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Segmentation of Multi Food Images Using Integrated Active Contour and K-means

[1]Hamirul Binti Hambali, [1,2]Salwa Khalid Abdulateef, [1]Massudi Mahmuddin,
[1]Nor Hazlyna Harun, [1]Fadzilah Siraj and [1]Hazaruddin Harun
[1]School of Computing, College of Art and Sciences, Universiti Utara Malaysia, Changlun, Malaysia
[2]College of Computer and Mathematics Sciences, Tikrit University, Tikrit, Iraq

Abstract: Image segmentation of food items is the most important stage in developing automated calorie estimation system. This stage refers to a process that classifies images into distinct regions with the aim to extract only the food image from the background. Currently, there are several segmentation methods which have been used in object identification. Active contour is one of the highly reputable method for image segmentation. However, this method suffers from few limitations in real world applications. Therefore, the goal of this study is to present a hybrid segmentation of multiple food items based on integrating active contour with K-means. After a theoretical reviewed of active contour, K-means is presented. Next, the segmentation process is presented starting from building the dataset, automating the contour initialization, conducting the homogenous test to determine the number of items in the region. The results show that, active contour has performed well for segmenting multiple food items when they were separated. However, it suffers from low capability in segmenting connected food items due to the similarity in visual metrics. Incorporating K-means with homogeneity test has shown good performance for segmentation of connected food items.

Key words: Image segmentation, active contour, K-means, level, region, initialization

INTRODUCTION

Image segmentation is one of the most important processes in a computer vision system which is used to extract meaningful information from images. It is useful for variety of applications such as industrial sensing, automotive field and robotics (Chack and Sharma, 2015). For this research, image segmentation is required for analyzing the interest food objects with the aim to calculate food calories in vision-based dietary assessment. Most of the computer vision and image analysis problems require segmentation process in order to detect objects automatically. This process divides a digital image into separate regions with the aim to define surface contour of each object in the image based on specific criterion, such as colour, motion, texture (Khan, 2014). Currently, there are several segmentation techiques which have been used in object identification. However, the segmentation process is more challenging for images which consist of several objects and categories.

This is due to similarity of region criteria that can be represented by several characteristics such as colour, shape and size. The similarity of the regions influences the appearance of the image and thus, misleads the object analysis. Furthermore, the segmentation process is more difficult for separating images with overlapped objects and variability in the illumination conditions (Thakur and Madaan, 2014). Active contour models have been broadly implemented in image segmentation (Derraz and Beladgham, 2004; Yazdanpanah *et al*., 2011). It has been used extensively in several applications in the past few decades including image segmentation and motion tracking. active contour is an energy-based segmentation method which aims to deform an initial curve to the boundary of object subject. This method has been used extensively for segmenting images due to many reasons (Liu *et al*., 2015). It is effective in finding the boundaries of the object even with large shape variety. In addition, it can generate closed parametric curve or surfaces from images directly and their incorporation of a smoothness constraint. However, active contour method suffers from high sensitivity to noise and initial contour where it depends on the choice of the initial points of the contour. This condition has caused some limitations of active contour in some types of applications. One of the limitations is its failure in segmenting connected objects. This is due to being trapped in local minima because the function used is restricted to neighborhood around the zero level set which makes the level set growth act locally.

Food item segmentation is an important application of segmentation. It is useful for food quantization, calories

Correponding Author: Hamirul Binti Hambali, School of Computing, College of Art and Sciences, Universiti Utara Malaysia, Changlun, Malaysia

estimation and as sensing data for assembly lines and food manufacturing. However, food segmentation is one of the challenging research in computer vision. This is because food comes with different shapes, colors and positions. In addition, most of the food images consist of several connected objects in one area or plate. At present, most existing methods have limitations in segmenting food images with several objects and cateogires. Therefore, the aim of this study is to incorporate K-means with active contour method for overcoming the problem of non-separtation of connected food items.

Literature review: Image segmentation process is very important in food research where it is required to isolate the area of interest or food item from the background. Several segmentation methods have been developed to segment and detect food automatically. Image segmentation can be accomplished by different techniques. The concept of energy minimization which based on snakes and splines guided by external and internal image forces was introduced firstly by Kass *et al*. (1988). In this study, the intensity and texture features were used for controlling the snakes to achieve a convergence toward object borders. Sun and Du (2004) proposed a Stick Growing and Merging (SGM) approach with Sobel filter constraints to segment complex food images such as pizza, apple and tomato. Manual smartphone based region-growing method was implemented by Morikawa *et al*. (2012). The method was proposed to segment meal images for personal dietary monitoring. However, these types of methods suffer from difficulty in identifying food regions accurately.

Zhu *et al*. (2010) have applied an active contour model for food segmentation by regional variance minimization of RGB color components. He *et al*. (2013) have used snakes or active contours for food images segmentation. The basic idea is to optimize an energy function for a selected area in the image by the contour. The global minimum of the energy function was reached when the contour is aligned with the edges of the food items. They improved the basic method by starting from equally distributed circles as initial contours. However, this approach was limited to evenly colored food items. In other words, the energy function will not reach its minimum value at the borders of the food item when there are internal edges in the item surface.

In a study conducted by He *et al*. (2012) local variation method has been used for image segmentation. This approach was an iterated food segmentation method where it used feedback based on the classifier confidence score in order to prevent under or over segmentation. However, this algorithm was exposed to two states of false segmentation: under-segmentation or over-segmentation. One of the possible solutions for this problem was to provide the number of segments initially to the algorithm before enabling it. Pouladzadeh *et al*. (2013) have used another approach for image segmentation phase. Their approach computed the mean of a set of clusters until it converges to a stable set of cluster samples iteratively by k-mean cluster. This study focused on creating regions of the same color depending on measure of the distance between color pixels. However, this method has several limitations. Firstly, it is sensitive to noise. Secondly, it is only applicable for segmenting simple food items and limited number of clusters. Thirdly, different initial centroids produce different results and computationally become more complex thus, increase the computational time.

From the above discussions, numerous segmentation algorithms have been used by researchers in segmenting food images. Nevertheless, each of the proposed algorithms has limited capability in producing good segmented images even in the same domain application. Furthermore, most segmentation algorithms aim to resolve the challenge of high similarity between the foreground and background of the objects in the image. This is a major challenge to the state of the art methods such as active contour. Other challenge is the lack of homogeneity in the object which leads to local minima and a failure in segmenting the whole object. In order to improve the segmented image of food objects, this research propose a method which combines active contour and K-means algorithms.

Segmentation methods: In this study, only two methods have been used which are active contour without edges and K-means methods. The description of both methods are presented in the following sub sections.

Active contour without edges concept: Active contour model was proposed by Chan and Vese (2001). It is based on the techniques of curve evolution, Mumford and Shah (1989) functional for segmentation and level sets. It was proposed to detect objects whose boundaries are not necessarily defined by gradient. This model focuses on minimizing energy to obtain the final result. The main objective of this method is to detect objects even in the absence of a strong gradient. In the traditional methods, the models rely on the edge-function which depends on the image gradient to stop the curve evolution. But the main drawback of this method is that it can only detect objects with edges defined by gradients and in practice, the discrete gradients are bounded and the stopping function is never zero near the edge which might lead to the leaking of the curve through the boundaries.

In the case of noisy images, isotropic smoothing Gaussian has to be strong which in turn will smoothen the edges. This might lead to detection of wrong edges, when the stopping function depends only on the gradient. In order to overcome this problem, this model uses the stopping term based on Mumford-Shah segmentation technique. Further the model uses the level set formulation. For the description of this model, let us consider an evolving curve C in Ω as the boundary of an open set ω of Ω ($\omega \subset \Omega$ and $C = \delta\omega$). For simplicity let us consider a image U_0 consisting of two regions of approximately piecewise-constant intensities of distinct values U_0^1 and U_0^o. The region to be detected is represented by the region with intensity U_0^1 and its boundary is denoted by C_0. The energy term that is used in this method is formulated as:

$$F1(C)+F2(C) = \int_{inside(c)} |U_0(x,y)-C_1|^2 dxdy + \int_{outside(c)} |U_0(x,y)-C_2|^2 \quad (1)$$

Where:

C = The Curve and the constants
C_1 and C_2 = The intensity averages
U_0 = (Image) inside C and outside C, respectively

This method views the segmentation problem as the energy minimization of the above function. It is obvious for this simple case that C_0 the object boundary minimizes the above function.

K-means clustering: K-means proposed by James MacQueen in 1967. The K-means clustering algorithm is a partition-based clustering. According to the algorithm, firstly select k objects as initial cluster centers, then calculate the distance between each cluster center and each object and assign it to the nearest cluster, update the averages of all clusters, repeat this process until the criterion function converged. The square error measure of clustering was (Vora and Oza, 2013).

$$SE = \sum_{i=1}^{k} \sum_{j=1}^{ni} \|a_{ij}-b_i\| \quad (2)$$

Where:

A_{ij} = The data point j of i-class
b_i = The meanof i-class
n_i = The number of points in i-class

The K-means algorithm is presented as follows:

Input:
N Objects to be cluster $\{a_1, a_2, ..., a_n\}$,
k Number of clusters

Output:
k clusters and the sum of dissimilarity between each object and its nearest cluster center is the smallest.

Process:

- Randomly select objects as initial cluster centers $b_1, b_2, ..., b_k$
- Calculate the distance between each object and each cluster center and then assign each object to the nearest cluster, distance calculating as:

$$dis(a_i, b_i) = \sqrt{\sum_{j=1}^{dis} (a_{i1}, b_{j1})} \quad (3)$$

d is the distance between data i and cluster a_i. Calculate the mean of objects in each cluster as the new cluster centers:

$$b_i = \frac{1}{N_i} \sum_{j=1}^{ni} a_{ij} \quad (4)$$

Where:

I = 1, 2, ..., k
N_i = The number of samples of current cluster i

MATERIALS AND METHODS

In the following sub sections, the segmentation process is presented. The construction of dataset is explained in Eq. 1. The initialization of the active contour mask is described in Eq. 2. The steps of the proposed method are shown in Fig. 1. Next, homogeneity test is presented in Eq. 3.

Data set construction: The data set construction is the first step which requires image capturing device to capture the images. In this study, all the food images were captured using a smartphone camera with a resolution of 8-mega pixel. The captured images were stored in the native RGB (Red, Green and Blue) colour format. RGB is chosen because this color format carries all the needed color and dimensional information for food recognition and estimation (Cheng *et al.*, 2001; Martin *et al.*, 2012). The angle for acquiring the image was 45° with respect to the food table in order to maintain capturing both vertical and horizontal information (Chae *et al.*, 2011). The food was arranged in a white plain round plate because white color is easy for segmentation (Zhu *et al.*, 2010; Anthimopoulos *et al.*, 2013). In this study, 50 images were captured where the plate in the images contains different multi-item food with no more than four items.

Initialization of active contour mask: In order to fully automate the segmentation process, there should be an automated mask initialization approach. Firstly, it has been assumed that the food items colors are different from the background color. The best mask is the mask with multiple holes where each hole is above a food item. In order to find this mask, image labeling has been used. Next, the image has been converted into a binary image by using an appropriate threshold. Then each region in the image has been given a distinct label. After determining the regions in the image, it is important to know the number of objects in the image.

Homogeneity test: The food thas was considered in this study is a combination of multiple connected items. Typically, active contour is not capable in separating connected objects when the color intensity is not different. Every segmented object of the result of the active contour is called a region. Homogeneity test is applied to check whether or not the region consist of multiple items. This test was based on the assumption that one food item is homogenous. In order to perform the homogeneity test, random points of the region were generated. The points were considered to be a testing cluster. The mean of the cluster, u and its standard deviation, d were calculated using Eq. 5 and 6, respectively:

$$u_i = \frac{1}{N_i}\sum_{j=1}^{N} f_{ij} \quad (5)$$

$$d = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(f_{ij}-u_i)^2} \quad (6)$$

Where:

F_{ij} = The value of the ith color component of the image pixel j

N = The number of pixels in the image

The value of the standard deviation was compared with pre-determined threshold. In the case of lower value, the region was considered to be homogenous and it consists of one food item. Otherwise, the region was considered to be non-homogenous and it consists of more than one food item.

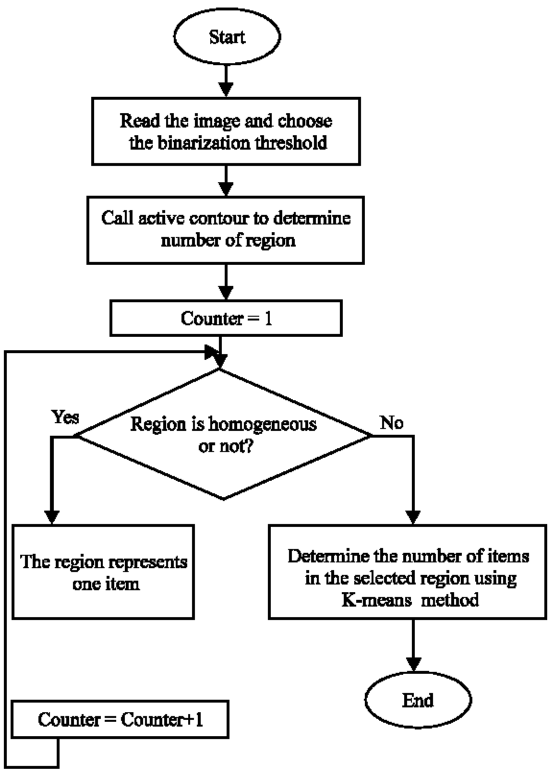


Fig. 1: Flow chart of integrated active contour and K-means algorithm

RESULTS AND DISCUSSION

In this study, two main scenarios have been considered in order to evaluate the active contour method for multiple food items segmentation. In the first scenario, five food images were used where all the food items were arranged separately. In the second scenario, another set of five images were used where some of the food items are connected and others are separated. Table 2 shows the results of the first scenario while Table 3 shows the results of the second scenario. All the experiments are conducted using MATLAB R2015a.

In Table 1, five images of various food with different shapes and colors are displayed. The positioning of the food items are different from one image to another. In these images, all the food items are separated.

In this experiment, a separated mask has been generated for each object in the image and one region indicated one food item. Based on the number of regions, it shows that the active contour method was able to identify the correct number of regions. For example, image 1 has two items and the result of number of regions has correctly produced two regions. For image 5, the original image has four items and the result also shows four regions. However, Table 1 shows that, the segmentation process using active contour method was not successful for the connected items. This is because the number of regions was wrongly identified. For example, image 2 consists of three conneted items but active contour was unable to separate the items. Thus, the number of regions are incorrectly identified as one item. The similar results were obtained for other images in Table 2. Therefore, the integrated active contour with K-means approach has been used to separate the multiple food items. The results of this method are shown in

Table 1: Segmentation of separated multiple food items

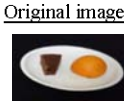
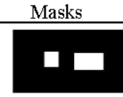
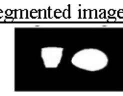
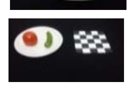
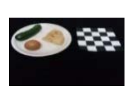
Original images	Masks	Segmented images	No. of regions
			2
			2
			3
			3
			4

Table 2: Segmentation of connected multiple food items

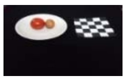
Original images	Masks	Segmented images	No. of regions
			2
			1
			1
			1
			1

Table 3: Segmentation of connected food using integrated active contour and K-means algorithm

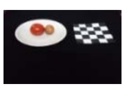
Original images	Segmented image using proposed methods	No. of items
		3
		3
		2
		2
		2

Table 3. As presented in Table 3, the proposed method has shown good performance in separating multiple connected food items. This method was able to produce a correct number of items according to the number of objects. The process was done by firstly measuring the homogenous of the region using the mean value of the cluster and standard deviation. Next, the comparison between the value of standard deviation and threshold was made. If the standard deviation value was bigger than the threshold, it indicated that the region is not homogenous and contained more than one item. Then, the K-means method was applied to determine the number of items. By using K-means, the number of items in each image were correctly indentified.

CONCLUSION

Image segmentation for connected food items is not an easy task in computer vision application. In order to solve the difficulty in segmenting such images, active contour method has been integrated with K-means algorithm. The results of the proposed method are encouraging where this method was able to determine the number of items correctly and accurately.

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REFERENCES

Anthimopoulos, M., J. Dehais, P. Diem and S. Mougiakakou, 2013. Segmentation and recognition of multi-food meal images for carbohydrate counting. Proceedings of the 2013 IEEE 13th International Conference on Bioinformatics and Bioengineering (BIBE), November 10-13, 2013, IEEE, New York, USA., ISBN:978-1-4799-3164-4, pp: 1-4.

Chack, S. and P. Sharma, 2015. An improved region based active contour model for medical image segmentation. Intl. J. Signal Process. Image Process. Pattern Recognit., 8: 115-124.

Chae, J., I. Woo, S. Kim, R. Maciejewski and F. Zhu *et al.*, 2011. Volume estimation using food specific shape templates in mobile image-based dietary assessment. Proceedings of the Computational Imaging IX, IS&T/SPIE Conference, Vol. 7378, January 23, 2011, International Society for Optics and Photonics.

Chan, T.F. and L.A. Vese, 2001. Active contours without edges. IEEE Trans. Image Process., 10: 266-277.

Cheng, H.D., X.H. Jiang, Y. Sun and J. Wang, 2001. Color image segmentation: Advances and prospects. Pattern Recognition, 34: 2259-2281.

Derraz, F. and M. Beladgham, 2004. Application of active contour models in medical image segmentation. Proceedings of the IEEE International Conference on Information Technology: Coding and Computing ITCC, April 5-7, 2004, IEEE, Las Vegas, Nevada, ISBN:0-7695-2108-8, pp: 675-681.

He, Y., C. Xu, N. Khanna, C.J. Boushey and E.J. Delp, 2013. Food image analysis: Segmentation, identification and weight estimation. Proceeding of the IEEE International Conference on Multimedia and Expo ICME, July 15-19, 2013, IEEE, San Jose, CA., ISBN:978-1-4799-0014-5, pp: 1-6.

He, Y., N. Khanna, C.J. Boushey and E.J. Delp, 2012. Snakes assisted food image segmentation. Proceedings of the 14th IEEE International Workshop on Multimedia Signal Processing MMSP, September 17-19, 2012, IEEE, Banff, Alberta, ISBN: 978-1-4673-4570-5, pp: 181-185.

Kass, M., A. Witkin and D. Terzopoulos, 1988. Snakes: Active contour models. Int. J. Comput. Vision, 1: 321-331.

Khan, M.W., 2014. A survey: Image segmentation techniques. Intl. J. Future Comput. Commun., 3: 89-93.

Liu, Z., J. Wang and Y. Zhu, 2015. A study of active contour segmentation models based on automatic initial contour. Intl. J. Signal Process. Image Process. Pattern Recognit., 8: 201-214.

Martin, C.K., S. Kaya and B.K. Gunturk, 2012. Quantification of food intake using food image analysis. Proceedings of the IEEE Annual International Conference of the Engineering in Medicine and Biology Societys EMBC, September 3-6, 2009, IEEE, Minneapolis, Minnesota, ISBN:978-1-4244-3296-7, pp: 6869-6872.

Morikawa, C., H. Sugiyama and K. Aizawa, 2012. Food region segmentation in meal images using touch points. Proceedings of the ACM Workshop on Multimedia for Cooking and Eating Activities, November 02-02, 2012, ACM, Nara, Japan, ISBN:978-1-4503-1592-0, pp: 7-12.

Mumford, D. and J. Shah, 1989. Optimal approximations by piecewise smooth functions and associated variational problems. Commun. Pure Applied Math., 42: 577-685.

Pouladzadeh, P., S. Shirmohammadi and T. Arici, 2013. Intelligent SVM based food intake measurement system. Proceedings of the 2013 IEEE International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA), July 15-17, 2013, IEEE, New York, USA., ISBN:978-1-4673-4702-0, pp: 87-92.

Sun, D.W. and C.J. Du, 2004. Segmentation of complex food images by stick growing and merging algorithm. J. Food Eng., 61: 17-26.

Thakur, P. and N. Madaan, 2014. A survey of image segmentation techniques. Intl. J. Res. Comput. Appl. Rob., 2: 158-165.

Vora, P. and B. Oza, 2013. A survey on k-mean clustering and particle swarm optimization. Int. J. Sci. Mod. Eng., 1: 24-26.

Yazdanpanah, A., G. Hamarneh, B.R. Smith and M.V. Sarunic, 2011. Segmentation of intra-retinal layers from optical coherence tomography images using an active contour approach. IEEE. Trans. Med. Imaging, 30: 484-496.

Zhu, F., M. Bosch, I. Woo, S.Y. Kim, C.J. Boushey, D.S. Ebert and E.J. Delp, 2010. The use of mobile devices in aiding dietary assessment and evaluation. J. Selected Top. Signal Process., 4: 756-766.