Thesis for Master's Degree

Feature extraction for non-textured object recognition using a stereo camera

Wonmin Byeon

Department of Information and Communications

School of Information and Mechatronics

Gwangju Institute of Science and Technology

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석 사 학 위 논 문

스테레오 카메라를 이용한 텍스쳐가 없는 물체 인식을 위한 특징 추출

변 원 민

정 보 기 전 공 학 부

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Advisor: Moongu Jeon

by

Wonmin Byeon

Department of Information and Communications

School of Information and Mechatronics

Gwangju Institute of Science and Technology

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Approved by

Professor Moongu Jeon

Thesis Advisor

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Wonmin Byeon

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Thesis Advisor ____________________
Prof. Moongu Jeon

Committee Member ____________________
Prof. Tae Sun Choi

Committee Member ____________________
Prof. Kuk-Jin Yoon

To my parents.

사랑하는 부모님께 바칩니다.

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Abstract

Recognizing an object is a central problem in computer vision. There are an amount of information used for recognizing an object, such as shape, color, and texture. Texture is particularly useful as distinguishing an object in natural scenes; e.g., illumination and scale changes, occlusion, and view point variation. Instead, to recognize an object with no distinctive texture pattern under the condition changes is difficult.

This paper presents a new method for non-textured object feature extraction using a stereo camera. Non-textured objects lack information for recognition. To deal with this problem, we consider the two kinds of information; color and three dimensional (3D) scale using the high-curvature points.

The first part of this dissertation is color feature extraction using the clustering method. It finds the principal colors to classify the object regions. In second part, the new feature extraction method (3D scale) for non-textured object recognition is proposed using curvature information. First, we obtain the scale invariant curve features from the boundary, then perform stereo matching for 3D depth computation. Finally, we can calculate the 3D maximum distance (3D scale).

In our experiments, we demonstrated on a number of challenging data sets; i.e., various condition changes, such as illumination, occlusion, scale, and rotation. We achieved significant recognition performance using the result of non-texture object feature extraction, and more robust recognition for non-textured objects in natural scenes.

M/SIM 20081034 변원민. 스테레오 카메라를 이용한 텍스쳐가 없는 물체 인식을 위한 특징 추출. 정보기전공학부. 정보통신공학과. 2010. 37p. 지도교수: 전문구.

국 문 요 약

물체 인식(Object Recognition)은 2차원 정지 영상 혹은 영상 시퀀스를 분석하여 주어진 데이터베이스 내에 일치하는 물체를 검출하고 인식하는 기술이다. 인간의 경우에는 물체가 일부 가려져 있거나 혹은 시점, 크기, 조명 변화가 있거나, 물체가 이동 및 회전이 있어도 큰 노력 없이 물체를 실시간으로 인식하지만, 컴퓨터 비전 분야에서 물체 인식은 이러한 여러 가지 변화 요인들로 인해 아직도 매우 어려운 주제 중 하나이다. 일반적인 물체 인식의 방법론들은 형태(shape), 색체(color), 재질(texture) 등의 특성을 이용하여 비례, 평행, 대칭, 균형 등의 구조적 특징을 추출하게 되고 이를 이용하여 물체를 분석하게 된다. 하지만 non-textured 물체의 경우에는 이러한 정보가 부족하기 때문에 일반적인 방법을 이용하여 물체를 인식 할 수 없다.

본 논문에서는 스테레오 카메라로부터 영상을 입력 받아 가려짐, 시점 변화, 조명 변화, 크기 변화 및 배경 변화 등에 강인한 고속의 non-textured 물체 인식을 위한 특징 추출 알고리즘을 제시한다. 이 때 기존의 많은 물체 인식 방법론들이 대상으로 하는 textured 물체와 다르게 non-textured 물체는 기존에 제안되었던 특징점 추출 기법의 사용이 어렵다. 이를 위해 non-textured 물체가 가진 고유의 특징을 추출해야 하는데 이를 위해 본 논문에서는 색과 곡률 정보를 이용한 스테레오 기반의 3D 크기를 이용하였다.

texture가 없는 물체의 경우 많은 색을 가지지 않기 때문에 물체의 각각의 영역이 가진 특징적인 색을 뽑아내기 위해 클러스터링 기법을 이용하였다. 먼저, 기준이 되는 모델 색들을 정한 다음 이 색과의 유사도를 계산하여 물체의 각 영역이 가진 색을 추출한다. 이 정보는 데이터베이스에 저장한 다음 다양한 배경의 테스트 영상에서 배경과의 분리를 위한 물체 영역 추출에 이용한다.

3D 크기 추출을 위해 본 연구에서는 물체의 외곽선 (boundary)에서 추출되는 높은 곡률을 가진 영역 (high-curvature point)을 이용하였다. 크기 변화에 강인한 scale invariant curve feature를 이용하여 물체의 3D 좌표를 구하게 되고 이들간의 최대값 비교를 통해 트레이닝 물체와 테스트 물체간의 최대 크기 유사도를 측정할 수 있다.

본 연구에서는 알고리즘의 성능을 분석하기 위하여 가려짐, 시점 변화, 조명 변화 및 크기 변화가 일어난 테스트 영상을 이용하였다. 또한, 기존의 알고리즘 (shape context)과 제안 기법의 인식률을 비교함으로써 성능의 우수성을 확인하였다. 하지만 크기가 비슷한 물체가 존재하는 경우 인식율 차이가 크게 나지 않거나 가려짐이 생기는 경우 오인식률이 높아졌다. 향후 물체의 높은 곡률을 가진 영역을 더욱 다양하게 활용하여 모양 (shape)정보를 효율적으로 사용한다면 보다 다양한 환경에 강인한 non-textured 물체 인식이 가능할 것이다.

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Chapter 1

Introduction

Object recognition is a well studied problem in computer vision. While this is a trivial task for the human visual system, it has proved to be very challenging for computer vision systems. Object recognition is a description of the 3D scene that accounts for the 2D image. This description may be in terms of models such as cylinders, rectangles, and ellipsoids; alternatively, the scene may be described at a higher level, referring to people, home appliances, and buildings. From the objects, multiple cues for recognizing objects exist, such as shapes, colors, and textures. This information is particularly useful for recognizing objects in natural scenes. There are a number of recognition approaches used to represent the feature space; i.e., model-based approaches, shape-based approaches, and appearance-based approaches. The properties of each approach are discussed in detail in Chapter 2.

Among them, the scale invariant feature transform (SIFT) is best known for scene recognition, image matching, and motion tracking [1]. An important aspect of this approach is that it generates a large number of features that densely cover the image over the full range of scales and locations. These feature point descriptors are highly distinctive. However, objects in SIFT are represented using a set of key-points from the texture information of the object. Thus, for a texture free object, the features from the object are lacking and give rise to many false matches for the recognition.

This study concerns recognition of the non-textured object. However, in the absence of texture information, we have limited cues for recognizing the object under natural conditions, such as during changes of the illumination, rotation, scale, and occlusion. This paper deals with the extraction of key information for non-textured object recognition, so we can recognize objects based on their color and geometric information using a stereo camera; e.g. 3D scale. A color could be good information to estimate the object without any complicate algorithm. To extract the scale features, we used boundary-based curve representation with stereo images.

1.1 Organization

The remainder of this dissertation is organized as follows:

Chapter 2 gives an overview of the feature descriptions for the object recognition. In chapter 3, we present our new feature extraction method for non-textured object recognition. In chapter 4, we discuss performance evaluation of the proposed method. Finally, chapter 5 summarizes and concludes the paper. Some directions for future work are also presented.

Chapter 2

Literature survey

2.1 Model-based approach

Model-based approaches try to represent the object as the shape model. It account for the variation of shape of an object by using the set of models. Feature is extracted from an image; then matched against one of the models. Most model-based object recognition approaches have described objects only in terms of their shape, without detailing additional properties such as color and texture [2]. Similarly, images have usually been described in terms of the visible manifestations of object shape − by the shape of intensity edges, for example, or the shape of the range surface [3, 4, 5]. This approach is matched well under the pre-specified models, but the feature is typically user-specified model which is not invariant to the various situations. Thus, the major challenge in model-based recognition is selecting the appropriate set of models. Also, it needs to construct the object model; it gives high computational complexity.

2.2 Shape-based approach

Shape-based approaches represent the object by shape or boundary which include Fourier descriptors, unorganized point sets, outline curves, and medial axis or shock-graphs. Object similarity is then measured by comparing this representation [6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 15, 17, 3, 4, 5, 18, 19, 20, 21, 22, 23, 24, 33, 26, 27, 28]. Fourier descriptors gives a compact representation of the shape as most shapes can be represented by a small number of coefficients [21, 22, 28]. Another type of shape representation model used the shape outline as a feature set and matched them using an assignment algorithm. Gold et al. used graduated assignment to match the image boundary features [29]. In a recent approach, Belongie et al. used the Hungarian method to match unordered boundary points using a coarse histogram of the relative location of the remaining points as features [6, 30]. Curvature scale space proposed in [31, 32]. In curve-based representation, the matching is typically based on either aligning feature points by an optimal similarity transformation, or by finding a mapping from one curve to another [8, 11, 23, 18, 33, 34, 35]. These methods are invariant to translations, rotations and other general linear transformations. However, all these approaches are global in nature and may have problems when dealing with noisy or partial data.

2.3 Appearance-based approach

Appearance-based approaches are usually obtained the features using different two dimensional views of the object. Based on the applied features these methods can be divided into two main classes; i.e., local and global approaches.

2.3.1 Global feature

A global feature covers the information with the whole image, i.e., all the pixels are regarded. There are various techniques such as the simple statistical measure (e.g., mean values or image histogram) and the dimensionality reduction method (e.g., principle component analysis (PCA), independent component analysis (ICA), or non-negative matrix factorization (NMF)) [36, 37, 38, 39, 40].

One of the simple methods for statistical measure is color histogram. It is simple and effective recognition scheme to represent images on the basis of color histograms as proposed by Swain and Ballard [41]. However, color histogram may not provide a good representation for an object region. W.Y ma, Yining Deng, and B.S. Manjunath proposed a compact color representation scheme which is applicable when the input image has been segmented into a number of regions [42]. The main problem is sensitive to changes in illumination and viewpoint variation.

The main idea of the dimension reduction is to project the original data onto a subspace, that represents the data optimally according to predefined criterion: minimized variance (PCA), independency of the data (ICA), or non-negative component (NMF). It is also sensitive to changes in illumination and occlusion.

2.3.2 Local feature

In contrast, a local feature is a distinctive property of an object located on a single point or small region; e.g., the color, gradient or gray value of a pixel or small region. The objects are represented using a set of key-points from the texture information of the objects; and then a matching algorithm is applied to find similar objects in the test data using a few training objects. The feature should be invariant to illumination changes, noise, scale changes and changes in viewing direction. However, it is difficult to satisfy the various condition changes because of the simpleness of the features itself. Thus, several features of a single point or interesting region in various forms are combined and more complex descriptors are used.

Most of the local appearance based object recognition needs to distinguish regions (i.e., exact position) in the image, which is great important to find such regions in a highly repetitive manner, and then find an appropriate descriptor for the distinguished regions.

The currently most popular distinguished region detectors algorithm, which gives sufficient performance results, as following:

- Harris- or Hessian point based detectors (Harris, Harris-Laplace, Hession-Laplace) [1, 43, 44]
- Difference of Gaussian Points (DoG) detector [45]
- Harris- or Hessian affine invariant region detectors (Harris-Affine, Hessian-Affine) [46]
- Maximally Stable Extremal Regions (MSER) [47]
- Intensity Based Regions and Edge Based Regions (IBR, EBR) [48, 49, 50]

Then, Table. 2.1 summarizes the properties of the detectors mensioned above.

Table 2.1: The properties of the detectors

detector	category	invariance	runtime	repeatability	number of detections
Harris	corner	none	very short	high	high
Hession	region	none	very short	high	high
Harris-Laplace	corner	scale	medium	high	medium
Hession-Laplace	region	scale	medium	high	medium
DoG	region	scale	short	high	medium
Harris-Affine	corner	affine	medium	high	medium
Hessian-Affine	region	affine	medium	high	medium
MSER	region	projective	short	high	low
IBR	region	projective	long	medium	low
EBR	corner	projective	very long	medium	medium

From the distinguished regions, the most important state of art is to describe the region or its local neighborhood by certain invariance properties; i.e., feature descriptors. Invariance means that the descriptors should be robust against various iamge variations such as affine distortions, scale changes, illumination changes, or compression artifacts (e.g., JPEG) It is obvious that the descriptors performance strongly depends on the power of the region detectors as shown above.

- Scale invariant feature transform (SIFT) [1, 51, 52]
- PCA-SIFT (gradient PCA) [53]
- Gradient location-orientation histograms (GLOH) [54]
- Shape context [55]
- Locally binary patterns (LBP) [56]
- Differential-invariants [57, 58]
- Moment-invariants [59, 49, 60]

Also, summary of descirptor is described in Table. 2.2.

The local approach is easy to construct the features and reduce the data from the original image using those method above. Also, it is not easily affected by partly occluded objects. On the contrary, the object should have principal information; i.e., texture.

Table 2.2: The properties of the descriptors

descriptor	rotational invariance	dimensionality	performance
SIFT	no	high(128)	good
PCA-SIFT	no	low(20)	good
GLOH	no	high(128)	good
Shape context	no	medium(60)	good
LBP	no	very high(256)	–
Differential-inv.	yes	low(9)	bad
Color moments	yes	low(18)	–
Intensity moments	yes	low	–
Gradient moments	yes	low(20)	medium

Chapter 3

Nontexture Feature Extraction using Stereo Camera

3.1 Color feature extraction

3.1.1 Introduction

Color gives powerful information for non-textured object recognition. This feature is simple and effective, but sensitive to condition changes such as illumination. However, it can be used for detecting an object area from background and good information to estimate the object candidate. Non-textured object has not many color regions compared with textured object in most natural scenes. However, the object in an image have plenty of color values in one region, so the color feature is only required a few number of colors to describe its color content without significantly affecting the perceptual quality. For example, a scene of a green bottle with a blue cap basically has two colors; green and blue. Thus, we can easily detect an object area using a few number of object color. For extracting representative colors in each area for an object, we used the clustering algorithm. The overall process of color feature extraction for non-textured object is shown in Figure. 3.1.

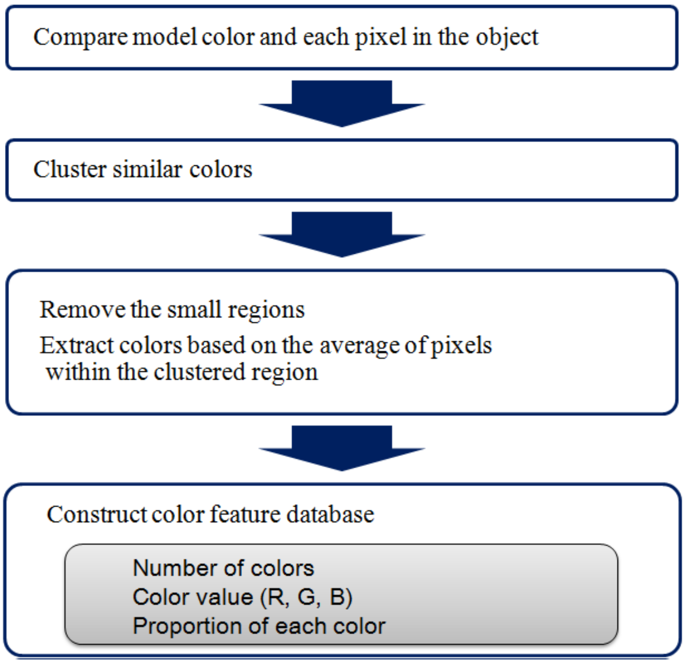

Figure 3.1: The Process of Color Feature Extraction

3.1.2 Color clusterion

In order to have a manageable number of colors to represent an object, clustering method was used to obtain the principal color in the RGB color space. First, we selected the number of colors called the model color according to the RGB color value and HSV color value; Red, Green, Blue, Hue, Saturation and Value. As stated in Figure. 3.2, we set the thirty colors for the model color. The color clustering basically contains the following steps:

1. Begin with the first pixel in an image.
2. Using Euclidean distance measurement, calculate the similarity between each pixel and given model colors.
3. Based on similarity measure (equation (3.1)), find the optimal partition in the

image. The model color can be the centroid of each region. An object is separated based on the closest model pixel.

$$S_i = \{x | dist(x, M_i) \leq dist(x, M_j) : i \neq j\} \tag{3.1}$$

x is object pixel, and M_i and M_j are model color. We used Euclidean distance for $dist(.)$.

4. Remove the small proportion of regions in the image. Finally, one or two portions of the largest pixel regions are remained.

Similar color regions were obtained from the result of color clustering, so we needed to express a color from the region. Thus, we represented the region based on the average of clustered pixels. From the result of the color clustering, color feature descriptor is constructed (see Figure. 3.1) and used for extracting the object area from the background in the test image.

R, G, B	H, S
128, 255, 0	100, 240
255, 255, 0	120, 240
128, 0, 255	220, 240
255, 0, 255	200, 240

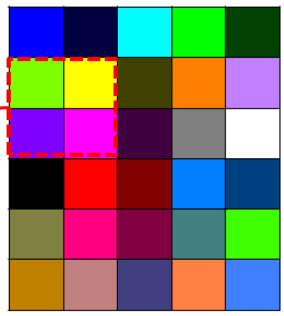

Figure 3.2: The model color

3.2 Curve feature extraction

3.2.1 Curve feature

The detection of feature points in an image is essential. The reason that this approach is so popular is that feature points provide a sufficient constraint to compute image displacements reliably, and that by feature points are reduced the data compared with the original image data, which is particularly important for running in real time. The most valuable information for non-textured object feature extraction is shape, because non-textured object does not have as much information as textured objects. Within shape features (straight and curved areas) curved areas are one of the most intuitive types of feature points which is similar to corner. Corners are image points that show a strong two dimensional intensity change, and are therefore well distinguished from neighboring points. Corner detectors have been widely used as feature point detectors because corners correspond to image locations with high information contents, and they can be matched between images (e.g. temporal sequence or stereo pair) reliably [61]. These matched feature point locations are then taken as an input to high level computer vision task.

To be useful for feature point matching, corner detector should satisfy the following criteria [61]:

- consistency: detected positions should be insensitive to the noise and should not move when multiple images with the same scene are acquired.
- accuracy: corners should be detected as closely as possible to the correct position;

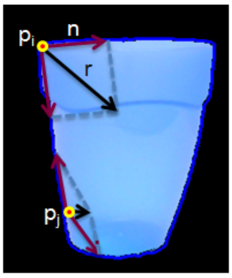

Figure 3.3: The curvature cost

- speed: even the best interest point detector is useless for real time tasks if it is not fast enough.

The well-known corner detector method is Harris interest point detector [62]. However, this is not invariant to scale changes and affine transforms. To deal with these problems, we considered more about curvature information from the object shape. Most of all the objects have curve areas which are easy to extract from the shape, and a subset of the features is simply presented in order to allow correspondence between training and test image. Also, this feature may gives own characteristics for distinguishing the object, so this information is popular to use for interest points.

For extracting a robust curve feature, we used curvature property from the boundary. This property is based on finding the maximum curvature cost of one point to the others in the boundary of the object. The cost of the curve point is defined using the vector scalar of each point on the boundary. Figure. 3.3 present how to calculate the curvature cost and select the curve point from each boundary point ($p_i = (x, y)$).

$$r = \|p_{i-n} - 2p_i + p_{i+n}\| \tag{3.2}$$

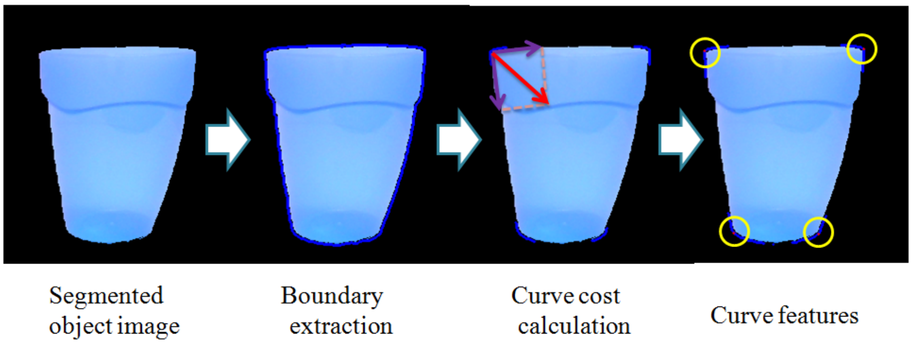

Figure 3.4: The Process of Curve Feature Extraction

Equation (3.2) provides curvature cost function of the boundary point.

From the boundary point p, two vectors n are decided based on the boundary length (object scale); then the scalar of the vector r is calculated between two vectors. Thus, each boundary point have curvature cost, and we can obtain the maximum curvature differences from the neighboring points; i.e., high-curvature point.

The overall process of curve feature extraction for non-textured object is provided in Figure. 3.4.

3.2.2 Scale Invariant Curve Feature

As stated in 3.2.1, the length of vector n is selected based on the boundary length; object scale. It is scale-dependent constraint. The problem is then cast as finding a scale invariant high-curvature point. If the scale change between images is known, we can adapt any interest point detector to the scale change and we then obtain points, for which the localization and scale perfectly reflect the real scale change between two images. If the scale change between images is unknown, a simple way to deal with scale changes is to extract points at several scales and to use all these points to represent an

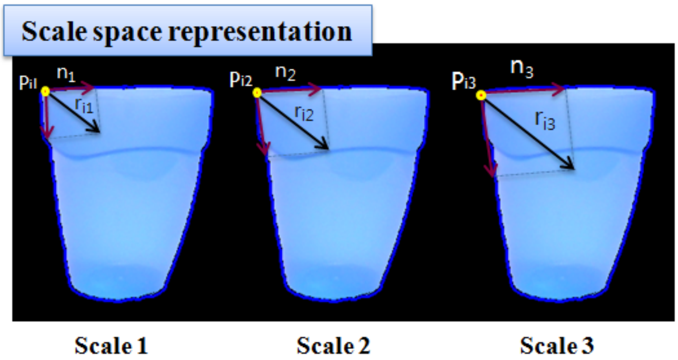

Figure 3.5: The curve point extraction in the scale spaces

image.

To be robust from general scale changes, we propose the scale invariant curve feature extraction.

Figure. 3.5 and Equation (3.3) indicates curve point extraction in the scale spaces.

$$r_{ij} = \left\| p_{i-n_j} - 2p_i + p_{i+n_j} \right\| \tag{3.3}$$

The number of scales j and the length of vectors n_j depend on the number of maximum boundary points i. If n_j is long, the obtained curve points are not sufficient when the size of the object in an image is small. Thus, we selected the highest n_j depending on the object size; i.e., the boundary length. In our experiments, we considered five scale spaces from the shortest n_j to the longest n_j. In each scale space, we can calculate the scalar of vector r_{ij} (the curvature cost) along the boundary. This r_{ij} need to be normalized along the scale space as shown in Equation (3.4).

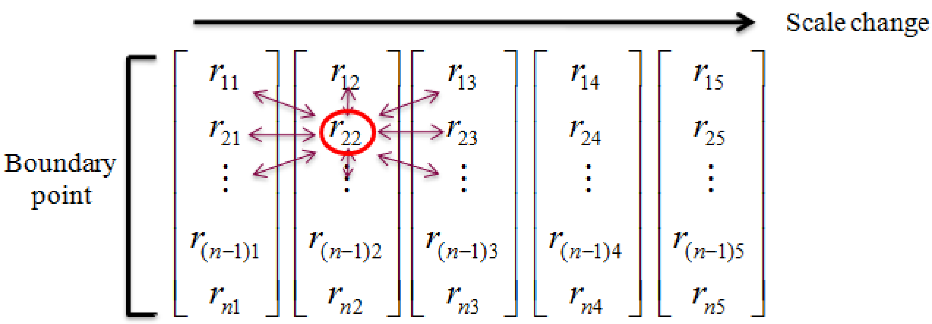

Figure 3.6: The curve point selection in the different scale spaces

$$normR_{ij} = \frac{r_{ij}}{n_j} \tag{3.4}$$

After, if r_{ij} is maximum compared to neighboring points and the points of neighboring scale space, the point is selected on each scale space. Figure. 3.6 illustrates how to select the point in the different scale space from the boundary points. The set of the selected points is the scale invariant curve area. In order to obtain highest-curvature points within the scale invariant curve area, the largest difference curve is then chosen in each curve area.

3.2.3 Curve feature selection in stereo matching

Once the curve feature candidate has been found by comparing a boundary point to its neighbors, the next step is to perform the feature matching in stereo images. From the natural scene, human easily perceive depth in 2D images but the process of doing is not well understood so is heavily used in computer visual system. Depth data derived from stereo has been used previously for application in a variety of domain such as robot vision and surveillance [63]. Barnard and Fischler presented a review covering the major steps involved in stereo analysis [64].

1. image acquisition
2. camera modeling
3. feature acquisition
4. image matching
5. depth determination
6. interpolation

The key step is a stereo image matching, that is, the process of identifying the corresponding points in two images that are cast by the same physical point in 3D space. For stereo matching, the search space can be reduced by observing that the points on one line in one image are constrained to match with points along a certain specific line in the other image; these sets of lines are known as epipolar lines. The epipolar lines are intersections of the two image planes with an epipolar plane, defined to the plane passing through an object point and the two camera foci. In a simple geometry, where the two cameras are related by a simple horizontal displacement, the epipolar lines are simply the horizontal lines; i.e., the matching points must have the same row values.

From the previous studies, two broad classes of techniques have been used for stereo matching, area-based and feature-based. Ideally, one would like to find a corresponding pixel for each pixel in each image of a stereo pair, but the semantic information conveyed by a single pixel is too low to resolve ambiguous matches, therefore area or neighborhood around each pixel is considered. Also, the commonly used feature based matching in the past using edge detection in the images.

However, both suffer from some limitations.

- Area-based matching require the presence of a detectable texture, so they tend to be failed in featureless or repetitive textured environments.
- Area-based matching is sensitive to absolute intensity and illumination.
- Area-based matching is confused in rapidly changing depth field.
- Feature-based matching is necessarily leads to a sparse depth map only and the rest of the surface must be reconstructed by interpolation.

Thus, the matching is made difficult by the lack of information in the non-textured object. From the result of the curve feature extraction, we only obtained the x coordinates, y coordinates and extracted scale information. As described in Figure. 3.7, we can calculate an angle from the curve feature. Finally, extracted curve features can have four kinds of descriptor, so stereo matching was performed using these descriptors; the relative column in the object, absolute row (epipolar line which we explained above), similar angle, and scale, which would be a corresponding point. From the process, we can finally extract the scale invariant curve feature in stereo images.

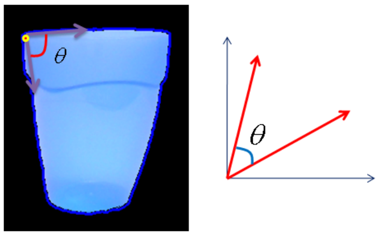

Figure 3.7: Curve angle calculation

3.3 Three dimensional scale extraction

Using the result of stereo matching, we can recover the depth of an object [65]. The purpose of obtaining depth is to estimate 3D structure of an object. The 3D coordinates can be obtained from the curve features, and most of all the objects have more than two curve features. Based on this constraint, we can calculate the distance between the two curve features called the pairwise feature. Thus, all object could have at least one pairwise feature. However, the problem is that the pairwise feature matching from similar curve feature between training and test image is difficult because of occlusion. The distance will be changed when occlusion is occurred in one of the curve part, but this wrong distance could be similar in another part of the object. To deal with this problem, we considered the maximum pairwise feature to estimate the object scale. Even if there was some occlusion, at least one maximum pairwise feature existed in an object (data not shown). This maximum distance would be the maximum scale for an object. To find the maximum pairwise feature, Euclidean distance was performed for each curve feature as following:

$$Pair = \max \sqrt{\sum_{k=1}^{3} \left(normR_{hj}^{k} - normR_{ij}^{k}\right)^{2}} \quad (3.5)$$

In Equation (3.5), $normR_{hj}^{k}$ is hth extracted curve cost (normalized cost),and k is for each x, y, z coordinates.

To evaluate the test object, the scale error with the training object was calculated. Equation (3.6) reveals the maximum pairwise feature error calculation between the training and test objects.

$$errorP = \frac{|trainD - testD|}{trainD + testD} * 100 \quad (3.6)$$

$trainD$ and $testD$ is the maximum distance for training and test, respectively. From Equation (3.6), the object ID is determined as a result of the object recognition.

Chapter 4

Experiment and performance evaluation

4.1 Experiment

To evaluate our approach, experimentation was performed on our own database as given in Figure. 4.1. It contains various condition changes such as occlusion, rotation (Roll= -180−180°, Yaw= -30−30°), illumination, and scale with the 640 × 480 image size. Figure. 4.2 gives an example of an object taken under these different conditions. The illumination is changed between 100 and 300 Lux, and the scales are changed between 0.5 times and 2 times. Also, we set the 20% for the maximum occlusion. In each condition, we divided 10 steps with 20 images in each step. Thus, each one of 11 non-textured objects has 1000 images; total 11000 images were used for the evaluation.

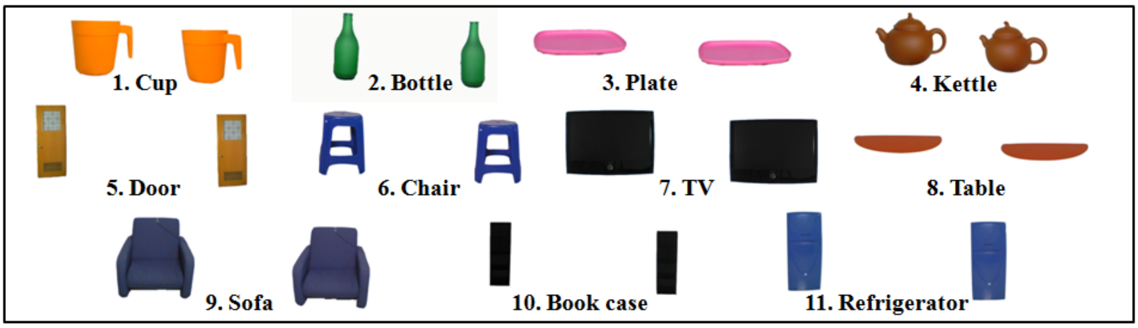

Figure 4.1: The database of non-textured object.

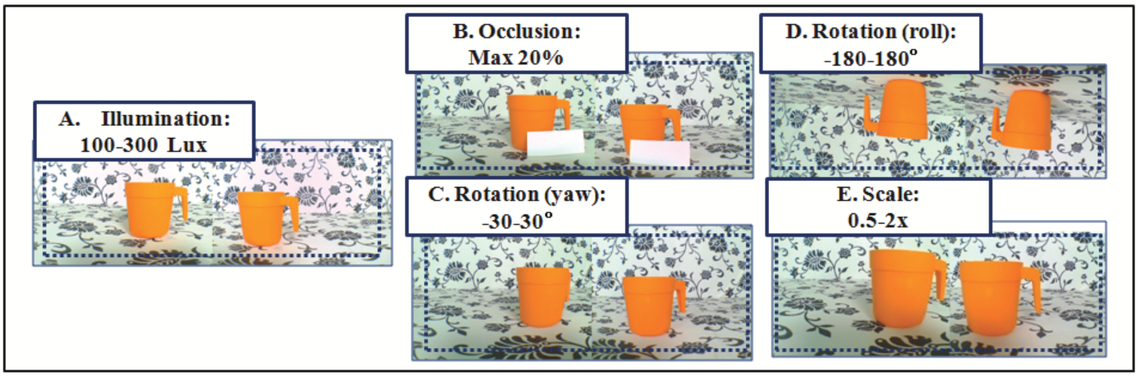

Figure 4.2: An example of condition changes in the database.

4.1.1 Color feature extraction

Figure. 4.3 presents the color clustering results. The color regions are divided by 1 or 2 colors; then we can calculate the average color feature from each region, i.e., color feature. As illustrated in Figure. 4.4, we can use the result of color feature extraction for object segmentation from the background.

4.1.2 Curve Feature Matching

Based on the scale invariant curve feature points, stereo matching is performed as given in Figure. 4.5.

4.2 Performance evaluation

Figure. 4.6 and Figure. 4.7 show that we compared the recognition performances between the shape context and the proposed algorithm. Based on the shape context, the overall recognition results were much lower than our approach (Figure. 4.6) because of some objects; i.e., Kettle, chair, and cup (Figure. 4.7). These results show that 3D

Figure 4.3: The result of color clustering

Figure 4.4: The result of the segmentation

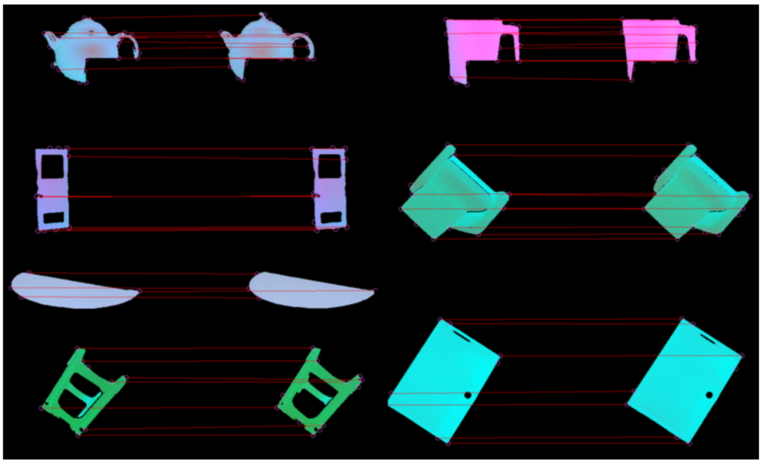

Figure 4.5: The result of the scale invariant curve feature and its stereo matching

scale information is much better than 2D shape information for non-textured object recognition.

Table. 4.1 demonstrates that proposed algorithm is invariant to illumination, occlusion and scale, but weak under rotation (yaw and roll); specifically, for TV, table, and door. The 3D scale of the TV is similar to the bookcase, so it is difficult to distinguish. Also, both ends of the table are very sharp, like a sharp half-moon; thus, it is difficult to obtain the scale invariant curve feature and correct 3D scale.

In addition, performance lagged in large objects (TV, door, and table), because the large objects need a long distance between the camera and the object. The short base-line in the stereo camera caused by obtaining less precise 3D coordinates with long distance from the object. As such, higher results obtained for small objects than large objects.

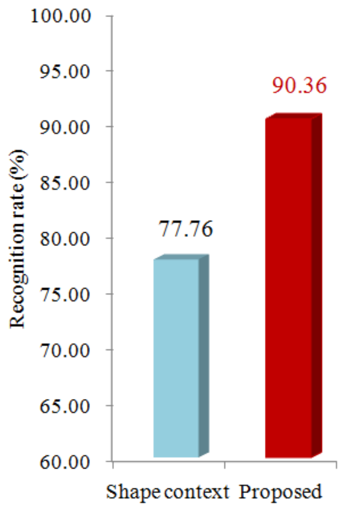

Figure 4.6: Recognition accuracy comparison between the shape context and Proposed method (overall)

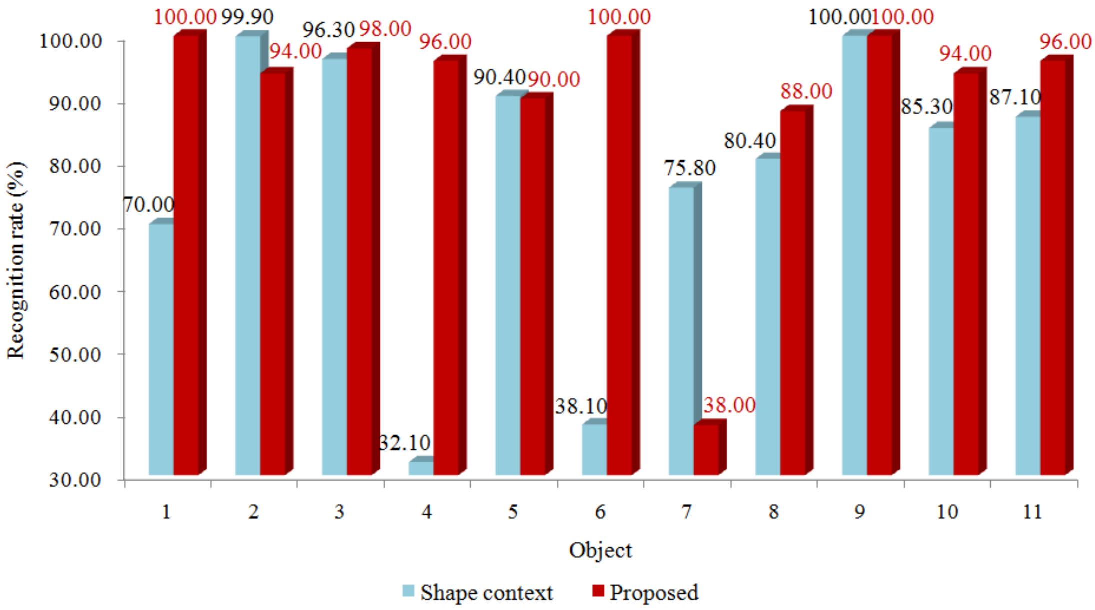

Figure 4.7: Recognition accuracy comparison between the shape context and Proposed method (each object)

Table 4.1: Recognition results under the various conditions

	A			B			C		
	correct (%)	False positive (%)	false negative (%)	correct (%)	false Positive (%)	false negative (%)	correct (%)	false Positive (%)	false negative (%)
1	100	0	0	100	0	0	94	0	6
2	99.5	0	0.5	93	0	7	100	0	0
3	100	0	0	99.5	0	0.5	99.5	0	0.5
4	100	0	0	100	0	0	75	0	25
5	94.5	0	5.5	100	0	0	86.5	0	13.5
6	96.5	0	3.5	99.5	0	0.5	98.5	0	1.5
7	98.5	0	1.5	75.5	0	24.5	42.5	0	57.5
8	87.5	0	12.5	98	0	2	92.5	0	7.5
9	100	0	0	100	0	0	100	0	0
10	99	1	0	100	0	0	96.5	0	3.5
11	100	0	0	82.5	0	17.5	86.5	0	13.5
	D			E			overall		
	correct (%)	false positive (%)	false negative (%)	correct (%)	false positive (%)	false negative (%)	correct (%)	false Positive (%)	false negative (%)
1	98	0	2	98	0	2	98	0	2
2	89.5	0	10.5	97	0	3	95.8	0	4.2
3	86	0	14	100	0	0	97	0	3
4	100	0	0	93	0	7	93.6	0	6.4
5	100	0	0	99	0	1	96	0	4
6	97.5	0	2.5	97.5	0	2.5	97.9	0	2.1
7	74.5	0	25.5	92.5	0	7.5	76.7	0	23.3
8	63	0	37	87.5	0	12.5	85.7	0	14.3
9	100	0	0	100	0	0	100	0	0
10	85	0	15	99.5	0	0.5	96	0.2	3.8
11	99.5	0	0.5	96.5	0	3.5	93	0	7

Chapter 5

Conclusions

We have conducted feature extraction for non-textured object recognition using a stereo camera. To recognize the non-textured object, we used color and 3D scale information. From a texture free object, a color could be good information to estimate the object without any complicate algorithm. Also, we could used actual object scale from the characteristic shape which is boundary-based curve representation with stereo images.

We performed experiments under the condition changes to evaluate our approach ; i.e., occlusion, rotation (roll, yaw), illumination, and scale. Experimental results indicated that the color feature is good for extracting object region from the background, and the 3D scale was much more robust than the shape context approach.

However, this approach has some difficulties under similar object scales. Therefore, prior to applying this method in the real world, more object information should be considered, such as the shape and pairwise feature correspondence. we leave for feature research the study of pairwise matching between training and test objects using more of object shape. Thus, we expect to overcome these problems to improve performance of the non-textured object recognition in the near feature.

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Curriculum Vitae

Name	:	Wonmin Byeon
Birth Date	:	March 7, 1985
Birth Place	:	Busan, Korea
Permanent Address	:	Samsung Apt. 7-906, Mandeok-dong, Buk-gu, Busan, Korea

Education

2008.3–2010.2 Master of Science, Information and Communications, Gwangju Institute of Science and Technology, Korea

20003.3–2008.2 Bachelor of Science, Computer Engineering, Dong-A University, Korea

Work Experience

2008.3–2010.2 Research Assistant, Applied Computing Laboratory, Gwangju Institute of Science and Technology (GIST), Gwangju, Korea

Professional Activities

2003.03–Present Member of Micro Computer Control Association (MICCA) in Dong-A University

2009.05–Present Regular Member of Korean Institute of Information Technology (KIIT)

Honors and Awards

2008.3–2010.2 Full-Scholarship, Gwangju Institute of Science and Technology, Ministry of Knowledge Economy, Korea

2008.7–2009.8 Research Fellowship from Korea Science and Engineering Foundation (KOSEF), Korea

2003.3–2008.2 Full tuition scholarship (B.S. Program), Dong-A University, Korea

2007.8 The Creative Work Competition: Second prize, Gwangju Institute of Science and Technology (GIST), Korea

2005.11 The Scientific Thesis Conference for Engineering College: First prize, Dong-A University, Korea

2005.11 The Creative Work Competition: First prize, Brain Korea 21 (BK21), Korea

2004.11 The Creative Work competition: First prize, Brain Korea 21 (BK21), Korea

Project Participation

2009 Research Assistant, *A study of the non-texture object recognition algorithm using stereo camera*, Supported by Samsung Electronics.

2008 Research Assistant, *A Development of Hardware Platform for Testing SMIA Camera Modules*, Supported by LG Innotek.

2008 Research Assistant, *A study of Vehicle Emulation system based on minute vehicle module*, Supported by the Korea Industry-Academic Cooperation Foundation.

2005 Undergraduate Research Assistant, *A study of combination system for safe driving from sleeping and prevention of robbery in a car*, Supported by Brain Korea 21 (BK21) and Dong-A University, Korea.

2004 Undergraduate Research Assistant, *A study of the system which can recognize another robot's color by image processing*, Supported by Brain Korea 21 (BK21) and Dong-A University, Korea.

2004 Undergraduate Research Assistant, *The Robot designed for a disaster probes*, Supported by Brain Korea 21 (BK21) and Dong-A University, Korea.

2003 Undergraduate Research Assistant, *Moving Flower Robot*, Supported by Brain Korea 21 (BK21) and Dong-A University, Korea.

Publications

International Conference Papers

1. **Wonmin Byeon** and Moongu Jeon, "Face Recognition Using Region-based Non-negative Matrix Factorization," *The 2009 International Conference on Future Generation Communication and Networking, Jeju, Korea, Dec. 10–12, 2009*

Domestic Conference Papers

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4. **Wonmin Byeon** Jilee Kim, and JungHaeng Kim, "Design and Implementation of a Drowsiness Prevention System for Safe Drive," *The Scientific Thesis Conference on an Engineering College in Donga University*, November 2005

Theses

1. **Master of Science**, *Feature Extraction For Non-textured Object Recognition Using A Stereo Camera*, School of Information and Communications, Gwangju Institute of Science and Technology, January 20010 (Thesis Advisor: Moongu Jeon)