Application of Panoramic Annular Lens for Motion Analysis Tasks: Surveillance and Smoke Detection

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Abstract

In this paper some applications of motion analysis are investigated for a compact panoramic optical system (Panoramic Annular Lens). Panoramic image acquisition makes multiple or mechanically controlled camera systems needless for many applications. Panoramic Annular Lens' main advantage to other omnidirectional monitoring systems is that it is a cheap, small, compact device with no external hyperboloidal, spherical, conical or paraboloidal reflecting surface as in other panoramic optical devices. By converting the annular image captured with an NTSC camera to a rectangular one, we get a low-resolution (cc. 2.8 pixels/degree horizontally and 3 pixels/degree vertically) image. We have developed algorithms, which can analyze this low-resolution image to yield motion information for surveillance and smoke detection.

1. Introduction

Surveillance with intelligent camera systems is becoming increasingly important in everyday life. It is widely used in traffic control, driving assistance and surgery. In these applications compactness is also essential.

It is well known that omnidirectional camera systems have many advantages compared to conventional optics. With large field of view we can avoid the use of multiple camera systems or mechanically controlled cameras. This is very useful in applications such as surveillance systems, intelligent vehicle control [2], endoscopic measurements [3], etc.

In our work we deal with a special lens called Panoramic Annular Lens (PAL) [1], which has different optical properties compared to other omnidirectional systems (Figure 1, 2). The main advantage of PAL is its small size, compactness, and sharp image mapping, although its vertical view angle is limited to about 50-70 degrees.

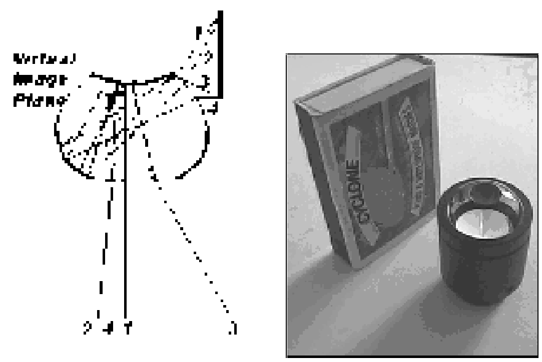

Figure 1. Image formation in PAL optics (left), and the PAL (right).

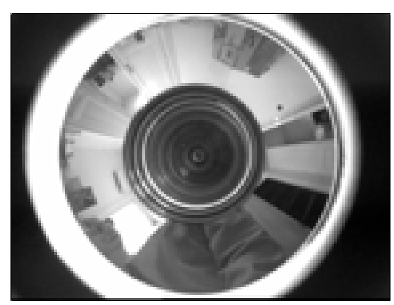

Figure 2. The annular image of the PAL.

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2. Motion analysis using the PAL optics

Surveillance systems employing omnidirectional optics have a lot of advantages against traditional systems that use pan-tilt-zoom (PTZ) cameras with conventional optics. Since they have full 360 degrees view, they are able to monitor the whole panorama around the camera and track any number of moving objects simultaneously without moving. These systems can substitute three or even more tracking PTZ cameras with only a single panoramic device.

Traditional controllable cameras are complex systems with several moving parts, thus they need heavy maintenance. On the other hand, omnidirectional optics are stationary devices. Furthermore, in case of moving or turning camera additional computations have to be carried out to identify the background in every camera position, and perspective distortion of the conventional optics has to be eliminated. Systems employing static omnidirectional devices do not have to deal with that difficulty. However, panoramic systems have special optical distortions that must be eliminated, and the annular input image must be transformed to a rectangular view before starting image processing. While systems with traditional optics project only a small portion of the panorama on the CCD array of the camera, omnidirectional optics projects the whole panorama on it. Thus, the resolution of objects is lower on the annular image than on the perspective image of the conventional optics. It is at most 2.8 pixels/degree horizontally and 3 pixels/degree vertically, with NTSC cameras.

In our system the PAL was used instead of omnidirectional optics equipped with hyperbolical mirrors.

2.1. Change detection

Our surveillance system uses statistical methods to find the background scene on the streaming video by extracting static regions from every frame and joining them together to the background image dynamically. Thereafter, foreground objects can be easily detected by simply subtracting the computed background from the actual image captured from the camera. A similar algorithm was developed at the University of Maryland [4] for mechanically controlled tracking cameras. In case of PAL this task is easier, because the background scene is a still image, so we do not have to deal with the always-changing distortion of the background.

In most cases, surveillance systems have to take care of the changing environment, especially when the system is installed outdoors. The method used for adaptation to the changing background is briefly described in Table 1.

Table 1. Adaptation to changing background.

- As a first step, a background image is maintained where the influences of illumination changes (e.g. shadows) are eliminated. See [5] for a similar illumination invariant method for background extraction.
- The second step is the maintenance of the changing statistics of regions, and the suppression of the influences of recurrent disturbances (e.g. shaking of the trees). These routines can learn disturbances locally, and ignore them in the detection process (Figure 3). It is simple and does not need special image processing hardware unlike most recent surveillance systems.

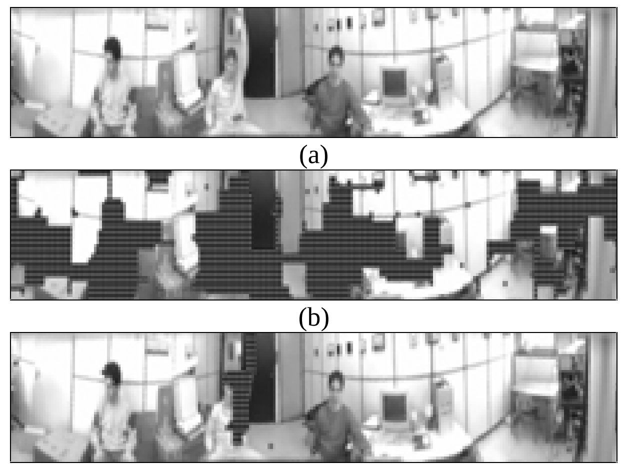

Figure 3. Motion detection: (a) noisy input (b) detection without filtering (c) detection with filtering out disturbances.

2.2. Tracking

The PAL makes tracking much easier in many cases. By the nature of the system it is possible to track any number of intruders simultaneously, without moving the camera. We developed two spatio-temporal estimation methods to track moving objects in the field of view of the PAL. The first method compares certain properties of found objects (e.g. size, shape, motion direction) on every two succeeding frames to find matching pairs of objects. In this way, real-time tracking (20-30 fps) with all preprocessing is possible even on a low cost PC.

2.3. Motion recognition

In intelligent surveillance applications it is important to recognize certain motion patterns or gestures, e.g. someone moves along a certain trajectory or sits down. We developed two kinds of motion recognition algorithms. One of them uses tracking information to find objects having special motion properties; the other computes the history of motion to find certain motion patterns. Finally, an advanced smoke recognition algorithm, detecting the special motion of smoke is presented in details.

2.3.1. Recognition based on tracking information. Using tracking information, several motion recognition tasks can be carried out. Our system uses them to filter out objects having certain properties, like certain size, shape, motion direction, relative velocity and trajectory.

2.3.2. Motion pattern recognition. History of the motion (Figure 4) is computed for every moving object with a method similar to [6]. The motion history image is obtained as a weighted time-average of the detected regions.

The motion history patterns are trained to a neural network. In the detection phase the neural network is able to recognize trained patterns, like someone sits down or lifts up his hand.

(a) (b)

Figure 4. Motion pattern recognition: (a) input sequence (b) motion history.

2.3.3. Smoke Motion Detection. Smoke detection is usually performed with chemical or optical sensors, but little is known about methods using digital image processing, although it may have advantages in situation where conventional sensors are less effective.

Difficulties arise with the discrimination of motion caused by non-smoke events (e.g. filter out human, vehicle or machine motion). We have developed a real-time smoke detection algorithm based on optical velocity field computation. The method detects irregularities in the optical velocity field due to smoke motion.

As a first step, we have give statistical characterisation of the computed velocity field. Two distinguished characteristics of velocity field were considered:

1. Non-self-similarity: motion of smoke tends to be non-self similar; in larger scales its motion is regular in smaller scales it is irregular.
2. Irregularities in motion due to non-rigidity: they are characterised through the statistics of the distribution of velocity vector orientations.

These assumptions were applied to analyse the optical velocity pattern. To account for non-self-similarity, a multiscale optical flow computation was applied with velocity warping [7]. The considerations above lead to the algorithm shown in Table 3.

The statistical analysis of irregularities in the motion field was performed as follows. In case of *n* orientations the interval $]0,\pi]$ is divided into *n* equal subintervals, and a distribution functions $f \in [0,1]^n$ is obtained. Some results obtained for smoke and non-smoke motions are shown in Figure 5(a) and 5(b). It is immediate that the distributions for smoke are more spread, and tend to be more uniform.

Since orientations 0 and π are identical, no mean and variance of the distribution exists. Therefore we tried to characterise distributions $f \in [0,1]^n$ by:

Entropy: $e_n(f) = -\frac{1}{\ln(n)}\sum_{i=1}^{n} f(i)\ln(f(i))$.

Variation: $v_n(f) = \left(\frac{1}{n}\sum_{i=1}^{n}\left(f(i) - \left(\frac{1}{n}\sum_{k=1}^{n} f(k)\right)\right)^2\right)^{1/2}$.

Maximum-norm: $\|f\|_\infty = \max\{f(k) \mid k = 1,\ldots n\}$.

Some of these values measured for test sequences are shown in Table 2. The entropy values separate quite well the two types of motion. The entropy distribution for a larger set of measurements is shown in Figure 5(c). Using these empirical data, we perform Bayesian threshold selection (t=0.68).

The system alarms if entropy exceeds the threshold. A detection example is shown in Figure 6.

Table 2 Statistics of orientation distributions.

$e_n(f)$		$v_n(f)$		$\|f\|_\infty$	
Smoke	Rigid	Smoke	Rigid	Smoke	Rigid
0.8993	0.7155	1.4982	1.7134	0.0191	0.0148
0.8276	0.2604	1.3461	1.9036	0.0041	0.0342
0.9522	0.3410	1.5380	1.2453	0.0221	0.0809

Table 3. The smoke detection algorithm.

1. Multiscale optical flow field computation.
2. Self-similarity test: Project back to the initial scale points that perform regular upward motion at the highest scale to obtain regions that contribute to that motion. Determine the local distribution of the velocity vector orientations for these regions.
3. Irregularity check: Compute irregularity measure (entropy) for the distributions.
4. Alarm if necessary: use a statistical (Bayesian) decision procedure.

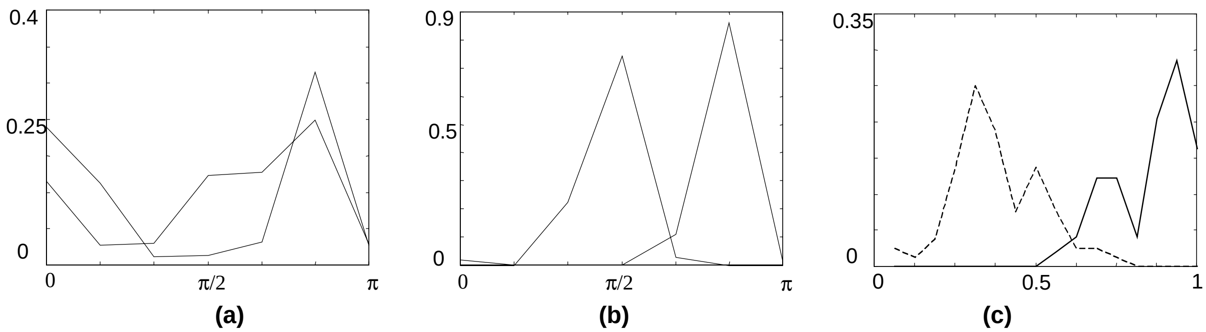

Figure 5 (a) Orientation distribution of the smoke motions. (b) Orientation distribution of non-smoke motions. (c) Entropy distribution: non-smoke (dashed line) and smoke motion (solid line).

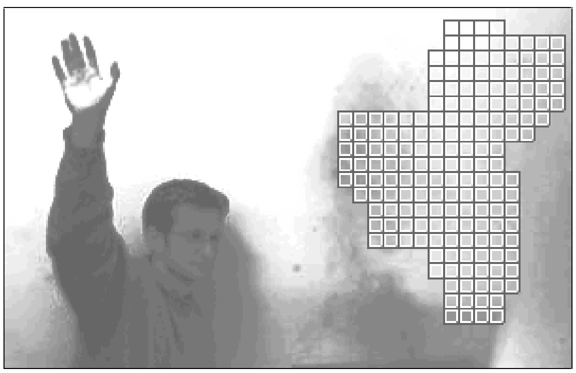

Figure 6. Snapshot of the detection alarm. The non-smoke motion (arm) is not detected.

3. Conclusion

In this paper we have shown that a simple and cheap panoramic system can be well applied for surveillance systems for different (e.g. motion detection and smoke alarm) purposes using only this simple-to-mount device and our robust motion-analysis algorithms. For the smoke-detection further research includes the improvement of the algorithm by temporal filtering and more adaptive classification.

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