Automatic X-ray Image Segmentation for Threat Detection

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Abstract

Multithresholding and data clustering techniques are used to segment X-ray images for low intensity threat detection in carry-on luggage. The widely used statistical validity indexes methods do not generate a reasonable estimation of the optimal number of clusters and produce a biased evaluation of the segmented images acquired by different segmentation methods. We propose a method based on the Radon transform to determine the optimal number of clusters and to evaluate the segmented images. The method utilizes both statistical and spatial information from the image and is computationally efficient. Experimental results show that the proposed method produces results consistent with human visual assessment.

1. Introduction

The detection of threat objects in X-ray images of carry-on luggage is of great importance to airports and airplane security. This paper considers the problem of detecting low intensity threats in raw X-ray images of carry-on luggage. A simple method to make the low intensity objects look more obvious is segmenting the image into several sub-images, each of which shows only a portion of the original image thus presenting less information and making the operator decisions hopefully easier and quicker. This is called scene decluttering and can be achieved by multithresholding [1, 2, 3] or data clustering [4, 5, 6] techniques. In general, the optimal number of thresholds or clusters for an image is not known in advance. To determine this parameter, a common approach is to segment the image with all feasible number of clusters and then use a validity measure to compare the segmentation results [7]. The main drawback of the validity indexes is that they only use the statistical information of the grayscale distribution, without considering the spatial information in the image. Thus, they generate biased evaluation results compared to human visual assessment.

This paper proposes a new method to determine the optimal number of clusters. The method determines the optimal number of clusters by comparing the spatial information changes between two consecutive segmented results. The Radon transform is used to measure the spatial information of the segmented image. The number of clusters increases until the spatial information of the segmented image stops increasing and the final number of clusters is chosen as the optimal number. The spatial information measure is also used to evaluate the segmented results obtained by different thresholding and clustering methods.

Drawbacks of the cluster validation methods to evaluate segmented images are analyzed in section 2. Our new method is proposed in section 3 and experimental results are presented in section 4. Conclusions are presented in section 5.

2. Image Segmentation and Evaluation

Thresholding is a simple but effective technique for image segmentation. A variety of thresholding methods have been developed [1, 2, 3]. The limitation of thresholding techniques is that they only apply to a single-band image, such as a grayscale image or a single band of a multi-band image. For most multithresholding methods, the appropriate number of thresholds should be estimated first.

Data clustering is another effective technique for image segmentation [4, 5, 6]. The advantage of the data clustering technique is that it can be applied to a multi-band image, such as a color image, a remote sensing image, or an image composed of multiple feature layers. The main disadvantage of the data clustering method is again that the number of clusters must be determined first.

Even for the same number of thresholds or clusters, different types of multithresholding/clustering methods are very likely to produce different segmented images because they utilize different image features. So the problem is: which segmented image is the best? Some various cluster validity indexes have been developed to compare the multithresholding/clustering results and therefore find the optimal number of clusters. Several widely used cluster validity indexes for hard clustering analysis include the Davies-Bouldin's index (DB) [8], the Beta Index [4], and the Generalized Dunn's Index (GD) [6], etc. These indexes fall into the category of statistical cluster validities. They use cluster properties such as compactness (intra-cluster distance) and separation (inter-cluster distance) to check the quality of the clustering results. Different validity indexes of this kind vary only in the way they measure the compactness and/or separation and in the way they combine information about these two properties [5]. When such indexes are used to evaluate image segmentation results, they tend to select a small number of clusters as the optimal solution, thus generating less-segmented images. These less-segmented images usually cannot provide enough spatial details about the low intensity objects in the image.

3. Evaluation of Segmented Image Based on Radon Transform

To overcome the drawbacks of statistical cluster validity indexes, a new method utilizing both spatial and statistical information to compare segmented images is proposed. The new method is based on the Radon transform. The widely used definition of the Radon transform is [9]

$$g(\rho,\theta) = \iint_{-\infty}^{\infty} f(x,y)\delta(\rho - x\cos\theta - y\sin\theta)dxdy, 0 \le \theta < \pi, \rho_{min} \le \rho \le \rho_{max}, \quad (1)$$

where $g(\rho,\theta)$ is the one-dimensional projection of image $f(x,y)$ at offset ρ and angle θ. $\delta(\cdot)$ is the Dirac delta function. The Radon transform is commonly used in algorithms for detecting linear features in an image. It has the advantage of preserving the spatial information of the original image.

We propose a method based on the Radon transform to determine the optimal number of clusters and to evaluate the segmented images acquired by different methods. After segmenting via a thresholding or clustering method, the original grayscale image $f(x, y)$ is transformed into a new image $s(x, y)$ with only K gray levels. K is the number of clusters. The gray values of $s(x, y)$ are set to

$$s(x, y) = \frac{k-1}{K}, \text{ if } f(x, y) \in kth \text{ cluster}, \tag{2}$$

where $1 \leq k \leq K$. For thresholding methods, the kth cluster is defined as

$$\{f(x, y)|T_{k-1} \leq f(x, y) < T_k\}, \tag{3}$$

where $T_0 < T_1 < \cdots < T_K$ are the thresholds with $T_0 = 0$ and $T_K = V_{max}$. V_{max} is the maximum gray level of the image.

For a specific thresholding or clustering method, we determine the optimal number of clusters in the following manner:

1. Initialization: given an initial number of clusters K_0, segment $f(x, y)$ into $s_0(x, y)$. Calculate the Radon transform of $s_0(x, y)$ in the horizontal and vertical directions, i.e., $\theta = 0$ and $\theta = \pi/2$ only. Denote $py_0 = g_0(\rho, 0)$ and $px_0 = g_0(\rho, \pi/2)$.
2. Segmentation: for cluster number K_i, segment $f(x, y)$ into $s_i(x, y)$.
3. Projection: calculate the Radon Transform of $s_i(x, y)$ in the horizontal and vertical directions and thus get py_i and px_i.
4. Correlation: let

$$corrX = h(px_i, px_{i-1}), \ corrY = h(py_i, py_{i-1}), \tag{4}$$

   where function $h(a, b)$ represents the correlation coefficient between vector a and b. If $corrX > \varepsilon$ and $corrY > \varepsilon$, go to step 5; else let $K_{i+1} = K_i + 1$ and go to step 2. Here $\varepsilon(> 0)$ is a given threshold to stop the segmentation procedure.
5. Conclusion: select the final K_i as the optimal number of clusters and $s_i(x, y)$ as the optimally segmented image.

Because the Radon transform preserves the spatial information, our method increases the number of clusters until the spatial information in the segmented image stops increasing significantly. Due to the integration process when calculating the Radon transform, our method erases the effect of noise points and small variations in the spatial information. Therefore the optimal segmented image contains enough spatial information and is not over-segmented.

The previous steps apply to one specific thresholding or clustering method. The optimal number of clusters and optimal segmented image are dependent on the segmentation method. A method based on the Radon transform is proposed to compare the segmented images obtained by different segmentation methods. The steps are:

1. Find the low intensity portion $f_L(x, y)$ of the original image $f(x, y)$:

$$f_L(x, y) = \begin{cases} f(x, y), & \text{if } f(x, y) < T, \\ 0 & \text{else}, \end{cases} \tag{5}$$

   where T is a given threshold to define the low intensity interval of the image.

2. Calculate the horizontal and vertical Radon transform of $f(x,y)$ and denote them by py_L and px_L, respectively.
3. Assume two segmented images $s^A(x,y)$ and $s^B(x,y)$ are being compared. Define the low intensity portion as

$$s_L^I(x,y) = \begin{cases} s^I(x,y), & \text{if } f_L(x,y) > 0, \\ 0 & \text{else}, \end{cases} \tag{6}$$

where $I = A$ or B. Then calculate the horizontal and vertical Radon transform of $s_L^A(x,y)$ and $s_L^B(x,y)$ and denote the results as py_L^A, py_L^B, px_L^A and px_L^B, respectively.
4. Define the correlation between the segmented image and the original image as

$$corrA = \frac{h(px_L^A, px_L) + h(py_L^A, py_L)}{2}, \quad corrB = \frac{h(px_L^B, px_L) + h(py_L^B, py_L)}{2}. \tag{7}$$

If $corrA < corrB$, we select $s^A(x,y)$ as the optimally segmented image. Otherwise select $s^B(x,y)$. We call this "the less correlated, the better" criterion.

This method can be easily extended to compare more than two segmented images. Equation (7) reveals the correlation of low intensity spatial information between the segmented image and the original image. The more clusters the low intensity portion of the original image is divided into, the more clear profiles of the low intensity objects that will be shown in the segmented image. Therefore more low intensity details are presented by the segmented image and, according to equation (7), the segmented image will be less correlated with the original image in the low intensity portion.

4. Experimental Results

A database of X-ray images of carry-on luggage was acquired. Four typical images (xray1 to xray4, respectively) were selected to test both the validity index method and our new algorithm. The threat objects contained in these images include: a carbon/epoxy fiber knife in xray1, an aluminum knife and an ice pick in xray2; a carbon/epoxy fiber knife, a plexiglass knife, and a green glass knife in xray3; and a plastic toy gun in xray4.

To segment these images, two multithresholding methods, Reddi's [1] and Wang's [2] method, and a data clustering method, hard c-means [6], were used. Three validity indexes, the DB [8], the Beta [4], and the GD (v_{53} as denoted in [6]), were used to evaluate the segmented images and to determine the optimal number of clusters.

The experimental results showed that these validity indexes tend to select a small number of clusters (mostly 2 or 3. The detail results are omitted for space considerations). This is because they only utilize statistical information from the image. A large inter-cluster distance value occurs when the number of clusters is small, resulting in the validity index value being small (for DB index) or large (for Beta and GD indexes), and relatively optimal. However, segmenting the original image into a small number of clusters can not isolate the objects from each other and is not helpful for low intensity threat detection.

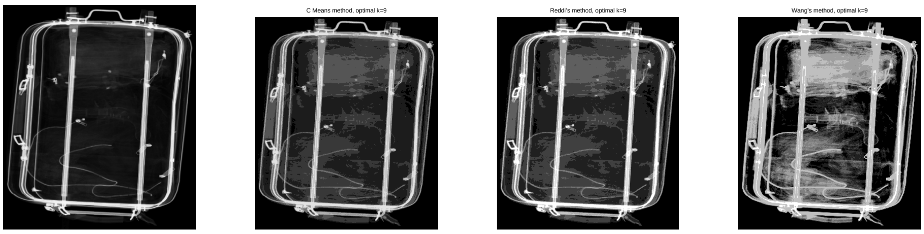
The results obtained by different segmentation methods were compared using the DB and GD v_{53} indexes. Some conclusions gained from the comparison are:

1. The DB index has nearly the same value using either the Reddi's or c-means methods. This is reasonable because if only grayscale information is used to segment the image,

Reddi's and c-means methods have the same objective, i.e., minimizing the intra-cluster distance.

2. The DB index ranks Wang's method lower than the Reddi's or c-means methods.
3. The GD v_{53} index ranks the c-means method best, then Reddi's method, and finally Wang's method.

However, we reached different conclusions from human assessment results. Figure 1 shows the original image of xray4 and the segmented images of it produced by c-means, Reddi's and Wang's method, respectively, with 9 clusters each. It can be seen that the segmented images using c-means and Reddi's method look alike (the result coincides with that of using validity indexes). The segmented image using Wang's method obviously has stronger contrast, clearer object edges, and provides more low intensity spatial details than the other two images. Considering the objective of detecting low intensity threats, Wang's segmented image looks more appealing. Similar conclusions exist for other X-ray images. The reason for the inconsistencies between the human assessment and the validity indexes results is that Wang's method uses edge information to segment the image. But the DB and GD indexes do not consider any spatial information from the images, therefore generate biased evaluations.



(a) (b) (c) (d)

Figure 1. Original image of xray4 (a) and segmented images of it produced by c-means (b), Reddi's (c) and Wang's method (d), respectively, with 9 clusters each

Table 1 shows the experimental results derived using our proposed Radon transform based correlation method. The results were verified by visually checking the segmented images with a continuously increasing number of clusters. It is very difficult to find noticeable spatial structure changes in the segmented images with cluster numbers larger than the values shown in Table 1. This indicates that it is reasonable to use the Radon transform of the segmented image as a signature to measure the spatial information contained therein. Our method needs not to enumerate all the feasible number of clusters and thus saves on computation time required to segment the original image into more clusters.

Table 1. Optimal number of clusters found by the Radon transform based correlation method

Image	Optimal number of clusters by		
	c-means method	Reddi's method	Wang's method
xray1	10	10	11
xray2	8	8	10
xray3	8	8	11
xray4	9	9	9

To compare the optimally segmented images obtained by different segmentation methods, the low intensity portion (T in equation (5) equals one thirds of the maximum intensity value) correlation coefficients between every optimally segmented image in Table 1 and the original image were calculated. Using our proposed "the less correlated, the better" criterion, we ranked all the results produced by Wang's method as the best-segmented images. The results are consistent with that of human visual assessment. This can be seen in Figure 2, which shows the low intensity portions of the optimally segmented images of xray4 obtained by the c-means, Reddi's and Wang's methods, respectively.

(a) (b) (c)

Figure 2. Low intensity portion of the optimally segmented image of xray4 produced by c-means (a), Reddi's (b) and Wang's (c) method

5. Conclusions

A new method is proposed to determine the optimal number of clusters when segmenting X-ray images and to evaluate the results acquired by different segmentation methods. Compared with the statistical validity index method, our method considers both the spatial and statistical information of the image. Preliminary experimental results show that our method produces results consistent with the human assessment. Another advantage of our method is that it is computationally efficient. Our procedure only calculates the Radon transform in two directions and does not need to enumerate all feasible number of clusters.

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