RESEARCH REVIEW FOR DIGITAL IMAGE SEGMENTATION TECHNIQUES

Ashraf A. Aly¹, Safaai Bin Deris², Nazar Zaki³

^{1, 2}Faculty of Computer Science, Universiti Teknologi Malaysia Ashraf.ahmed@uaeu.ac.ae, safaai@utm.my ³College of Information Technology, UAE University, UAE nzaki@uaeu.ac.ae

ABSTRACT

Evaluating the previous work is an important part of developing segmentation methods for the image analysis techniques. The aim of this paper is to give a review of digital image segmentation techniques. The problems of digital image segmentation represent great challenges for computer vision. The wide range of the problems of computer vision may make good use of image segmentation. This paper study and evaluate the different methods for segmentation techniques. We discuss the main tendency of each algorithm with their applications, advantages and disadvantages. This study is useful for determining the appropriate use of the image segmentation methods and for improving their accuracy and performance and also for the main objective, which designing new algorithms.

KEYWORDS

Active Contour, Segmentation Enhancement, Topological Alignments, Boundary Detection, image Segmentation, Inversion Technique.

1. INTRODUCTION

Digital image processing is important domain for many reasons. Actually Digital image processing is a recent subject in computer history. In 1960s; Bell Labs and University of Maryland, and a few other places started to develop several techniques for digital image processing. With application to satellite imagery, wire photo standards conversion, medical imaging, videophone, character recognition, and photo enhancement. But the cost of processing was fairly high with the computing equipment of that era. In the 1970s, image processing proliferated, when cheaper computers and dedicated hardware became available. Images could then be processed in real time, for some dedicated problems such as television standards conversion. As general-purpose computers became faster, they started to take over the role of dedicated hardware for all but the most specialized and compute-intensive operations.

In digital image processing, we use computer algorithms to perform image processing. Actually digital image processing has several advantages over the analog image processing; first it gives a high number of algorithms to be used with the input data, second we can avoid some processing problems such as creating noise and signal distortion during signal processing. In 2000s, fast computers became available for signal processing and digital image processing has become the popular form of image processing. Because of that, signal image processing became versatile method, and also cheapest.

Image segmentation is important part in many signal processing technique and its applications. The segmentation procedure is to find the better positions of the shape points according to the

appearance information. Algorithms based on classifiers have been widely applied to segment organs in medical images like cardiac and brain images. The goal of image segmentation process is partitioning the image into regions. Image segmentation applications identifying objects in a scene for object-based measurements such as size and shape, identifying objects in a moving scene for object-based video compression, identifying objects which are at different distances from a sensor using depth measurements from a laser range finder enabling path planning for mobile robots. The purpose of image segmentation is to cluster pixels of an image into image regions. We can use segmentation for image compression, object recognition, and image editing processing.

2. RELATED WORK

The problems of digital image segmentation represent great challenges for computer vision. The wide range of the problems of computer vision may make good use of image segmentation. Many researchers had created several methods to deal with the problem of image segmentation. Zimmer et al. [10] created a method to detect the mobility of live cells using the active contour (snakes) method. Mukherjee et al. [30] modified a method to handle the tracking problem using threshold method. Coskun et al. [4] used the inverse modelling to detect the mobility of living cells. Recently there have been a number of researchers has tried to create several image segmentation algorithms as in (Krinidis et al., Mélange, et al., Mignotte et al.).

In this paper we managed to review and summarized the major techniques for digital image segmentation. We categorized these techniques based on the segmentation method which the technique is using. In Table 2.1 a comparison of the image segmentation methods.

3. DIGITAL IMAGE SEGMENTATION METHODS

In the following subsection, we will review the methods applied to segment images. The segmentation of an image *I*, which represent a set of pixels is partitioning into *n* disjoint sets $R_{1,R_{2,...,R_{n}}}$, called segments or regions such that their union of all regions equals *I*, $I = R_{1} U R_{2} U U R_{n}$.

3.1 Inversion technique

The principle of the inversion is to continuously update the muscle activity to produce a face movement following a given face trajectory (*Smith et al., 1986; Terzopoulos et al., 1991; Press et al., 1992; Waters et al., 1996).* When the inversion had been carried out for all frames, the inverted activity was used to generate an animation. A conventional nonlinear optimizer minimizing a cost function was selected to implement the inversion. The cost function E was the sum of the squares of the Euclidean distances between the markers and the corresponding face model nodes:

$$E = \sum_{i=1}^{N} | m_i - n_i |^2$$
 (1)

where *mi* and *ni* are the 3-D positions of the *i*th marker and face model node, respectively, *N* is the number of nodes used in the inversion, and $||^2$ is the vectorial magnitude square operator, i.e., the sum of the squares of each coordinate of the vector.

The inversion could produce different activity patterns, depending on the initial conditions. Constraints may be added to the inversion to limit the number of solutions. In all analyses, the

inversion was carried out without constraints; then with the constraint that the inverted filtered EMG values had to be positive. The new positive constraint cost function E' was redefined in the second case by:

$$E' = \sum_{i=1}^{N} |m_i - n_i|^2$$
, if all filtered EMG ≥ 0 (2)

$$E' = 10^6 (1 + \sum EMG0 \), \text{ if at least one filtered EMG} \ge 0$$
 (3)

Where m_i and n_i are the 3-D positions of the i^{th} marker and face model node, respectively, N is the number of nodes used in the inversion, and EMG0 is the set of negative muscle activity levels. The constraint that all filtered EMG had to be greater than zero will be called the positive constraint. The advantage of the method is the high quality of the animation and also the data is very good, but the different EMG patterns can produce the same kinematic output which affects the accuracy.

3.2. Pattern Recognition Techniques

Pattern Recognition Techniques is a non-linear modelling tools and we can be used to model the inputs and outputs relationships (*fukunaga et al., 1990; Awwal et al., 1992; Portegys et al., 1995; Coskun et al., 2007; Baum et al., 1998*). Weights in the classifier are selected through optimizing energy functional defined by the features of structures and are updated through processing each sample in the training set.

The extracted information from the training set provides important cues of the structures such as intensity, position and shape, which can be valuable complementary information for the segmentation of test images. Active appearance models (AAM) are statistical models of the shape of structures. Training samples are used to extract the mean shape, mean appearance and define ranges of shape parameters. Restrictions on shape parameters guarantee the similarity between the segmentation result and the training samples. The segmentation procedure is to find the better positions of the shape points according to the appearance information. Algorithms based on classifiers have been widely applied to segment organs in medical images like cardiac and brain images. If properly modelled, supervised classification algorithms can greatly enhance the segmentation accuracy. However, supervised classification algorithms are sensitive to the initial conditions. To guarantee the correctness of the results, the training set must contain enough samples and the samples should be representative and segmented accurately.

3.3. Active contour models

Active contour models (snakes) goal is to apply segmentation process to an image by doing deformation to the initial contour towards the boundary of the object of interest. We do that by deforming an initial contour to minimizing the energy function which defined on contours (*Kass et al. 1987; Ray et al., 2002; Zimmer et al., 2002; Kruse et al., 1996; Sacan et al., 2008)*. There are two components in this energy: the potential energy, which is small when the contour is aligned to edges of the image, and the internal deformation energy, which is small when the contour is smooth. Both components are contour integrals with respect to a parameter of the contour.

An Active contour can be parametrically represented by v(s) = (x(s), y(s)) and its energy functional can be written as:

$$E = \int_{0}^{l} E_{int}(v(s)) ds + O \int_{0}^{l} E_{image}(v(s)) ds + \int_{0}^{l} E_{ext}(v(s)) ds$$
(4)

Where E_{int} represents the spline internal energy and E_{image} represent the image forces and E_{ext} represent to the external forces. The spline energy controlled by a(s) and by B(s). Therefore, the internal spline energy can be written as:

$$E_{\rm int} = \frac{(a(s)|v_s(s)|^2 + B(s)|v_{ss}(s)|^2)}{2}$$
(5)

The total image energy can be represented as a combination of three weighted energy functions and can be written as:

$$E_{image} = w_{line}E_{line} + w_{edge}E_{edge} + w_{term}E_{term}$$
(6)

Active contour models (Snakes) can be represented by two models: region based models and edge-based models. The characteristics of the image determine the model we should choose. The main advantage of snakes models is the ability of snakes to give a linear description of the object shape during the time of convergence without adding extra processing. But what scientifically limits the use of snakes is the need of the method to have strong image gradients to be able to drive the contour.

3.4. Threshold Method

Thresholds in these algorithms can be selected manually according to a priori knowledge or automatically through image information. Algorithms can be further divided to edge-based ones, region-based ones and hybrid ones (*Canny, 1986; Gonzalez et al., 2002; Mukherjee et al., 2004; Sezgin et al., 2004)*. Thresholds in the edge-based algorithms are related with the edge information. Structures are depicted by edge points. Common edge detection algorithms such as Canny edge detector and Laplacian edge detector can be classified to this type. Algorithms try to find edge pixels while eliminate the noise influence. For example, Canny edge detector uses the threshold of gradient magnitude to find the potential edge pixels and suppresses them through the procedures of the non maximal suppression and hysterics shareholding. As the operations of algorithms are based on pixels, the detected edges are consisted of discrete pixels and therefore may be incomplete or discontinuous. Hence, it is necessary to apply post-processing like morphological operation to connect the breaks or eliminate the holes. The method has the ability to segment 3D image with good accuracy, but the disadvantage of this method is the difficulty of the method to process the images of textured blob objects.

3.5. Topological Alignments Method

Topological Alignments Method depends on formalize the problem of aligning two consecutive frames as a generalized assignment problem (*Miura et al., 2005; Danuser et al., 2005; Zimmer et al., 2006; Ersoy et al., 2007*). The algorithm links the segmentation of two frames from the video sequence. The process starts from the output of the segmentation procedure, the algorithm work by finding the maximum weighted solutions to a generalized matching between two segments, and derive weights from relative sets of segments.

In this method we identify the segmentation of the first image into *m* segments with an index set $P = \{1, ..., m\}$, and the second image segmentation into *n* segments with an index set $Q = \{1, ..., n\}$. Then, alignments between these sets can be introduced through partitioning *P* and *Q* into an equal number of subsets.

Assuming that cells move moderately between two consecutive frames, we assign the relative overlap of p and q as their weight, formally defined as

 $w(p,q) := |A(p) \cup A(q)| / |A(p) \cup A(q)|$ (7)

In general, we consider the sets of segments which have overlap close to 1 as one cell, but the sets of segments which have overlap close to 0 not to be considered as one cell. Based on these weights, we can consider the notions of the topological alignments. We denote PL(M) for the

set of all L-partitioning's of a finite set M; note that given a partition $S \in PL(M)$, we consider S as a family of sets and hence can identify the L subsets by writing S = (S1,..., SL). This allows us to state our alignment as finding those partitioning's S and T that realize the maximum in the target function.

The topological alignments method improves the performance of segmentation of cell tracking by explicitly taking into account the inherent problems of over (one cell is split into two segments) and under (one segment fully covers two cells) segmentation, while still allowing the detection of cell division. The algorithm links segments between every frame and the next one, that will reduce the number of false trajectories and false detections. The method can deal with low contrast images and shape cells and improves the filtration efficiency. The advantage of the method is the ability of topological alignments to mitigate the image noise and cell deformation.

3.6. Watersheds Method

Watershed image segmentation is based on the theory of Mathematical Morphology (*Beucher et al., 1979; Najman and Schmitt, 1996; Meyer et al., 1996; Lezoray et al., 2003; Huguet et al., 2004*). Numerous techniques have been proposed to compute watersheds. The classical idea for building the watershed is using a geographical analogy, begin by piercing the regional minima of the surface. Then slowly immerse the image into a lake. The water progressively floods the basins corresponding to the various minima. To prevent the merging of two different waters originating from two different minima, we erect a dam between both lines. Once the surface is totally immersed, the set of the dams thus built is the watershed of the image. In one dimension, the location of the watershed is straightforward: it corresponds to the regional maxima of the function. In two dimensions, one can say in an informal way that the watershed is the set of crest lines of the image, emanating from the saddle points.

The method stick this initial contour to the maximum contained watershed contour. For label image G = [R, E], we assume each edge *eij* $\in E$ is a directing curve with the direction the same as clockwise direction of region *ri*'s contour.

Watershed contour discriminate to initial contour. A watershed contour is also a closed contour, but it is exactly along the watershed edges, i.e., it is composed of watersheds. When we input an initial manually delineated contour, we need to push (or expend) it to the nearby watershed edge to facilitate the later calculation. The method helps to improve the capture range but it has disadvantage of over segmentation.

Method	Advantage	Disadvantage
Inverse dynamics method	 Data are very good. Animation is of high quality. Using a nonlinear optimizer. 	 Many different EMG patterns can produce the same kinematic output
Active contour method	 Use active contour models Preserves global line shapes efficiently 	 Should find strong image gradients to drive the contour. Lacking accuracy with weak image boundaries and image noise
Watersheds Method	 Based on Mathematical Morphology Helps to improve the capture range 	Over segmentation
Novel edge-based method	 Algorithm based on an energy minimization procedure. 	 depends on the assumption that the deformation and movement of the tracked object is small between the frames.
Topological alignments method	 Improve the filtration efficiency. Using linkage clustering. 	• Complicated.
Pattern Recognition method	 Pattern recognition fields used to perform the segmentation. The method used to model relationships between inputs and outputs. 	 Restrictions on shape parameters. Complicated
Threshold method	 Try to find edge pixels while eliminate the noise influence. Use gradient magnitude to find the potential edge pixels. 	 The detected edges are consisted of discrete pixels and may be incomplete or discontinuous. Computationally expensive

International Journal of Computer Science & Information Technology (IJCSIT) Vol 3, No 5, Oct 2011 Table 2.1 Comparison of the Image Segmentation Methods.

4. CONCLUSIONS

From the previous review, we classify the current methods and summarize their features. Also each method has its suitable application fields, and researchers should combine the application background and practical requirements to design proper algorithms. Accuracy, complexity, efficiency and interactivity of a segmentation method should all be the considered factors.

This paper makes a review on the current segmentation methods, and the main tendency of each method with their principle ideas, application field, advantages and disadvantages are discussed.

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