OBJECT RECOGNITION USING MULTIPLE THRESHOLDING AND LOCAL BINARY SHAPE FEATURES

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Abstract: Traditionally, image thresholding is applied to segmentation - allowing foreground objects to be segemented. However, selection of thresholds in such schemes can prove difficult. We propose a solution by applying multiple thresholds. The task of object recognition then becomes that of matching binary objects, for which we present a new method based on local shape features. We embed our recognition method in a system which reduces the computational increase caused by using multiple thresholding. Experimental results show our method and system work well despite only using a single example of each object class for matching.

1 INTRODUCTION

Object recognition methods have many applications including; database image retrieval, landmark detection, manufactured part inspection, target identification and scene analysis. In this paper, we are concerned with providing a count and localization of different object types present in an image.

Objects extracted from an image can be classified, image thresholding can be used for such extraction. Typical use of image thresholding is that of image segmentation, (Cao et al., 2002). For example, (Chang and Wang, 1997) segment image grey values into a desired number of classes by applying either Guassian smoothing or high-pass filtering to the image histogram, creating the desired number of valleys in the histogram which are then used as thresholds. (Cao et al., 2002) present a method for threshold selection based on the maximum entropy theorem, utilizing the probability of pixel value occurences in an image. More recently, (Malisia and Tizhoosh, 2006) apply Ant Colony Optimization, using ants to search for low value grey regions. Image segmentation by thresholding can be utilized for object extraction (Ridler and Calvard, 1978). For example, (Kamgar-Parsi and Kamgar-Parsi, 2001) present a method which extracts objects in infra-red images. Assuming objects have a higher temperature than the background, localising the area of greatest temperature provides the object centroid area. Expanding this area and locating the highest drops in heat provides the edge between object and background. (Ridler and Calvard, 1978) present an iterative method for the selection of segementation threshold. Whereby background samples close to objects are used to determine the appropriate threshold. The method presented by (Revankar and Sher, 1992) uses *a priori* knowledge to determine if a threshold should be used to segement thin lines from an image or the entire object region. (Park, 2001) present a method of selecting locally optimum thresholds to segment vehicles from image backgrounds. These locally optimum thresholds are selected by preventing regions created merging and by preserving the compactness of these regions. (S. Bhattacharyya and Bandyopadhyay, 2002) describe a method of using thresholding to generate a region of interest in an image which is, in turn passed to a Hopfield network to extract the present object. More recently, (Yu Qiao, 2007) present a method to segment small objects from a background, using the intensity contrast between object and background.

Our method is different, producing multiple thresholded versions and searching within these thresholded versions. Figure 1 illustrates why this approach is adpoted. Figure 1(a) shows an image and Figure 1(b) the corresponding histogram. This clearly shows no single threshold can be computed for object segmentation from the background. However, by stepping through thresholds of the image, definite areas relating to the objects can be identified, Figure 1(c) - 1(d). This use of multiple thresholds is similar to that presented by (Jiang and Mojon, 2003).

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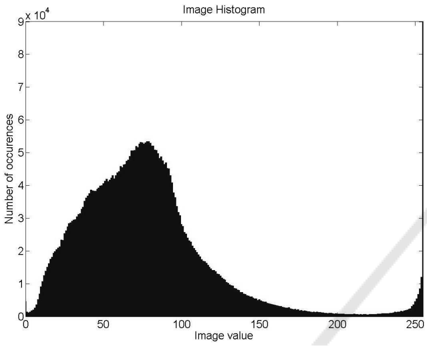
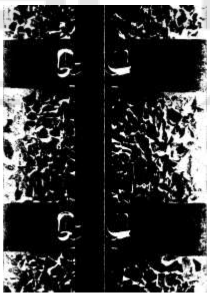
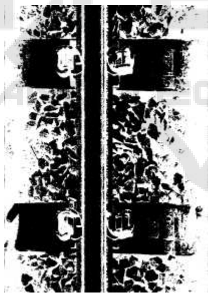
(a) Image with objects of interest in white boxes



(b) Histogram of grey values in image (a)



(c) Threshold value of 40



(d) Threshold value of 70

Figure 1: Example image.

However, we counteract the computational increase caused by processing multiple thresholded versions of an image. First, image regions of interest are selected, using an iterative area decomposition method. Secondly, we embed the object recognition method in a multi-resolution hierarchy, which have been shown to be computationally efficient for image processing problems, (Cantoni et al., 1991; Cantoni and Lombardi, 1995). Finally, the system learns spatial relationships between observed objects, allowing for a more efficient search for objects in image space, (Wixson, 1992).

Our method is presented in section 2. Experimental setup and results are presented in section 3. Finally, section 4 presents conclusions drawn from these experiments.

2 METHOD

Our system is composed of three stages - training, image pre-processing and object recognition.

2.1 Training

Ideal Template Creation. Templates are created by a user, applying an arbitrary threshold to an example of the object to be searched for.

Learning Spatial Relationships. The spatial relationships between objects are learnt from a set of ground truthed images. We categorize these relationships into one of four types - *above*, *below*, *left* and *right*.

2.2 Image Pre-Processing

The image pre-processing phase creates multiple thresholded versions of an input image and identifies candidate areas. The following describes this process.

1. Initialise the list of areas (*AreaList*) with M thresholded versions of the original image
   (a) Read and store the area at the head of the *AreaList* - $area = Pop(AreaList)$
   (b) Calculate the horizontal (hp) and vertical (vp) projections of *area*, dividing by the height ($height$) and width ($width$) of *area* respectively.
   (c) Replace all values in hp and vp which are either above or below chosen upper or lower bounds, respectively, with -1.
   (d) If ($Contains(hp, -1)$ or $Contains(vp, -1)$)
      i. Using the combination hp and vp, extract coordinates representing bounding boxes segmented by the elements set to -1 and *Push* each bounding box onto *AreaList*.
      ii. Goto step 2.
   (e) Accept *area* as a candidate area.
   (f) If *AreaList* is not empty, goto step 2.

2.3 Object Recognition

We compare two methods, a simple differencing method which subtracts two binary images and our new method which compares shapes created by white pixels in a windowed neighbourhood.

2.3.1 Simple Difference Method (SDM)

For each position in an area (A), a slice (I) the same size as the template (T) used for comparison is extracted. The similarity between these is calculated as:

$$SD(I,T) = 1 - \frac{\sum_{i=0}^{width}\sum_{j=0}^{height} ABS(I(i,j) - T(i,j))}{width \times height} \quad (1)$$

where $width$ and $height$ are the width and height of I and T. The highest value of $SD(I,T)$ in A is taken as the response.

2.3.2 Local Shape Matching Method (LSMM)

For each pixel in an area, a slice (I) of the same size as a template (T) being matched is selected. For every position of a white pixel in T, (x_w,y_w), $Neighbourhood_I$ is the set of white pixels in the region $I(x_w - K, y_w - K) \rightarrow I(x_w + K, y_w + K)$ where K relates to the size of the window. Similarly, $Neighbourhood_T$ is the set of white pixels in region $T(x_w - K, y_w - K) \rightarrow T(x_w + K, y_w + K)$. These neighbourhoods of pixels are compared using the centroid and principal axis angle. If $(x_1,y_1),(x_2,y_2),...,(x_N,y_N)$ are members of a neighbourhood, the centroid $(\bar{x},\bar{y})$ is calculated as:

$$\bar{x} = \frac{1}{N}\sum_{n=1}^{N} x_n,\ \bar{y} = \frac{1}{N}\sum_{n=1}^{N} y_n \quad (2)$$

The principal axis angle through pixels in a neighbourhood is calculated as (described in (Chaudhuri and Samal, 2007)):

$$tan\ 2\theta = \frac{2\sum_{n=1}^{N}(x_n - \bar{x})(y_n - \bar{y})}{\sum_{n=1}^{N}[(x_n - \bar{x})^2 - (y_n - \bar{y})^2]} \quad (3)$$

The similarity between two neighbourhoods ($LSM(x_w,y_w,I,T)$) is then calculated as:

$$\frac{1}{2}\left(\frac{|\bar{x_I} - \bar{x_T}| + |\bar{y_I} - \bar{y_T}|}{V} + \frac{Abs(\theta_I) - Abs(\theta_T)}{2\pi}\right) \quad (4)$$

where, $V = 4K$. Note, if $Neighbourhood_I$ is empty, $LSM(x_w,y_w,I,T)$ is set to 0. The similarity between a template area and area slice is the average similarity for every neighbourhood, centred around a white pixel of T:

$$S(I,T) = \frac{\sum_{m=1}^{M} LSM(x_m,y_m,I,T)}{M} \quad (5)$$

where $(x_1,y_1),(x_2,y_2),...,(x_M,y_M)$ are the white pixels in T. As with the simple difference method, the highest value of $S(I,T)$ in an area is taken as the response for the corresponding area of the image.

2.3.3 Multi-Resolution Hierarchy

In the multi-resolution hierarchy, an object is searched for at the lowest resolution. If the maximum response achieved is greater than a predetermined acceptance threshold, the object is classified as found. If the response is less than an acceptance threshold but greater than a predetermined removal threshold, the area is searched at the next highest resolution in the hierarchy. If the response is less than a removal threshold, search in the area stops.

2.3.4 Spatial Relationships

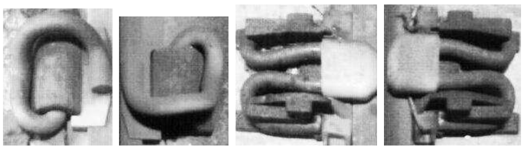
If an object is found, the spatial relationships are used to generate image areas to search for more objects. Since objects are expected to appear in these areas, the acceptance threshold is reduced. It should be noted that results found in areas selected using spatial relationships may themselves create more areas due to different spatial relationships (the effects of reducing the acceptance threshold are not cumulative).

3 EXPERIMENTS

For experimentation, grey-scale input images were taken from a camera looking down onto a rail track. Examples of these images can be seen in Figure 2. A total of 5000 images were used for testing. Within these images, we search for instances of rail clips (examples shown in Figure 3).

(a) (b)

Figure 2: Example images.



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

Figure 3: Example objects.

The previously described object recognition system was executed, using our data set, once using *SDM* and once using *LSMM*. The results of which can be found in Table 1. For each method, we show the correct percentage of objects found and the average number of false positives per image.

Table 1: SDM and LSMM results.

Method	Percentage Correct (%)	False Positives per image
SDM	80.39	1.19
LSMM	91.6	0.16

Results show that *LSMM* outperforms *SDM* in terms of average percentage of objects found and number of false positives found. Note, without the spatial relationship component in the system, *LSMM* achieved an average recognition rate of 82.0% and a similar number of false positives.

4 CONCLUSIONS

We have presented a method for object recognition which achieves high recognition rates despite similarities in grey-level values between objects and image background. This was achieved by using a multiple thresholding approach. For the object recognition phase of our system, we presented a new local shape matching method for binary objects, which performs well despite using a single example of each object for reference. We were also able to show that recognition performance can be enhanced through the use of learnt spatial relationships between objects.

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