Segmentation Techniques for Target Recognition

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Abstract **:** This paper presents an overview of the methodologies and algorithms for segmenting 2D images as a means in detecting target objects embedded in visual images for Automatic Target Detection/Recognition applications.

Keywords **:** Target Detection, Image Processing, Pattern Recognition, Segmentation

1. INTRODUCTION

Automatic Target Detection/Recognition (ATDR) is an application of pattern recognition for image processing that detects and identifies types of target objects.

ATDR is a major objective in processing digital images for detecting, classifying, and tracking target objects embedded in an image. Various methods exist for detecting objects of known type in a particular environment or image.

The traditional approach to automatic target detection/recognition is to convert the signal from the sensor into a digital image for further processing. Next step is to separate the target from its background or surrounding area by extracting a coarse shape or outline of the target object and then to identify the object from features describing the target object.

2. ATDR THROUGH SEGMENTATION

One of the common problems encountered in object detection/recognition is choosing a suitable approach for isolating different objects from each other as well as from the background. This separation of an image into object/s and background is usually done by simplifying and/or changing the representation of an image by enhancing the visual representation of boundaries (lines, curves, etc.). This makes the object differentiation, isolation and detection task easier. The process is known as image segmentation. Image segmentation is one of the primary steps in image analysis for object Detection, recognition and identification

Thus segmentation refers to the process of partitioning a digital image into multiple regions (sets of pixels). The result of image segmentation is a set of regions that collectively cover the entire image, or a set of contours extracted from the image. Each pixel within a region is uniquely similar with respect to some characteristic or computed property, such as color, intensity, or texture. Pixels from adjacent regions are significantly different with respect to the same characteristic(s).

Issues related to segmentation involve choosing good segmentation algorithms, measuring their performance, and understanding their impact on the image analysis system. One of the main challenges is to recognise homogeneous regions within an image as distinct and belonging to different objects. Segmentation stage does not worry about the identity of the objects. They can be labelled later. The segmentation process discussed in this paper is focussed on finding the maximum homogeneity in grey levels within the regions identified.

3. SEGMENTATION TECHNIQUES

Several general-purpose techniques and algorithms have been developed for image segmentation. Since there is no general solution to the image segmentation problem, these techniques often have to be combined with domain knowledge in order to effectively solve an image segmentation problem for a problem domain. Thus Image segmentation needs to be approached from a wide variety of perspectives [1].

In this paper, we review primarily those methods that are based on finding object regions in grey-level images though some of the approaches may be suitable for colour segmentation also. The following approaches of image segmentation are reviewed in this paper.

1. Edge Detection Methods
2. Histogram Based Methods
3. Tree/Graph Based Methods
4. Region Splitting Methods
5. Region Growing Methods
6. Model Based segmentation
7. Neural Network Based segmentation
8. Clustering Methods
9. Graph Partitioning Methods
10. Watershed Transformation
11. Multiscale segmentation
12. Probablistic and Bayesian approaches

3.1 Edge-Detection Methods

Edge detection is a well-developed field on its own within image processing. Region boundaries and edges are closely related, since there is often a sharp adjustment in intensity at the region boundaries. Edge detection techniques have therefore been used as the base of another segmentation technique.

The edges identified by edge detection are often disconnected. To segment an object from an image however, one needs closed region boundaries. Discontinuities are bridged if the distance between the two edges is within some predetermined threshold.

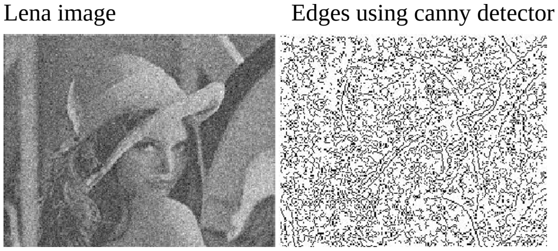
Because of its simplicity and accuracy, the most popular edge detection approach is the Canny Edge detector [Canny [2]].

One major advantage of this method is that it is easy to integrate into a large number of object recognition algorithms used in computer vision and other image processing applications.

However, The degree of success of an edge-detector depends on its ability to accurately locate true edges which may not be always possible due to noise and quantization errors. The addition of noise to an image can cause the position of the detected edge to be shifted from its true location as shown in Fig. 1. As noise is usually high frequency component of the image, Low Pass filters are used as smoothing filters.

The amount of smoothing applied depends on the size or scale of the smoothing operator. Marr, et al. suggested filtering the images with the Gaussian before edge detection ([3]-[4]); Hueckel [5] and Haralick [6] proposed to approximate the image with a smooth function known as multiscale segmentation which is described later.

Lena image Edges using canny detector



Lena image with noise Edges with noise

Fig 1

3.2 Histogram-Based Methods

In this technique, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram are used to locate the clusters in the image. Color or intensity can be used as the measure.

A refinement of this technique is to recursively apply the histogram-seeking method to clusters in the image in order to divide them into smaller clusters. This is repeated with smaller and smaller clusters until no more clusters are formed [8].

Histogram-based methods are very efficient when compared to other image segmentation methods because they typically require only one pass through the pixels

One disadvantage of the histogram-seeking method is that it may be difficult to identify significant peaks and valleys in the image. In this technique of image classification distance metric and integrated region matching are familiar.

3.3 Tree/Graph Based Methods

Cho and Meer[13] proposed a new approach for segmentation, which is derived from the consensus of a set of different segmentation outputs on one input image. Instead of statistics characterising the spatial structure of the local neighbourhood of a pixel, for every pair of adjacent pixels the collected statistics are used for determining local homogeneity. From the ensemble of these initial segmentations, for every adjacent pixel pair a co-occurrence probability is derived, which captures global information (about the image) at the local level (pixel level). The final segmentation of the input image is obtained by processing the co-occurrence probability field.

3.4 Region Splitting Methods

This is ***divide and conquer*** or ***top down*** method.

In this method, the image is split or broken into a set of disjoint regions which are similar within themselves

- Initially the entire image is treated as area of interest.
- Next identify a region within the image which satisfy some similarity constraint.
- If **TRUE** then the area of interest corresponds to a region in the image.
- If **FALSE** split the region of interest and consider each of the sub-regions as the region of interest in turn.
- This process continues until no further splitting occurs.
- In the worst case this happens when the areas are just one pixel in size.

If only a splitting schedule is used then the final segmentation would probably contain many neighbouring regions that have identical or similar properties.

Thus, a ***merging*** process is used after each split which compares adjacent regions and merges them if necessary. Algorithms of this nature are called ***split and merge*** algorithms.

3.5 Region Growing Methods

Region growing is the opposite of the split and merge approach, Thus it is a **bottom-up** Approach.

The steps are as below

- An initial set of small areas are identified and iteratively merged according to similarity constraints.
- An arbitrary ***seed pixel*** is choosen to begin with and is compared with neighbouring pixels.
- Similar neighbouring pixels are added to the seed pixel and the region is ***grown*** by increasing the size of the region.
- When no more similar pixels are available, another pixel which does not yet belong to any region is selected and the process is started again.
- The process is continued until all pixels belong to some region.

For Example, with intensity as the selected feature, the difference between a pixel's intensity value and the region's mean, δ, is used as a measure of similarity

A variant of the above technique, proposed by Haralick and Shapiro (1985), [22] is based on pixel intensities. The mean and scatter of the region and the intensity of the candidate pixel is used to compute a test statistic. If the test statistic is sufficiently small, the pixel is added to the region, and the region's mean and scatter are recomputed. Otherwise, the pixel is rejected, and is used to form a new region

Region growing methods often give very good segmentations that correspond well to the observed edges.

However starting with a particular seed pixel and letting this region grow completely before trying other seeds biases the segmentation in favour of the regions which are segmented first.

This can have several undesirable effects:

- Current region dominates the growth process -- ambiguities around edges of adjacent regions may not be resolved correctly.
- Different choices of seeds may give different segmentation results.
- Problems may occur if the (arbitrarily chosen) seed point lies on an edge.

To counter the above problems, ***simultaneous region growing*** techniques have been developed.

- Similarities of neighbouring regions are taken into account in the growing process.
- No single region is allowed to completely dominate the process.
- A number of regions are allowed to grow at the same time.

3.6 Model based Segmentation

The central assumption of Model Based approach is that structures of interest/objects have a repetitive form of geometry. Therefore, one can seek for a probabilistic model towards explaining the variation of the shape of the object and then when segmenting an image impose constraints using this model as prior. Such a task involves

(i) Registration of the training examples to a common pose,

(ii) Probabilistic representation of the variation of the registered samples, and

(iii) Statistical inference between the model and the image. State of the art methods in the literature for knowledge-based segmentation involve active shape and appearance models, active contours and deformable templates and level-set based methods.

3.7 ANN Based segmentation

Artificial Neural Network segmentation relies on processing small areas of an image using a neural network or a set of neural networks. After such processing the decision-making mechanism marks the areas of an image accordingly to the category recognized by the neural network.

Campbell et al.[9] proposed a automatic segmentation and classification method for outdoor images using neural networks. First, the images are segmented using Self-Organising Feature Maps (SOFM) based on texture and colour information of the objects. SOFMs used consisted of 64x64 nodes for best segmentation. A set of 28 features is then extracted from each region. The features include: average colour, position, size, rotation, texture (Gabor filters) and shape (using principal components). Classification is then performed using a Multi Layer Perceptron with 28 input nodes and 11 output nodes. The training is performed on 7000 regions and testing is done on a independent set of 3000 samples. Over 80% regions were classified correctly using Learning Vector Quantisation and 91.9% regions were classified correctly using the Multi Layer Perceptron.

Papamarkos et al.[10] have developed the procedure of image segmentation using self organising maps. The use of these neural network paradigms is considered equivalent to multithresholding where the output of the network defines a number of homogeneous clusters. One of the interesting note from this paper is the technique used for finding the optimal number of thresholds or in other words the number of segmented regions. Considering that grey level distributions within the region are Gaussian, it is suggested that the linear combination of probability density functions for individual regions should match the overall density of the global histogram of the original image. For different number of segmented regions, we can find which result minimises the error.

Pulse coupled neural network can be implemented on image processing , such as image segmentation and edge detection effectively for the processing of gray images or binary images.

Zhou Liang , Zheng Jianguo [11] have proposed using PCNN in the color image segmentation with the parameters determined by images' spatial and gray characteristics automatically at the first ,then use the above method to obtaine the edge information . The experiment results shows its validity and robustness.

3.8 Clustering Method segmentation

Image segmentation can be performed effectively by clustering image pixels. Cluster analysis allows the partitioning of data into meaningful subgroups and it can be applied for image segmentation or classification purposes. Clustering analysis either requires the user to provide the seeds for the regions to be segmented or uses non-parametric methods for finding the salient regions without the need for seed points. Clustering is commonly used for image segmentation and unsupervised learning [12].

The **k-means algorithm** is an algorithm to cluster n objects based on attributes into k partitions or groups, $k < n$. The K-means algorithm is an iterative technique that is used to partition an image into K clusters. The basic algorithm is:

1. Pick K cluster centers, either randomly or based on some heuristic
2. Assign each pixel in the image to the cluster that minimizes the variance between the pixel and the cluster center
3. Re-compute the cluster centers by averaging all of the pixels in the cluster
4. Repeat steps 2 and 3 until convergence is attained (e.g. no pixels change clusters)

In this case, variance is the squared or absolute difference between a pixel and a cluster center. The difference is typically based on pixel color, intensity, texture, and location, or a weighted combination of these factors. K can be selected manually, randomly, or by a heuristic.

This algorithm is guaranteed to converge, but it may not return the optimal solution. The quality of the solution depends on the initial set of clusters and the value of K.

Kurita [14] developed an efficient agglomerative clustering algorithm for region growing. The algorithm starts with an initial partition of a given image into N segments and sequentially reduces the number of segments by merging the best pairs of segments among all possible pairs in terms of a given criterion. The merging process is repeated until the required number of segments is obtained.

Frigui and Krishnapuram [17] have addressed the major issues associated with conventional partitional clustering.

Pauwels et al.[16] investigated non-parametric clustering for image segmentation. They propose a robust and versatile method that is able to handle unbalanced and highly irregular clusters using intermediate level processing.

Ohm and Ma[18] proposed a feature based cluster segmentation method for image sequences. The algorithm analyses specific features from the image sequence and checks their reliability and evidence locally for images in order to build segments that are probably part of one object.

Ng[19] describes an extension to the conventional k-means algorithms by modifying the splitting rule in order to control the number of cluster members. By adding suitable constraints into the mathematical program formulation, the author developed an approach that allows the use of k-means paradigm to efficiently cluster data sets with a fixed number of elements in each cluster.

The comparison of various clustering techniques and studying their behaviour is important. It is important that an optimal clustering technique is able to choose the correct number of clusters. Dubes and Jain[20] detail comparisons on three classes of clustering techniques.

Zahid et al[15] proposed a new heuristic method for fuzzy cluster-validity. Its principle is based on the evaluation of fuzzy separation and fuzzy compactness of clusters.

3.9 Graph Partitioning Method

The "normalized cuts" method was first proposed by Shi and Malik [23] In this method, the image being segmented is modelled as a weighted undirected graph. Each pixel is a node in the graph, and an edge is formed between every pair of pixels. The weight of an edge is a measure of the similarity between the pixels. The image is partitioned into disjoint sets (segments) by removing the edges connecting the segments. The optimal partitioning of the graph is the one that minimizes the weights of the edges that were removed (the "cut"). **Shi's** algorithm seeks to minimize the "normalized cut", which is the ratio of the "cut" to all of the edges in the set.

3.10 Watershed Transformations

The Watershed transformation considers the gradient magnitude of an image as a topographic surface. Pixels having the highest gradient magnitude intensities (GMIs) correspond to watershed lines, which represent the region boundaries. Water placed on any pixel enclosed by a common watershed line flows downhill to a common local intensity minima (LMI). Pixels draining to a common minimum form a catchment basin, which represent the regions. Brequelaire and Brun [24]

3.11 Multiscale segmentation

Scale-space segmentation or multi-scale segmentation is a general framework for signal and image segmentation, based on the computation of image descriptors at multiple scales of smoothing.

Witkin's [25][26] included the notion that a one-dimensional signal could be unambiguously segmented into regions, with one scale parameter controlling the scale of segmentation.

Lindeberg [27] studied the problem of linking local extrema and saddle points over scales, and proposed an image representation called *the scale-space primal sketch* which makes explicit the relations between structures at different scales, and also makes explicit which image features are stable over large ranges of scale including locally appropriate scales for those. Bergholm [28] proposed to detect edges at coarse scales in scale-space and then trace them back to finer scales with manual choice of both the coarse detection scale and the fine localization scale.

3.12 Probabilistic and Bayesian approaches

Haddon and Boyce [29] use co-occurrence based approach to image segmentation making use of region and boundary information in parallel for improved performance on a sequence of images.

In this method, initial segmentation is done based on the location of the intensities of each pixel and its neighbours in the co-occurrence matrix. Each pixel is then associated with a tuple which specifies whether it belongs to a given region or if it is a boundary pixel. This tentative segmentation was then refined.

The algorithm is less effective if the clusters in the co-occurrence space have substantial overlap due to the imposition of local consistency. Since the techniques use global information in a local context, it was possible to adapt it to varying image characteristics i.e. variation in colour and texture.

3.13 Other segmentation approaches

Medioni and Yasumoto[30] proposed using fractal dimension method for image segmentation.

The main drawback of this method is that segmentation based on single feature extracted from images is not always possible.

Pentland [31] addressed the problem of fractal based description of natural scenes. The authors addressed the following problems:

(i) Representing natural shapes such as mountains, trees, and clouds, and

(ii) Computing such description from image data.

Xu et al.[32] present a segmentation algorithm that is based on partitioning the image into arbitrarily shaped connected regions to minimise the sum of grey level variations over all partitioned regions under the constraints that each partitioned region has a specified number of pixels and that two adjacent regions have significant differences in average of grey levels. A minimum spanning tree has been used to construct these partitions and as such the segmentation problem reduces to tree partitioning problem.

Ojala and Pietikäinen [33] presented an unsupervised texture segmentation method using feature distributions. The proposed algorithm uses distributions of local binary patterns and pattern contrasts for measuring the similarity of adjacent image regions during the segmentation process. Texture information is measured with a method based on local binary patterns and contrast (LBP/C). The segmentation method consists of three phases: hierarchical splitting, agglomerative merging and pixel-wise classification.

Yoshimura and Oe [34] proposed a segmentation algorithm for texture images using genetic algorithms that automatically determines the optimum number of segmentation areas. The authors concluded that the methods are effective for the segmentation of images that contain similar texture fields.

Perner [35] presents a methodology for a case based reasoning image segmentation system. The image segmentation is performed by looking up a case base for similar cases and using the segmentation parameters associated with the matched case. Hence, images are first matched for similarity on the basis of features such as image moments. Similarity is determined on the basis of measure proposed by Tversky [36] for non image information and a weighted similarity measure for image data. If ideal segmentation parameters are known for reference images, by matching new images to these reference images, the same segmentation parameters can be used. The system is shown to perform well on brain CT segmentation.

Kwangsoo Hahn, Youngjoon Han, Hernsoo Hahn [37] have proposed a new ellipse detection scheme using a Randomized Hough Transform (RHT) modified to use line segments. It detects line segments in an edge image and selects every pair of them to test whether they are pertained to the same ellipse of not using the RHT. If they pass the test, they are merged. Since the proposed algorithm uses line segments, it reduces the computation time of the RHT significantly, and detects all ellipses included in an image without missing. The experimental results have shown that its performance is more prominent in detection of ellipses when they are overlapped and partially occluded.

4. Conclusion

This paper discussed the importance of segmentation in image analysis and various methods of segmentation with references for further studies. The evaluation of image segmentation programs is an important field of study. The segmentation method depends heavily on the type of application like 2D Vision (Pictures), 3D Vision (Medical Imaging), Robot Vision etc An Evaluation of Object Segmentation Algorithms for robot vision is given in [38].

Almost all image segmentation techniques proposed so far are *ad hoc* in nature. There are no general algorithms that will work for all images. One of the main objective of segmentation algorithm is to precisely segment the image without under or over segmentation. Kitchen and Rosenfeld [39] discuss the various issues related to under- and over-segmentation of images. The fact that context information is not used in segmentation algorithms is the main reason for segmentation to be inaccurate. For example, a difference in brightness that is not significant in some contexts (such as in fluctuation in a textured background) may well be significant in other backgrounds (such as part of a low contrast border of an object with its surrounding).

Under-segmentation is considered as a much more serious problem as it is easier to recover true segments through a merging process after over-segmentation rather than trying to split a heterogeneous region.

References:

[1] T. Pavlidis, Algorithms for graphics and image processing, Springer, Berlin, 1982.

[2] J. Canny, 1986, “A computational approach to edge detection,” IEEE Trans. Pattern Anal. Machine Intell., vol. PAMI-8, pp. 679-698.

[3] D. Marr, E. C. Hildreth, 1980, “Theory of edge detection,” Proc. R. Soc., B 207, pp. 187-217, London, U.K..

[4] D. Marr, T. Poggio, 1979, “A theory of human stereo vision,” Proc. R. Soc., London, U.K., B 204, pp. 301-328.

[5] M. Hueckel, 1971, “An operator which locates edges in digital pictures,” J. ACM, vol. 18, no. 1, pp. 113-125.

[6] R. M. Haralick, 1984, “Digital step edges from zero crossing of second directional derivatives,” IEEE Trans. Pattern Anal. Machine Intell., vol. PAMI-6, no. 1, pp. 58-68.

[7] Ron Ohlander, Keith Price, and D. Raj Reddy (1978): “Picture Segmentation Using a Recursive Region Splitting Method”, Computer Graphics and Image Processing, volume 8, pp 313-333

[8] Linda G. Shapiro and George C. Stockman (2001): “Computer Vision”, pp 279-325, New Jersey, Prentice-Hall, ISBN 0-13-030796-3

[9] N.W. Campbell, B.T. Thomas and T. Troscianko, Automatic segmentation and classification of outdoor images using neural networks, International Journal of Neural Systems, vol. 8, no. 1, pp. 137-144, 1997a.

[10] N. Papamarkos, C. Strouthopoulos and I. Andreadis, Multithresholding of colour and gray-level images through a neural network technique, Image and Vision Computing, vol. 18, pp. 213-222, 2000.

[11] Zhou Liang , Zheng Jianguo, 554-082, A New Approach for Color Image Edge Detection Using Improved PCNN, Proceedings of the 7th WSEAS International Conference on Simulation, Modelling and Optimization, Beijing, China, September 15-17, 2007, pp. 6-11.

[12] A.K. Jain and R.C. Dubes, Algorithms for clustering data, Prentice Hall, Englewood Cliffs, N.J., 1988

[13] K. Cho and P. Meer, Image segmentation from consensus information, Computer Vision and Image Understanding, vol. 68, no. 1, pp. 72-89, 1997.

[14] T. Kurita, An efficient agglomerative clustering algorithm using a heap, Pattern Recognition, vol. 24, no. 3, pp. 205-209, 1991.

[15] N. Zahid, M. Limouri and A. Essaid, A new cluster validity for fuzzy clustering, Pattern Recognition, vol. 32, pp. 1089-1097, 1999.

[16] J. Pauwels and G. Frederix, Finding salient regions in images, Computer Vision and Image Understanding, vol. 75, pp. 73-85, 1999.

[17] H. Frigui and R. Krishnapuram, A robust competitive clustering algorithm with applications in computer vision, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 21, no. 5, pp. 450-465, 1999.

[18] J.R. Ohm and P. Ma, Feature-based cluster segmentation of image sequences, Proc. IEEE International Conference on Image Processing, pp. 178-181, 1997

[19] M.K. Ng, A note on constrained k-means algorithm, Pattern Recognition, vol. 33, pp. 515-519, 2000.

[20] R.C. Dubes and A.K. Jain, Clustering techniques: the user's dilemma, Pattern Recognition, vol. 8, pp. 247-260, 1976

[21] Dzung L. Pham, Chenyang Xu, and Jerry L. Prince (2000): “Current Methods in Medical Image Segmentation”, Annual Review of Biomedical Engineering, volume 2, pp 315-337

[22] R.M. Haralick and L.G. Shapiro, Survey- image segmentation techniques, Computer Vision Graphics and Image Processing, vol. 29, pp. 100-132, 1985

[23] Jianbo Shi and Jitendra Malik (1997): "Normalized Cuts and Image Segmentation", IEEE Conference on Computer Vision and Pattern Recognition, pp 731-737

[24] J.P. Braquelaire and L. Brun, Image segmentation with topological maps and inter-pixel representation, Journal of Visual Communication and Image Representation, vol. 9, no. 1, pp. 62-79, 1998.

[25] Witkin, A. P. "Scale-space filtering", Proc. 8th Int. Joint Conf. Art. Intell., Karlsruhe, Germany,1019--1022, 1983.

[26] A. Witkin, "Scale-space filtering: A new approach to multi-scale description," in Proc. IEEE Int. Conf. Acoust., Speech, Signal Processing (ICASSP), vol. 9, San Diego, CA, Mar. 1984, pp. 150—153

[27] Lindeberg, T.: Detecting salient blob-like image structures and their scales with a scale-space primal sketch: A method for focus-of-attention, International Journal of Computer Vision, 11(3), 283--318, 1993.

[28] Bergholm, F: Edge focusing, IEEE Transactions on Pattern Analysis and Machine Intelligence, 9:6, pages 726 - 741, 1987.

[29] J.F. Haddon and J.F. Boyce, Image segmentation by unifying region and boundary information, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 12, no. 10, pp. 929-948, 1990.

[30] G.G. Medioni and Y. Yasumoto, A note on using fractal dimension for segmentation, Proc. IEEE Computer Vision Workshop, pp. 25-30, 1984.

[31] A. Pentland, Fractal-based description of natural scenes, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 6, no. 6, pp. 661-674, 1984.

[32] Y. Xu, V. Olman and E.C. Uberbacher, A segmentation algorithm for noisy images: design and evaluation, Pattern Recognition Letters, vol. 19, pp. 1213-1224, 1998.

[33] T. Ojala and M. Pietikäinen, Unsupervised texture segmentation using feature distributions, Pattern Recognition, vol. 32, pp. 477-486, 1999.

[34] M. Yoshimura and S. Oe, Evolutionary segmentation of texture image using genetic algorithms towards automatic decision of optimum number of segmentation areas, Pattern Recognition, vol. 32, pp. 2041-2054, 1999.

[35] P. Perner, An architecture for a CBR image segmentation system, Engineering Applications of Artificial Intelligence, vol. 12, pp. 749-759, 1999.

[36] A. Tversky, Feature of similarity, Psychological Review, vol. 84, no. 4, pp. 327-350, 1977.

[37] Kwangsoo Hahn, Youngjoon Han, Hernsoo Hahn, 540-341, Ellipse Detection Using a Randomized Hough Transform based on Edge Segment Merging Scheme, Proceedings of the 6th WSEAS International Conference on Signal Processing, Robotics and Automation, Corfu Island, Greece, February 16-19, 2007, pp. 1-6

[38] Stefan Florczyk, Evaluation of Object Segmentation Algorithms as Components of Autonomous Video Based Robot Systems, 443-159, Proceedings of the 2002 WSEAS International Conferences, Cadiz, Spain June 12-16, 2002, pp. 1591-1596

[39] L. Kitchen and A. Rosenfeld, Scene analysis using region-based constraint filtering, *Pattern Recognition*, vol. 17, no. 2, pp. 189-203, 1984