Optical Flow Estimation versus Motion Estimation

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August 9, 2012

1 Image based motion estimation

Optical flow estimation is often understood to be identical to dense image based motion estimation [3,5]. However, only under certain assumptions does optical flow coincide with the projection of the actual 3D motion to the image plane [8, 16]. Most prominently, transparent and glossy scene-surfaces or changes in illumination introduce a difference between the motion of objects in the world and the apparent motion. Unfortunately, in the real world, glossy and (semi-) transparent objects as well as changes in illumination, e.g., cast shadows, are rather frequent.

In the proposed challenge we aim to estimate the physical motion of objects. In industrial applications, information on surrounding objects and their motion is used for numerous purposes, e.g., to find obstacles in the path of a robot or the trajectories of objects [7, 12, 13, 17].

Video cameras provide information on a scene with low cost in acquisition, space and energy, and at the same time high spatio-temporal resolution. Therefore video-based motion estimation is considered to have a high potential to serve for the purpose of motion estimation over a wide range of applications. However, the method of acquiring and correlating images of visual light does not always back up the aim of measuring physical motion. Physical motion and the apparent motion of the measured light might be considerably different. Our aim is to determine the physical motion.

In the following, we give some examples of visual phenomenons and the motion information we wish to estimate. At this place we do not intend to give an exhaustive list but merely mention some current phenomena and give examples for them.

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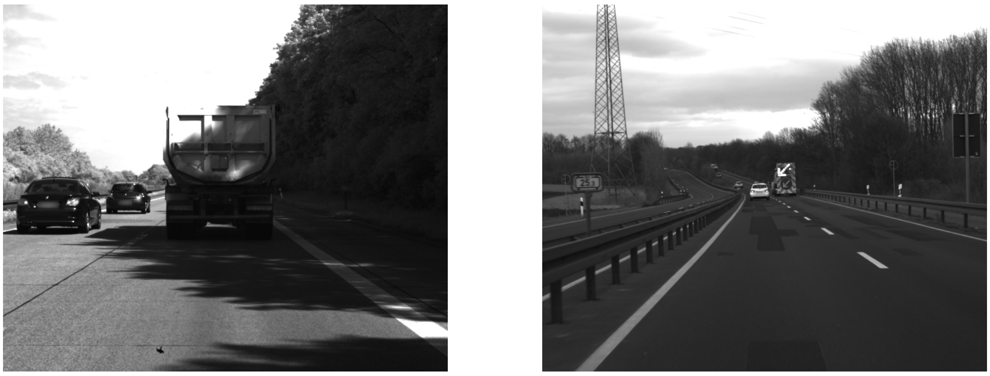
2 Situations in which optical flow and physical motion differ

2.1 Changing Illumination

In the case of changing illumination, Fig. 1, the physical motion does not coincide with the apparent motion that is estimated by traditional optical flow algorithms. In physical motion estimation we expect the following behavior:

- Motion should be estimated independently of the illumination.
- Shadows are not considered as objects and should not be assigned any motion. The motion of the surface on which the shadow falls should be estimated correctly independently of cast shadows and shading.
- Changing the illumination of a static scene should not result in any motion assignment.
- A static light bulb should be identified as static even if the light is switched on/off between two frames.

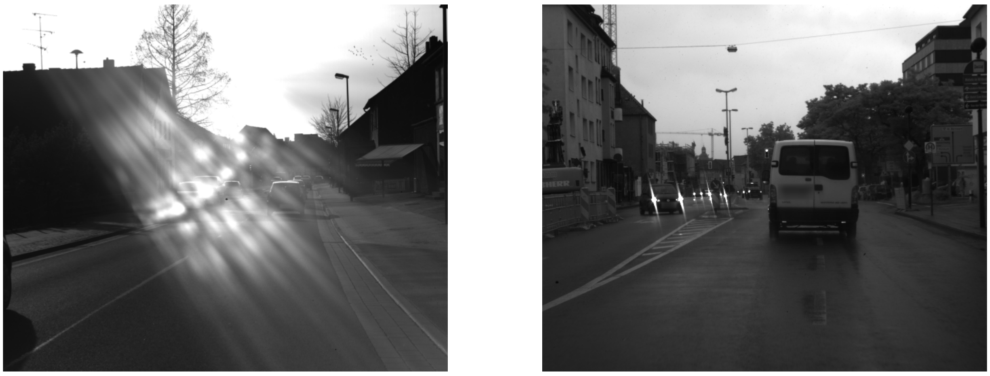


(a) (b)

Figure 1: In motion estimation the subject of interest is the motion of the object and not the changes in illumination: A static shadow on a moving object should not interfere with the motion estimation of the object (a) while a static blinking light should not have any motion assigned (b).

2.2 Noise, Dirt and Reflections in the Camera System

In industrial applications, sufficient illumination cannot always be provided. This can induce a high noise level.
In outdoor scenarios, sunlight might enter the system at an adverse angle, Fig. 2.
Additionally, during the life of a camera system dirt will accumulate in the optical path.



(a) (b)

Figure 2: Motion estimation should be robust against perturbations in the optical path such as lens-flare (a) or rain-streaks (b).

- Ideally, the underlying object motion should be estimated in spite of noise and disturbances of the optical system.
- If the estimation of the underlying motion is not possible due to noise or system flaws, a label "indeterminable" should be returned.
- As a minimum requirement, the flaws should not disturb the motion estimation to such an extend that the motion of a spurious, non-neglectable object is suggested (false alarm).

2.3 Motion Boundaries and Occlusion

Different objects in a scene move into different directions, rising the need to detect motion boundaries and find suitable solutions for (possibly large) occlusions, Fig. 3.

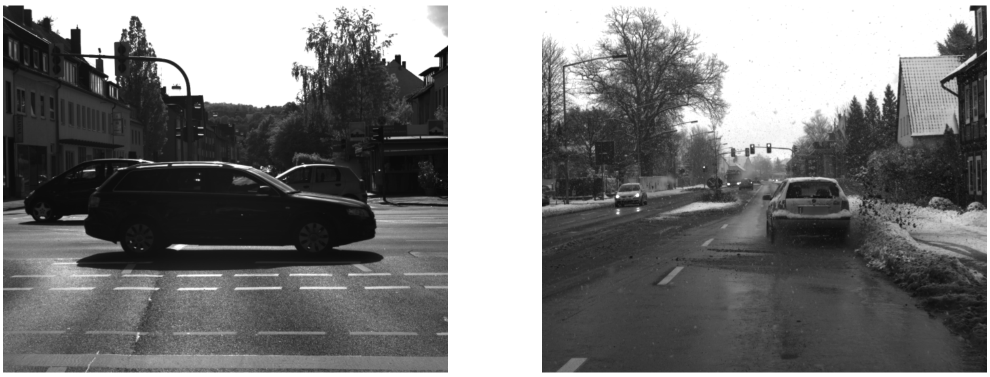
- Ideally, motion boundaries should be sharp and occluded points should be detected as such.
- However, over-smoothing of the motion estimate should not induce spurious motion to entire neighboring objects and occluded points should not appear to have a motion considerably different from their true motion.

2.4 (Semi-)Transparency

A transparent object - in spite of being transparent - might be a substantial obstacle. The common model assumption of one motion per pixel is violated in the presence of transparent objects, Fig. 4.

Figure 3: Even in the case of complex occlusions, the motion estimation algorithm should not induce spurious motions that can cause false alarms.

- Ideally, the motion of solid transparent objects should be detected. Although this seems to be quite impossible for fully transparent objects, approaches for semi-transparent objects have been presented [9–11].
- In any case, the admission of several motions per pixel is advantageous.
- Realistically, the motion of the first opaque object behind transparent objects should be detected.



(a) (b)

Figure 4: Transparent objects (a) and phenomena (b) violate the assumption of one motion per pixel. For a pixel affected by transparency the motion of transparent foreground objects as well as the motion of opaque background objects is of interest.

2.5 Reflecting and Glossy Surfaces

Scene objects might reflect incoming light. In reflecting or glossy surfaces the (relative) motion of other scene objects might be visible and simulate motion that is physically not present in the scene, Fig. 5.

- Theoretically, reflected motion could be used to gain further information on the motion in the 3D scene.
- The physical motion of the glossy surface should be estimated correctly.
- As a minimum requirement, the reflections should not generate spurious motion estimates. A label "indeterminable" might be returned.

(a)

(b)

Figure 5: Glossy objects (a) or surfaces (b) can simulate motion that is physically not present in the scene.

3 The Applicability of Motion Estimation

Apart from the difference between the optical flow and physical motion, there are some further problems that affect the applicability of modern optical flow algorithms in industry.

3.1 Large Motions and Large Motion Differences

Even modern optical flow algorithms put severe limits on the maximal extend of the assessable apparent motion. In variational optical flow estimation, the considered energy functionals depend on the highly non-convex image function. Therefore, early approaches with a linear brightness constancy assumption are applicable only to small motion within monotonous image regions [8]. Using an image pyramid [2] and iterative warping [1, 6] modern optical flow approaches can approximate larger motions across non-monotonous regions. However, the largest assessable motion difference between neighboring objects remains limited by the objects size, rendering the detection of fast motions for small objects impossible [18].

In matching based optical flow estimation, usually a maximal search range and a minimal template size is assumed [4, 15]. This also limits the extend of the maximal motion and the minimal size of moving objects.

- Large motion as well as large motion differences should be estimated faithfully.
- Motion of delicate objects such as tree-branches and bicycle should be estimated robustly.

3.2 Model Assumptions

Different approaches have shown to deal favorably in some of the above cases making strong assumptions on the underlying motion model [14]. However, strong assumptions on the expected behavior reduce the range of possibly estimable motions and the flexibility of the applications that can be constructed from these motion estimates.

- Motion models should be used only to an extend that can cope with all expected situations in a real-world scenario. E.g. assuming only rigid motion in driver assistance functions does not model the motion of walking pedestrians. As pedestrians are part of common traffic situations, motion estimation building on a rigidity-assumption will be of limited applicability in this case.

3.3 Hardware Resources

Some models for image based motion estimation require the solution of complex and computation-intensive equations. However, for industrial applications the consideration of the required resources are an important aspect.

- Motion should be estimable in real-time.
- Motion estimation should be transferable to low-power/embedded hardware.

3.4 Reliability and Prevention of False Alarms

Industrial applications must ensure a certain level of quality for applications that are based on motion estimation algorithms.

- Motion estimation should be robust. That is, motion should be estimated also under adverse conditions and with poorly adjusted or fixed parameters. However, a label that motion estimation is not possible or highly redoubtable for certain pixels or certain frames is a viable alternative.
- Motion estimation should be reliable. If a motion estimate is returned this motion should be present in the scene so that the risk of false alarms is minimized.

3.5 Real Time Applicability

In many applications for motion estimation, the availability of the motion information with only a short delay from the moment of image recording is crucial, e.g. in driver assistant applications.

- Future frames must not be included into the estimation of the motion in the present frame.

4 Conclusion

For industrial applications of computer vision the distinction between apparent motion and physical motion is important. Examples for situations where apparent motion and physical motion do not coincide occur commonly. While any approach to solve the physical motion estimation problem is generally interesting for application in industry, additional requirements such as hardware costs and reliability set up strong restrictions.

Although the current state of research makes it difficult to satisfy all desired properties simultaneously, we are sure that research which addresses even only one or few of the mentioned problems will eventually contribute to implement robust and reliable real time computer vision applications.

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