Detecting and Tracking Gaseous Objects in Video Data

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화상 데이터에서 기체의 감지 및 추적

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Abstract

기체에 대한 영상처리 기술은 그 응용 분야가 매우 넓고, 그에 따른 산업적·경제적 중요성도 증가되게된다. 한 예로서 자동으로 공장오염 감시나 산불감시등에 사용되는 영상기기에 곧바로 기체에 대한 영상처리 기술들이 필요하다. 그러나 기체는 고체와는 다른 다음과 같은 특성들을 가지고 있다. 첫째, 고체의 경우 물체의 경계선이 비교적 분명하지만, 기체의 경우 하나의 기체 내에서도 밀도 분포가 다르기 때문에 그 경계선에서도 밀도가 불규칙하여서 기체의 경계선을 정확히 정의하기 힘들다. 둘째, 기체 분석을 위한 영상들은 대체로 잡음이 많고, 기체의 크기에 비하여 해상도가 낮다. 따라서 기체 영상은 픽셀(pixel) 단위로 분석 처리하기가 어렵다. 위와 같은 기체가 가지는 특성 때문에 고체에 대한 영상 처리 기술을 기체에 직접적으로 적용하기는 불가능하다. 본 연구에서는 화상 데이터에서 기체를 감지하여 추적하는 시스템을 개발하고자 한다.

I. Introduction

Segmentation and identification of moving objects are crucially important tasks for video analysis applications such as robot vision, airborne surveillance and content-based video codin[1]. The purpose of segmentation is to automatically detect object movements and track the object regions. The purpose of identification is to extract the target object features and pick objects based on their features.

So far, there has been extensive research on segmenting and identifying rigid objects or model-based deformable objects. However, the segmentation and tracking of gaseous objects is rarely studied. In this work, we develop a system for tracking gaseous objects via image segmentation and identification[2].

Difficulties in tracking gaseous objects arise from the irregularity of objects' shapes and motion behavior and the low resolution of the image. Since the intensity of a gaseous object is variable at the boundary, the object's boundaries can not be well defined. Furthermore, since the motion of gaseous objects depends on air turbulence, it is hard to decide time order of gas motion and region of a same gas may be spatially disconnected. Therefore, modeling such an object's shape and motion behavior is very intractable. In many practical image sequences, object images are noisy and object sizes are small compared to the image resolution. Thus, the texture patterns on objects are indiscernible, which makes object identification more

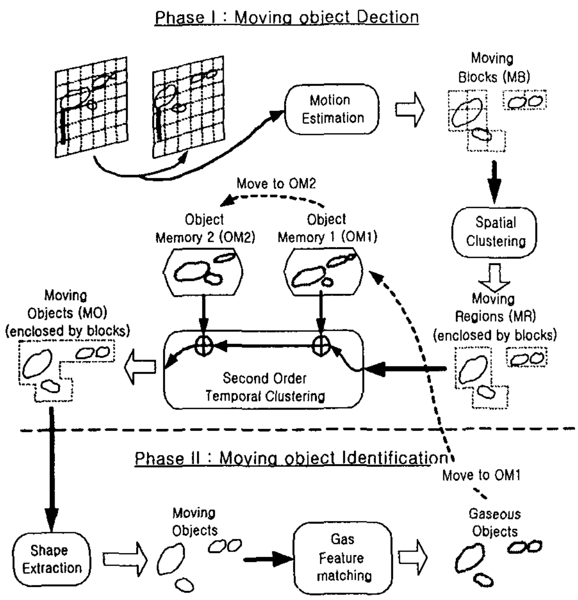

Fig. 1 Overall procedure for tracking gaseous objects

difficult.

Figure 1 illustrates the overall view of the proposed gaseous object tracking system. The motion block matching method detects moving blocks. The spatial clustering clusters the blocks into objects. The temporal clustering tracks motion behavior of the spatially clustered objects and clusters the objects following the same motion path into the same object. The results of temporal clustering are saved as object memories. The object memories provide object motion behaviors for the next temporal clustering process. At a given frame time, the object identification process extracts features of the objects obtained after temporal clustering and targets the objects that match with the desired object features.

II. Moving Object Segmentation

2.1 Block-Matching Motion Estimation

In order to find gaseous objects, the very first step is to detect moving objects. we use block-matching motion estimation which is used in current MPEG coding standards[3]. We slice an image plane into blocks of size $n \times n$ pixels. The value of n depends on object size and resolution. We adopt the three step search method for motion displacement search. At each sequential step, the search ranges are 3-pixel, 2-pixel and 1-pixel. We use mean square error (MSE) as a matching criteria since MSE is more convenient for determining a proper moving block threshold. The moving blocks detected by motion estimation may include irrelevant detected blocks due to noise or noise-like motion such as motion of leaves on trees.

To distinguish such noisy motion blocks, the block-matching MSE of real moving blocks must be larger than a certain value, that is, a threshold. So, the decision of the threshold value is crucial in motion estimation performance. We set up the block-matching MSE threshold through a significance test. Let I_t be the image frame at a time t. So, $I_t(x,y)$ is the image pixel intensity at (x,y). At (x,y) where no pixel movement occurs, $d(x,y) = I_t(x,y) - I_{t+1}(x,y)$ is a camera noise. It is well-known that camera noise follows a zero mean Gaussian distribution with a variance σ^2 equal to twice the variance of the camera noise. So, if we let H_0 be the null hypothesis that there is no change at (x,y), the probability density function (*pdf*) of the camera noise is

$$p(d(x,y)|H_0) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{d^2(x,y)}{2\sigma^2}\right\}.$$

We can define T as the normalized block-matching MSE such as

$$T = \frac{1}{\sigma^2 \cdot n^2} \sum_{(x,y)\in B_i} d^{2(x,y)}$$

where B_i is a block of size *nxn* pixels, and σ^2 is twice the camera noise variance.

Assuming that camera noise $d(x,y)$ is statistically independent, the variable T follows a χ^2 distribution with n^2 degrees of freedom. We choose the threshold t_α through the significance test. A significance level α corresponding to t_α is

$$\alpha = p_{\chi^2}(T > t_\alpha | H_0)$$

where $p_{\chi^2}(T)$ is a χ^2 distribution.

Thus, α is the probability of type I. The significant level α can be considered as the probability of detecting a block B_i as a moving block although the block does not move. For blocks of *16x16*, we set t_a to be 1, which corresponds to 90% confidence.

2.2 Spatial Clustering for Moving Region

In the motion estimation process, an image plane was divided into blocks. So, a moving region is set of moving blocks. We need to merge similar moving blocks to recover moving regions, which means motion block clustering in the spatial domain. We perform a non-supervised clustering method. For clustering features, we use block connectivity, normalized difference of block-matching MSE and normalized difference of block displacement. We do not use intensity since gaseous object intensity varies even within a single object.

We say two blocks to be neighbors if they share an edge or vertex, that is, they are in 8-connectivity. Given two moving blocks B_i, B_j, B_i, B_j are merged into the same object region if the similarity distance is less than a certain threshold value. Otherwise, B_i, B_j are regarded as different object blocks.

We perform clustering with the one-path region growing method. At first, each cluster is initialized as a single moving block. If the first moving block and the next moving block are to be merged, those blocks are merged to the first cluster. Otherwise, the next block remains as a cluster. This process is continued for each new moving block until all moving blocks are tested.

2.3 Temporal Clustering for Moving Object

Moving Object Clustering in the Temporal Domain} One difficulty in segmenting gaseous objects is that regions of a gaseous object may be disconnected. Such separated regions should be observed as a single object region. To overcome this phenomenon, we exploit inter-frame motion tracking. Although the regions formed by an object might not be connected in a single frame, the motion trajectories of such objects will intersect. This means that the separated objects can be connected in the temporal domain.

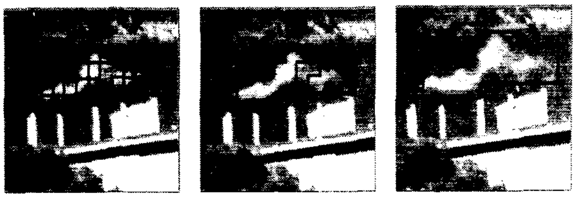

Fig. 2 Results of a gaseous object segmentation

We perform second order temporal clustering. The object regions of the previous two frames are stored for tracking object motion paths. The motion trajectory of a region in the current frame is constructed by combining the current region and all regions in the previous frame that touch the current region. Object regions on a same trajectory are clustered as the same object.

Figure 2 illustrates the result of a plume object segmentation. At first, motion estimation detects moving blocks. At the spatial clustering step, the moving blocks are clustered to moving regions. The temporal clustering step clustered the moving regions to a single object.

III. Gaseous Object Identification

One feature that is commonly used for object identification is texture. In most of video data, textures of gaseous object images are neither distinct nor discernible. Therefore, instead of texture we must exploit other features. The features we exploit are boundary direction pattern.

Gaseous object shapes are arbitrary and irregular. The boundary directions of such irregular shapes must also be arbitrary. This implies that the directions between successive boundary pixels are much less correlated for gaseous objects than for rigid objects. We calculate the correlation of boundary directions to quantify the degree of shape irregularities. To record boundary directions, we use the 8-direction chain coding method[4]. Figure 3 describes the chain code algorithm. Starting at a boundary pixel, the algorithm records the orientation of the next edge pixel. The boundary pixel

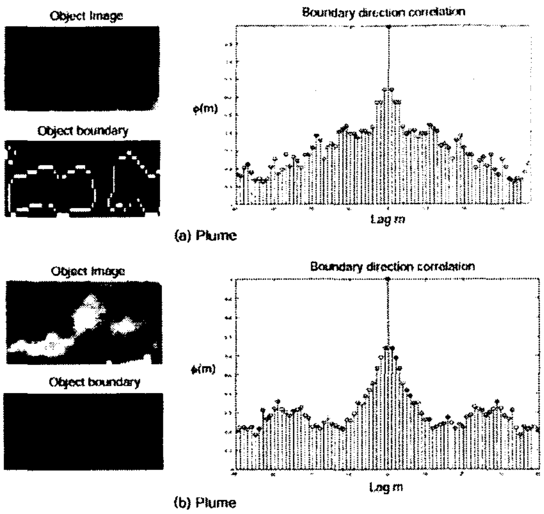

Fig. 3 Gaseous Objects (Plumes) and their boundary chain-code correlations

orientations follow 8-neighbor connectivity. So, each direction can be labeled from 0 to 7. If a boundary has branches, there must be multiple directions at the boundary branches. In this case, the smallest label is chosen. The same process is continued until all boundary pixels have been visited.

Let $\theta(n)$ be a boundary direction code. Then the correlation coefficient at m-lag is

$$\phi(m) = \frac{\sum_{n=-\infty}^{+\infty} \theta(n+m) \cdot \theta(n)}{\sum_{n=-\infty}^{+\infty} \theta(n)^2}.$$

Figure 4 and 5 compares the correlation coefficients for gaseous objects and rigid objects. We measure the degree of the boundary irregularity with the average of one- and two lag correlation. We decide an object to be a gasesous object when the correlation average of the object is less than 0.75.

IV. Test Results

We test the proposed system for tracking plumes. The plumes spreading more in one direction due to strong winds are easily detected. This is because strong wind makes the plume movement apparent. Where there is no wind flow or very little air density variation, plumes move very slowly. Then

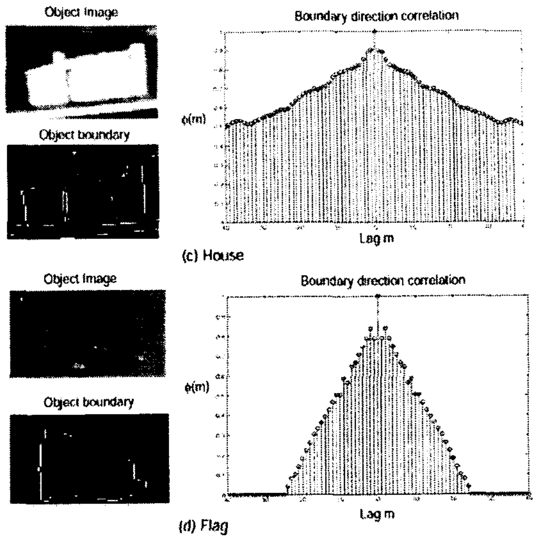

Fig. 4 Rigid objects and their boundary chain-code correlations

it is difficult to detect such plumes. For small size plumes, we reduce the motion dection block size to increase the motion estimation resolution. However, if we further reduce the block size, the proposed method fails to detect any plumes because of too many noise blocks. This implies that the confidence test for noise threshold does not work if the blocks are too small blocks. So, we need to find the proper block size which can detect small motion object but is not vulnerable to noise. The issue of standard versus non-standard block size is also a relevant engineering design consideration.

Reference

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