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Activity Structures Based Framework for Image Segmentation

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Abstract: Despite the numerous work in image segmentation many people are still looking for a segmentation methodology that can succeed with general images. Activity Structures proved to be successful in designing various knowledge-based systems. This paper focuses of this methodology for image segmentation. It starts by introducing the modeling formalism and showing that it can be used to model linear systems such as image segmentation whose coefficients are rational. Colors are represented as fuzzy sets and any operation on such colors can be then be achieved via the fuzzy disjunction operators. Image regions are represented as fuzzy relations and operations on their similarities and differences can be achieved via the BK-Relational products. The image segmentation system is considered as a reasoning system that can analyse its performance and make necessary changes to their behaviour in order to satisfy certain predefined control goals. Four types of hybrid controllers have been considered for the physical representation of the reasoning system. Every hybrid controller contains a fuzzy classifier and a self-organizing neural network.

Key Words: Activity Structures; BK-Products; Fuzzy Controller, Self-Organizing Map, Neural Networks, Image Segmentation

Introduction

Activity Structures and Image Segmentation Modelling: One of the primary issues in Artificial Intelligence has been the choice between two fundamentally different approaches of building Intelligent Systems-traditional symbolic approach and the numeric artificial neural networks. Activity Structures approach is an attempt to bridge the gap between these two paradigms and to take advantage of the relative merits of each. Research on Activity Structures started by L.J. Kohout (1976) in modelling the human brain activities and structures. For the last three decades it has been extended and applied to conceptual and structural design of several sophisticated systems such as, Information Retrieval System (Kohout, Keravnou and Bandler, 1984), Survivable Computer Architectures (Kohout and Mohammed, 1992), Medical Diagnostic Systems (Kohout, Stabile, Bandler and Anderson, 1995) and Engineering Front-End Systems (Granville and Kohout, 2001).

Activity structures model systems using three representational structures (Kohout and Mohammed, 1990); the functional substrata, the knowledge substrata and the physical substrata. The knowledge substrata models the system's objects and relations. The functional substrata identifies the static primitive operations/operators for organizing computations around objects and relations. The physical substrata represents the underlining inferential and control engine for manipulating the knowledge based on the primitive operations. Activity Structures represents knowledge using a Relational Architecture. Relations play an important role in building architectures of intelligent systems for information processing as well as control engineering. The main advantage of relational computations is that they are inherently parallel and can work with imprecise information expressed by interval fuzzy logics. Relational representation of knowledge makes it possible to perform all computations and decisions in a uniform way by means of Relational Products or the BK-products (Kohout and Bandler, 1992). Basically, the inferential and control engine utilizes a Fuzzy Controller that infers its decisions using the BK-Products. The relational products make it possible to discover and further analyze structural relationships between individual items of data, which can not always be adequately analyzed by the methods using conventional probability based statistics for lack of a sufficient volume of data.

However, in the field of image processing the uncertainty of knowledge is a significant factor. This happens in many directions, for example in the capturing process, where digitization effects and noise reduces the amount of visual information. The Human Perceptual System also includes a natural and almost unnoticed process that is performed in order to identify portions of a visual image as consistent objects. This is an adaptive operation, which takes into consideration several static and dynamic attributes. Calculating some of these attributes, is an essential task for the image segmentation problem. This kind of uncertainty strongly influences the segmentation results where the objects of the image have to be identified and partitioned. Fuzzy logic is therefore considered as a useful tool to represent and handle ambiguity in this application as well.

Indeed, effective image segmentation modelling is a very difficult task and many algorithms have been proposed for the segmentation of images, but none have shown widespread applicability (Beauchemin and Thomson, 1997). For this reason, image analysts had a pragmatic, as opposed to dogmatic, approach to segmentation: use whatever gives the best results. This leads the image analyst to enhance existing techniques and propose their own. Eventually there will exist virtual environments inhabited by variety of segmentation techniques. Because of these variations, increasing research attention is brought to issues of good segmentation and detection.

Mathematically speaking, image segmentation is the process of partitioning the image into a set of uniform and disjoint regions. This process is carried out on the basis that objects (or substantial parts of them), are represented by regions, which are homogeneous according to intensity, color and texture. The segmentation task is a significant stage for machine vision, image and video compression, content based information retrieval and other applications. Several methods have been presented in the literature, which attempt to solve the problem from different viewpoints including (Haralick and Shapiro, 1985):

- Histogram Thresholding.
- Edge Detection.
- Tree/Graph based Approaches.
- Region Growing.
- Clustering.
- Probablistic and Bayesian Approaches.
- Neural Network Segmentation.
- Fractal Segmentation.
- Topological Segmentation.

That is beside many other hybrid segmentation techniques. However, there is no way to decide which method/technique is suitable for isolating different objects from their background. Almost all image segmentation techniques proposed so far are ad hoc in nature. There is no general algorithm that will work for all images (Fu, Mui, 1981).

The Image Representation Substrata: Traditionally, image representation resembles what image acquisition devises stores in the computer memory. It is a matrix of colored pixels. At hardware level, color images are usually captured, stored and displayed using elementary R, G, B component images on n X n matrix of k grey levels (where k:2→256). The color attributes of a color image pixel can be represented as a 3-D vector in the color space as shown in Fig. 1. RGB color model is an additive model suitable for CRT screen devices. CMY color model is a subtractive model which suitable for color devices that reflects light. We can represent the RGB model by using a unit cube. Each point in the cube (or vector where the other point is the origin) represents a specific color. This model is the best for setting the electron guns for a CRT. Note that for the "complementary" colors the sum of the values equals white light (1, 1, 1). For example:

red (1,0, 0) + cyan (0, 1, 1) = white(1, 1, 1)
green (0,1,0)+magenta (1,0,1) = white(1, 1, 1)
blue (0, 0, 1)+yellow (1,1,0) = white (1, 1, 1)

The color space distribution h(r,g,b) of a color image can be spread and can also be condensed. Its diversity and complexity are well acknowledged. The only constraint is that the visible color space volume is limited. For simple colors it tends to be condensed on a few locations but the condensation itself may still be broadly spread. Because of its 3-D nature, it is not easy to visualize a color space distribution when we are analyzing the colors.

The luminance values can be extracted from the RGB representation using a simple linear transformation (Gevers and Smeulders, 1996):

wb = R+G+B
rg = R-G
yb = 2B-R-G

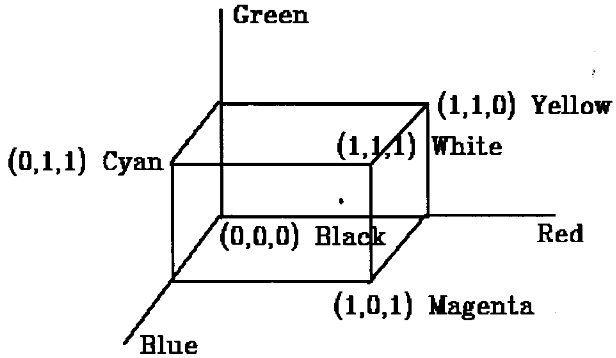

Fig. 1: RGB Color Model

Using the above imagination, the color segmentation process recognizes colors as crisp values and often it comprises two stages: coarse segmentation and refinement. In that direction, the segmentation of a color image means that it has to be decomposed into identifiable items. For this purpose most of the crisp segmentation techniques utilizes the pixels histogram: a plot of the number of pixels in the image with each of the possible brightness levels. Based on this knowledge advanced traditional edge finding techniques has been created. Variety of such techniques are well known in the literature. For example, the sharpening Laplacian operators and the Gradient neighborhood operators such as the Sobel and Kirsch operators produce an image in which the pixel brightness is proportional to the maximum gradient of brightness in the original image.

On more broad sense, an image is a group of components, which may consist of sub-components. By continually group these sub-components, the description of the image yields. Image segmentation techniques are used to obtain these components of the image, in the form of image segments and regions. Regions should provide a rich set of representation descriptors to cover colour, texture, shading, shape and context. In fact segmenting images into regions is a knowledge-based process. There are many issues involved with the regional segmentation-regions similarity, regions subsethood and region relationships. Such issues require expressive representational models - which gives the ability to treat images more efficiently and at a higher level of abstraction.

Fuzzy logic introduces very powerful tool in this direction. Having such representation theory, an image color value can be interpreted as a fuzzy set. There are many techniques proposed for transferring the hardware representation color image file into fuzzy color sets, such as; Fuzzy labelling (Plataniotis and Venetsanopoulos, 1998), Fuzzy Distance (Chatzis and Pitas 1999) and Color Space (Sharma and Trusell 1997). With such color representation one can perform variety of image arithmetic. This includes adding, blending (adding different fractions of two images), subtracting, multiplying, dividing, taking the absolute difference, or keeping the brightest or darkest pixel values at each location. . In order to perform such color arithmetics one must model the fuzzy union of color sets. For this purpose, let A and B are two color sets, their disjunction U can be measured using one of the following formulae (Zimmermann 1996):

AuB = max(A,B)
AuB = A+B-AB
AuB = min(1,A+B)
AuB = (A+B-2AB)/(1-AB)
AuB = (A+B)/ (1+AB)

The Color set compliment can be calculated as follows:

A^(x) = 1 - A(x).

The intersection of two color sets can be defined as follows:

(AnB)(x) = min[A(x),B(x)]

Fuzzy color interpretation is of importance in order to increase robustness, versatility and reliability of technical vision systems. With crisp color sets a pixel is either a member of the specific set or not. Fuzzy color sets, on the other hand, allow elements to be partially in a set. Each element is given a degree of membership in a set. This membership value can range from 0 (not an element of the set) to 1 (a member of the set). It is clear that if one only allowed the extreme membership values of 0 and 1, that this would actually be equivalent to crisp sets. A membership function is the relationship between the values of an element and its degree of membership in a set. The value, M, is the amount of membership in the set. Given three fuzzy sets (A, B, C), they each have associated membership functions (Ma, Mb, Mc). Since there is no ambiguity, A can be interchanged with Ma, B with Mb and C with Mc. If x is the parameter or value that determines which set(s) the data belongs to, the membership functions can be written as A(x), B(x) and C(x).
Such arithmetic can also help in developing primitive segmentation. A simple color threshold operation can be defined, which can be used to characterize objects according to the pixel attributes that it constitutes. In this direction, one can use Fuzzy C-Mean technique (Chuai-Aree *et al.,* 2001) for defining the threshold function. This technique utilizes simple statistical features for comparing pixel blocks based on their mean and standard deviation. We can define also further primitives operations such as; alpha-cut, support-set, and core-set. The alpha-cut operations are used for extracting crisp regions. An alpha-cut of the membership function A (denoted aA) is the set of all x such that A(x) is greater than or equal to alpha (a). Similarly, a strong alpha-cut (denoted a+A) is the set of all x such that A(x) is strictly greater than alpha (a). Mathematically,

aA = {x | A(x) >= a}
a+A = {x | A(x) > a}

"That is, the alpha-cut (or the strong alpha-cut) of a fuzzy set A is the crips set aA (or the crisp set a+A) that contains all the elements of the universal set X whose membership grades in A are greater than or equal to (or only greater than) the specified value of alpha." aA and a+A are crisp sets because a particular value x either is or isn't in the set; there is no partial membership. Moreover, the "support" of a fuzzy set A is all x in X that have nonzero membership in A, which is identical to the crisp set 0+A. 1A represents all x in X that are completely in a (no other sets) and is called the "core" of A. The "height" of a fuzzy set A, h(A), is simply max(A(x)) for all x in X, or all x in the support, 0+A. A fuzzy set is "normal" when h(A)=1 and "subnormal" when h(A)<1.
A fuzzy set A on R (a membership function that depends upon one variable) is convex if
A(k*x1 + (k-l)*x2) >= min[A(x1),A(x2)]
for all x1 and x2 in R and all k in the range [0,1]. As k varies from 0 to 1, x=k*x1+(k-1)*x2 varies from x2 to x1. This definition states that a fuzzy set if convex if any point in between two other points resides in the alpha-cut that is largest. If A(x1)=a1 and A(x2)=a2, and a1<a2, they x2 has to lie in a1A (also a1+A since a1 is less than a2) and all points between x1 and x2 must lie in a1A. This would be true, for example, if the membership function A(x) were a gaussian function. Note that this function is not convex in itself since points on the line joining two interior points can be outside the curve, but the fuzzy set defined by this membership function would be convex by the proceeding definition. If this membership function had a dip at the maximum (for form a 2-hilled function), then the fuzzy set would not be convex since x1 and x2 could be on either side of the central minimum and a1 and a2 greater than the central minimum.

The Image Functional Substrata: Although many research available on fuzzy color modeling and their direct statistics and arithmetic's, there is no significant research on treating color sets as higher level constructs. Many relations exit among these color sets which are of great value to the process of interpreting image segments. One can treat image segments within the paradigm of Relational architectures. Surely, fuzzy relational architectures and methods are helpful in discovering meaningful structural relationships implicit in scientific, engineering, business or medical data (Kohout and Bandler, 1992). In particular fuzzy relational products and algorithms for computing of fuzzy closures and interiors, make it possible to discover and further analyze structural relationships between individual items of data, which can not always be adequately analyzed by the methods using conventional probability based statistics for lack of a sufficient volume of data (Kohout and Bandler, 1992). When using relations in intelligent systems, not only quantitative numerical and formal logic but also qualitative semiotic notions, are involved. In order to use these mathematical structures to represent knowledge, each set and relation has to have assigned a linguistic label (as in image quantization). Using such linguistic interpretations and with the introduction of operators and quantifiers one infer valuable segmentation knowledge (e.g whether "almost all" of the color sets are dark grey). Hence, each relation acquires non-mathematical meaning carried by its linguistic labels. Each label has a concrete interpretation valid within a particular knowledge domain represented relationally. The relational products can be used to compute with these structures effectively.
The activity structures functional substrata provides higher level of knowledge representation along with their inferential operators. A color image can be represented as set of fuzzy regions. Each region represents a fuzzy relation. A fuzzy relation can be characterized by the membership function with at least two variables. It is referred to as a binary relation, triadic relation,..,fuzzy relation, according to the

number of variables. Hence, given two color regions, E_1 and E2, the fuzzy relation R is characterized as follows: $M_R = E1 \times E2 \rightarrow [0,1]$.

If we have two finite universes, the fuzzy relation can be represented as a matrix whose elements are the intensities of the relation. Hence, fuzzy relations are fuzzy sets and so the operations on fuzzy sets (union, intersection, etc) can be applied to them.

Using fuzzy relations, we can define many image segmentation relationships such as regions similarity, re-semblance and order especially for the overlapped regions. In this direction, the BK-Products provides the basic operators for inferring the similarity of regions as well as other computational issues. There are four different types of BK-Products. Each one represents a different level of restriction on the similarity of relations. The circle product is the composition of *R* and *S*, denoted as $R \circ S$, is defined as:

$R \circ S = \{ (x,z) \mid$ there exists an element y in Y such that xRy and $yRz\}$.

Not that the set of columns that have relations with rows are called the R-afterset of an element x of X, denoted xR, consists of all elements of Y that are R related to x , and similarly the set of rows that have relations to the columns as the R-foreset of an element y of Y, denoted Ry, consists of all elements of X that are R related to y. We can then easily rewrite the composition condition in terms of fore- and aftersets as

R Circle S= { (x,z) | xR Intersection Sy <> nil},

or, in words, the intersection of the R-afterset of x and the S- foreset of z is not empty. The non emptiness of the intersection of xR and Sz obviously is not a very strong condition. This makes it on the one hand easy to satisfy. The other types of BK compositions impose stronger conditions on the intersecting set xR Intersection Sz, and hence are more difficult to satisfy. The first such composition is the so called triangular sub-composition of R and S, denoted as R Sub Composition S, and defined as:

R Sub Composition S= { (x,z) | xR Intersection Sz <> nil and xR is a subset of Sz}.

In addition to the non-emptyness condition of the circular composition, the triangular sub-composition requires that the R- afterset of x is a subset of the S-foreset of z. In the same spirit, the (triangular) super-composition of R and S, denoted as R Super Composition S, is defined as:

R Super Composition S = { (x,z) | xR Intersection Sz <> nil and Sz is a subset of xR}.

The super-composition switches the roles of xR and Sz, now requiring that the S-foreset of z is a subset of the R-afterset of x. Finally, the square composition of R and S, denoted as R Square S, is defined as:

R Square S= { (x,z) | xR Intersection Sz <> nil and xR = Sz}.

Clearly, the square composition is the intersection of the super- composition and the sub-composition, i.e.,R Square S = (R

Sub Composition S) Intersection (R Super Composition S), meaning that the square composition is the most restrictive type of composition.

Only recently, two researchers from the MIT (Stauffer and Grimson, 2001) proved the importance of having new representational method for color images in order to detects the similarity of pixels in an image patch. For this purpose, the relational products represent very promising tools for object recognition and detection.

The Image Segmentation Physical Substrata: The activity structures physical substrata refers to the action of hybrid controllers that can analyze their performance and make necessary changes to their behaviour in order to satisfy certain predefined control goals (Kohout, 1981; Kohout and Gaines, 1975). In this direction, fuzzy set theory and neural networks are the foundation for many existing intelligent controllers (Kohout, 1990; Kohout, 1992). In this project we are proposing the use of hybrid controllers that utilize the advantages of both techniques. Such intelligent hybrid controllers then can play an important role in segmenting images and prepare it for the other operations, such as edge detection, image understanding and image retrieval. We are proposing four types of hybrid controllers (Fig. 2).

Each type of configuration (serial or parallel) may have its own advantage over the others. The first parallel configuration (Fig. 2: Bottom Left) the Neural Network is used to generate and tune the membership functions of the Fuzzy Classifier. The second parallel configuration (Fig. 2: Bottom Right) uses the Neural Network to fine-tune the output of the Fuzzy-Classifier to suite the segmentations' preferences. The two serial configurations depends on whether the image input knowledge is not suitable for the Fuzzy Classifier (Fig. 2: Top Left) or the output of the Fuzzy Classifier is not suitable for direct interpretation to the external devise (Fig. 2: Top Right).

The Fuzzy classifier uses fuzzy rules for reasoning about how to control regions classification. It uses three steps: Fuzzification (Scales and maps input variables to fuzzy sets using membership functions), Rule evaluation (to deduce the control actions by applying fuzzy rules) and Defuzzification (Obtaining the crisp results). In designing such classifier, the user must tune by trial and error the membership functions of the fuzzy sets defined in the input and output universes of discourse. This drawback can be eliminated by using an artificial neural network. Though, neural networks require a training data set to learn the trend of data. In this direction we are proposing the use of Kohonen SOM that is popular form of unsupervised artificial neural network, mainly used to find patterns in and classify high dimensional data. Images can then be processed to become the input signals for the Self-Organizing Maps (SOM) (Kohonen, 1988) and the output neurones that have adapted to the image, present interesting segmentation features.

Conclusion

Designing a successful image segmentation module will effect directly any image understanding and retrieval system. What is needed is not an image filter module but a sound modelling methodology. A methodology that is capable of representing the static nature of the image color pixels and features as well as the dynamics of identifying the image regions and constructs. Activity Structures proved to be very successful design methodology in various systems. This paper proposes the use of activity structures for image segmentation.

Activity Structures starts by representing the image knowledge, provide the primitive processing operator and constructs the physical processing machine through designing a Self-Organizing Fuzzy Controller. Fig. 3 illustrates the effects of using the four BK-Products for color image segmentation.

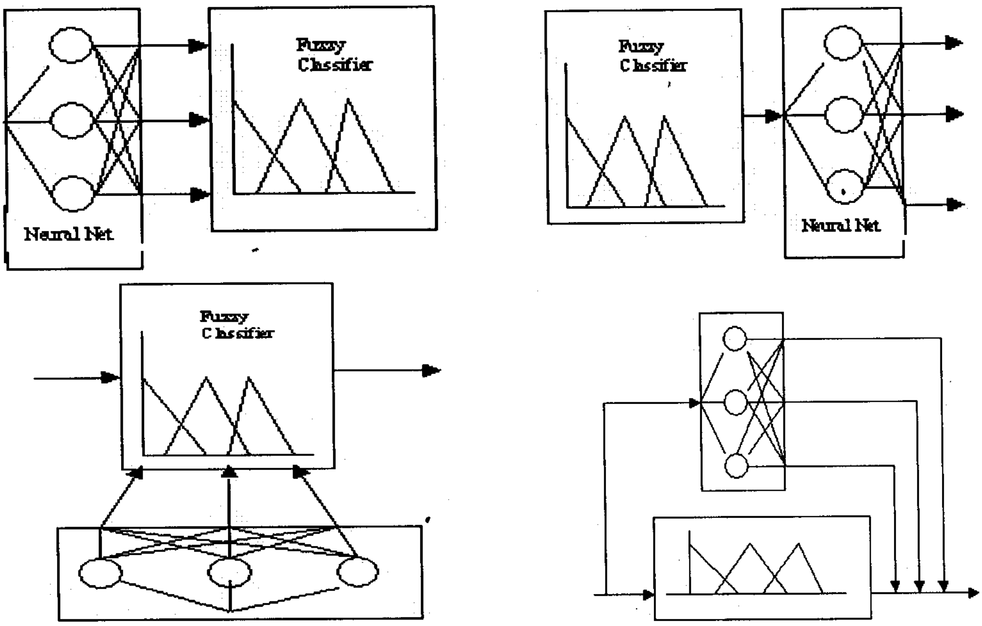

Fig. 2: Image Segmentation Hybrid Controllers

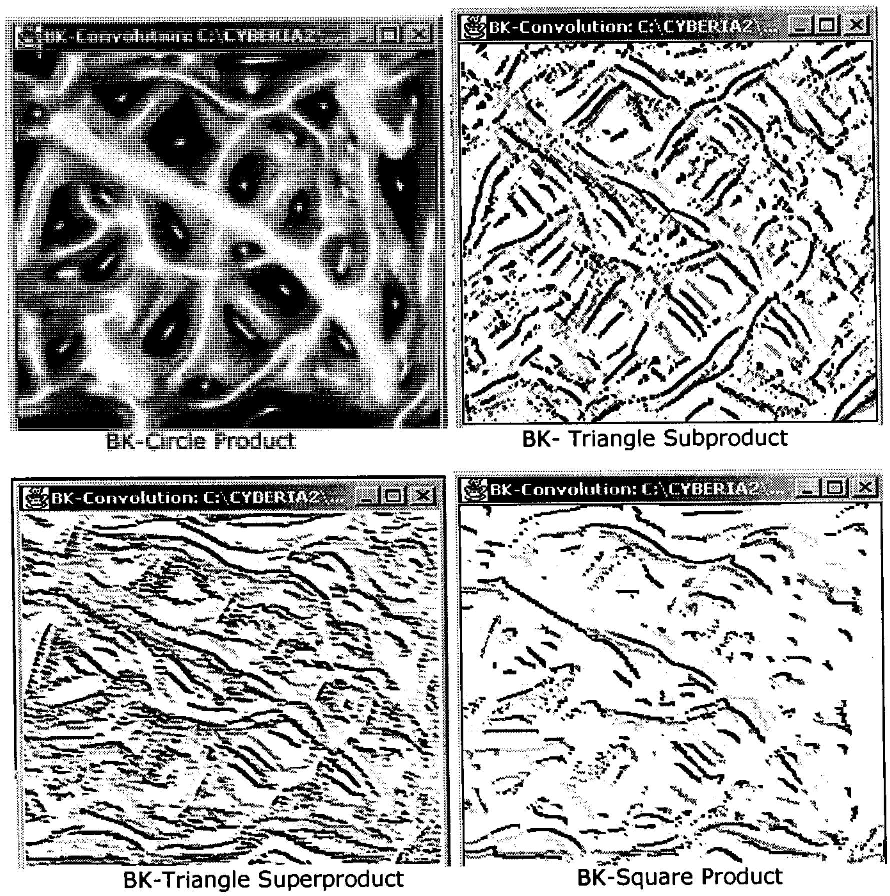

Fig. 3: The Effects of using Different BK-Products on the Rot Color Image

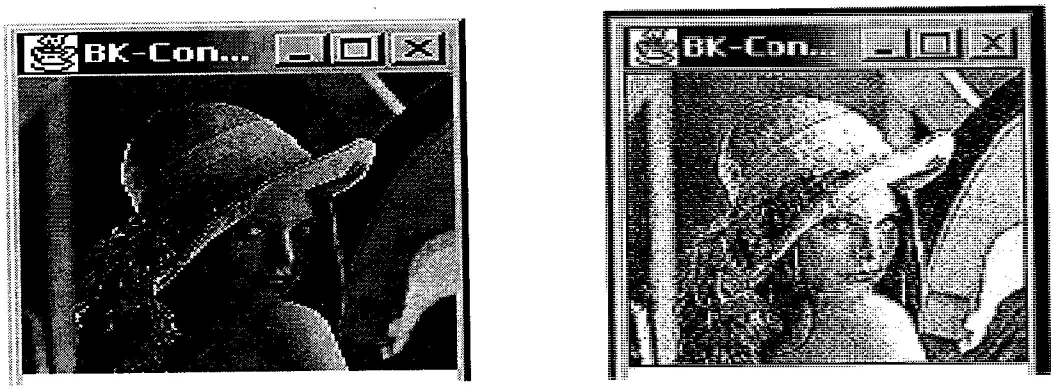

Fig. 4: The Effects of the BK-Circle Product on Lena Image

It is so clear from Fig. 3 that the circle product produced the best segmentation result of the rot image because it is less restrictive. The other BK-products detect lesser edges because of their increasing restrictions. The circle BK-product segmentation produced better results that the systematic convolution based segmentation. Fig. 4 illustrates the effect of the BK-circle product segmentation on the lena standard image.

The experimentation and the full scale Activity-Structures based image segmentation system is still at its initial research stage. The ultimate goal of this paper is to present an innovative framework for image segmentation.

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