Traffic Sign Detection by Template Matching based on Multi-Level Chain Code Histogram

Rongqiang Qian, Bailing Zhang, Yong Yue
Department of Computer Science & Software Eng.
Xi'an Jiaotong-Liverpool University
Suzhou, 215123, China

Frans Coenen
Department of Computer Science
The University of Liverpool
Liverpool, UK

Abstract—**This paper proposes a real-time system for traffic signs detection, which features of template matching based on a new feature expression for geometric shapes, namely, multi-level chain code histogram (MCCH). For all of the different shapes associated with Chinese traffic signs, e.g., circle, triangle, inverted triangle and octagon, MCCH is a robust feature expression with remarkable low computational cost, which is particularly important for real-time applications. The proposed system consists of three stages: 1) segmentation based on color; 2) MCCH extraction; 3) template matching. Extensive experiments were conducted using different datasets, demonstrating outstanding performance with regard to high processing speed and accuracy. The system robustness to rotation, scale, and illumination has also been illustrated.**

Keywords-component; traffic sign detection; driving assistance system; template macthing.

I. INTRODUCTION

Traffic signs designed to help people streamline traffic flow, achieve area ordinances and post parking requirements to improve the safety. Drivers should make appropriate response to different traffic signs such as various warning and speed limits to secure safety. Generally, traffic signs are designed with regular shapes and attractive color to be easily noticed. Accordingly, the information of geometric shape and color is most relevant for traffic signs.

The detection and recognition of traffic sign have been studied for many years, mainly motivated by the applications such as unmanned vehicles and advanced driver assistance systems [1-2]. Despite the progresses made, many challenges remain in the development, for example, illumination variations and shadow.

Automatic traffic sign detection and recognition is expected to capture information from open environment and guide vehicles during driving. Such a system usually consists of three stages: 1) segmentation; 2) detection; and 3) recognition. The segmentation is usually based on color; the detection aims at finding out the region of traffic sign; and the recognition is to classify traffic signs.

Previous works on traffic sign detection could be roughly categorized into color-based method, shape-based method and machine learning-based method [2-3]. Color-based methods rely on color to segment the regions that belong to traffic sign [3], with main advantages of being low computational cost and robust to projective deformation. However, color-based methods are sensitive to illumination changes. In order to overcome the problem, a number of color space thresholding methods have been proposed [3-4]. However, these methods share a common disadvantage of large number of thresholds to be adjusted. To generate adaptive threshold, support vector machine (SVM) based color segmentation [5] was proposed.

Based on the intuition that traffic signs have regular geometry, different shape-based methods have been proposed to detect traffic signs [5-8]. As Hough transform is a convenient tool in detecting regular shapes, such as circle and square, Hough-like scheme [6] has been proposed to detect the shape of traffic signs. Though the shape-based methods are usually robust to projective deformation and illumination, a disadvantage is also obvious, i.e., their higher computational cost comparing with color-based methods.

Being similar to many other computer vison tasks, traffic sign detection and recognition have become inseparable with machine learning [9-13], with the most noticeable example of the Viola-Jones-like methods for object detection. A large number of classification techniques, such as artificial neural networks and support vector machine [11, 14-16], have also been applied to solve traffic sign recognition. While machine learning is generally promising, the conventional sliding window approaches for detection associate with heavy computation cost and classification performance usually depends on the feature used.

To further address the aforementioned problems, we proposed a novel shape-based method for traffic sign detection, which is characterized by our proposal for an efficient shape feature expression with multi-level chain code histogram.

The rest of this paper is organized as follows. Section 2 presents a brief introduction on the whole traffic sign detection system. Section 3 explains the color space thresholding method for segmentation. Section 4 presents the feature expression method which is based on multi-level chain code histogram. Section 5 shows the method used in template matching. Section 6 introduces the experiment results, followed by conclusion in Section 7.

II. SYETEM OVERVIEW

The proposed TSD system consists of three modules, as illustrated in Fig.1a. In the first module, the input image is segmented by using Ohta Space Thresholding. In the second module, traffic sign detection by Multilevel Chain code Histogram. In the third module, the distance between current contour and template will be estimated.

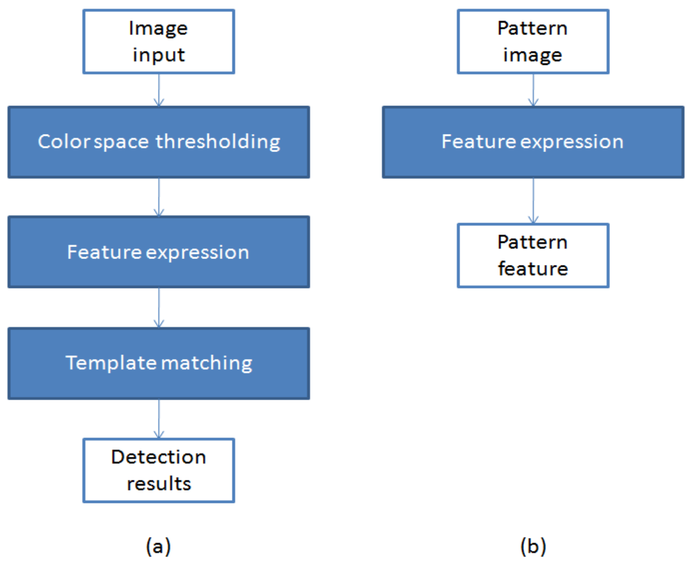

Figure 1. System overview

The traffic sign detection procedure can be described in the following steps in detail:

Step1. Color space thresholding. The original input RGB image is converted into binary image by applying Ohta Space Thresholding, followed by edge detection and Connected Component Analysis (CCA) [17] to produce corresponding contour images. In order to decrease computational cost and eliminate some fake matching, some regions with small areas (< 20 pixels) will be removed.

Step2. Feature expression. For each contours produced in the Step 1, calculate their feature by using the Multi-level Chain Code Histogram [18].

Step3. Template matching. By comparing the MCCHs of the three patterns in Fig.2 with all of the MCCHs of the contours produced from last step, histogram intersection distances [19] are calculated which estimate the matching degree between the template and a contour. The histogram intersection distances will be generated for each contour from step 2. Finally, a threshold will be used to measure the similarity and reject poor matches.

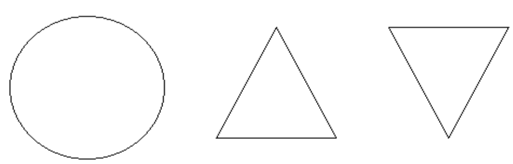

Figure 2. Pattern image

III. Color Space Thresholding

Ohta Space Thresholding: A color space is a specific organization of colors. The research for an effective color space in color-based segmentation has resulted in variety of color models, such as CIEXYZ, CIELUV, CIELAB, and YIQ. Among the variety of spaces, Ohta space [3-4] shows some significant characteristics. Firstly, the implementation of Ohta space is quite simple and it has very low computational cost. Secondly, another characteristic is that the aim of Ohta space is focus on finding the best uncorrelated components, thus, all the components are independent to each other. Finally, Ohta space is belonging to the family of Opponent Color Spaces [3-4].

After performing extensive experiments, the authors of [3] invented a set of features for three colors that are derived from RGB. The set of colors are very effective for image segmentation,

$$\begin{bmatrix} I_1 \\ I_2 \\ I_3 \end{bmatrix} = \begin{bmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ 1 & 0 & -1 \\ -\frac{1}{2} & 1 & -\frac{1}{2} \end{bmatrix} = \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{1}$$

According to Eqn. 1, the component I_1 is mapped to illumination; therefore, only the rest components I_2 and I_3 are used for color categorization. These two components can be used in segmentation directly. Moreover, in order to increase the robustness to illumination changes, normalization should be performed [3]. The specific designed normalized components P_1 and P_2:

$$\begin{aligned} P_1 &= \frac{1}{\sqrt{2}}\frac{R-B}{R+G+B} = \frac{1}{3\sqrt{2}}\frac{I_2}{I_1} \\ P_2 &= \frac{1}{\sqrt{6}}\frac{2G-R-B}{R+G+B} = \frac{2}{3\sqrt{6}}\frac{I_3}{I_1} \end{aligned} \tag{2}$$

By using the normalized components, the three colors can be calculated according to the following formulations:

$$\begin{aligned} \mathrm{Red}(i,j) &= \begin{cases} \mathrm{True}, & \text{if } P_1(i,j) \geq ThR_1 \\ & \text{and } P_2(i,j) \leq ThR_2 \\ \mathrm{False}, & \text{otherwise} \end{cases} \\ \mathrm{Blue}(i,j) &= \begin{cases} \mathrm{True}, & \text{if } P_1(i,j) \geq ThB_1 \\ & \text{and } |P_2(i,j)| \leq ThB_2 \\ \mathrm{False}, & \text{otherwise} \end{cases} \\ \mathrm{Yellow}(i,j) &= \begin{cases} \mathrm{True}, & \text{if } P_1(i,j) \geq ThY_1 \\ & \text{and } |P_2(i,j)| \leq ThY_2 \\ \mathrm{False}, & \text{otherwise} \end{cases} \end{aligned} \tag{3}$$

All the threshold values selected are shown in Table 1.

TABLE I. OHTA SPACE THRESHOLD VALUES [3-4]

Threshold name	Value
ThR_1	0.024
ThR_2	-0.027
ThB_1	-0.04
ThB_2	0.082
ThY_1	0.071
ThY_2	0.027

IV. Feature Expression

Template matching is a simple methodology for object detection within images. The main advantages include the efficiency of its implementation and its effectiveness with respect to the detection of low-textured objects or objects characterized mainly by shape. In this paper, we proposed to implement traffic sign detection with template matching by proposing a Multi-level Chain Code Histogram (MCCH). A chain code is a traditional method used to describe an object boundary with an ordered sequence of n straight line segments $\{c_i,\ i = 1, 2, ..., n\}$, where c_i is a vector of connecting neighboring contour pixels. The directions of c_i are coded with integer values k = 0, 1, ..., K −1 in a counter clockwise fashion starting from the direction of the positive x-axis, where K is the number of directions defined by an integer value 4 or 8 [18].

To better characterize a contour as an efficient shape descriptor. The chain code histogram (CCH) has been proposed based on the Freeman chain code, which can be described by a discrete function:

$$\mathrm{CCH}(k) = \frac{n_k}{n}, k = 0,1,\ldots,K-1 \qquad (4)$$

where n_k is the number of chain code values k in a chain code, and n is the number of links in a chain code. The definition can be further explained with reference to Figure 3. Fig. 3(a) shows the directions for the "eight connected" chain code. Fig. 3(b) shows a sample object, a circle, in terms of its contour. The starting point for the chain coding is marked with a black circle, and we use clockwise as the direction of chain coding. In Figures 3(c)-(d) the chain code and the CCH of the contour for the digit contour are shown.

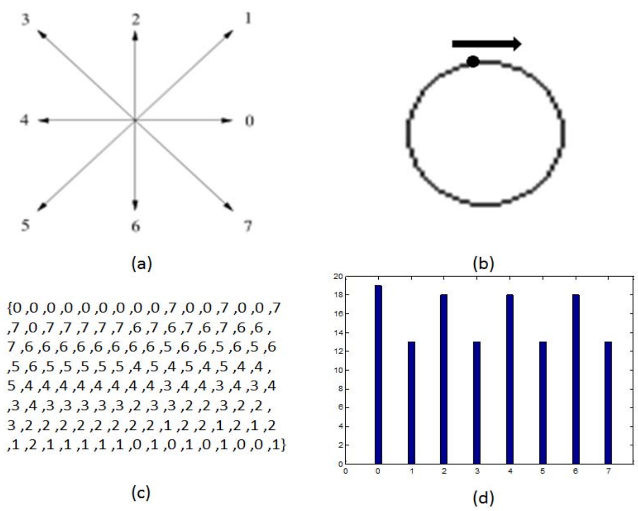

Figure 3. Illustration of chain code histogram for describing a contour

A chain code histogram is a global feature for describing a shape. To achieve higher distance of chain code histogram between different contours, a local chain code histogram can be created by breaking the original contour into small contour fragments and analyzing their CCHs accordingly. To be more specific, a cascaded chain code histogram can be defined as the following. The chain code of a contour is first divided into a number of small fragments, and the fragment size is chosen empirically. And the CCH for each fragment is calculated and concatenated. If the original chain code is equally divided into m parts, all the CCHs at different parts are concatenated to form a cascaded histogram. Thus, the Cascaded CCH descriptor is a vector with dimension of 8m. The improvements can be illustrated by Fig.4, where the chain code of the contour in Fig. 1 is divided into 4 sequences and their corresponding CCHs are concatenated together.

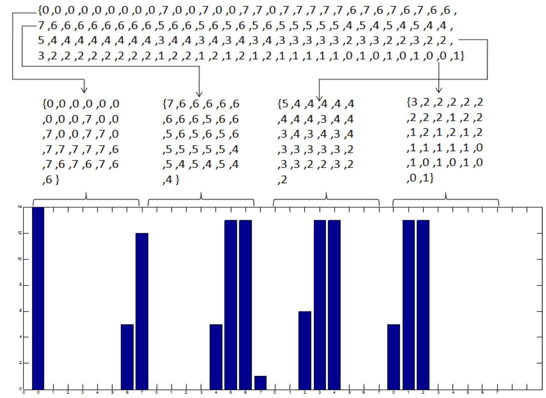

Figure 4. Illustration of cascaded chain code histogram

Comparing with the original CCH, Cascaded CCH is much more powerful on distinguishing contours with less skew and distortion. However, in a lot of situations, skew and distortion is unavoidable. Thus, in order to achieve better robustness and rotation invariance, Cascaded CCH can be further extended to Multi-level CCH (MCCH). In detail, a MCCH can be defined as in the following. The first level CCH is original CCH. From the second level, chain code of a contour is divided into different number of small fragments. And then the CCH for each fragment is calculated and concatenated. As Fig.5 presents, a 2-level MCCH can be simply achieved by cascading the original CCH and a Cascaded CCH with 4 part CCHs. Since the length for each small CCH is 8, the final 2-level MCCH has a length of 40.

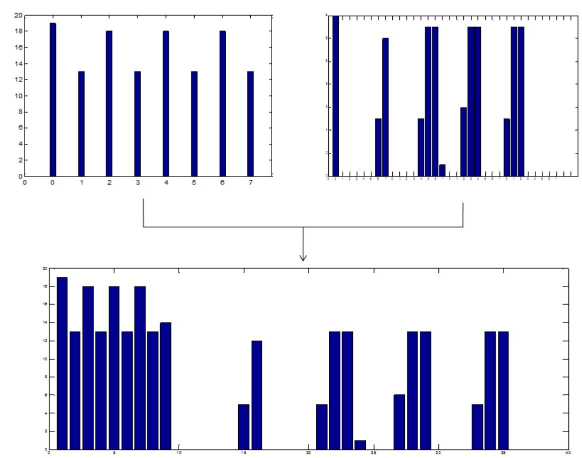

Figure 5. Illustration of multi-level chaincode histogram (MCCH).

V. TEMPLATE MATCHING

In template matching, several methods can be applied to calculate the distance between the MCCHs in library and the current MCCH, such as histogram intersection [19], chi-square, match distance and Euclidean distance.

In order to test the performance of different methods, a dataset with 100 positive images and 50 negative images were built. All the mentioned methods were tested by using this dataset. The results can be shown in the following Table 2.

TABLE II. PERFORMANCE COMPARISON FOR CALCULATING HISTOGRAM DISTANCE

Method name	True positive	False positive
histogram intersection	95	3
chi-square	94	4
match distance	94	3
Euclidean distance	95	5

According to the results, histogram intersection is the best method that gives the most true-positive number with the least false-positive number. Therefore, histogram intersection is used in this paper.

VI. EXPERIMENT

In the experiment, the proposed method was verified on a field-captured traffic sign dataset. The details of the experiments will be presented in the following subsections.

A. Dataset collection

The dataset was recorded by a camera set up in vehicle. It includes three categories of traffic signs that based on their shape and color:

Prohibitory: circle, red rim, white or red inner.

Mandatory: circle, blue rim, blue inner.

Danger: triangular, black rim, yellow inner.

Images in dataset were captured by a camera with 640×480 resolution. The total number of the images is 300. To be more detail, 150 images contain prohibitory signs, 80 images contain mandatory signs and 70 images contain danger signs. The sizes of traffic sign in the images vary from 25×25 to 80×80. Some examples can be found in Fig.6.

Figure 6. Illustration of some sample images

B. Detection results

For the purpose to observe the performance of the proposed detector, different decision thresholds of template matching are used. The details are shown in the following precision-recall plots.

Figure 7 indicates the detection results of prohibitory signs. As the threshold of template matching increasing, the recall rate is also rising with the decreasing of the precision rate. From the figure, the suggested trade-off is got at the position with recall value equals 0.95 and precision value equal to 0.9.

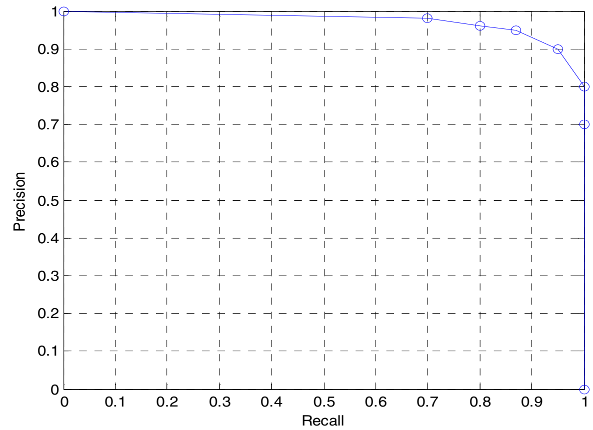

Figure 7. Precision-recall curve for detecting prohibitory sign.

Figure 8 indicates the detection results for mandatory signs. The area under curve (AUC) here is slightly lower, because the mandatory sign collected has lower resolution and quality compare with prohibitory signs.

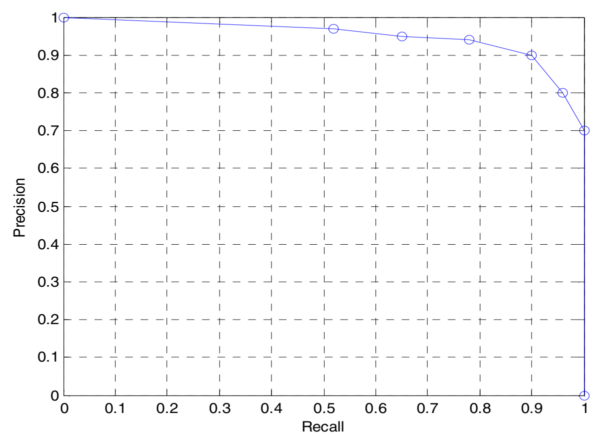

Figure 8. Precision-recall curve for detecting mandatory sign.

Figure 9 indicates the detection results for danger signs. Different from the previous two main categories of traffic signs, the shape of danger signs is triangular. This means detection of danger signs is easier affected by skew or deformation. Thus, the performance is lower compare with previous two classes of traffic signs.

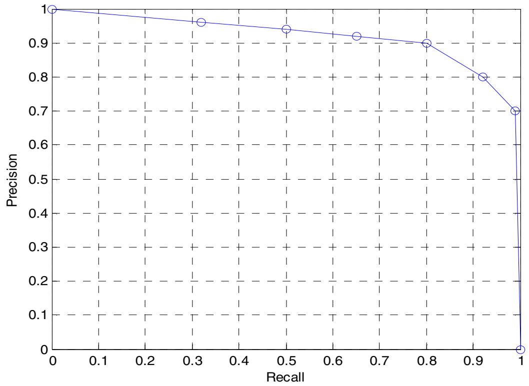

Figure 9. Precision-recall curve for detecting danger sign.

C. *Failed detection*

As Fig. 10 displays, the proposed method failed to detect traffic signs at the conditions, such as very low quality, strong illumination and occlusion.

Figure 10. Illustration of failed detection

D. *Detection speed*

A computer with Xeon 4-core 3.4GHz, 16GB and OpenCV was employed to execute the proposed algorithm. The computational duration for each image is about 50ms-100ms, which means the possibility of real-time detection.

VII. CONCLUSTION

In this paper, we proposed a traffic sign detection method based on template matching, which main consists of three stages. In the first stage, the input image is segmented using Ohta space thresholding. Secondly, edge detection and Connected Component Analysis is performed, with the aid of an efficient feature extraction based on multi-level chain code histogram. In the final stage, the similarity of each contour is estimated by utilizing histogram intersection. Experiments verified that the system is robust to small skew and deformation, with low computational cost. Evaluation results from experiment also confirmed that the proposed method achieves high accuracy for prohibitory signs, mandatory signs and danger signs. Further improvement will be made toward better detection accuracy when partial occlusion and low quality images are taken into account.

REFERENCES

[1] S. Houben, J. Stallkamp, J. Salmen, M. Schlipsing, and C. Igel, Detection of traffic signs in real-world images: The German Traffic Sign Detection Benchmark," IJCNN, 2013.

[2] A. Møgelmose, M. Trivedi, and T. Moeslund, "Vision based traffic sign detection and analysis for intelligent driver assistance systems: Perspectives and survey," IEEE Trans. ITS, Special Issue on Machine Learning for Traffic Sign Recognition, 2012.

[3] H.Gomez-Moreno,S.Maldonado-Bascon,P.Gil-Jimenez,and S. Lafuente-Arroyo, "Goal evaluation of segmentation algorithms for traffic sign recognition," IEEE Trans. ITS., vol. 11, no. 4, pp. 917–930, Dec. 2010.

[4] Y. Ohta, T. Kanade, and T. Sakai, "Color information for region segmentation," Comput. Graph. Image Process., vol. 13, no. 3, pp. 222–241,Jul. 1980. [Online]. Available:www.ri.cmu.edu/pubs/pub_2487.html

[5] M. liang, M. Yuan, X. Hu, J. Li, and H. Liu, "Traffic Sign Detection by ROI Extraction and Histogram Features-based Recognition," IJCNN, 2013.

[6] N. Barnes, A. Zelinsky, and L. Fletcher, "Real-time speed sign detection using the radial symmetry detector," IEEE Trans. ITS, vol. 9, no. 2, pp. 322–332, Jun. 2008.

[7] A. Gonzalez, M. Garrido, D. Llorca, M. Gavilan, J. Fernandez, P. Alcantarilla, I. Parra, F. Herranz, L. Bergasa, M. Sotelo, and P. Revenga de Toro, "Automatic traffic signs and panels inspection system using computer vision," IEEE Trans. ITS, vol. 12, no. 2, pp. 485–499, Jun. 2011.

[8] R. Belaroussi and J.-P. Tarel, "Angle vertex and bisector geometric model for triangular road sign detection," WACV, 2009, pp. 577–583.

[9] G. Wang, G. Ren, Z. Wu, Y. Zhao, and L. Jiang, "A robust, coarse-to-fine traffic sign detection method," IJCNN , 2013.

[10] M. Mathias, R. Timofte, R. Benenson, and L. V. Gool, "Traffic sign recognition - how far are we from the solution?" IJCNN , 2013.

[11] S. Maldonado-Bascon, S. Lafuente-Arroyo, P. Gil-Jimenez, H. Gomez-Moreno, and F. López-Ferreras, "Road-sign detection and recognition based on support vector machines," IEEE Trans. ITS,vol. 8, no. 2, pp. 264–278, Jun. 2007.

[12] X. Baro, S. Escalera, J. Vitria, O. Pujol, and P. Radeva, "Traffic sign recognition using evolutionary adaboost detection and forest-ECOC classification," IEEE Trans. ITS, vol. 10, no. 1, pp. 113–126, Mar. 2009.

[13] M. Meuter, C. Nunn, S. M. Gormer, S. Muller-Schneiders, and A. Kummert, "A decision fusion and reasoning module for a traffic sign recognition system," IEEE Trans. ITS, vol. 12, no. 4, pp. 1126–1134, Dec. 2011.

[14] D. Ciresan, U. Meier, J. Masci, J. Schmidhuber, A committee of neural networks for traffic sign classification, in: Neural Networks (IJCNN), IJCNN , 2011, pp. 1918–1921

[15] P. Sermanet, Y. LeCun, Traffic sign recognition with multi-scale convolutional networks, in: Neural Networks (IJCNN), IJCNN , 2011, pp. 2809–2813.

[16] J. Jin, K. Fu, C. Zhang, Traffic sign recognition with hinge loss trained convolutional neural networks, Intelligent Transportation Systems, IEEE Trans. ITS, 15 (5) (2014) 1991–2000

[17] K. R. Castleman, Digital Image Processing, Prentice Hall; 2nd edition, 1995.

[18] J. Iivarinen, A. Visa, Shape recognition of irregular objects. Proc. SPIE, Intelligent Robots and Computer Vision XV: Algorithms, Techniques, Active Vision, and Materials Handling, (Proc. SPIE 2904), pp.25–32, 1996.

[19] K. Grauman and T. Darrel. The pyramid match kernel: Discriminative classification with sets of image features.In ICCV, pages 1458–65, 2005