Omnidirectional Vision and Inertial Clues for Robot Navigation

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Abstract

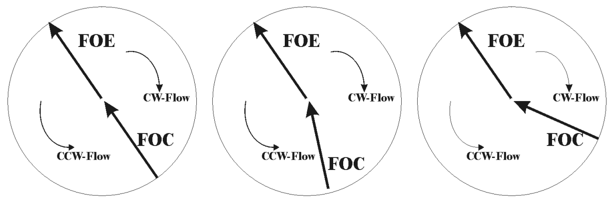
The features inherent in the visual motion field of a mobile robot indicate important clues about its navigation and environment. Combining these visual clues with additional inertial sensor information allows reliable detection of navigation direction for a mobile robot and the independent motion which may be present in the scene. The motion field, which is the 2D projection of the 3D scene variations induced by the camera-robot system, is estimated through optical flow calculations. The singular points of the global optical flow field of omnidirectional image sequences indicate the translation direction of the robot as well as the deviation from its planned path. It is also possible to detect motion patterns of near obstacles or independently moving objects of the scene. In this paper, after reviewing the image velocity measurement techniques shortly, we introduce the analysis of the intrinsic features of the omnidirectional motion fields for motion detection, giving some preliminary examples of this analysis.

1 Introduction

Robot navigation requires relevant motion sensing mechanisms, specially in the case of a dynamical interaction with the environment. Tasks like object avoidance or path finding rely on the estimation of the ego motion and the motion of the environment. Expanded field of view, provided by omnidirectional vision sensors, enables visual motion detection mechanisms similar to some biological species like insects. The role of wide angle view and optical flow in insect navigation has been researched in the past [6]. The quintessence of this research is that bees and other insects rely on the basic properties of an estimated visual motion field for navigation. Some robotic applications have followed the insights gained on this topic [4, 9]. A similar motivation has given many researchers an impulse to look for methods to gain preliminary navigational information using catadioptric sensors. These sensors are constructed using a curved mirror combined with a vision sensor. Different types of curves have been applied for the mirror design, e.g., parabolic, hyperbolic. Special curves preserving spatial features of the projection like range and angle have been introduced, too. (For a review on panoramic imaging techniques and mirror design see [2]) The motion field, which is captured using a wide angle panoramic sensor, introduces significant structural features, like vanishing and emerging points of velocity vectors, that indicate the ego motion direction. Also, dense flow fields contain patterns of different motion regions, which may indicate independently moving obstacles. Our aim is to combine this structural information with standard inertial information as provided by a gyroscope and examine their usefulness in indoor navigation of a mobile camera-robot system. This paper is organized as follows: section 2 discusses the inherent features of omnidirectional motion fields achieved by the optical flow estimation. Section 3 shortly reviews the optical flow estimation techniques and introduces methods for ego- and independent motion detection using the omnidirectional optical flow fields and gyroscope. The last section (4) describes the preliminary experiments.

2 Inherent features of omnidirectional optical flow fields

In the spherical views of a 3D scene, the Focus of Expansion (FOE), the points on the motion field where the flow vectors seem to be emerging, and the Focus of Contraction (FOC), the points where the flow vectors are vanishing, are always in the field of view and span an angle of 180°, if the camera motion is purely translatory. By pure rotational motion neither FOE nor FOC are in the field of view. In real robotic applications, though, there is mostly a translatory component in the motion field. A rotational component in a translational motion field causes the relative positions of FOE and FOC to vary (see Fig.1). Nelson



(a) (b) (c)

Figure 1: *(a) FOE and FOC lines by pure translational motion of the camera system. (b) relative positions of both lines change as the camera system follows a curvilinear path with a rotation to the left side. (c) rotational movement to the right side.*

and Aloimonos [8] have proposed to use the spherical projections of a scene to calculate the translational and rotational components of the motion fields with a qualitative analysis of flow fields.

Similar features are also present in the flow field of omnidirectional scenes captured by catadioptric cameras. Translational or curvilinear motion of the robot-camera system induces global flow fields with singular points on the translational direction. This fact enables determining the navigation direction, which can constitute a prediction for an inertial measurement model. Additionally, the regions with significant high flow values in the dense motion field can be detected by a simple pattern analysis. These values are mostly caused by very near stable or independently moving objects.

3 Optical Flow

Projected relative motion of one image pixel can be represented as a vector $\mathbf{V}(v_x, v_y)$and can be evaluated from the analysis of the instantaneous changes in the brightness values at this pixel point (x, y). For the calculation of the optical flow field, one may assume that intensity is conserved throughout the image and the only reason for the brightness changes is the relative motion. Given a brightness function $I(x, y, t)$ at a pixel position (x, y) and time t, this brightness conservation condition (BCC)([5]) can be formulated as:

$$I(x, y, t) = I(x + v_x t, y + v_y t, 0) \tag{1}$$

where v_x und v_y define the components of the motion velocity in x and y directions respectively. Assuming that the image intensities of the scene points are preserved, the motion field can be estimated by using the spatiotemporal differentiation of the image intensity function $I(x, y, t)$. The classical formulation of this method given by [5] (shown below), depends on two assumptions. The first one, conservation of intensities, has already been discussed above. The next assumption is the smoothness of the motion in given scene points, which means that the neighboring points on the image move with the same velocity. This last assumption assures the differentiability of the image intensity signal $I(x, y, t)$. Differentiating $I(x, y, t)$ with respect to t and assuming that this is zero, yields the following equation:

$$\frac{dI}{dt} = \frac{\partial I}{\partial x}\frac{dx}{dt} + \frac{\partial I}{\partial y}\frac{dy}{dt} + \frac{\partial I}{\partial t} = 0 \tag{2}$$

Partial differences of I ($\frac{\partial I}{\partial x}$ and $\frac{\partial I}{\partial y}$) indicate the motion components in x, y directions respectively. They will be represented with v_x and v_y.

From the above equation it is clear that only the normal velocity component, that is the image velocity in the direction of the image gradient, can be solved from the BCC alone (1). This is also known as the aperture problem. To solve this problem and calculate the actual velocity vectors, one needs to consider additional information about the motion, e.g. smoothness, occlusion or disocclusion etc. Depending on the assumptions made on the features of the global motion, many methods for the optical flow calculation have been proposed. (For a comprehensive review of the methods see [1]). A popular method that can be found in many implementations is the method proposed by Lucas and Kanade [7]. It is based on a Linear Least Squares Estimate fit of the normal flow vectors to a constant velocity model $\mathbf{v}$ over a small neighborhood Ω. It requires the minimization of the function:

$$\sum_{x \in \Omega} \omega(\mathbf{x}) \left[\nabla I(\mathbf{x}) \cdot \mathbf{v} + I_t(\mathbf{x})\right]^2 \tag{3}$$

where $\omega(x)$ in Ω are set to give more importance to the pixels in the center of the window than at its periphery. ∇ indicate the gradient operator applied on to I and I_t represents the temporal derivative of the intensity function. This method seems to be more appropriate for the applications that have to cope with object deformations.(For a qualitative comparison of the different methods see ([10])) The robustness of the method results from the assumption of a local smoothness of the motion in a small area of the image rather than a global smoothness. It is also inexpensive in the sense that only five convolutions over the spatial neighborhood Ω are needed to compute the terms in (3).

3.1 Determining the FOE and FOC Positions

Smooth changes of the omnidirectional scenes as provided by the catadioptric sensors, cause harmonical distributions of the optical flow vectors in the dense flow field. The histogram of these flow field vectors captured in the angular direction, vary in significant patterns as the mobile visual system moves in translational or curvilinear paths. The analysis of the singular points of this histogram, which resembles a sine-like distribution, allows the detection of the direction of the camera-robot motion. The zero-crossings of the distribution indicate the FOE and FOC. These points are shifted proportional to the motion direction. The angular distance between two crossings (FOE and FOC) may vary between 180°, where the FOE and FOC divide the flow field into two equal parts and indicate a pure translational motion, and 0°, where there is no distinguishable FOE and FOC, indicating purely rotational motion.

Measurement of the rotational motion should be supported by additional instruments. It can be measured using an odometry instrument, but this is mostly imprecise due to wheel-slippage, or errors that stem from a navigation on uneven floors. Therefore gyroscopes are widely used to measure rotational speed and also absolute angles by integrating sensor readings over time. During the last years the physical dimensions of the gyroscopes have reduced remarkably, and even more important, they have become very cheap compared to former Ring Laser Gyroscopes (RLG) or Fiber Optical Gyroscopes (FOG). This was achieved by using cheap vibrating piezo elements, which are subject to secondary vibration when rotated and silicon microstructures consisting of a ring shaped vibrating element that changes its direction of vibration during rotation. The directional variations of the original motion can be sensed and the rate of turn can be evaluated. With these cheap and small sensors, it is now possible to equip our mobile robot to improve and to ease the motion analysis with the omnidirectional camera. Combination of the two different sensor information was realized using a Kalman-Model which can be outlined as in figure 2. In this model we combine the two sensory information, gyroscope measurement and angular direction estimation, which is expected to be less precise. Local position and independent motion measurement are not considered to be part of the Kalman-Model yet.

3.2 Detection of independently moving scene objects

Independent motion causes distinct changes on the global flow pattern of a moving camera-robot system. While the background motion occupies the larger part of the global flow field, independent motion arise as regions of disturbances in this pattern. Static objects which are located in the near regions of the mobile robot may also cause greater flow vectors which differentiate in the value but not in the direction of the ego motion. The analysis of distinct regions of the global flow field enables the detection of such static and/or independently moving objects. Both cases might be interesting from the navigational point of view. If the major goal is to determine the dynamical objects in the scene, then it might be necessary to look at the changes of the flow field over time. One efficient way to do so is to warp the given image applying the previously estimated flow field. If the general motion of the robot is of constant velocity, any object moving with an independent speed and direction will produce a difference between the warped image and the real following image. The region where this warp error is maximal, indicates independent object motion. This procedure can be outlined as follows:

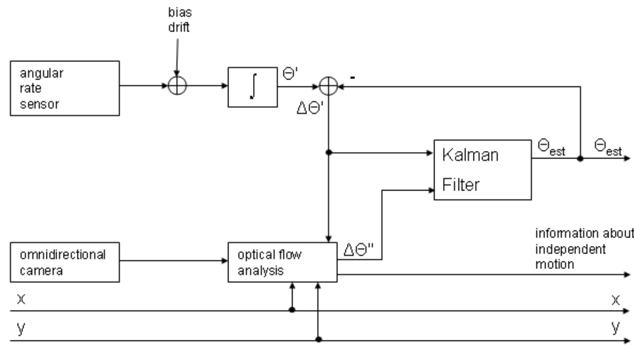


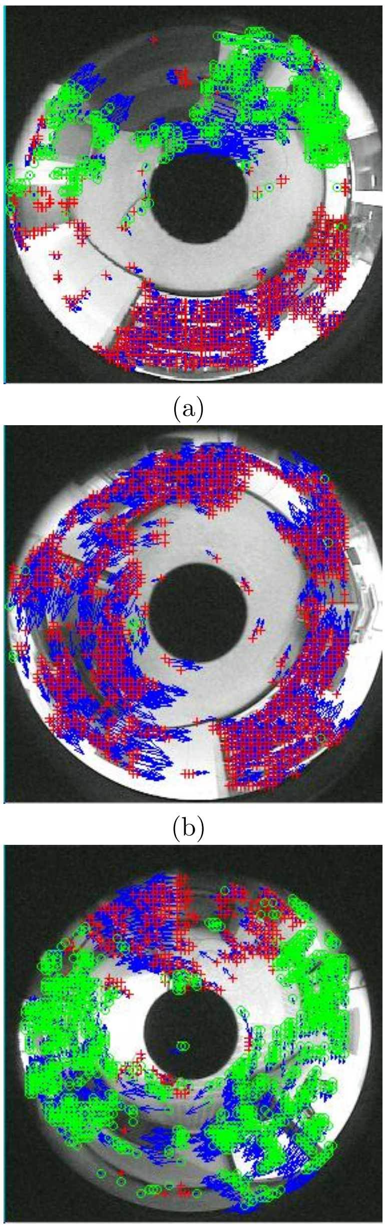
Figure 2: *Flow diagram of the sensory system that detects ego- and independent motion on a mobile robot. θ': gyroscope measurement, θ'':angular translation direction evaluated by optical flow field analysis, θ_{est} is the estimated navigation direction*

- calculate the flow field using the first two images
- generate a pseudo image by warping the second image using the estimated flow field
- calculate the difference between the third image and the pseudo image and detect the regions of maximum difference

4 Experiments

The image sequences are acquired by means of a catadioptric sensor with a specially curved mirror surface that preserves the linear angular relationship of incoming rays and their projections on the image plane (designed as proposed in [3]). It is mounted on a mobile robot that follows translational and curvilinear paths. In the first case, it is expected that the FOE and FOC vectors have opposite directions, spanning an angle of 180°. As the rotational component affects the motion field, it is expected that this angle decreases on one side of the field. Purely rotational motion causes the FOC and FOE vectors to vanish.

The analysis of the clockwise (CW) and counter-clockwise (CCW) flow vectors, marked in the images,



(a)

(b)

(c)

Figure 3: *(a) In the scene there is only translational motion. Red (+) indicate counterclockwise, green (o) indicate clockwise motion (b) only rotational motion (c) curvilinear motion.*

render the regions with contradirectional flow fields. The proportions of these fields indicate the positions of the FOE and FOC. Ideally, this should lead to a unique detection of both of the lines. In figure 3, we present the resulting images.

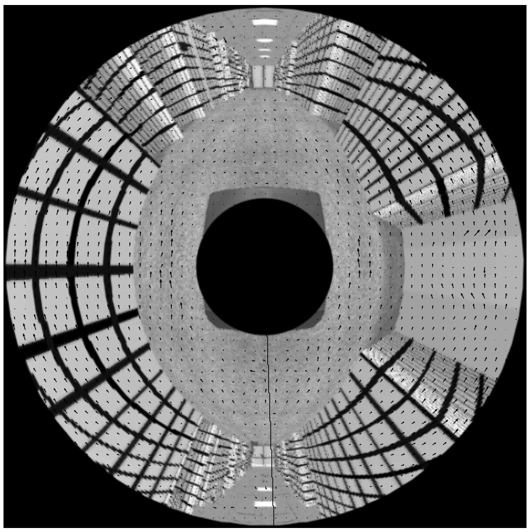
To enable a quantitative and controlled analysis, we have generated synthetical images distorted with the given mirror properties simulating the omnidirectional camera at hand. The camera-robot system navigates in a virtual corridor with a known direction and speed. For the sequence from which the image in figure (4) was taken, the camera moves to the angular direction of 270°, beginning from the right horizontal direction and incremented counterclockwise. (The robot navigates in the direction of the 6:30 position of an analog clock and the beginning of the angular coordinate is at the 3:15 position) The angular distribution of the flow vectors on the omnidirectional field shows a sine-like pattern (Figure 4(b)). The angular direction of the minima of this distribution indicates the motion direction. In the pure translatory case, these minima are exactly 180° apart. Deviation from the pure translatory motion causes the phase of the sine function to vary. Quantitative analysis of the synthetical image sequences showed that it is possible to detect the navigation direction of the camera-robot system with up to a maximal error of 5° image.

In the real scenes, more accurate results can be achieved by combining and evaluating additional inertial information from a gyroscope. The currently used sensor (ADXR300, Analog Devices Inc.) can measure up to 300 degrees per second, which is sufficient for most applications in mobile robotics where vision is also applicable. Since the integration from rates to absolute angles is required, even small errors are accumulated over time and this would lead to large deviations if no recalibration takes place. This problem is bypassed by only integrating over a short period of time between two pictures. With our current camera setup, we're able to process a frame every 4 seconds which is sufficient to neglect the error.

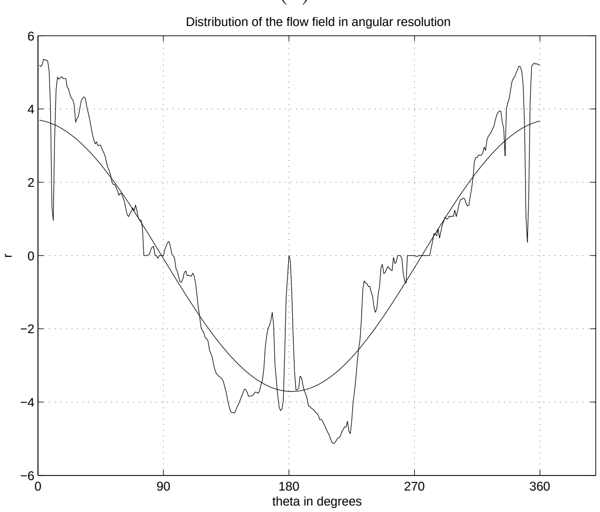
4.1 Independent Motion

In Fig.5, two real images of an indoor navigation sequence is shown. Fig.5d, presents the results of distinct flow region detection. Note that in Fig.5d the algorithm detects independent object movement as well as the static near objects. Because the significant regions on the global flow pattern are also caused by depth changes, differentiation between these two object categories cannot be done until applying the warping analysis, that was outlined above (see section 3.2). Warping the image introduces a temporal analysis which assumes that the robot ego motion is smooth and independently moving objects differ significantly in their motion direction and speed. In Fig.5e, the detected silhouette of the person on the right, who is moving independently from the robot-camera system, is shown. The detection is quite stable if the independently moving objects are in the near region of the camera. Distant objects are reduced in their size due to the distortions of the catadioptric sensor. Their motion can be detected using a special analysis which considers the outermost regions of the omnidirectional images, where distant object movement can be expected, seperately.

Currently it is only possible to detect the angular direction of the independent motion. We will be considering additional measurement techniques to determine the depth measurement of the objects, which will enable determining the exact position of the objects in the scene.



(a)



(b)

Figure 4: *Flow field calculated on synthetical image sequence with known FOE and FOC positions. The direction of the two singular points span exactly a* 180° *angle. The black line on the image represents the estimated navigation direction. The images also include the artificial scene distortion due to the mirror surface.*

5 Summary and Future Work

Visual information provided by omnidirectional cameras include features of significant importance for a robot navigating in a dynamical environment. Estimation of the ego motion direction and detection of the objects in the environment can help avoid obstacles or plan the navigation path. Such an estimation can be done by considering the inherent features of the global flow fields of omnidirectional image sequences in combination with standard inertial sensors. This paper has introduced techniques for gaining navigational information from visual motion fields of omnidirectional image sequences. The global structure of those motion fields gives hints about the navigation direction of a robot in translational or curvilinear motion. The angular position of the singular points of such a field, where the flow vectors seem to be emerging and vanishing (the Focus Of Expansion and the Focus Of Contraction) indicate the navigation direction. These points are related to the translational component of the navigation. Refining this analysis, specially for the purely rotational case, has required the use of a gyroscope.

The regions with significant and rapid changes in the global flow field indicate near obstacles or independently moving objects in the omnidirectional scene. The motion pattern analysis detects such regions. Independently moving objects with different velocity and/or motion direction can be detected by following the changes in the motion field in time, since omnidirectional scenes allow these objects to track for a longer time and in a larger field of view.

Future Work. Our future work aims to refine the analysis for detecting independent motion patterns. Depth estimation and distant object detection are two of the topics that will be considered. We are also concerned with the refinement of the navigation modeling of an autonomous mobile robot using visual motion patterns and additional sensory input.

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References

[1] J. L. Barron, D. J. Fleet, and S. S. Beauchemin. Performance of optical flow techniques, systems and experiments. *International Journal of Computer Vision*, 12(1):43–77, 1994.

[2] R. Benosman and S. Bing Kang, editors. *Panoramic Vision, Sensors, Theory, and Applications*. Springer, 2001.

[3] J. S. Chahl and M.V. Srinivasan. Reflective surfaces for panoramic imaging. *Applied Optics*, 36(31):8275–8285, 1997.

[4] N. Franceschini, J.M. Pichon, and C. Blanes. From insect vision to robot vision. *Philosophical Transactions of the Royal Society London: Biological Sciences (SeriesB)*, (337):283–294, 1992.

[5] B. K. P. Horn and B. G. Schunck. Determining optical flow. *Artificial Intelligence*, 17:185–203, 1981.

[6] A. Horridge. *Visual Navigation: From Biological Systems to Unmanned Ground Vehicles*, chapter Pattern and 3D Vision of Insects. Lawrence Erlbaum Associates,Inc., 1997.

[7] B. D. Lucas and T. Kanade. An iterative image registration technique with an application to stereo vision. In *Proceedings of the Seventh Int. joint Conf. on AI, IJCAI.81*, volume 2, pages 674–679, 1981.

[8] R.C. Nelson and J. Aloimonos. Finding motion parameters from spherical motion fields (or the advantages of having eyes in the back of your head). *Biological Cybernetics*, (58):261–273, 1988.

[9] J. Santos-Victor, G Sandini, F. Curotto, and S. Garibaldi. Divergent stereo for robot navigation: Learning from bees. In *Proceedings of ICRA'93*, 1993.

[10] Irem Stratmann. Omnidirectional imaging and optical flow. In *Proc. Workshop on Omnidirectional Vision 2002*, pages 104–111.

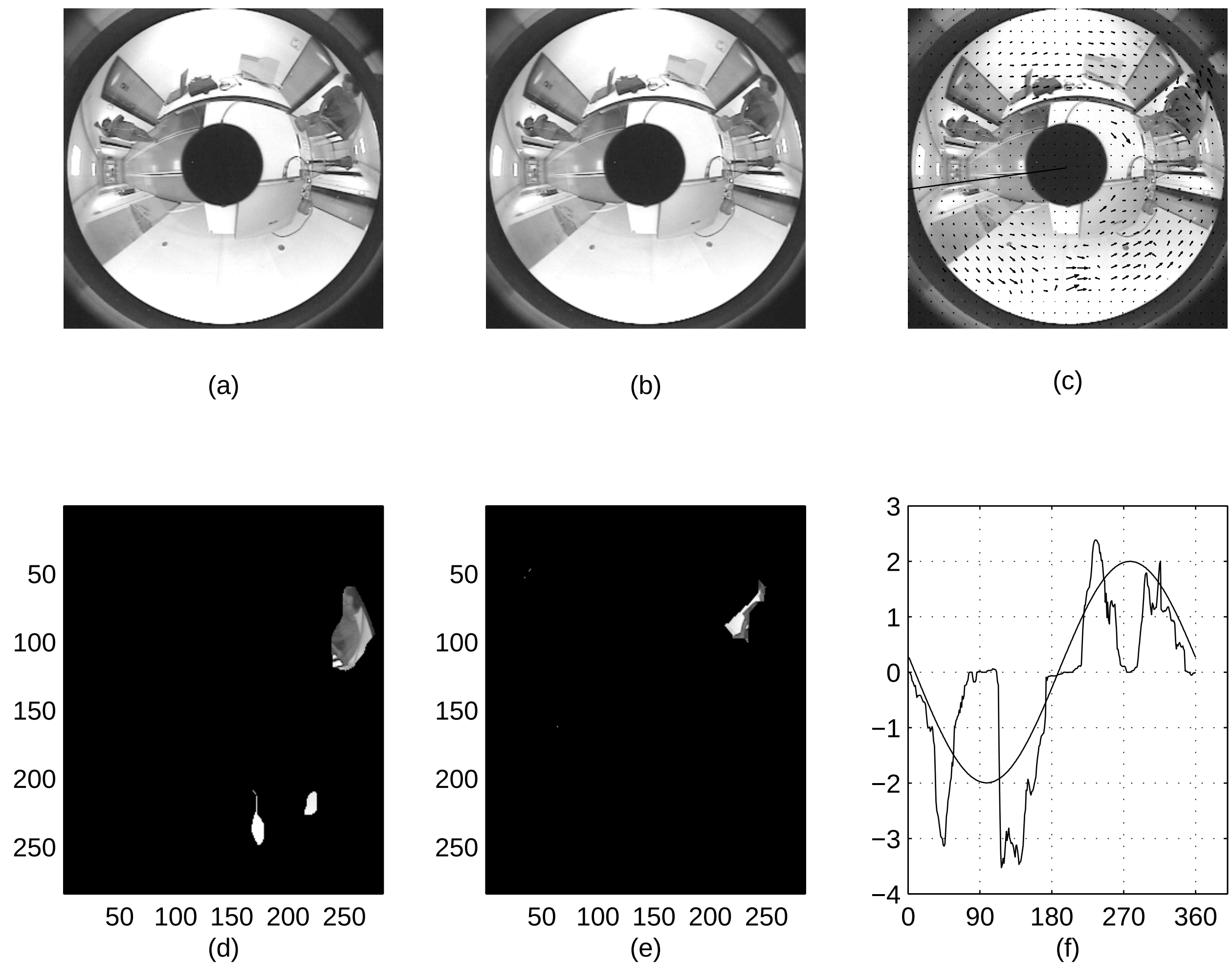

Figure 5: *(a) First image of a sequence taken from a camera moving through a corridor (b) Second image of the sequence, note that the person on the right moves independently to the left (c) Flow field superposed onto the second image, the line on the left indicates the estimated translation direction (d) Flow regions with significant changes with respect to their background (e) Region with the maximum warping error (f) Distribution of the flow vectors in angular resolution and the (sine) fitting function*