Object-oriented Hybrid Segmentation Using Stereo Images

Woontack Woo and Yuichi Iwadate
Media Integration & Communications Labs
Advanced Telecommunications Research
Kyoto 619-0288, Japan
E-mail:{wwoo,yiwadate}@mic.atr.co.jp

ABSTRACT

In this paper, we have developed the theoretical framework for coherent image segmentation using stereo images. The robust segmentation is performed by combining multiple cues such as shape, intensity (color) and depth. Though image segmentation has been an active research field over last few decades, segmentation based on individual cue has several well-known drawbacks. For example, intensity-based schemes tend to generate detailed but inaccurate edges, and motion-based schemes only help segment moving objects. In addition, depth-based schemes may not yield satisfactory segmentation results because disparity estimation itself is a well-known ill-posed problem. Therefore, the main issue in segmentation is how to combine various cues to achieve robust segmentation results. In the proposed scheme, robust and consistent segmentation is achieved by properly combining several cues using MRF/GRF model. We first estimate intensity edges of the image and then re-evaluate the edges based on disparity edge information. In turn, the resulting intensity edges can help estimate an accurate disparity field. In addition, occlusion area can be segmented by properly combining intensity edges of stereo images.

Keywords : stereo image, hierarchical segmentation, disparity estimation, occlusion detection, MRF

1 Introduction

In this paper, we focus on the segmentation of the reference image under assumption that object-oriented video compression can be achieved using MPEG-4 [1,2]. Adopting "visual objects" instead of square blocks has been regarded as a new ways to flexible and interactive manipulation of visual data. For example, object or content-based coding schemes allows for each object to have its own bit rate and refresh rate according to channel condition, which is an important task in limited channel bandwidth environment. Over last few decades, object-oriented image segmentation has been an active research field because segmentation of an image into meaningful regions is a key step to achieve object or content-based functionalities [3]. Nevertheless, fully automatic segmentation schemes are still open problems.

In conventional approach, a scene is segmented based on intensity (or color), dense motion field or both information. Won proposed segmentation scheme for image coding using Bayesian framework [4]. Chu et al. showed that edge information could help segment range images effectively [5]. Marques et al. have adopted object based segmentation approaches in motion compensated coding [6]. However, the performance of conventional segmentation schemes depends on the various factors. For example, intensity-based segmentation is not fit for coding because the description cost of the resulting segments is too high, in general. In addition, while motion-based segmentation may suffer from inaccurate motion estimation, combined schemes may also suffer from the fact that motion information only helps segment moving objects [7–9]. Note also that depth-based schemes may yield unsatisfactory segmentation results because disparity estimation itself is a well-known ill-posed problem [10].

We propose a novel hybrid segmentation scheme using stereo images, which helps separate objects (or area of interest) from a scene under assumption that pixels within a rigid object have smoothly changing disparity vector as well as similar intensity. The proposed hybrid segmentation scheme consists of two parts [11–13]: (i) disparity estimation and segmentation and (ii) image segmentation based on the intensity and disparity edges. In the proposed scheme, we first estimate a consistent disparity field using hierarchical block segmentation and segment the resulting disparity field using MRF/GRF model. Then, given the disparity edge, disparity and intensity information, we segment the image. The boundaries of segments are smoothly connected and the resulting disparity field are globally smooth, which helps segment an image into meaningful areas and results in a clue on objects in the scene.

The novelty of the proposed hybrid scheme is in that the proposed scheme overcomes the disadvantages of conventional segmentation schemes by combining several visual cues such as intensity and disparity edges. As explained, in video coding, motion information has been used to estimate the boundaries of moving objects according to motion homogeneity, under assumption that the objects have rigid motion. Therefore, the applications have been restricted to simple video-phone-like sequences. Meanwhile, using stereo images can segment an image into different objects because all objects in the scene, as well as moving objects, have disparity vectors. In addition, the proposed scheme can improve the performance of object-based displacement (motion and disparity) estimation/compensation, which reduces both inaccuracies in displacement estimation and blocking artifacts in the decoded image simultaneously. Note also that the cost of stereo-based segmentation may be cheaper than that of the other segmentation schemes. Even in 2D infrastructure, the resulting disparity information is useful for giving a look-around capability because intermediate views can be synthesized using disparity based interpolation.

This paper is organized as follows. In Section 2 and 3 the MRF/GRF model and the proposed hybrid segmentation algorithm are described more in detail. Some experimental results and possible extension of this research are given in Section 4.

2 MRF/GRF Model for Image Processing

In the past few years, Bayesian estimation with MRF/GRF model has been successfully employed and shown great potential in many image processing applications [14]. For computer vision problems, the Bayesian approach seeks to extract scene information from an image or sequence of images by balancing the content of the observed image with prior knowledge. A growing number of applications of the MRF model in the field of image processing and computer vision have been proposed since Besag's work [15]. Geman *et al.* considered images as realization of a stochastic process that consists of an observable noise process and a hidden edge process [16]. Konrad *et al.* proposed the MRF based approach and used stochastic relaxation to estimate motion vectors from time-varying images [17]. Woo extended this stochastic model to modeling of the disparity field for stereo image coding [11].

The main advantage of the MRF model based approach is that it provides a rigorous mathematical framework and a general model for the interaction among spatially related random variables. Another advantage of the MRF model is its ability to combine discontinuity into the energy equation. It reduces the error resulting from an oversmoothing effect by adopting the *line process*. It is also easy to integrate different information such as stereo and motion [18]. The resulting algorithm also can be implemented in parallel due to its inherent localization property [19].

Figure 1 shows commonly used neighborhood systems in image processing. These neighborhood system can be defined similarly for disparity (or motion) and occlusion fields.

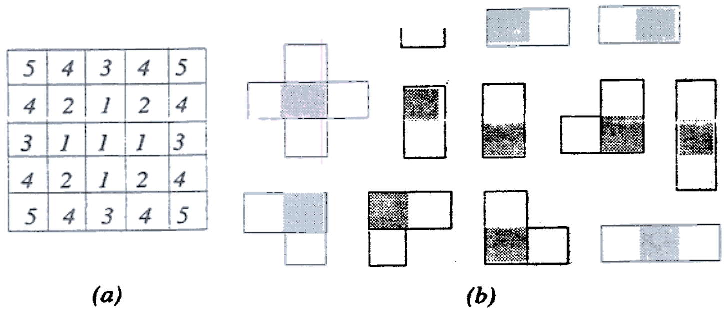


Figure 1: Neighborhood systems and cliques: (i) Geometry of neighborhoods; the number denotes the order of the neighborhood system. (ii) First order neighborhood η^1 and cliques used for intensity, the disparity and the occlusion; we can quantify the effect of each clique according to the characteristics of the random fields.

Figure 2 shows two different neighborhood systems for line (or edge) processes, horizontal and vertical edges, respectively [19]. Considering the model constraint, an isolated edge is inhibited and a connected edge is encouraged even if the intensity (or disparity) changes slightly.

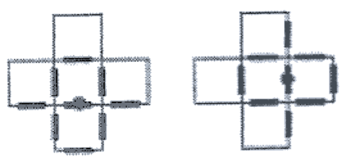


Figure 2: Neighborhood System for Edge Process for: (a) Horizontal Edge (b) Vertical Edge

We model both image and disparity field using MRF model with appropriate *a priori* assumptions on its smoothness. In fact, disparity fields are generally very smooth - much smoother than images themselves. According to the theory of equivalence of MRF and Gibbs random fields [15], we can then drive a cost function, which takes into account the smoothness in both intensity and disparity, allowing to minimize the noise effects in segmentation and disparity estimation. The main advantage of representing each probability in the Gibbs distribution form is in that it can be formulated with energy function and thus the multiplication of the probabilities can be replaced by the sum of the energy equations. Therefore, the problem of maximizing the *a posteriori* probability (MAP) can be replaced by the problem of the finding a solution minimizing the energy equation.

3 Image Segmentation Using Stereo Images

3.1 Problem Formulation

Let F_1 and F_2 be, respectively, the segmentation target and reference images in a stereo pair. Then, the image can be represented as a set of pixels, *e.g.* $F_1 = \{f^1_{ij}, 0 \leq i < N_x, 0 \leq j < N_y\}$, where f_{ij} denotes (i,j)th pixel and the index 1 represent the target image. The number of pixels is $N_x \times N_y$. The resulting pixelwise disparity vector field (V) can be represented as $V_1 = \{v_{ij}, 0 \leq i < N_x, 0 \leq j < N_y\}$. Then, $\hat{f}^1_{ij} = f^2_{ij \oplus v_{ij}}$, where $\oplus$ denotes the displacement of the block.

We formulate the problem, object-based segmentation using stereo images, as follows. For a given stereo pair, F_1 and F_2, we estimate segmentation, S_1, intensity contour, L_1, disparity contour L_{V_1}, and disparity, V_1, such that the solutions of MAP estimation, $P(S_1, L_1, V_1, L_{V_1}|F_1, F_2)$. Bayes theorem allows decomposing the posteriori probability and then the MAP estimation problem is replaced by the energy minimization problem, according to Clifford-Hammersley theorem [15]. According to the process as we did in [11–13], we define segmentation problem as follows.

$$\begin{aligned} \hat{X} &= \arg\max_X P(S_1, L_1, V_1, L_{V_1}|F^1, F^2) \qquad (1) \\ &= \arg\max_X P(S_1, L_1|F_1, F_2, V_1, L_{V_1}) \cdot P(V_1, L_{V_1}|F_1, F_2) \\ &= \arg\min_X U(S_1, L_1|F_1, F_2, V_1, L_{V_1}) + U(V_1, L_{V_1}|F_1, F_2)\} \end{aligned}$$

where the first term related to image segmentation and the other to disparity estimation and disparity segmentation, respectively.

According to (1), the proposed hybrid segmentation scheme consists of two steps: (a) estimation and segmentation of an disparity field and (b) segmentation of the image based on the intensity, disparity and disparity edges. First, we perform an initial segmentation of an image and then the resulting edge can be used as an initial disparity edge. To estimate a consistent disparity field, we estimate an initial disparity field based on hierarchical block segmentation with higher energy level in the disparity compensated difference frame [20]. Then, we estimate pixelwise disparity field with sharp boundaries using MRF model. Finally, given intensity and disparity edges, we segment image based on the MRF model, which generates smoothly connected boundaries.

Initial Segmentation

Before performing pixelwise disparity estimation, we segment the image and use the resulting edge as an initial disparity edge. We decide edge process initially by the intensity difference of the noisy image. The initial discontinuity process is defined as

$$l_{ij} = \begin{cases} 1, & |f_{ij} - f_{ij}^{\eta}| \geq T_e \\ 0, & o.w. \end{cases} \qquad (2)$$

where T_e is threshold for edge decision. If the difference between the intensity and its neighborhood exceed a threshold T_e, then there is discontinuity. In case $l_{ij} = 1$, the smoothness constraint should not be performed across this discontinuity. The resulting intensity edge is a good initial guess of the disparity edge, though the intensity discontinuities may not correspond to physical boundaries [5].

3.3 Disparity Estimation

Hierarchical Disparity Estimation

In intensity-based disparity estimation, pixels or regions are used to measure the similarity between stereo pair. Note however that they usually tends to fail to provide good matching results. For example, as the block size becomes larger, the level of estimation error increases, especially the block includes object boundaries. By reducing the block size, the estimation error can be reduced but the resulting disparity field may not be homogeneous because the estimation is subject to various noise effects. Various estimation schemes have been proposed to overcome the drawbacks of block matching, which include estimation schemes with MRF model [11], overlapped block matching (OBM) with modified MRF model [21]. Nevertheless, conventional block-based approaches only relieve parts of drawbacks.

A way to overcome the dilemma between robustness and consistency of intensity-based disparity estimation is hierarchical disparity estimation. The main advantage of the disparity estimation with hierarchical segmentation is that it can overcome mismatching problem (inconsistency of the disparity field) by considering a large area for the initial disparity field estimation. It however frequently fails to provide an accurate disparity along object boundaries. To yield a robust and consistent disparity field, we adopt two step approach, *i.e.* hierarchical disparity estimation and then pixelwise refinement. We start from a large block and segment the block with higher energy level in the disparity compensated difference. Then, given a disparity field, we perform pixelwise disparity estimation using MRF model, which results in smooth disparity field with smoothly connected boundaries.

The basic idea of block segmentation is that the disparities of subblocks are accepted only when they are ***significantly*** different with the disparity of their upper block. We first define a segmentation cost. Let r and d represent blockwise rate and distortion. Then, blockwise segmentation cost c_{ij}^k for the hierarchical disparity estimation can be defined as follows

$$c_{ij}^k = \sum_{l \in M} \{d_l^k + \lambda r_l^k\}, where\ M = \begin{cases} 4^k, & \text{for quadtree} \\ 2^k, & \text{for binarytree} \end{cases} \tag{3}$$

where k and l denote the level of the segmentation and the indices of the block, respectively. The weight between d and r is controlled by the Lagrange multiplier λ.

A basic procedure of hierarchical block segmentation-based disparity estimation is as follows. First, the disparity is estimated at the coarsest level, *e.g.* block size of 32×32, using full search BLOCK MATCHING. The block is segmented into smaller blocks, *e.g.*, 32×16 or 16×16, if the cost of the block is higher than that of subblocks. Lagrangian costs defined in (3) are compared to determine segmentation of the block and the block segmentation is performed, only if $c_{ij}^k > c_{ij}^{k+1}$. Segmentation is repeated until the coding cost of the block is smaller than that of segmented subblocks or the block size is reached the preselected size.

3.3.2 Estimation and Segmentation of Dense Disparity Field

To estimate a dense disparity field, we consider a disparity field, V_1, a coupled MRF model with respect to a neighborhood system $\eta = \{\eta_{ij}, (i,j) \in \Omega\}$, where η_{ij} is the neighborhood of v_{ij} such that $(i,j) \notin \eta_{ij}$ and $(k,l) \in \eta_{ij}$, *i.e.*

$$P\{v_{ij} | v_{kl}, (k,l) \in \Omega\} = P\{v_{ij} | v_{kl}, (i,j) \neq (k,l), (k,l) \in \eta_{ij}\} \tag{4}$$

where Ω represents a discrete and finite rectangular lattice with the same size as the disparity field. We then derive a cost function based on the MRF/GRF model, which allows estimating a smooth disparity field with simple boundaries.

The second term, $U(V_1, L_{V_1} | F_1, F_2)$, of the cost function in (1) corresponds to disparity estimation and disparity segmentation, *i.e.* to estimate the most likely solution for the disparity field, V_1, with disparity edge, L_{V_1}, from the observations of a stereo pair, (F_1, F_2). As explained, the solution minimizing the cost maximizes the *a posteriori* probability in (1). The corresponding cost function for disparity estimation can be defined as follows.

$$\begin{aligned} U(V_1, L_{V_1} | F_1, F_2) &= U(F_1 | F_2, V_1, L_{V_1}) + U(V_1 | L_{V_1}) + U(L_{V_1}) \\ &= \sum_{(i,j) \in \Omega} \{(1-\alpha) \| f_{ij}^1 - f_{ij \oplus v_{ij}}^2 \|^2 + \alpha \sum_{\eta_{ij}} (v_{ij} - v_{ij}^{\eta})^2 (1 - l_{ij}^{\eta}) + \beta \sum_{c \in C} V_c(l_{ij}, l_{ij}^{\eta})\} \end{aligned} \tag{5}$$

where Ω and C represent a rectangular lattice and a pre-specified set of cliques, respectively. In the above equation, f, v and l represent a pixel, a disparity, and a disparity contour, respectively. The disparity edge l controls the discontinuity between the disparity, v, and its neighborhood, v^{η}. The parameters α and β are weighting constants controlling the weight among similarity, smoothness and discontinuity. $\oplus$ represents a movement along the disparity.

In (5), the first term corresponds to the constraint on the similarity of intensity between corresponding stereo images along the disparity. In general, the intensity levels in a stereo pair may not be the same, even if the images are captured at the same time and at the same place. Note that the evaluation of estimation has to take into account properties of human visual perception, *i.e.* the preservation of 3D perception. However, subjective evaluation of the quality is still an open probiem and is not very reliable and repeatable yet. Thus, in this framework, we use simple objective measures such as mean squared error (MSE) between f^1 and f^2.

The second terms in (5) corresponds to the *a priori* assumption on the smoothness of the disparity field given disparity edges, L_{V_1}. We assume that the real disparity field is smooth except for the object boundaries that are related to the depth discontinuities. Note that generating a smooth disparity field not only mitigates the effects of noise, it can also increase the encoding efficiency for the disparity (similar disparities in adjacent blocks results in lower entropy).

The last term in (5) represents a cost function for the disparity edge, which controls the discontinuity between the disparity and its neighborhood. The main role of the disparity edge is to prevent disparity from being oversmoothed across object boundaries. Thus, smoothness constraint should not be performed across this discontinuity. The smooth contours are also used to compactly represent segmented disparity fields.

For the disparity estimation we only use the first and the second term in (5) because only two terms are direct function of disparity. We estimate disparity by tradeoffs between similarity of intensities and smoothness of the disparity field. Similarly, the disparity edge is decided using the second and the third term. In this case, the role of the second term is a kind of dynamic thresholding for the decision of an edge according to the state of the neighboring edges.

In this experiment, for simplicity, we estimate the disparity with a minimum energy by full search within a search window. In this process, outliers in disparity fields are reduced and smooth boundaries are estimated by MRF-based approach. Note that it also results in the reduced bit rates for the disparity field since fewer numbers of region and shorter boundary length requires less bit rate. The resulting contours will be used to help segment the image, because the disparity contours could correspond to the boundaries of the objects or meaningful regions in the image.

3.4 Refinement of Image Segmentation

Our final goal is to segment an image to meaningful areas using the MRF/GRF model. In general, contours or object boundaries provide compact representation and convey much of the semantic content [3, 22]. Note that contour-based coding is also more suitable for upcoming multimedia applications requiring object-based manipulation or transmission. In addition, the reconstructed image less suffers from the visual artifacts along the object boundaries.

The first term of the cost function in (1) correspond to the constraint on the intensity field. The cost function for image segmentation can be defined as follows.

$$\begin{aligned} U(S_1, L_1|F_1, F_2, V_1, L_{V_1}) &= U(F_1|S_1, L_1) + U(S_1|L_1) + U(L_1|L_{V_1}) \\ &= \sum_{(i,j)\in\Omega} \{(1-\alpha_s)||s^1_{ij} - f^1_{ij}||^2 + \alpha_s \sum_{\eta_{ij}} (s_{ij} - s^{\eta}_{ij})^2 (1 - l^{\eta}_{ij}) + \beta_s \sum_{c\in C} V_c(l_{ij}, l^{\eta}_{ij})\} \end{aligned} \tag{6}$$

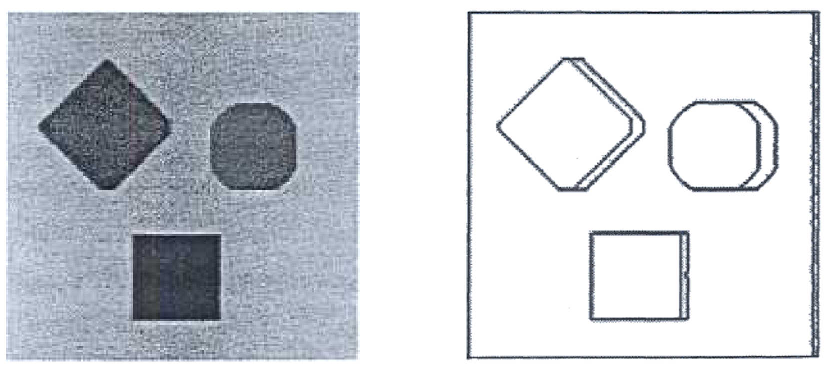
where Ω and C represent a rectangular lattice and a pre-specified set of cliques, respectively. In the above equation, f, s and l represent a pixel, an error-free pixel and an edge, respectively. The disparity edge l_v is used as an initial edge and the intensity edge l controls the discontinuity between neighboring pixels in the segmented image, *i.e.* s and s^{η}. The parameters α_s and β_s are weighting constants controlling the weight among similarity, smoothness and discontinuity.

In (6), the first term corresponds to the noise reduction process. In general, the noise is added when the image is captured. The second terms corresponds to the *a priori* assumption on the smoothness of the image, S_1, given intensity edges, L_1. The last term represents a cost function for the intensity edge, which controls the discontinuity of intensity levels between the pixel and its neighborhood. The main role of the edge is to prevent intensity from being oversmoothed across object boundaries.

As explained, the resulting segmentation of an image is used to refine disparity field and vice versa. By repeating disparity estimation and image segmentation, we segment an image and estimate disparity, where both intensity image and disparity field have smoothly connected boundaries.

4 Experimental Results

The preliminary experimental results illustrate the effectiveness of the proposed scheme, hybrid segmentation by properly combining several cues such as intensity, disparity and disparity edges using MRF/GRF model. Figure 3 shows the original image and segmentation result, which corresponds to objects and occlusion areas in a scene. As shown in Figure 3 (b), by combining intensity edges of stereo image, we can estimate an occlusion areas, which is an important step to remove occlusion effect. Especially in z-keying, proper treating of occlusion is crucial for providing the photo-realistic mixed reality.



(a) (b)

Figure 3: Image segmentation using disparity and intensity edges (Block.pgm) (a) target image (b) resulting contours.

In this paper we have developed the theoretical framework for coherent image segmentation using stereo images. In general, efficient and flexible representation is important for achieving object-based functionalities in interactive multimedia applications, such as object-based query, editing, manipulation, etc. Interactive image/video management can be achieved by adopting *visual objects* instead of square blocks. As explained, nevertheless, the new standards, such as MPEG-4 and MPEG-7, are not addressing detailed segmentation schemes because fully automatic segmentation schemes are still open problems. The proposed scheme is the first step toward object-based coding.

Even in mono sequence transmission scenarios, the proposed segmentation scheme is useful because the cost of stereo-based segmentation may be cheaper than that of the other segmentation schemes at the encoder. The remaining problem is the RD-based representation of the boundaries for the segmented image. Object-based dependent quantization is another problem to be solved to optimize the encoding performance [23]. This research will be extended to support 3D-look-around-capability at the decoder based on intermediate scene synthesis [24].

Another direction of this research will be generating photo-realistic mixed reality environment using multiview images, which requires pixelwise accurate depth map.

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