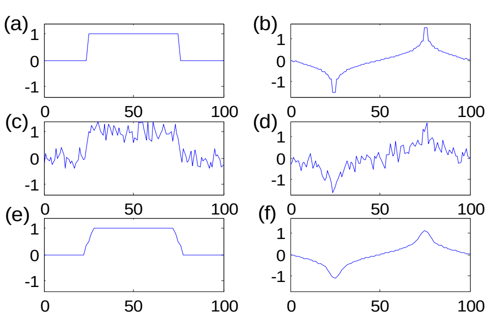

***Fig**.1 Using HLTs to detect (a) the sharp edges, (c) the step edges with noise, and (e) the ramp edges. (b)(d)(e) are the results of the HLTs of (a)(c)(e)*

II. SHORT RESPONSE HILBERT TRANSFORM (SRHLT)

Author discussed in [5] on Canny's criterion, we improve the short response Hilbert transform (SRHLT), which is the intermediate of the original HLT and the differentiation operation. For edge detection, the SRHLT can compromise the recompenses of the HLT and differentiation. It can well distinguish the edges from the non-edge regions and simulataneously are robust to noise. We also find that there are numerous ways to describe the SRHLT. Thus it needtobe combine the HLT and differentiation to define the SRHLT. From the theorem of the Fourier Transform,

$$\mathrm{csch}(\pi x) \xrightarrow{FT} -j\tanh(\pi f) \quad ,………………..$$

(5)

where

$$\mathrm{csch}(x) = 2/(e^x - e^{-x})$$
$$\tanh(x) = (e^x - e^{-x})/(e^x + e^{-x}),$$

…………….(6)

Therefore, from the scaling property of the FT:

$$g(bx) \xrightarrow{FT} |b|^{-1} G(f/b),$$

……………. (7)

we obtain

$$|b|\,\mathrm{csch}(\pi bx) \xrightarrow{FT} -j\tanh(\pi f/b)$$

……………….(8)

From 8, we can define the **short response Hilberttransform** (**SRHLT**) as:

$$g_H(\tau) = h_b(x) * g(x), \quad \text{where } h_b(x) = |b|\,\mathrm{csch}(\pi bx)$$
$$G_H(f) = H_b(f)G(f) \text{ where } G_H(f) = FT[g_H(\tau)],$$
$$G(f) = FT[g(\tau)], \qquad H_b(f) = -j\tanh(\pi f/b).$$

……………..(9

In fact,tonegotiation the goals of "higher distinction"and"noise immunity"andaccomplish the prerequisite of "good detection"suggested by Canny, the impulse response of the edge detection filter should satisfy:

(Constraint 1) The impulse response $h(x)$ is neither too short nor too long. If we describe

$$T = \int_{-\infty}^{\infty} |x||h(x)|^2\, dx \quad ,……..(10)$$

then$T$ should satisfy

$$A_1 < T < A_2, \qquad ……..(11)$$

whereA_1andA_2 are some thresholds. To achieve higher immunity to noise, T should be larger than a certain threshold A_1. To make the filter have higher ability for distinguishing the edge from the non-edge region, T should be smaller than a certain threshold A_2.

(Constraint 2) $Max\{|h(x)|\} = h(x_0)$

…………………. (12)

where $x_0 = 0$ or x_0 is very close to 0.

(Constraint 3) $|h(x_1)| > |h(x_2)|$ if $|x_2| > |x_1| \geq |x_0|$, …….(13)

or although in some conditions the impulse response is not strictly descending but the local peak is much smaller than the global peak $|h(x_0)|$.

$$|h(x_1)| < |h(x_2)|, \quad |x_2| > |x_1| \\ \text{but } |h(x_2)| \ll |h(x_0)|. \quad ….(14)$$

(Constraint 4) $h(x) = -h(-x)$. …… (15)

In detail, there are many alternative ways to outline the SRHLT. There are also other functions that satisfy Canny's criterions and can be treated as the impulse responses of SRHLTs. For instance,

$$\frac{4\pi b^{-2}x}{1+(2\pi b^{-1}x)^2} \xrightarrow{FT} -je^{-|b\,f|}\,\mathrm{sgn}(f)$$

when b=1 (2.1)

$$\frac{4\pi b^{-2}x}{1+(2\pi b^{-1}x)^2} \approx \frac{1}{\pi x}$$ when b=0... (16)

$$\frac{1}{\pi x}\Pi(bx/2) \xrightarrow{FT} -i\frac{2}{\pi}Si(2\pi b^{-1}f)$$ where

$$Si(x) = \int_0^x \frac{\sin t}{t}\,dt$$

$$\frac{\sin c(bx)}{b\pi x} \xrightarrow{FT} H_5(f)$$ where b sinc(x) = sin(πx)/(πx),…… (17)

$$\frac{\sin c^2(bx)}{b\pi x} \xrightarrow{FT} H_6(f)$$ ……..18)

Particle Swarm optimization

PSO is a population-based randomly searching process. Here we supposed that there are N "particles" randomly seem in a "solution space". Indication that we are solving the optimization problem and for data clustering, there is always a criteria (for instance, the squared error function) for every single particle at their position in the solution space. The N particles will keep moving and calculating the criteria in every position the stay (we call "fitness" in PSO) until the criteria reaches some threshold we require. Each particle keeps track of its coordinates in the solution space which are related with the best solution (fitness) that has attained so far by that particle where its value is named personal best, *pbest.*An additional best value that is tracked by the PSO is the best value attained so far by any particle in the neighborhood of that particle. This value is called global best, *gbest*. We introduce the exact statement in mathematics below :

$$v_{i,j}(t) = w \cdot v_{i,j}(t-1) + c_1 \cdot r_1(p_{i,j}(t-1) \\ - x_{i,j}(t-1)) + c_2 \cdot r_2(p_{g,j}(t-1) \\ - x_{i,j}(t-1))$$

………..(19)

$$x_{i,j}(t) = x_{i,j}(t-1) + v_{i,j}(t)$$

…………………(20)

where x_i is the current position of the particle, v_i is the current velocity of the particle, p_i is the personal best position of the particle, w, c, are all constant factors, and r are the random numbers uniform distributed within the interval [0,1].We custom last velocity and last position of personal and global best to predicate the velocity now.The position we stay is predicated by last position plus velocity now.By using PSO, we can solve the initial problem of "K-means" and still maintain the whole partitional clustering scheme. The utmostimperative thing is to ponder about it as an optimization problem.

III. PROPOSEDCONTROL STRATEGY

The main goal for us to segment an image is that we focus on Thresholding may be viewed as a statistical-decision theory problem whose unbiased is to diminish the average error incurred in assigning pixels to two or more groups.

Let{0,1,2,…,*L-1*}denote the L distinct intensity levels in a digital image of size $M \times N$ pixels, and let n_i denote the number of pixels with intensity i. The total number, MN, of pixels in the image is $MN = n_0 + n_1 + n_2 + \ldots + n_{L-1}$. The normalized histogram has components $p_i = n_i / MN$, from which it follows that

$$\sum_{i=0}^{L-1} p_i = 1, \; p_i \geq 0 \qquad (21)$$

Now, we select a threshold $T(k) = k, 0 < k < L-1$, and use it to threshold the input image into two classes, C_1 and C_2, where C_1 consist with intensity in the range $[0, k]$ and C_2 consist with $[k+1, L-1]$.

Using this threshold , $P_1(k)$,that is assigned to C_1 and given by the cumulative sum.

$$P_1(k) = \sum_{i=0}^{k} p_i \qquad \ldots\ldots(22)$$

$$P_2(k) = \sum_{i=k+1}^{L-1} p_i = 1 - P_1(k) \qquad \ldots..(23)$$

The validity of the following two equations can be verified by direct substitution of the preceding result:

$$P_1 m_1 + P_2 m_2 = m_G \ldots\ldots \qquad (24)$$

$$P_1 + P_2 = 1 \qquad \ldots..(25)$$

In order to evaluate the “goodness” of the threshold at level k we use the normalized, dimensionless metric

$$\eta = \frac{\sigma_B^2(k)}{\sigma_G^2} \qquad \ldots\ldots\ldots(26)$$

Where σ_G^2 is the *global variance*

$$\sigma_G^2 = \sum_{i=0}^{L-1} \left(i - m_G\right)^2 p_i \qquad (27)$$

And σ_B^2 is the *between-class variance*, define as :

$$\sigma_B^2 = P_1(m_1 - m_G)^2 + P_2(m_2 - m_G)^2 \qquad \ldots\ldots(28)$$

$$\sigma_B^2(k) = P_1 P_2 (m_1 - m_2)^2 = \frac{(m_G P_1(k) - m(k))^2}{P_1(k)(1 - P_1(k))} \qquad \ldots\ldots\ldots.(29)$$

Indicating that the *between-class variance* and η is a measure of *separability* between class.

Then, the optimum threshold is the value, k^*,that maximizes $\sigma_B^2(k)$

$$\sigma_B^2(k^*) = \max_{o \leq k \leq L-1} \sigma_B^2(k) \qquad \ldots\ldots30)$$

In other word, to find k^* we simply evaluate (2.7-11) for all *integer values* of k

Once k^* has been obtain, the input image $f(x, y)$ is segmented as before:

$$g(x, y) = \begin{cases} 1 & \text{if f(x,y)≥k*} \\ 0 & \text{if f(x,y)≤k*} \end{cases}$$

For x = 0,1,2,…,M-1 and y = 0,1,2…,N-1. This measure has values in the range

$$0 \leq \eta(k^*) \leq 1$$

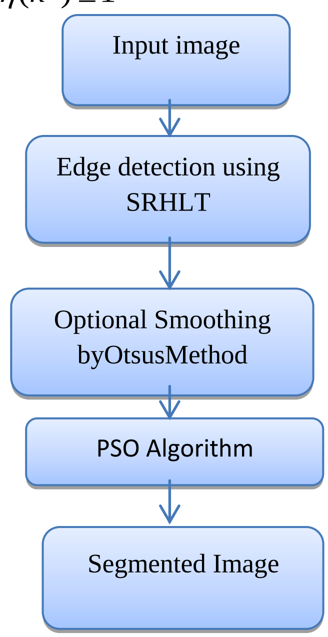

Fig.2 PSO Based Image Segmentation of a image.

The solicitation of this algorithm to the imagesegmentation problem can be kept in the subsequentway:

Step 1: Read the input image to be segmented.

Step 2: Select PSO method to be applied on thatimage with a particular threshold level

Step 3:for each particle in the population doupdateparticle‟s fitness in the search space andupdateparticle‟s best in the search spacemove particle in the population

Step 4: for each particle doif swarm gets better then reward the swarmspawn the particle: extend the swarm/particlelife

Step5: for each particle doif swarm is not improving its performance thenpunish swarm:remove the swarm/particle: ordiminish the swarm life.

Step 6: Spread out the swarm to spawn (the swarm isdeliberated for succeeding iteration)

Step 7: Delete the "failed" swarms.(the swarm willnever come into search space) andReset threshold counter load.

IV. CONCLUSION

In the study, we have numerous approaches to make edge detections, such as first-order derivative edge detection, second-order derivative edge detection, HLT and SRHLT.SRHLT has advanced robustness for noise than HLT and can efficaciously detect ramp edges that could elude the pixels that near to an edge be predictable as an edge pixel.The PSO basedsegmented images are usually well segmented into regionsof homogeneous colour and are perceptually expressive tohuman‟s vision and can identify, automatically, very well thenumber of regions.

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