내용기반으로한 이미지검색에서 이미지 객체들의 외형특징추출

조 준 서†

요 약

이 논문의 주요 목적은 내용을 기반으로 하는 이미지 검색에서 이미지 객체의 외형특징을 추출하는 방법을 제시하는 것이다. 대부분의 실질적인 객체들의 외형은 불규칙적이고, 이러한 객체를 수치화하기위한 일반적인 방법은 없다. 특히 전자 카타로그들은 상품들을 나타내는 많은 이미지를 포함하고 있다. 이 논문에서는 이미지 전체가 아닌 이미지내의 개별 객체들을 기반으로 특징을 추출하는 방법을 제시한다. 왜냐하면 제시된 방법은 한 이미지내에서 RLC lines을 사용하여 각 객체들의 외형을 기반으로하는 방법을 사용하기 때문이다. 실험결과는 일반적으로 가장 많이 사용하는 특징인 Texture와 비교를 했고 제시된 외형을 나타내는 변수들이 전자카타로그의 이미지 객체들을 뚜렷하게 나타냈고, 보다 정확하게 객체들을 분류하고 구별하였다.

Feature Extraction of Shape of Image Objects in Content-based Image Retrieval

June-Suh Cho†

ABSTRACT

The main objective of this paper is to provide a methodology of feature extraction using shape of image objects for content-based image retrieval. The shape of most real-life objects is irregular, and hence there is no universal approach to quantify the shape of an arbitrary object. In particular, electronic catalogs contain many image objects for their products. In this paper, we perform feature extraction based on individual objects in images rather than on the whole image itself, since our method uses a shape-based approach of objects using RLC lines within an image. Experiments show that shape parameters distinctly represented image objects and provided better classification and discrimination among image objects in an image database compared to Texture.

키워드 : 객체(Object), 특징(Feature), 외형(Shape), Run Length Code, 표면 규칙성(Surface Regularity), 원형성(Roundness), 외형요소(Form Factor), 종횡비(Aspect Ratio)

1. Introduction

The goal of this paper is to explain methodologies for feature extraction of image objects in image databases. This paper describes a new methodology that is feature extraction of image objects based on shape.

Among image features, we focus on shape since it is an important characteristic in identifying objects. The shape of most real-life objects is irregular, and hence there is no universal approach to quantify the shape of an arbitrary object. However, the shape of an object can be parameterized with the help of some measurable properties. A good choice of a parameter should yield a known value in the ideal case [21]. We use rotational invariants using *Run Length Code lines* to extract shape parameters from image objects. In this paper, we perform feature extraction based on individual objects in images rather than on the whole image itself, since our method uses a shape-based approach of objects within an image. Our working environment is electronic catalogs since they contain many image objects for products.

Within an object-oriented paradigm, an object in an image can be represented by a set of run length code lines. Run length code is developed for compacting image data [3, 10]. Run length code lines (RLCs) of image objects are also used to compute measurements such as area, perimeter, and other measurements. From these parameters measured by RLC, one can compute shape parameters, such as form factor, roundness, and surface regularity, calculated by measurements. Moment invariants are used as a set of features representing shape parameters, which are invariant under scale and rotation. Textural parameters of images include entropy, angle of second moment, contrast, and mean of

※ 이 연구는 2003학년도 한국외국어대학교 교내학술연구비의 지원에 의하여 이루어진 것임.
† 정 회 원 : 한국외국어대학교 경영학과 교수
논문접수 : 2003년 5월 20일, 심사완료 : 2003년 10월 7일

selected objects.

In experiments, shape parameters distinctly represented image objects in our image database. Shape feature parameters provided better classification and discrimination among image objects in an image database. In addition, results of the retrieval performance demonstrated that queries using shape parameters performed better than those using other feature parameters such as entropy and contrast.

The rest of this paper is organized as follows. In Section 2, we briefly review related work.

In Section 3, we describe a methodology for feature extraction of objects. In Section 4, we discuss the experimental results. Finally, we conclude in Section 5.

2. Related Work

In recent years, research and development in content-based image retrieval has mainly focused on image features, such as color, shape, texture, and spatial relationships [1, 12, 14, 16, 17, 20]. The retrieval of shape is one of the most challenging aspects to content-based image retrieval. Shape matching is an important image processing operation and image retrieval method by content. Jagadish provides image indexing methods based on shape and uses a few MBRs (Minimum Bounding Rectangle) to extract features from shape [10]. Faloutsos et al. [6] use the area, circularity, major axis orientation and a set of algebraic moment invariant for features. Pentland et al. [17] use eigenvectors to extract shape features from images. In addition, the shape-based technique allows users to ask for objects similar in shape to a query.

Texture is also an important element to human vision, based on homogeneous patterns or spatial arrangement of pixels [6]. Texture is enhanced by the features of directionality, coarseness, granularity, and contrast [4, 8]. The most widely used collection of features is Brodatz's image texture [2], which is used in techniques for texture analysis. Smith and Chang [19] describe a texture set approach for indexing in order to extract spatially localized texture information.

Many different types of shape analysis use boundary features such as chain codes of contour segments or high-curvature points. Unlike current feature extraction methods, our approach proposes a feature extraction method that is based on the shape of objects using run length code lines. Run length code lines can be used directly for area and position measurements, with even less arithmetic than pixel array techniques. In other words, run length code lines are more useful for some specific purposes. Most measurements, such as feature area and position, can be directly calculated by simple counting procedures. To measure the perimeter of an object, a simple polygonal approximation to the boundary can be produced by using the end points of the series of run length code lines.

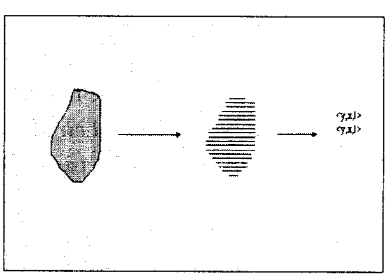
3. The Proposed Methods

We propose a methodology for content-based image retrieval in an electronic commerce environment that is a feature extraction focusing on individual objects in an image rather than whole images. One of the main features of this work is to extract image features based on the shape of objects. We use RLCs, a method to calculate features of image objects such as roundness, aspect ratio, surface regularity, and form factor. Other important image features are texture, represented by entropy, angle of second moment, contrast, and mean of selected objects. Texture parameters are computed by pixels of selected objects in images.

3.1 Measuring Image Objects based on RLC

In order to compute the image parameters, we need to compute several measurements of the image objects. These measurements include the area and perimeter. We discuss in the following how these measurements are computed from the RLC of an image object.

Objects can be represented by Run Length Code lines, a set of lines that covers the interior of the image [3, 4]. It represents them by triplets $<y, x, l>$, where y and x are the starting coordinates of the line of length l. An example of the RLC lines is shown in (Figure 1). Line records are sorted with respect to their coordinates and stored in sequential order. The structure is homogeneous since the representation of all types of entities including points, lines, and entities of extended type are permitted. Run length code lines of image objects are also used to compute image parameters such as area, perimeter, and other measurements. In addition, we compute shape parameters, such as form factor, roundness, and surface regularity, calculated by the combination of measurements.



(Figure 1) Run Length Code Lines

- Area : The area of a polygonal object can be determined from the RLC lines using Equation (1), which calculates the area covered by a trapezoid enclosed by any two RLC lines. The total area enclosed by an image object is calculated by the sum of the areas enclosed by any two consecutive RLC lines.

$$a=0.5 \times \sum_{i=0}^{n} y_i \times (x_{i+1}-x_i) \tag{1}$$

- Perimeter : The perimeter length is calculated by adding the lengths of the line segments connecting the endpoints of each RLC line, as shown by Equation (2). In Equation (2), l_1 and l_2 represent the lengths of the line segments at the two extreme end-points of the image object.

$$l= l_1+l_2+ \sum_{i=0}^{n} \sqrt{(y_{i+1}-y_i)^2+(x_{i+1}-x_i)^2} \tag{2}$$

3.2 Shape Parameters

Since we use images of electronic catalogs, the shape of objects is the most distinguished feature of image features. Because the texture represents patterns of objects, it is also a useful feature to recognize objects in images.

We have selected four shape parameters that describe two orthogonal shape characteristics of an object : surface regularity (irregularity) and roundness (elongation). The shape parameters are described in more detail below. The above shape parameters are adopted from [9, 18]. If the object were a perfect circle, all of the shape parameters would be equal to 1, which satisfies the requirement in [21].

- Surface Regularity : Surface regularity refers to the smoothness of the surface of an object. Surface regularity is described by two shape parameters : *surface regularity* (*S*) and *form factor* (*F*), defined in Equations (3) and (4) respectively. The form factor in Equation (4) is high for objects that have a high area to perimeter ratio.

$$S = \sqrt{\frac{a}{a_c}} \tag{3}$$

$$F = \frac{4\times\pi\times Area}{(perimeter)^2} \tag{4}$$

Surface regularity in Equation (3) is measured in terms of the amount of area covered as compared to a circle of equal perimeter. Thus, and are the areas of the image object and a circle with equal perimeter respectively. The form factor in Equation (4) is high for objects that have a high area to perimeter ratio. Form factor and surface regularity are positively correlated.

- Roundness (elongation) : Roundness (*R*) is inversely proportional to elongation and is described by Equation (5).

$$R=\frac{4\times Area}{\pi\times(MaximumDiameter)^2} \tag{5}$$

Roundness is high for objects that are well-rounded in every direction. Thus objects with long extremities will have relatively low roundness. Elongation (*A*) is measured by aspect ratio (defined by Equation (6), which is high for objects that are elongated in one or more directions.

$$A=\frac{MaximumDiameter}{MinimumDiameter} \tag{6}$$

Maximum diameter (in Equation (6)) is computed as the distance between two extreme boundary points. The minimum diameter in Equation (6) is obtained by computing the minor axis of an ellipse whose area is equal to that of the object and whose major axis is equal to the maximum diameter.

All shape parameters are ratios, a consequence of which is that if the shape of an object remains constant but its size varies. The values of the parameters would vary relatively slowly as compared to when the shape varies but the size remains constant. Thus, two objects with the same shape but different sizes will be detected to be more similar than two objects with different shapes but the same size.

3.3 Texture Parameters

One of the most informative properties in recognizing visual objects is their texture. Among image features, texture is an important characteristic for the analysis of images. In this section, we describe the textural feature extraction method for images.

The basic textural unit of some textural primitives is called a *texel*, for texture element. Gray level primitives are regions with gray level properties. The gray level primitive can be described as the average level or maximum and minimum levels of its region. The gray level spatial dependence approach characterizes texture by the co-occurrence of its gray levels. The gray level co-occurrence can be specified in a matrix of relative frequencies $P_{i,j}$ with which two neighboring pixels, one with gray level and the other with gray level *j*.

In terms of texture features, we include the angle of second moment *ASM*, the entropy *E*, the contrast *C*, and Mean *M*. They can be defined by the co-occurrence as follows :

- Angle of second moment : This measure is small when the $P_{i,j}$ are nearly equal, it is large when some values are high and others are low, for example, when the values are clustered near the main diagonal.

$$ASM = \sum_{i,j} (P_{i,j}^2) \quad (7)$$

- Entropy : The entropy of the image is the number of bits per pixel needed to represent the image. This measure is the largest for equal $P_{i,j}$.

$$E = -\sum_{i,j} P_{i,j} \log P_{i,j} \quad (8)$$

- Contrast : This is essentially the moment of inertia of the matrix around its main diagonal. It is a natural measure of the degree of spread of the matrix values.

$$C = \sum_{i,j} (i-j)^2 P_{i,j} \quad (9)$$

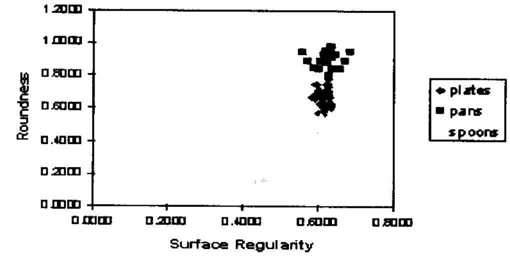
- Mean : This measure is a first order property of texture region. Mean of the distributions of brightness values is accumulated in the x and y directions.

$$M = \sum_{i,j} i P_{i,j} \quad (10)$$

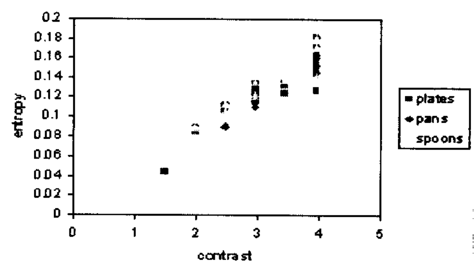
4. Experimental Results

Our image database consists of 524 image objects from electronic catalogs found on the Internet. The number of sample images is 311 and they are drawn from current online shopping sites on the Internet such as "macys.com", "jcpenney.com", "cratebarrel.com", "potterybarn.com", and so on. The objects in the images are categorized by semantics, such as pans, pots, cups, plates, spoons, and forks. In addition, the objects are categorized in a hierarchy where pan and pot categories are considered as subcategories of cookware, plate and cup categories are considered as subcategories of dinnerware, and spoon and fork categories are considered as subcategories of flatware. Image parameters used in the categorization include surface regularity, roundness, form factor, aspect ratio, angle of orientation, contrast, entropy, and mean value.

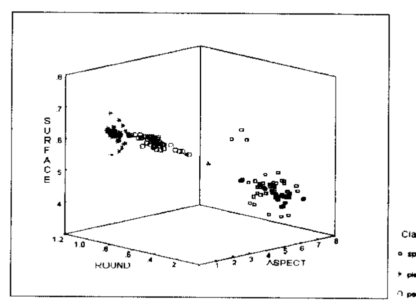
The shape feature parameters are computed by several measurements, which are extracted by RLC lines. Among these parameters, surface regularity and roundness provide the best means to discriminate objects as shown in (Figure 2). In (Figure 4), the clusters of shape are obtained by 3D scatter plot of the shape parameters such as roundness, surface regularity, and aspect ratio. Because form factor and surface regularity are highly correlated, we only used surface regularity. In (Figure 2) and (Figure 4), we can see the differences of classes, such as spoons, plates, and pans. Typical texture feature parameters [1, 7, 13, 15, 16, 20] including entropy and contrast, cannot distinctly discriminate objects as shown in (Figure 3). Texture feature parameters used are



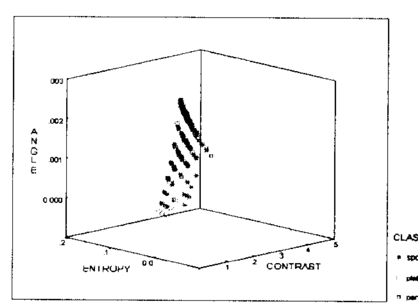
(Figure 2) Clustered objects of Pans, Plates, and Spoons with Roundness and Surface Regularity. The clusters show the differences of classes



(Figure 3) Clustered objects of Pans, Plates, and Spoons with Contrast and Entropy. The clusters did not show the differences of classes



(Figure 4) Clustered objects of Pans, Plates, and Spoons based on Shape Features such as Surface Regularity, Roundness, and Aspect Ratio



(Figure 5) Clustered objects of Pans, Plates, and Spoons based on Texture Features such as Angle of Second Moment, Entropy, and Mean

angle of orientation, entropy, contrast, and mean. In (Figure 5), the clusters of texture are obtained by a scatter plot of the texture parameters such as angle of second moment, entropy, and mean since these parameters provide better means to discriminate objects. In (Figure 3) and (Figure 5), we cannot see the differences of classes with texture parameters. These scatter plots show that shape feature parameters provide better classification and discrimination among image objects in our image database.

One of the prominent examples of content-based image retrieval system is QBIC [7, 15]. QBIC uses features such as color, texture and shape. The major difference between QBIC and our method is that QBIC uses pixels in shape to compute measurements like area and perimeter. In our method, we used run length code lines to compute several shape measurements like area, perimeter, maximum and minimum diameters. In addition, QBIC's main feature is a color feature instead of shape and texture features. However, our approach ignores color since it does not fit into image objects in our image database

Feature extraction is implemented using Oracle tools and image processing tools, specifically Visilog, and WIT, Oracle tools are used to perform similarity search and store datasets. We used image processing tools to detect edges, compute RLC lines, and extract texture parameters of image objects.

Among feature parameters, we select roundness, surface regularity, entropy, and contrast to evaluate retrieval rate since these parameters are distinctly represented or typically used features of image objects. Based on these feature parameters, we have performed similarity search in image databases. We randomly selected 30 query images from a given image database, and retrieved similar images from a database. Typically, the retrieval performance is measured in terms of the average retrieval rate, which is defined as the average percentage of number of objects belonging to the same class as the query object in the top 10 matches. We retrieved the top 10 matched images per query and averaged. The results of the retrieval performance are shown in <Table 1>.

The results show that queries using shape parameters performed better than those using other feature parameters.

〈Table 1〉 Average Retrieval Rate : Similarity Search with Feature Parameters

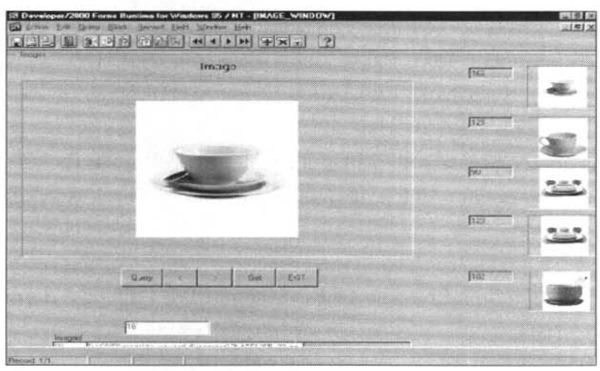
Classes	*Features based on RLC*		*Texture features*	
	Roundness	Surface Regularity	Entropy	Contrast
Pan	92%	93%	85%	62%
Cup	94%	96%	75%	54%
Plate	95%	94%	78%	53%
Spoon	97%	91%	84%	68%

The recall and precision measurement commonly used to evaluate the effectiveness of image retrieval is shown in <Table 2>. The subsequent experiment used query results based on the top 10, 20, 40, 60, and 80 matched images per query. The results of image retrieval consistently show that shape features produced high precision and recall scores compared to texture features.

〈Table 2〉 Precision and Recall in Image Retrieval

Classes	*Shape based on RLC*		*Texture*	
	Precision	Recall	Precision	Recall
Pan	92%	20.6%	73%	16.4%
Cup	95%	21.1%	65%	14.4%
Plate	94%	19.3%	66%	13.5%
Spoon	95%	23.5%	76%	19%

A prototype has been implemented for similarity search using Oracle tools as shown in (Figure 6). (Figure 6) shows the results of the similarity search based on shape features of a Cup. The results show the top 5 matched image objects against a given query object.



(Figure 6) A prototype for similarity search.

5. Concluding Remarks

Feature extraction is the foundation of our methodology to perform shape-based image retrieval by content. Since we used a shape-based approach, feature extraction was focused on texture and shape of objects. We used rotational invariants using Run Length Code lines. RLC lines can distinctly represent shape parameters, which are better discriminating features than parameters such as texture for recognizing image objects in electronic catalogs.

In this paper, we performed feature extraction based on individual objects in images rather than whole images from electronic catalogs. In order to compute the image parameters of shape, we have extracted measurements of the image objects such as area, perimeter using RLC lines. With these measurements, we have computed several shape parameters such as surface regularity, aspect ratio, form factor, roundness. For texture parameters, we have computed texture parameters based on pixels of images such as angle of second moment, entropy, contrast, and mean. Shape feature parameters provided better classification and discrimination among image objects.

In addition, we have performed similarity search based on these parameters. Queries using shape parameters performed better retrieval rates than other feature parameters such as entropy and contrast. The system enables a user to ingest images into the system, generate RLC lines for the image features, and calculate size and shape parameters.

References

[1] J. R. Bach, C. Fuller, A. Gupta, A. Hampapur, B. Horowitz, R. Humphrey, R. Jain and C. Shu, The Virage image search engine : An open framework for image management, In Storage and Retrieval for Still Image and Video Databases, 1996.

[2] P. Brodatz, Textures ; a photographic album for artists and designers, Doer Publications, 1966.

[3] Shi-Kuo Chang, Principles of Pictorial Information Systems Design Prentice Hall, 1989.

[4] S.-K. Chang and E. Jungert, Symbolic Projection for Image Information Retrieval and Spatial Reasoning, Academic Press, 1996.

[5] W. Equitz, Retrieving images from a database using texture algorithms from the QBIC system, IBM Technical Report, 1993.

[6] C. Faloutsos, W. Equitz, M. Flickner, W. Niblack, D. Pekovic and R. Barber, Efficient and effective querying by image content, IBM Technical Report, 1993.

[7] M. Flickner, H. Sawhney, W. Niblack, J. Ashley, Q. Huang, B. Dom, M. Gorkani, J. Hafner, D. Lee, D. Petkovic, D. Steele and P. Yanker, Query by Image and Video Content : The QBIC System, IEEE Computer, 28, pp.40-56, 1995.

[8] Robert M. Haralick and Linda G. Shapiro, Computer and Robot Vision Addison Wesley, 1992.

[9] M. A. Ireton and C. S. Xyedeas, Classification of Shape for Content Retrieval of Images in a Multimedia Database, In Proceedings of the Sixth International Conference on Digital Processing of Signals in Communication, 1991.

[10] H. V. Jagadish, A Retrieval Technique for Similar Shapes, In ACM SIGMOD '91, 1991.

[11] Erland Jungert, Run length code sn object-oriented sp tiald ta structure, In Proceedings of IEEE workshop on language and automation, 1986.

[12] W. Li, K. S. Cadan, K. Hirata and Y. Hara, SEMCOG : An Object-based image Retrieval System and Its Visual Query Interface, In ACM SIGMOD '97, 1997.

[13] S. Mehrotra, Y. Rui, K. Chakrabarti, M. Ortega and T. Huang, Multimedia analysis and retrieval system, In The 3rd International Workshop on Information Retrieval Systems, 1997.

[14] A. Natsev, R. Rastogi and K. Shim, WALUS : A Similarity Retrieval Algorithm for Image Databases, In ACM SIG MOD International Conference on Management of Data, 1999.

[15] W. Niblack, R. Barber, W. Equitz, M. Flickner, E. Glassman, D. Petkovic, P. Yanker, C. Faloutsos and G. Taubin, The QBIC Project : Querying Images by Content Using Color, Texture and Shape, In Proceedings of the SPIE Conference on Storage and Retrieval for Image and Video Databases, pp.173-187, 1993.

[16] V. E. Ogle and M. Stonebraker, Chabot : Retrieval from a Relational Database of Images, IEEE Computer, 28(9), pp. 40-56, 1995.

[17] A. Pentland R. W. Picard and S. Sclaro, Photobook : Tools for Content-Based Manipulation of Image Databases. In Proceedings of the SPIE Storage and Retrieval Image and Video Databases II, 1994.

[18] John C. Russ, The Image Processing Handbook, CRC Press, 3rd edition, 1998.

[19] John R. Smith and Shi-Fu Chang, Automated Image Retrieval Using Color and Texture, Columbia Technical Report, 1995.

[20] John R. Smith and Shi-Fu Chang, VisualSEEK : A Fully Automated Content-Based Image Query System, In ACM Multimedia 96, 1996.

[21] D. Unwin. Introductory Spatial Analysis, Methuen, London, 1981.

조 준 서

e-mail : jscho@hufs.ac.kr
1989년 경희대학교 무역학과(학사)
1993년 New York University Computer Science(이학석사)
2001년 Rutgers University Computer Information Systems(경영학박사)
2000년~2001년 IBM T. J. Watson Research Center 연구원
2003년~현재 한국외국어대학교 경영학과 MIS 전공교수
관심분야 : Multimedia Database, Electronic Commerce, M-Commerce, Security