IMAGE SEGMENTATION [1]

Introduction

Over the years there has been numerous papers published on image segmentation techniques, far too many for even a small subset to be cited here. A few references are however given at the end of these notes, in particular the paper by Haralick and Shapiro [15] may provide a useful introduction to the subject.
Image segmentation is the decomposition of an image into a set of disjoint nonoverlapping regions. The regions should be uniform and homogeneous with respect to some suitable criteria, such as gray level or texture.
Image segmentation may be performed in order to isolate some object from the background such as an engineering component in a box, a component on a conveyor belt, roads or urban regions in airbourne or satellite imagery, objects or roads in forward looking imagery for an autonomous vehicle. The list is almost endless and there are many techniques that can be used to segment images. A few of these techniques are described briefly in these notes, for example, thresholding, Hough transforms, clustering and Markov Random Fields. For more detail on any of these techniques the reader is refered to the references or to the vast amounts of information which are available on the internet, in particular the search engines and bibliographies located at

- UCLA - 'http://iris.usc.edu/Vision-Notes/bibliography/contents.html'
- Rosenfeld's -
  'ftp://telos.com/VISION-LIST-ARCHIVE/ROSENFELD-BIBLIOGRAPHY'
- The technical University of the Delft -'http://www.ph.tn.tudelft.nl/biblio.html'

searches of these for work on segmentation will result in an ample amount of bedtime reading for those interested in taking the subject further.
Also on the internet are many multimedia sites which provide tutorial information on subjects in image processing in particular

- The hyper-media Image Processing Reference at Edinburgh
  'http://www.dai.ed.ac.uk/staff/personal_pages/simonpe/hipr/html/hipr_top.htm'.
- The Computer Vision home page located at 'http://www.cs.cmu.edu/ cil/vision.html'.

Thresholding

Introduction

The technique of thresholding is particularly useful in image processing as a tool for segmentation as it is simple and returns the required disjoint, connected regions with closed boundaries. Essentially, at each pixel a decision is taken regarding its status, either above or below the chosen threshold. Ideally all image pixels that are below the threshold will be outside the object, whilst those pixels that are above the threshold will be in the object. This works well if the object being segmented is of uniform gray level and is well distinguished from its background.

[1]Lecture given at course on 'Advanced Image Processing', 17-18 April 1996, SIRA technology Center,Chislehurst, Kent, UK.

Global, Adaptive and Optimal thresholding

In global thresholding the value of the threshold is maintained at a constant level throughout the image, this approach being the simplest and being suitable under the previous mentioned conditions.

For cases where the background gray level varies and perhaps also the contrast of the object itself adaptive thresholding is useful. A threshold that works well in one area of the image may be very poor in another area hence it may be desirable to use a threshold that varies with position. This could be based on some suitable image statistic, Castleman [4] and Kittler [22].

Objects which have smoothly varying boundaries will cause segmentation problems as small changes in thresholds may produce large changes in the boundaries of the objects. An image that contains an object against a background has a bimodal histogram, that is one for which there are two peaks. The first (*and possibly larger*) peak corresponds to the background whilst the second corresponds to the object. The minimum between the two peaks will correspond to the pixels that are on and around the boundary between the object and its background. Optimal thresholding can be used by selecting this optimal point (*minimum*) between the two peaks and thus minimising the likelihood of errors in the boundary. There is also the technique described by Kullback [23] which assumes that the image histogram is composed of a mixture of two gaussians, the task being to again to locate the optimal threshold.

Although thresholding is very useful it can be difficult to locate an optimal threshold, particularly if the original image is subject to noise or has a significantly skewed histogram. Another and newer technique for segmentation which may avoid these problems is called 'Region Competition', this attempts to provide a new framework which will unify many of the existing ideas behind image segmentation. The interested reader is refered to Zhu et. al. [33].

Hough Transforms

Introduction

The idea behind the original Hough transform (Hough [17]) was for the detection of collinear features within images. This being achieved by mapping features from image space into a parameter space describing the feature required. The work was later extended to generalised shapes as described in Ballard [1].

Line and Circle detection

Given a point (x_i, y_j) together with the equation for a line $y_i = m.x_i + c$, there are an infinite number of lines that pass through the point (x_i, y_j). If however we consider the same equation in parameter space $c = -mx_i + y_i$ then we have a straight line for a given point (x_i, y_i). Another point (x_j, y_j) will have a straight line associated with it and this line will intersect the line associated with (x_i, y_i) at some point $(m^{'}, c^{'})$, figure 1 illustrates the idea behind this.
Unfortunately this parameterisation experiences difficulties particularly with singularities occurring with near vertical lines as $m \to \infty$. This is overcome using a different parameterisation

$x \cos\theta + y \sin\theta = \rho$

where ρ is the length of a normal from the origin to the line and θ is the orientation of ρ with respect to the x-axis. The points (x_i, y_i) are the coordinates of edge segments [2] in the image. These points are known and serve as constants in the parametric equation leaving (ρ, θ) as the unknowns. Plotting possible (ρ, θ) values defined by each (x_i, y_i), then points in image space map to curves in polar Hough parameter space. This point-to-curve transformation is the Hough transformation for straight lines.

The algorithm is implemented by applying a quantisation to the parameter space resulting in a set of finite intervals (*accumulator cells*). The algorithm runs on a gradient (*edge*) image and for each (x_i, y_i) in the gradient image space the transformation is applied resulting in a set of (ρ, θ) parameterisations, the *accumulator cells* for these are then incremented. Resulting peaks in the accumulator array correspond to evidence implying straight lines in the image space.
The same procedure can be used for the detection of circles in imagery using the parametric equation for a circle

$(x - a)^2 + (y - b)^2 = \rho^2$

where a and b are the coordinates of the center of the circle and ρ is the radius.

Figure 2, shows an experiment concerning the segmentation via the location of wheels of a car. The two black peaks in the lower image corresponding to the location of the wheels of the vehicle.

Fast Implementations

The disadvantage of the Hough transform technique may appear to be the computational complexity of the algorithm. However work has been done on fast and parallel versions of the algorithm together with hardware implementations.
For an overview of some of these see Hussain [18], for various types of parallel and hardware implementations see for example the papers by Hanahara [14], Chung [5] and Rosenfeld [32].

Clustering via Belief Networks

Introduction

The technique of standard clustering for image segmentation uses the measurement space clustering process to define a partition in measurement space. Each pixel is then assigned the label of the cell in the measurement space partition to which it belongs. The image segments are defined as the connected components of the pixels having the same label. The essential clustering techniques are well documented and again the reader is again refered to the paper by Haralick [15] for full details.

Clustering of evidence can be used to deal with situations in which the required region to be segmented is more complex. One technique is that described by Ducksbury [8], [10] and [11] which uses a Pearl Bayes (*Belief*) Network to cluster evidence for the location of urban regions in airborne infra-red linescan images and for the location of driveable regions in autonomous land vehicle imagery.

The problem is generically defined as the location of some region in an image. This problem will be approached by taking several statistical measures from small patches of an image these are treated as a set of judgements (*virtual evidence in Pearl's notation*) about the content of

[2] obtained after the application of some suitable edge operator (SOBEL, Canny etc)to the image

the patches. This evidence is then combined into a belief of the patch belonging to the defined region. Figure 3 shows a conceptual diagram of the process in which the raw image is at the bottom of the pyramid with higher levels of extracted knowledge at the following levels.

Pearl Bayes (Belief) Network

Definition 0.1 *Bayesian networks are directed acyclic graphs, such that a graph G is a pair of sets (V,A) for which V is non-empty. The elements of V are vertices (*nodes*) and the elements of A are pairs (x,y) called arcs (*links*) with* $x \in V$ *and* $y \in V$*.*

Figure 4, shows a simple Pearl Bayes network (Pearl [27]). If we consider the link from node B to A then the graph G consists of the two subgraphs G^+_{BA} and G^-_{BA}. These two subgraphs contain the datasets D^+_{BA} and D^-_{BA} respectively. Node A separates the two subgraphs $G^+_{BA} \cup G^+_{CA} \cup G^+_{EA}$ and G^-_{AF}. Given this fact we can write the equation :

$$P(D^-_{AF}|A_i, D^+_{BA}, D^+_{CA}, D^+_{EA}) = P(D^-_{AF}|A_i) \tag{1}$$

by using Bayes rule the belief in A_i can be written as

$$BEL(A_i) = \alpha\lambda_F(A_i).\sum_{j,k,l} P(A_i|B_j, C_k, E_l).\pi_A(B_j).\pi_A(C_k).\pi_A(E_l) \tag{2}$$

This equation is computed using three types of information

- Causal support π (*from the incoming links*).
- Diagnostic support λ (*from the outgoing links*).
- A fixed conditional probability matrix (*which relates A with its immediate causes B,C and E*).

It is the multi-dimensional fixed conditional probability matrix that forms the clustering of the evidence (*this being the prior knowledge in the model*) according to the following rules.

$$P(Bf_i|s1_j, s2_k, s3_l) = \begin{cases} 0.75 & if \;\; i = j = k = l \\ 0.25/\alpha & if \;\; (i \neq j = k = l) \wedge (0 < |i-j| \leq C) \\ 1.0/\beta & if \;\; \neg\,(j = k = l) \\ & \quad \wedge(\max(j,k,l) - \min(j,k,l) \leq 2C) \\ & \quad \wedge(\min(j,k,l) \leq i \leq \max(j,k,l) \\ 0.0 & otherwise \end{cases} \tag{3}$$

such that $\sum_{j,k,l} P(Bf_i|s1_j, s2_k, s3_l) \leq 1 \;\; \forall i$
where $C = 1$,
i,j,k,l range over the number of variables in Bf, $s1$, $s2$ and $s3$ respectively.
α and β represent the number of different values of i satisfying the constraint.
A similar set of rules applying for $P(B|Bf, Bc)$.

These rules cluster the evidence along the assumption that if all the evidence is in agreement then we would naturally have a higher confidence in some event (*a region existing*) occurring than if the evidence was in disagreement. Results of this segmentation are shown in figure 6.

Markov Random Fields

Introduction.

This work is based upon an algorithm which uses a third order Hidden Markov Mesh Random Field (HMMRF) for the segmentation of images, the algorithm was described initially by Devijver [6], [7]. The main emphasis of this section is to illustrate two important uses of the algorithm. Firstly, how the basic algorithm can be used to segment out objects from background in infrared images as well as urban and non-urban regions from airborne images. Secondly it will be illustrated how the algorithm can be enhanced in order to model textures, the resulting 'texture models' can then be fused together and used to segment images which contain several Brodatz textures.

The fundamental idea behind this work is that given some image, we wish to segment it into a number of homogenous regions. The grouping of the pixels in the image into these regions is based upon local properties and neighbourhood relationships. It is these neighbourhood relationships (*that will be referred to as 'contextual information'*) that are encoded into a set of transitional probabilities in the Markov model.

The basic algorithm [3] has essentially two stages namely the labeling stage and the learning stage. The former is concerned with the modeling of the image (*the segmentation of the image into homogeneous regions ie. the assignment of an optimum label to each image pixel*) whilst the latter is concerned with the parameter estimation problem (*ie. taking the current optimum labeling and using it to improve the model parameters*). The algorithm processes an image pixel by pixel in a raster manner and has the advantage in that the learning stage is unsupervised and the only essential parameter required to be entered by the user is the number of states that are required in the model.

Definition of a 3rd order HMMRF.

Firstly, let the image be $M \times N$ in size and then $\mathbf{X}_{M,N}$ denotes a set of feature vectors $X_{m,n}$. In the simplest case these feature vectors will simply be the gray level intensity. Let $\mathbf{\Lambda}_{M,N}$ denote a set of labels $\lambda_{m,n}$, where a label will define the class to which a particular pixel of the image belongs.

$$P(\lambda_{m,n}/\{\lambda_{k,l}|k < m \quad or \quad l < n\}) = P\left(\lambda_{m,n} \Big/ \begin{array}{l} \lambda_{m-1,n-1}\ \lambda_{m-1,n} \\ \lambda_{m,n-1} \end{array} \right)$$

for all points (m,n) such that $1 < m \leq M$ and $1 < n \leq N$, with boundary conditions existing along the first row and column.

The MMRF is said to be 3rd order due to the fact that $\lambda_{m,n}$ has a dependency [4] upon its three neighbouring labels, namely $\lambda_{m-1,n-1}$, $\lambda_{m-1,n}$ and $\lambda_{m,n-1}$.

The model is assumed throughout to be *spatially homogeneous*, meaning that we can assume that the transitional probabilities are totally independent from the position in the image. This allows us to write $P_{q/rst}$ as an abbreviation of $P(\lambda_{m,n}=q/\lambda_{m-1,n}=r;\, \lambda_{m-1,n-1}=s;\, \lambda_{m,n-1}=t)$

[3] *limited space prevents a complete description of the mathematics of both the algorithm and its derivation, for those interested refer to [6] and [7].*

[4] *In a second order MMRF the dependency of $\lambda_{m,n}$ would exist with the two neighbours $\lambda_{m-1,n}$ and $\lambda_{m,n-1}$.*

where q, r, s and t are contained within the state-space of the model. This is read as the probability of label q being chosen given the three neighbouring labels r, s and t.

The Algorithm.

In the initial stages of the algorithm a model is created by fitting a set of Gaussian distributions (*one per state, denoted by* $p_q(X)$) to the histogram of the image. The model also consists of an initial set of transitional probabilities which are defined under the assumption that any two neighbouring pixels in the image are more likely to have values close to each other than at either end of the gray level spectrum.

The labeling stage is then a 2-dimensional set of recurrence relations described in [6] and [7] which uses the information contained in $p_q(X)$ together with the set of transitional probabilities $P_{q/r,s,t}$ in order to cluster the image pixels into a set of homogenous regions.

The learning stage is based upon a class of techniques which are known as *decision directed*. The decision directed re-estimation technique effectively transforms the updating formula into a set of relatively simple counting formula, where $\mathbf{I}[:]$ is taken to be an indicator function[5]. The learning stage can now be described as follows, the $P_{q/r,s,t}$ is given by the following expression.

$$\frac{\sum_{m=2}^{M}\sum_{n=2}^{N}\mathbf{I}\begin{bmatrix} \tilde{\lambda}_{m-1,n-1}=s & \tilde{\lambda}_{m-1,n}=r \\ \tilde{\lambda}_{m,n-1}=t & \tilde{\lambda}_{m,n}=q \end{bmatrix}}{\sum_{m=2}^{M}\sum_{n=2}^{N}\mathbf{I}\begin{bmatrix} \tilde{\lambda}_{m-1,n-1}=s & \tilde{\lambda}_{m-1,n}=r \\ \tilde{\lambda}_{m,n-1}=t & \end{bmatrix}}$$

with special cases existing for the first row and column. For instance the first column is defined as

$$P_{q/r} = \frac{\sum_{n=2}^{N}\mathbf{I}[\tilde{\lambda}_{n-1,1}=r, \tilde{\lambda}_{n,1}=q]}{\sum_{n=2}^{N}\mathbf{I}[\tilde{\lambda}_{n-1,1}=r]}$$

and similarly for $P_{q/t}$ along the first row. The set of distributions p_q are given by

$$p_q(\zeta_i) = \frac{\sum_{m,n|x_{m,n}=\zeta_i}\mathbf{I}[\tilde{\lambda}_{m,n}=q]}{\sum_{m,n}\mathbf{I}[\tilde{\lambda}_{m,n}=q]}$$

The above equations are performed for all combinations of q, r, s and t in the state space. Essentially therefore it is simply examining every possible 2×2 neighbourhood throughout the image and counting the number of occurrences of particular combinations (*or patterns*) of labels. A resulting 4-state segmentation of an infrared image is shown in figure 5, where the three lower states (*labels*) have been merged into the background.

Segmentation of Urban Regions.

In this instance the images that we are dealing with are infra-red linescan images taken over the Bedfordshire area at a height of 3000 feet. We wished to look at techniques for the automatic location of features such as urban regions (*also, but not mentioned here, the location of road networks*). Because of certain constraints such as being limited to single band 8-bit data the approach taken is as follows. The image is preprocessed to obtain some statistical information

[5] *If the expression within the brackets is true then the indicator function returns a 1 otherwise it returns a 0.*

which can be used in an attempt to classify its content into urban/non-urban. It will be seen that this statistical classification is noisy and rather basic, the HMMRF algorithm is then used to 'tidy up' this classification by segmenting it into homogeneous regions. A mesh of windows is placed over the image, with each window being typically 16×16 pixels in size. For each window a set of elementary statistics are computed.

- the number of significant edges.
- the number of significant extrema.
- comparison of the histogram using a chi-squared measure with a set of standard Gaussians.

These are presented in order of their effectiveness and are coded into a single statistic per window. Figure 6 shows an original image with an outline of the urban region indicated. The results are interpreted as follows, for a simple 2-state model we have only urban or non-urban regions, for any model with more than 2 states we have regions of high probability of being urban through to regions of low probability of being urban. The result shown is for a 4-state model with a single iteration, here only the region that has the highest probability of being urban is illustrated[6].

The window size can be reduced to give a finer outline of the urban region and a number of iterations can be used to allow the learning stage to improve the initial estimate. In practice it has been found that although the window size can be reduced to 6×6 pixels the best results do occur at around 16×16. This is partly due to the fact that as the window size is reduced the statistics being used become less reliable and in addition to this the number of learning iterations required to remove errors in the classification increases. One of our main objectives is for a coarse level processing of an image in the shortest possible time.

Segmentation of Brodatz Textures.

For the segmentation of Brodatz textures [3] the basic idea is that if it is possible to derive a model [7] which describes a texture then it should also be possible to fuse several of these models together. We should then be able to segment a composite texture image using the new composite model that has been obtained.

Combining Markov Models

The process of combining several models together itself makes use of a model which describes the rules for the merge. Figure 7 illustrates this procedure for the merging of two 2-state models into one 4-state model. The notation $m^3_{i,j}$ denotes the probability of making a transition from model i to model j. Whereas previously for a two state model the process could either remain in the current state or make a transition into its neighbouring state, now however a transition can also be made into either of the states that are in the second model.

Each texture is histogram equalised independently prior to the start of the process to remove the possibility of detection due to first order statistics. The method has the property of rapid convergence to a local maximum and for all of these tests the algorithm was run with a 2-state

[6] *These regions could be considered as a set of contours .*

[7] *the use of the word derive in this sense means to train on a given texture using the learning stage of the algorithm.*

model for 10 learning iterations to obtain the set of model parameters p_q, P_q, $P_{q/r}$, $P_{q/t}$ and $P_{q/r,s,t}$ for each texture. Once these have been obtained the models will then be merged into a composite model and this can be applied to a composite image of the two textures. The transitional probabilities used in model 3 allowed for a 90% probability of staying in the current texture model and a 10% probability of making a transition into another texture model.

Figures 8 shows a 4-state segmentation of a composite texture (*2 states per texture*), first with the contextual information from the transitional probabilities $P_{q/r,s,t}$ removed and then with the contextual information included. (*the results are displayed such that if a given pixel has a label with a value corresponding to either of those in model 1 then it is displayed as black , otherwise it is displayed as white*).
The segmentation without contextual information is basically the segmentation using knowledge of the differences in the histograms of the two textures. Whilst the segmentation with contextual information is where the Markov Model is used to resolve the ambiguities.

Discussion

The work illustrates that the basic algorithm proposed by Devijver can be used and readily extended for a number of cases; firstly, as a standard (*contextual*) segmentation tool used on preprocessed data for the location of urban and non-urban regions in airborne images, secondly, for the development and fusion of texture models which can then be used for the segmentation of images composed of several textures.
The performance can be greatly improved through the use of parallel architectures. At present the quality of the segmentation appears comparable with those from the standard sequential case, but the approach will need to be examined in more detail with reference to this and also other possible architectures and approaches for parallelism.

References

[1] Ballard D.H., et al., *'Generalising the Hough Transform to detect arbitrary shapes'*, Pattern Recognition, 13:111-122, 1981.

[2] Bhanu B., Lee S., Ming J., *'Adaptive image segmentation using a genetic algorithm'*, Proceedings, Image Understanding Workshop (Palo Alto, CA, May 23-26, 1989), Morgan Kaufmann, San Mateo, CA, 1043-1055.

[3] Brodatz, P., 1966, *'Textures - a photographic album for artists and designers'*. Dover, New York.

[4] Castleman K.R., *'Digital Image Processing'*, Prentice Hall, 1996

[5] Chung H.Y.H., Li C.C., *'A systolic array processor for straight line detection by modified Hough transform'*, IEEE Workshop Comput. Arch. Pattern Analysis Database Mgmnt., pp 300-303, 1985.

[6] Devijver, P.A., Oct 1986, *'Segmentation of binary images using 3rd order Markov Mesh image models'*, Proc. 8th Int. Conf. Pattern Recognition, Paris, pp 259 - 261.

[7] Devijver, P.A., 1988, *'Image segmentation using Causal Markov Random Field models'*. Pattern Recognition. J.Kittler (ed) Lecture Notes in Computer Science 301, Springer-Verlag.

[8] Ducksbury P.G., *'Parallel texture region segmentation using a Pearl Bayes Network'*, British Machine Vision Conference BMVC-93, University of Surrey, Giuldford, Sept, 1993.

[9] Ducksbury, P.G., 1991, *'Parallel Model based texture segmentation using a 3rd order Hidden Markov Model'*, 4^{th} Int Conf. Image Prcoessing and its Applications, April 1992, pp 514-517, Maastricht, The Netherlands.

[10] Ducksbury P.G., *'Driveable region detection using a Pearl Bayes Network'*,IEE Colloqium on Image Processing for Transport Applications, London, 9 Dec 1993.

[11] Ducksbury P.G. Booth D.M., Radford C.J., *'Vehicle detection in infrared linescan imagery using belief networks'*, 5^{th} Int. Conf. Image Proc. and Applications, Heriot-Watt University, Edinburgh, 3-5 July 95.

[12] Gong, X., Huang, N.K., 1988, *'Textured image recognition using Hidden Markov Model'.* ICASSP, 1128-1131.

[13] Gunsel B., Panayirci E., *'Segmentation of range and intensity images using multiscale Markov random field representations'*, ICIP-II, 187-191.

[14] Hanahara K., Maruyama T., Uchiyama T., *'A real-time processor for the Hough transform'*, IEEE PAMI 10:121-125, 1988.

[15] Haralick R.M., Shapiro L.G., *'Image segmentation techniques'*, Computer Vision, Graphics, and Image Processing, vol. 29, 1985, 100-132.

[16] Hassner, M., Sklansky J., 1980, *'The use of Markov Random Fields as models of texture'.* CGIP, 12, 357-370.

[17] Hough P.V.C., *'Method and means for recognising complex patterns'*, US. Patent 3,069,654; 1062.

[18] Hussain Z., *'Digital Image Processing'*, Ellis Horwood, 1991.

[19] Jain A.K., Nadabar S.G., *'MRF model-based segmentation of range images'*, Third International Conference on Computer Vision (Osaka, Japan, December 4-7, 1990), IEEE Catalog No. 90CH2934-8, 1990, 667-671.

[20] Khotanzad A., Bouarfa A., *'Image segmentation by a parallel, non-parametric histogram based clustering algorithm'*, Pattern Recognition, vol. 23, 1990, 961-973.

[21] Khotanzad A., *'Unsupervised segmentation of textured images by edge detection in multidimensional features'*, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 11, 1989, 414-421.

[22] Kittler J., Illingworth J., *'Threshold selection based on a simple image statistic'*, CVGIP 30, pp 125-147, 1985.

[23] Kullback S., *'Information theory and Statistics'*, Wiley, New York, 1959.

[24] Lerner B.T., Campbell W.J., LeMoigne J., *'Image segmentation by integration of edge and region data: The influence of edge detection algorithms'*, Proceedings, ARPA Image Understanding Workshop (Monterey, CA, November 13-16, 1994), Morgan Kaufmann, San Francisco, CA, 1994, 1541-1545.

[25] Pavlidis T., *'Why progress in machine vision is slow'*, Pattern Recognition Letters 13, pp 221-225, 1992.

[26] Parvin B., Medioni G., *'Segmentation of range images into planar surfaces by split and merge'*, Proceedings, CVPR '86 (IEEE Computer Society Conference on Computer Vision and Pattern Recognition, Miami Beach, FL, June 22-26, 1986), IEEE Publ. 86CH2290-5, 415-417.

[27] Pearl J., *'Fusion, Propagation, and structuring in Belief Networks'*, Artificial Intelligence 29 (1986) pp 241 - 288.

[28] Perez A., Gonzalez R.C., *'An iterative thresholding algorithm for image segmentation'*, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 9, 1987, 742-751.

[29] Perry A., Lowe D.G,*'Segmentation of textured images'*, Proceedings, CVPR'89 (IEEE Computer Society Conference on Computer Vision and Pattern Recognition, San Diego, CA, June 4-8, 1989), Computer Society Press, Washington, DC, 319-325.

[30] Radford C.J., *'Vehicle Detection in Open world scenes using a Hough Transford Technique'*, 3^{rd} Int Conf. Image Prcoessing and its Applications, pp 78-80, University of Warwick, July 1989.

[31] Rosenfeld A., *'Some pyramid techniques for image segmentation'*, in: V. Cantoni, S. Levialdi, eds., Pyramidal Systems for Computer Vision (Proceedings of a NATO Advanced Research Workshop, Maratea, Italy, May 5-9, 1986), Springer, Berlin, 1986, 261-271.

[32] Rosenfeld A., Ornelas J., Hung Y., *'Hough transform algorithms for mesh-connected SIMD parallel processors'*, CVGIP, 41:293-305, 1988.

[33] Zhu S.C., Lee T.S., Yuille A.L. *'Region Competition : Unifying Snakes, Regions Growing, Energy/Bayes/MDL for Multi-band Image Segmentation'*, Division of Applied Sciences, Harvard University, Cambridge, MA 02138, USA, 1995.

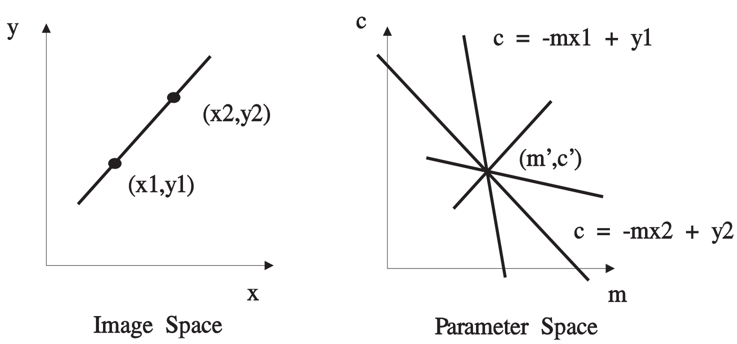

Figure 1

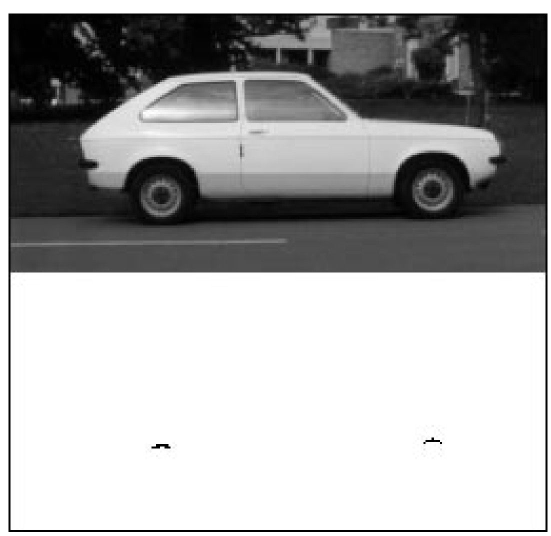

Figure 2

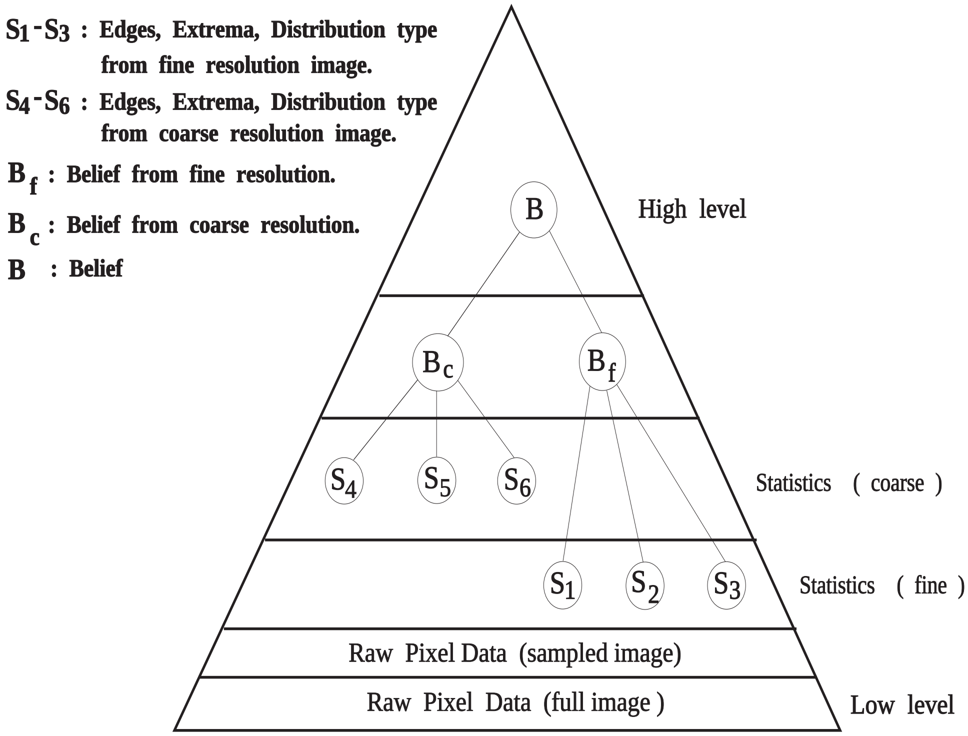

Figure 3

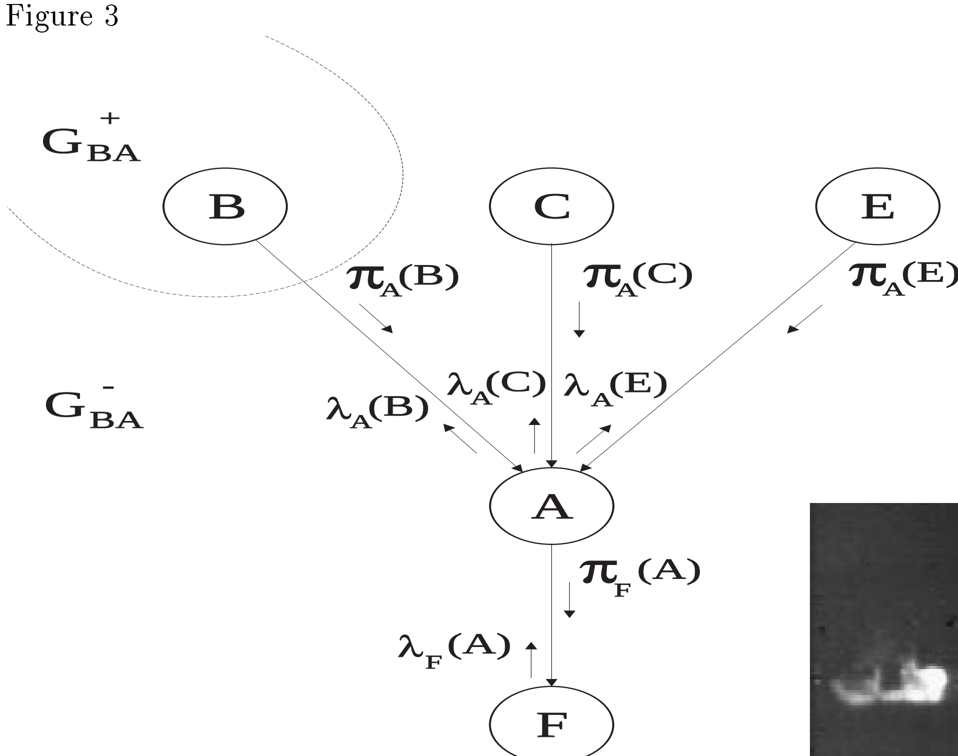

Figure 4

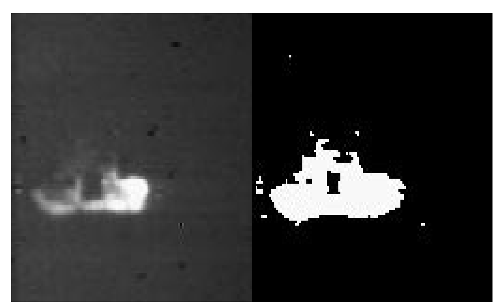

Figure 5

Figure 6

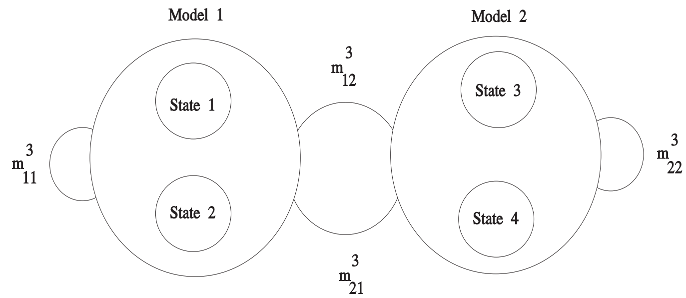

Figure 7

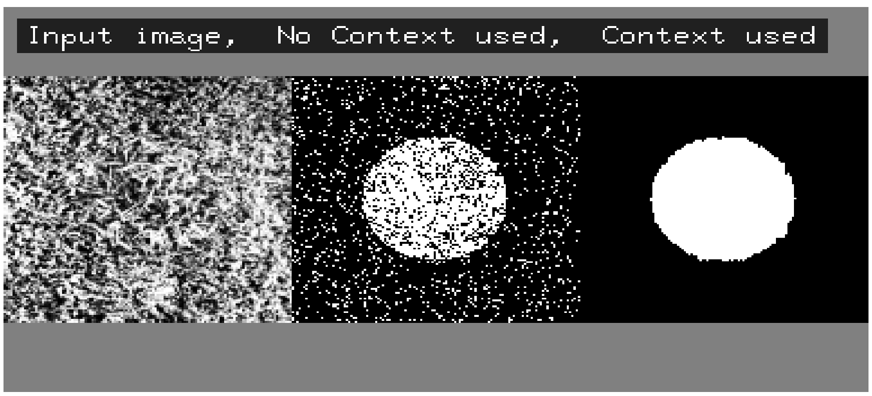

Figure 8