A Recursive Segmentation and Classification Scheme for Improving Segmentation Accuracy and Detection Rate in Real-time Machine Vision Applications

Yuhua Ding, George J. Vachtsevanos, Anthony J. Yezzi Jr., Yingchuan Zhang and Yorai Wardi

School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA 30332, USA
{gte788q, gte386w}@prism.gatech.edu, {ayezzi, george.vachtsevanos}@ece.gatech.edu

ABSTRACT

Segmentation accuracy is shown to be a critical factor in detection rate improvement. With accurate segmentation, results are easier to interpret, and classification performance is better. Therefore, it is required to have a performance measure for segmentation evaluation. However, a number of restrictions limit using existing segmentation performance measures. In this paper a recursive segmentation and classification scheme is proposed to improve segmentation accuracy and classification performance in real-time machine vision applications. In this scheme, the confidence level of classification results is used as a new performance measure to evaluate the accuracy of segmentation algorithm. Segmentation is repeated until a classification with desired confidence level is achieved. This scheme can be implemented automatically. Experimental results show that it is efficient to improve segmentation accuracy and the overall detection performance, especially for real-time machine vision applications, where the scene is complicated and a single segmentation algorithm cannot produce satisfactory results.

1. INTRODUCTION

Segmentation is a low-level description on which image understanding is based. It supports high level concepts such as shape and adjacency. Accurately segmented images are easier to interpret, and the performance of classification is better. However, despite the huge literature that addresses image segmentation, objective performance assessment of an algorithm remains an open topic. It has been a painful task for machine vision application developers to choose suitable segmentation algorithms with desired accuracy. For real-time machine vision applications, where time constraint is stringent and various uncertainties need to be accommodated, we need a general methodology for performance evaluation of the segmentation results so that the results can be interpreted easily.

It is normally required that the segments must be homogeneous and statistically distinct from their neighbors. Homogeneity measures have been used widely for performance assessment of segmentation algorithms [2]. Unfortunately, in machine vision applications, the scene is often complicated. Depending on the lighting conditions and the possibility of occlusion, the image does not always meet the homogeneity requirements. When the segmentation fails, either segments lie across true edges in the scene (under-segmentation) or true homogeneous areas in the scene have been split into several segments (over-segmentation). As a consequence, the extracted features lie in either the wrong clusters or the overlapping areas in the feature space. The former case results in classification error, while the latter causes classification ambiguity.

In this paper, a recursive segmentation and classification scheme is proposed. The confidence level of classification results is utilized to evaluate the accuracy of segmentation algorithms. When classifier finds it hard to decide the identity of the object, the segmentation is repeated until a decision with high confidence is made. This mechanism is effective to improve segmentation accuracy and classification performance, especially for real-time applications, where human feedback is not available.

In the following sections, first the relationship between confidence level and segmentation accuracy is constructed. Then, the recursive scheme of segmentation and classification is described. A brief guideline is given afterwards to choose the segmentation algorithm and classifier in each iteration. Finally, the scheme is applied to automated real-time fan bone detection in deboned poultry meat, and the results show that the scheme is efficient in improving the segmentation accuracy and the overall classification performance.

2. SEGMENTATION ACCURACY AND CONFIDENCE LEVEL OF CLASSIFICATION

The accuracy of a segmentation routine plays an important role in image understanding. It affects its following steps of feature selection and classifier performance. For accurately segmented images, the overlapping between features of different classes tends to be small, and therefore, training of classifier is easy and the classification results are more accurate.

0-7803-7503-3/02/$17.00 ©2002 IEEE

2.1 Test bed – automated inspection of fan bones in deboned poultry meat

The on-going project of automated inspection of fan bones in deboned poultry meat serves as a test bed for the methodology proposed in this paper. The objective of this project is to detect the deboned chicken meat that contains fan bones (fan-shaped surface bones) using vision-based inspection. The chicken parts move on the conveyor belt at 60 ft/minute and the inspection is real-time and fully automated. The contrast between fan bone and meat is prominent after a carefully designed imaging scheme is adopted. However, there are other spots on the image that may appear similar in color and shading to bones. These include shadows and edge characteristics that must be distinguished from fan bones.

The algorithm shown in Figure 1 is developed and the region-based snake algorithm [4] is adopted for segmentation purpose. The snake algorithm uses region-based curve evolution equations to "pull apart" the mean intensity values between the interior of the contour and the background. A penalty term on the total arc length of the contour prevents the contour from wrapping around noise. After 50 iterations of evolution, the initial contour evolves to capture three types of darker regions (Figure 2 (a)): *fan bone*, *edge*, and *shadow*. *Fan bone* regions indicate the existence of fan bones (Figure 2 (b)); *edge* regions refer to the transition regions from meat to the background (Figure 2 (c)); and *shadow* regions include dark meat, topological variations on the meat surface, bruises, etc. (Figure 2 (d)). The *edge* and *shadow* regions result in additional regions apart from *fan bone* regions for further identification, and both classes are classified as *non-fan*.

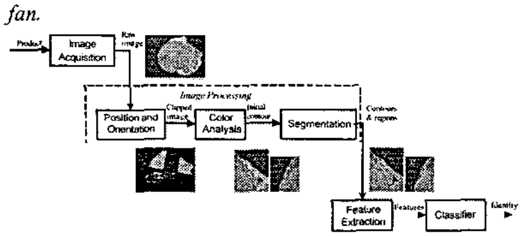


Figure 1. Vision-based inspection of fan bones.

The snake algorithm turns out to be efficient and accurate when the fan bone has good contrast with respect to its neighboring tissues. However, there are cases the algorithm fails. Figure 3 is a typical example of segmentation inaccuracy, where under-segmentation occurs around the fan bone region. The failure is caused by the penalty term on total arc length and the closeness of fan bone to the transition region. The under-segmentation totally changes the shape of the binary region and therefore, causes misclassification.

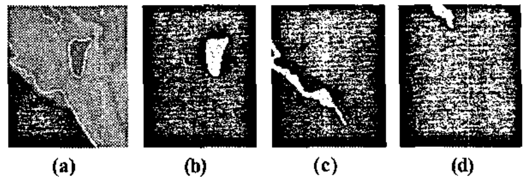


Figure 2. The result of the snake routine on a clip of chicken part image. (a) Final contour (b) A *fan bone* region (c) An *edge* region (d) A *shadow* region

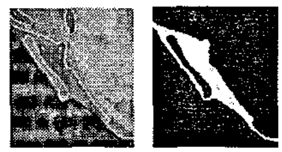


Figure 3. An unsuccessful example of the snake routine.

Various color and shape features have been tested to select the features with good distinguishibility and high robustness to color variations and segmentation error. The selected features include the distance from the region to the background, mean intensity differences of any two channels, histogram overlapping between red and blue channels, circularity factor, and aspect ratio.

A probabilistic neural network (PNN) classifier claims a region as class i if

$$P_i = \max_j P_j, \quad i, j = 1, \cdots, N$$

where N is the total number of classes, and P_i is the probability that a region belongs to class i.

Totally 834 regions (204 *fan bone*, 402 *edge*, 228 *shadow*) are generated by the snake algorithm from 280 chicken images. Features are extracted from each region. 100 samples from each class are selected arbitrarily to train the PNN classifier and the others are used for testing. The classification result is shown in Table 1. The overall accuracy achieved is 90.4%.

Table 1. The classification results.

fan bone regions		*non-fan* regions	
total	**correct**	**total**	**correct**
104	88	430	395
detection rate = 84.62%		false alarm rate = 8.14%	

2.2 Effect of segmentation accuracy on feature distribution and classification performance

To show the relationship between segmentation accuracy and classification performance, each *fan bone* region is assessed visually by the authors as *well-segmented* or *poorly-segmented* according to the closeness of the final contour to the true boundary of fan bone region. Of the 204 *fan bone* regions, 154 are segmented accurately, and the segmentation accuracy is 75.5%. Figure 4 plots the normalized histograms of one feature value: the distance from the mass center of a region to the background, for *edge* regions, *well-segmented fan bone* regions, and *poorly-segmented fan bone* regions, respectively. The *poorly-segmented fan bone* regions have more overlapping with the *edge* regions, which causes a very low detection rate of 40.9%, as shown in Table 2.

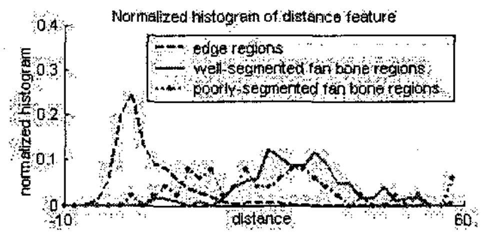


Figure 4. Normalized histogram of distance feature.

Table 2. The classification results of fan bone regions.

region type	*well-segmented*	*poorly-segmented*
total	82	22
detected	79	9
detection rate	96.34%	40.91%

To improve the overall classification accuracy, a more accurate segmentation scheme is needed. However, due to the complexity of the problem, it is hard to find a single segmentation routine that meets the accuracy requirement. An alternative scheme is to modify the segmentation result using another segmentation scheme, if the result is found to be inaccurate. One way of assessing the segmentation accuracy is to use the classification confidence.

2.3 Confidence level of classifier

For the PNN classifier, the confidence level that a region belongs to class i (L_i) is defined as

$$L_i = \min_j (P_i - P_j), i, j = 1, \cdots, N \cdot$$

In Figure 5, the distributions of the confidence level that a fan bone region belongs to class *fan bone* are plotted for well- and poorly-segmented fan regions. It is found that the well-segmented regions' onfidence level for *fan bone* are normally higher than those of poorly-segmented ones. So the confidence level can be utilized as a measurement of segmentation accuracy.

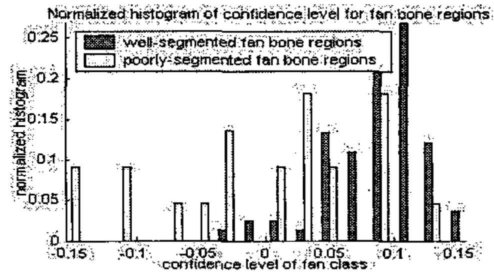


Figure 5. The normalized histogram of confidence level for *fan bone* regions.

3 RECURSIVE SEGMENTATION AND CLASSIFICATION

The recursive scheme of segmentation and classification is shown in Figure 6.

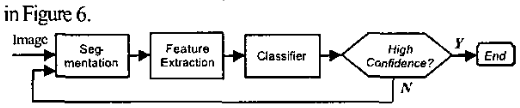


Figure 6. Recursive segmentation and classification.

Using the concept of confidence level, identity i is assigned to a region only when the confidence level L_i is higher than a positive threshold. Otherwise, the region is claimed as *not sure* or *unclassified*, and segmentation needs to be re-performed until a classification result with desired confidence level is achieved.

The concepts of *absolute accuracy* (a), *relative accuracy* (A), and *repetition ratio* (r) are defined for the classifier as follows. Assume of M regions, m_c regions are classified correctly, m_e are incorrect, and m_u are unclassified, then

$$a = m_c / M,$$

$$A = m_c / m_c + m_e,$$

$$r = m_u / M,$$

and the following relationship is established easily as

$$a = A(1 - r).$$

Note that A can be made close to 1 by eliminating as many as possible classification errors. However, this is normally achieved by decreasing m_c and increasing m_u, which results in low a and high r.

4 SELECTION OF SEGMENTATION ALGORITHM AND CLASSIFIER

In each iteration of segmentation and classification, the characteristics of the images (especially those with poor segmentation in previous iteration) are examined, and effective segmentation and classification schemes are chosen accordingly. The segmentation algorithm and classifier for each stage can be the same or different, depending on the problem requirements and algorithm performance.

The final accuracy and the total cost for segmentation and classification are estimated as follows. Assume in each iteration, the absolute accuracy a and repetition rate r are the same. Then after n rounds of segmentation and classification, the accuracy and total cost are

$$\text{total cost} = 1 + r + \cdots + r^{n-1} = \frac{1-r^n}{1-r}$$

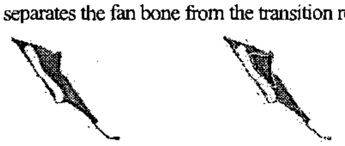
$$\text{accuracy} = a\frac{1-r^n}{1-r}.$$

Note that as n goes to infinite, the final accuracy approaches $a/(1\text{-}r)$=A, and the segmentation cost approaches $1/(1\text{-}r)$.

There is a trade off between the final accuracy and the total cost. The algorithms can be chosen to achieve high accuracy, but the repetition rate r will be high and the overload caused by additional segmentation and classification will increase accordingly. On the other hand, the relative accuracy A puts an upper bound on the final accuracy. Therefore, we need to choose the algorithms to achieve high accuracy while keeping the computation overload reasonable.

5 EXPERIMENTAL RESULTS

In this section, the recursive scheme is applied to the fan bone detection problem to improve the segmentation accuracy and classification performance. Two iterations of segmentation and classification are applied. Segmentation algorithms for both rounds are the same snake routine based on the curve evolution model but using different parameters and initial contour estimate. Figure 7 is the result of reapplying the snake algorithm to the under-segmented region in Figure 3. By taking the under-segmented clip as a bimodal image, the snake algorithm successfully separates the fan bone from the transition region.



(a) raw clip **(b) final contour**

Figure 7. The result of reapplying the snake algorithm to the under-segmented region in Figure 3.

The classifiers for both iterations are the PNN classifier, where the first one has a threshold of 0.05 for confidence levels.

Testing is performed on the same image sets as Section 2. The results after the first and the second stage are shown in Table 3. Compared with the results in Table 1, the detection rate is increased while the false alarm rate is decreased. The overall accuracy is increased from 90.4% to 92.88%.

The new classification results on *fan bone* regions are shown in Table 4. The detection rate for poorly-segmented fan bone regions is improved from 40.9% to 77.3% by using the recursive scheme.

Table 3. The classification results using the recursive scheme.

	***fan bone* regions**				***non-fan* regions**			
	total	**correct**	**incor-rect**	**unclas-sified**	**total**	**correct**	**incor-rect**	**unclas-sified**
1^{st} rnd	104	84	5	15	430	367	15	48
2^{nd} rnd	15	12	3	/	48	33	15	/
	detection rate =(84+12)/104 = 92.3%				**false alarm rate** =(15+15)/430 = 6.98%			

Table 4. The classification results for fan bone regions using the recursive scheme.

	well-segmented				***poorly-segmented***			
	total	**correct**	**incor-rect**	**unclas-sified**	**total**	**correct**	**incor-rect**	**unclas-sified**
1^{st} rnd	82	78	0	4	22	6	5	11
2^{nd} rnd	4	1	3	/	11	11	0	/
	detection rate = (78+1)/82 = 96.34%				**detection rate** = (6+11)/22 = 77.27%			

6 CONCLUSION

The recursive scheme of segmentation and classification is proposed to improve segmentation accuracy and classification performance in real-time machine vision applications. The experimental results on automated fan bone inspection show that the scheme is efficient.

7 REFERENCES

[1] M. Blumenstein and B. Verma, "Analysis of Segmentation Performance on the CEDAR Benchmark Database," 6th *Intl. Conf. Document Analysis and Recognition*, pp.1142–1146, 2001.

[2] R. Caves, S. Quegan, and R. White, "Quantitative Comparison of the Performance of SAR Segmentation Algorithms," IEEE Tran. Image Processing, vol.7, no.11, pp.1534-1546, Nov. 1998.

[3] O. Pichler, A. Teuner, and B. J. Hosticka, "A multichannel algorithm for image segmentation with iterative feedback," *Fifth*

Intl. Conf. Image Processing and its Applications, pp. 510 –513, 1995.

[4] A. Jr. Yezzi, A. Tsai, and A. Willsky, "Medical Image Segmentation via Coupled Curve Evolution Equations with Global Constraints," *Mathematical Methods in Biomedical Image Analysis, 2000. Proc. IEEE Workshop on Biomedical Image Analysis.* pp. 12-19.