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Improving Visibility of Gall Stones from Gall Bladder in Ultrasound Images Using Clustering

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ABSTRACT

Gallstones are crystalline concretion that forms in the gallbladder and causes pain, infection, or other serious complications in humans. In this paper we propose a technique, a combination of mathematical morphology and Maximum Entropy to cluster image pixels representing gallstones in the gall bladder. Morphological operations are applied to the image to strengthen the edges followed by preprocessing. Threshold of the image is obtained using Maximum Entropy and further optimized by Particle Swarm Optimization to improve the performance in terms of segmentation results and computation time . The experiments are conducted on ultrasound images and the segmented results are highlighted and observed that the performance of this method better than other standard methods.

Key words: PSO, Maximum Entropy, Mathematical Morphology ,Structuring Element and Gall Stone.

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1. INTRODUCTION

Segmentation is very important as a preprocessing for many image analysis and computer vision tasks ranging from medical image processing, industrial quality control, to robot navigation. Segmentation is the process of partitioning an image into constituent regions or objects and is a very commonly used in medical image analysis . The purpose of image segmentation is to decompose an image domain into a number of disjoint regions so that the features within each region have visual similarity, strong statistical correlation and reasonably good homogeneity.

Image segmentation techniques may be classified into a number of groups depending on the approach of the concerned algorithm and are classified as Region based techniques, Feature thresholding, Contour based techniques ,Clustering, Watershed segmentation using the Distance Transform, Watershed segmentation using gradients and Marker-Controlled Watershed segmentation.

ROI(Region Of Interest) detection of Medical images is a pre-processing step in medical image segmentation and 3D reconstruction and is detected according to some early brought forward algorithms but the performances of these algorithms depends on the type of medical image. Detection of abnormal structures with their location and orientation is an extremely important task in the diagnosis stage, in the planning and analysis of various treatments. The proposed method is to automate the manual process detecting gall stones (ROI) present in the gall bladder . Image noise comes from a variety of sources and no imaging method is free of noise. A segmentation algorithm often needs a preprocessing step like noise reduction to minimize the effects of undesired perturbations like impulse noise, salt and pepper noise ,Gaussian and speckle noise etc that may cause over or under segmentation. Computed tomography (CT) , 3D ultrasound and PET are often characterized by quantum (in low-dose CT) ,speckle (in ultrasound) or synthetic(in PET) noises. Noisy images must be enhanced prior to image segmentation.

2. RELATED WORK

A Fast clustering segmentation algorithm has been proposed in [5] to improve the clustering performance of basic FCM. Generalized rough fuzzy c-means algorithm is proposed for accurate and reliable segmentation of brain images. The method is more robust to initialization and noise [6]. The effect of Ostu thresholding and morphological reconstruction has been demonstrated to segment breast cancer images and results have been compared with other standard methods[7].

To determine global and multilevel thresholds and to remove false modulus maximum points, an extended Ostu thresholding has been applied with wavelet transform for analyzing medical images[8]. To facilitate medical image segmentation by considering the fact of fuzziness in pixel distribution, Fuzzy clustering has been demonstrated to extract objects of interest from abdominal aortic aneurysm and degraded human brain imaging[9]. An improved Biogeography based optimization technique using the principle of maximizing fuzzy entropy has been applied on CT images of human head and analyzed that its performance is better than GA, PSO and basic BBO [10]. A swarm intelligence inspired algorithm is presented to detect contours in images where the agents are distributed over important positions of image and the positions of agents are changed according to fitness value. The authors propose that the boundary detection is an important step in image segmentation and the algorithm is evaluated on Berkeley segmentation data set(BSDS)[11] and compared with other standard methods.

An automated pulmonary disease detection such as lung cancer, tumor, and mass cells aids for diagnosis and treatment planning. The 2D Ostu image thresholding plays vital role in segmenting CT images but the process suffers from high computation time and complexity. The combination of PSO and Ostu introduced to find optimal threshold for segmentation and to improve the efficiency of Ostu algorithm[13]. To identify early diagnosis of brain tumor Fuzzy C-means clustering has been optimized with GA and PSO[12] . Data mining techniques are used to extract and identify abnormal ROI present in the medical images. The statistical features of ROI from the mammogram images and clinical data set are identified and grouped by K-means clustering followed by SVM classification and the accuracy has been compared with traditional method [13]. Ultrasound images have inbuilt noises and requires a highly experienced and skilled operator to detect a malignant region. Mathematical Morphology deals with geometric features of objects such as size, shape, contrast or connectivity .In this paper we propose a new technique to segment ultrasound images and to extract pixels represent gall stones in the gall bladder, a combination of multiscale morphological gradients and maximum entropy to find threshold of an image. Further, the obtained threshold is being optimized for good accuracy and reduced computation time. The paper is organized as follows. The steps for preprocessing to remove noises from ultra sound images and edge enhancement have been discussed in Section 3 and the optimization of Maximum Entropy with PSO is elaborated in Section 4. The experimental results and its analysis are dealt in Section 5 while in section 6 conclusions are mentioned.

3. MORPHOLOGICAL PREPROCESSING

A segmentation algorithm often needs a preprocessing step like noise smoothing to reduce the effect of undesired perturbations, which might cause over- and under-segmentation. The very small scale details (i.e., the sudden discontinuity in gray-value over very small regions) are usually considered as noise. It is a necessity to estimate the scale (or size) of noise particles before removing them. Here, the preprocessing technique soothes out noise by applying iterative filtering until the spatial variation of intensity becomes locally monotonic with respect to the SE. The steps of the preprocessing operations are:

1. Perform conventional morphological opening and closing on the input image using an SE of small size. The size of the SE is greater than that of noise particles.
2. Construct the output image by averaging the images resulting after opening and closing.
3. Compare the output image with the input image. If they are identical then halt. Otherwise consider the output image as the input image to the next iteration and go to step 1.

The main problem of this approach is to determine the size of SE. Based on the domain knowledge and sensor parameters (namely, resolution and magnification factor) minimum size of the features of interest in the image can be determined in terms of pixels. Any feature of size smaller than that may be treated as noise. Size of isotropic SE to eliminate such noise can then simply be computed. The goal of preprocessing is to suppress non-significant features, which disturb the segmentation.

3.1 Multiscale Edge Detection

The multiscale gradient method employs group of structuring elements SE_i for $0 \leq I \leq n$ where n+1 is the number of structuring elements. The size of SE_i is (2i+1)X(2i+1) pixels i.e, SE_0 contains only one pixel and SE_1 is a 3x3 square and so on. The structuring elements SE_i could be of any shape satisfying the relation $B_0 \subseteq B_1 \subseteq \ldots B_n$.

The Morphological Gradient MG(f) with a Structuring Element SE_n is defined as $\delta(f)-\varepsilon(f)$ [Dilation-Erosion]. In order to detect ramp edges and avoiding found edges being thick and are merged, it is necessary to use an SE of large size for the former and an SE of the small size for the latter. In order to overcome this problem, a Multiscale mophological gradient is defined as in Eqn(1)

3.1.1 Multiscale Morphological Gradient Algorithm

$$MG(f)=1/n \sum_{i=1}^{n} [\varepsilon(\delta(f,SE_i)- \varepsilon(f,SE_i),SE_{i-1})] \quad (1)$$

Where SE_i is a SE of size (2i+1)x(2i+1). we use a dilation with a small Structuring Element B of size 2x2 on (MG(f)),i.e., $(MG(f)\oplus B)$, to eliminate irrelevant minima. To further remove the local minima with low contrast, a constant h is added to the gray value of the dilated image. Then the local minima with a contrast lower than h can be filled using the reconstruction by erosion of MG(f) from $(MG(f)) \oplus B + h$.

The final gradient image FG(f) can be expressed as

$$FG(f)=\varphi^{(rec)}[(MG(f)) \oplus B + h,MG(f)] \quad (2)$$

In our experiment ,h is determined as the value of 35 percentile of the histogram on gray image of $(MG(f) \oplus B)$.

- Multiscale Morphological gradient image obtained as:

  $$MG(f)=1/n \sum_{i=1}^{n} [\varepsilon(\delta(f,SE_i)- \varepsilon(f,SE_i),SE_{i-1})]$$

  Where SE_i is a SE of size (2i+1)x(2i+1 and n=2.
- $(MG(f)\oplus B)$ - dilation with a small Structuring element B of size 2x2 on (MG(f)).
- $(MG(f)) \oplus B + h$
  h is determined as the value of 35 percentile of the histogram on gray image of $(MG(f) \oplus B)$.

4. MAXIMUM ENTROPY

Entropy based methods exploits the entropy on the distribution of gray levels, the maximum entropy being an indication of detecting objects of interest in the thresholded image. Threshold T lies in range (0<T<L-1, L=0, 1, 2….255) and the image is divided into two classes or two regions C_O and C_B based on T, where C_O is the object region and C_B is the background region. Shannon's entropy[3] is defined as

$$H = -\sum_{i=0}^{n} p_i \log(p_i) \quad (3)$$

where p_i is the probability of occurrence of gray value i. The theory of maximum entropy is to select i which makes entropy as the maximum one.

When the sum of two class entropies, the image foreground and the image background reaches its maximum then the image is said to be optimally thresholded and it is defined as;

$$T_{opt} = \arg\max[H_F(T) + H_B(T)] \quad (4)$$

$$H_F(T) = -\sum_{g=0}^{T-1} \frac{p_g}{P_F} \log \frac{p_g}{P_F} \quad (5)$$

and

$$H_B(T) = -\sum_{g=T+1}^{255} \frac{p_g}{P_B} \log \frac{p_g}{P_B} \quad (6)$$

$$Fitness=H(t) =H_F(t)+H_B(T) \quad (7)$$

2-D maximum entropy considers distribution of the gray information as well as the spatial neighbor information to obtain entropy value. To optimize threshold value, PSO has been successfully applied with 2-D maximum entropy for segmenting infrared images in less computation cost[2]. To seek optimum threshold value, QPSO is combined with maximum entropy to segment vehicle brand images[3]. Diversity controlled revised QPSO introduced by adding iterative equation with QPSO to prevent from local minima to be trapped has been tested against medical image registration[4]. Particle Swarm Optimization (PSO) is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995[14], inspired by social behavior of bird flocking or fish schooling. Intelligent optimization algorithms have been proved themselves as an effective tool to find optimal results. The system is initialized with a population of random solutions and searches for optima by updating generations.

4.1 MEPSO Thresholding

Particle Swarm Optimization (PSO) is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995[14], inspired by social behavior of bird flocking or fish schooling. Intelligent optimization algorithms have been proved themselves as an effective tool to find optimal results. The system is initialized with a population of random solutions and searches for optima by updating generations. In PSO, the potential solutions, called particles, searches the whole space guided by its personal best position (pbest) and best position of the swarm (gbest).

The velocity and position of the particles are updated based on their best experiences. During particles movement, every visited point will be evaluated by fitness function. And those points with highest fitness are assigned as the best positions. Then the particles keep moving around until some stop conditions are met. The i^{th} particle of swarm is represented as $X_i = (X_{i1}, X_{i2}, \ldots, X_{iD})$ while the velocity for i^{th} particle is represented as $V_i = (V_{i1}, V_{i2}, \ldots, V_{iD})$. The best previous position (the position giving the best fitness value) of the i^{th} particle is recorded and represented as $P_i = (P_{i1}, P_{i2}, \ldots, P_{iD})$. At each step, the particles are manipulated according to the following equations (6) and (7):

$$V'_{id} = \omega V_{id} + c_1 rand()(P_{id} - X_{id}) + c_2 rand()(P_{gd} - X_{id}) \quad (8)$$

ω represents the inertia weight to control the speed of each generation of particles, V_{id} is the velocity of i^{th} particle in dimension d. P_{id} is the best position achieved by particle i, P_{gd} is the best positions found by neighbors of particle i and c1,c2 are two positive constants known as cognitive and social components.

$$X'_{id} = X_{id} + V'_{id} \quad (9)$$

The image matrix is projected into a two dimensional feature space, and PSO is applied to search over this 2D space and converge to global optima which are useful to extract object features.

The pseudo code of MEPSO is presented below;

1. Generate random population of N solutions(particles);
2. For(i=0;i<popsize;i++)
3. Evaluate fitness f(X[i]) as in eqn (2);
4. Initialize the value of weight factor, ω;
5. while (termination condition is not true)
6. for(i=0;i< popsize;i++)
7. if(f(X[i])>pbest$_i$) pbest$_i$=X[i];
8. Update gbest;
9. Update(Position X[i], Velocity V[i]);
10. Evaluate f(X[i]);
11. endfor
    Endwhile
12. If gbest(global best position)<X[i] Tseg=1; else Tseg=0;
13. Endif

The population size of particles refers the number of particles involved in obtaining solution at each iteration.

5. EXPERIMENTAL RESULTS

The proposed work is demonstrated on ultrasound images downloaded from open source repository shown in Figure 1(a),Figure 2(a) and Figure 3(a) where arrows show presence of abnormalities/gall stones, the image of size 371 x 266 as shown in Figure 1(a) , the simplified image after morphological processing is shown Figure 1.b and the final result obtained using Maximum Entropy is shown in figure 1.c.

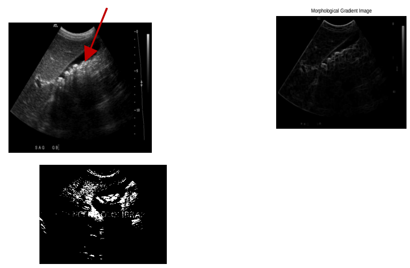

Figure 1.a: **1.b:** **1.c:**

Figure 1.a) Original image **b)** Image after Morphological Filtering **c)** Result after MEPSO

Figure 2.a: **2.b:** **2.c:**

Figure 2.a) Original image **b)** Image after Morphological Filtering **c)** Result after MEPSO

Figure 3.a: **3.b:** **3.c:**

Figure 3.a) Original image **b)** Image after Morphological Filtering **c)** Result after MEPSO

Figure 2(a), image of size 100 x 97, the simplified image after morphological processing and the final result obtained using Maximum Entropy is shown in figure 2.a and 2.c respectively.

The simplified image of size 350x297 shown in Figure 3.a after morphological processing and the final result obtained using Maximum Entropy is shown in figure 3.b and 3.c respectively. Figure 4. Shows the threshold value obtained in respective iterations. The population size of 20 is considered in MEPSO. The value of cognitive and social components are set as c1=c2=2 and the inertia weight set as wmax=0.9 and wmin=0.4 in MEPSO. The maximum number of iterations MAXITER=100.

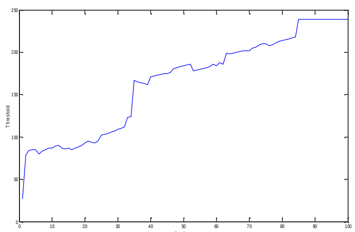

Figure 4: Threshold values obtained in MEPSO

6. CONCLUSION

In this paper we propose a new method, a combination of Mathematical Morphology and maximum entropy optimized with PSO for finding optimal threshold value to segment gall stones present in the gall bladder .Intensity values belonging to the abnormality region have been successfully grouped and isolated from the other parts of the image and in less computation time. Future work is to concentrate on application of this method on various medical imaging technologies to identify the defects present in the images and to perform comparative study both analytically and experimentally.

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