A biologically motivated mid-level stage of robust optic flow processing

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Abstract: We test a biologically motivated filtering method [9] for noise decreasing in optical flow fields.Our filter model adopts a property of a particular motion sensitive area of the brain which represents the average incoming motion signals over domains whose size increases with the distance from the center of the projection. We use the task of heading detection from optic flow as a way to estimate improvements of flow fields generated by a standard algorithm. First we test our model on flow fields generated with a modified Nagel-Algorithm from image sequences which are directly calculated from three dimensional real world data assuming a given self motion. Thus we retain the control about the exact heading and rotation and have ground truth. Not surprisingly, due to the noise and the aperture problem the results for the raw flows are often incorrect. In contrast the filtered flows allow correct heading detection. Furthermore we apply our filtering model to flow fields which are calculated from image sequences recorded by a rigid installed camera during car motion. For the unfiltered flow the estimated heading directions differs widely for different subsampled calculations. In contrast, the results obtained from the space- variant filtered flows are much less variable and therefore more confidential.

1 Introduction

The patterns of optical flow fields elicited on optical detectors of visual systems by self motion encode much information about the direction of motion, the velocity and the direction and magnitude of camera rotation. It is assumed that biological systems use such information for path planning, obstacle avoidance, ego-motion control and also for foreground-background segregation to recognize external moving objects. Such abilities are also used for vision based technical applications like driver assistance systems or autonomous robots. Especially during car driving a correct heading detection is necessary to estimate the current driving situation. For example a driver assistance system, which is capable to estimate heading visually rather than from sensors in the car, such as the positions of the wheels or their rotation, could warn the driver about any sideward drifting and unintended lane changing in the case of slippery roads or take appropriate action. A system, which can estimate self motion directly from the visual informations provided by a camera could therefore support and complete the already developed driving assistance and car stabilizing systems and could enter into the cases where other systems cannot provide enough information.

Optical flow fields obtained from flow algorithms applied to camera image sequences are usually very noisy. Estimate of self motion from such flow is error prone. Since biological systems have no superior detectors they are likely to face the same problematic optic flow on the input stage. But they are able to estimate self motion rather exact. Somehow, therefore, the brain must have developed methods to remedy the shortcomings of the flow detectors. We searched for features which enable biological vision systems to handle noisy flow fields successfully. The visual system of primates contains an area that is specially devoted to processing of visual motion. This area, the middle-temporal or MT area, establishes a space variant map of the visual motion field. Based on the properties this map [9] proposed a method to decrease the noise of the optical flow by averaging flow vectors over image areas which increase in size d proportional to the eccentricity ϵ from the center of the field of view (see [1])

$$d = 0.018 + 0.61\epsilon.$$

In [9] one can find an application of this method and an implementation of the Heeger-Jepson [3] heading detection algorithm in terms of a neural network model. The network was tested with artificial motion fields of simulated self movements through three dimensional random scenes. The flow fields contained translation and rotation components and noise was added. The results show that noise is reduced and heading detection is possible with errors up to 4 degrees for a signal to noise ratio of 1.

The main goal of the present paper is to apply the *space-variant filtering* model to optical flow fields obtained from camera recorded image sequences with an optical flow algorithm and to test its implication on the quality of heading detection. However, before using sequences obtained by a camera we calculate the basic image sequences from three dimensional data sets of several natural environments (Brown Range Image Database, available on *http://www.dam.brown.edu/ptg/brid/range/*). The advantage of this procedure is that we have the exact knowledge about the correct heading direction of the simulated self movements and of the true flow field and we are able to evaluate the results of the used method quantitatively against ground truth.

2 Methods

We used for our first investigation the Brown Range Image Database (brid) , a database of 197 range images collected by Ann Lee, Jinggang Huang and David Mumford at Brown University ([4]). The range images are recorded with a laser range-finder. Each image contains 44×1440 measurements with an angular separation of 0.18 degree. The field of view is 80 degree vertically and 259 degree horizontally. The distance of each point is calculated from the time of flight of the laser beam, where the operational range of the sensor is $2 - 200$m. The laser wavelength of the laser beam is $0.9\mu m$ in the near infrared region. Thus the data of each point consist of 4 values, the distance, the horizontal angle and the vertical angle in spherical coordinates and a value for the reflected intensity of the laser beam.

The knowledge of the 3 dimensional data of a given environment makes it possible to simulate the view of a moving camera in this scene and calculate both the image on the camera as well as the true motion field. The first image of Figure 1 shows an example of a projection of a range image onto a plane.

Figure 1: Projection of a range-image onto a plane. The ratios between width and hight and the focal length are chosen as 1 and 0.7 respectively.

The basic image sequences for our second examination are recorded by a camera rigid installed closely behind the front shield of a moving car. The view direction of the camera is approximately parallel to the longitudinal axis of the vehicle.

The optical flow algorithm we use is a combination of the Nagel-algorithm [11] with the concept of local multi-modal primitives [7]. These primitives are motivated by processing in the human visual system as well as by functional considerations and are regarded as functional analogues of the hyper-columns in the primary visual cortex [7]. The algorithm calculates the local displacement by the Nagel-algorithm and afterwards performs a neighborhood averaging for each local primitive allowing to obtain either the correct flow for a near intrinsic two dimensional structure like corners or resulting in the normal flow for a near intrinsic one dimensional structure like an edge within the particular primitive.

For a pure forward motion without rotation the heading direction would be identical with the "focus of expansion". Apart from the fact that this is not true in the case where the flow field is affected by rotational components, the position of the "focus of expansion" cannot easily be found with high precision because at the image position of the "focus of expansion" the intensity shifts between different frames are very small, thus the noise to signal ratio around the "focus of expansion" is very high. Furthermore the "focus of expansion" is usually close to the center of the view field where the filter only averages over small domains and consequently the amount of noise remains high. Therefore the global information encoded in the entire structure of the flow field should be used for heading estimation. To this end, heading detection is performed by global optimization algorithm [3]. During our test calculations the algorithm operates on 150 randomly selected flow vectors for each run and the results are accumulated for 60 runs.

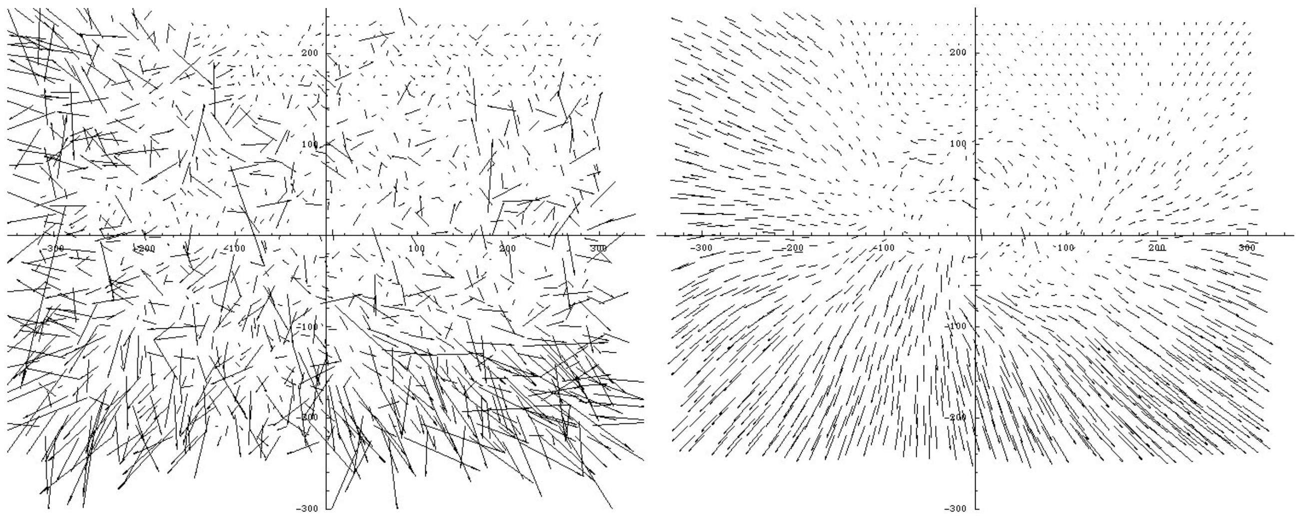

Figure 2: Left image: Flow field obtained from the Nagel-algorithm. Right image: Space-variant filtered flow.

3 Results

First we tested the space-variant filtering model for three flow fields belonging to three different image sequences generated from several range-images. Figure 2 shows on the one hand an examples of the flow fields calculated with the Nagel-algorithm applied to those image sequences and on the other hand the same flow field space-variant filtered. Clearly the noise occuring in the unfiltered flow field is decreased in the filtered flow and the most outliers seem to be removed.

The qualitative supported presumption about the improving of the raw flow by space-variant filtering is quantitative assisted by the application of the heading-detection algorithm to the filtered flow. Examples of the results are shown in figure 3. The green points represent the estimated heading directions of the individual runs, the blue point represent the mean value of the estimated headings and the red point represent the correct heading. The accumulations of estimated headings for the unfiltered flows are spread over ranges of 25 as far as 35 degree. In contrast the distributions of the estimated headings for the space-variant filtered flows have standard-deviations of 4 till 7 degree and the differences between the mean-values and the correct headings are 1,5 as far as 9 degree.

The results for the image sequences generated by three dimensional range images are very promising and justify the space- variant filtering method. However, the grey-scale for the projected range images are very different from real camera-recorded images and it is not excluded that also the concerning flow fields have some strange qualities falsifying the results. Thus, it is inevitable to apply the space-variant filtering method to real camera-sequences. We tested the space-variant filtering model on eleven raw flow fields belonging to different frames of the image sequence. The left image of figure 4 shows an example of an unfiltered flow field obtained by the Nagel-algorithm. In addition to the observable noise the effect of the aperture problem is clearly visible. Many estimated flow vectors are perpendicular to horizontal and vertical lines.

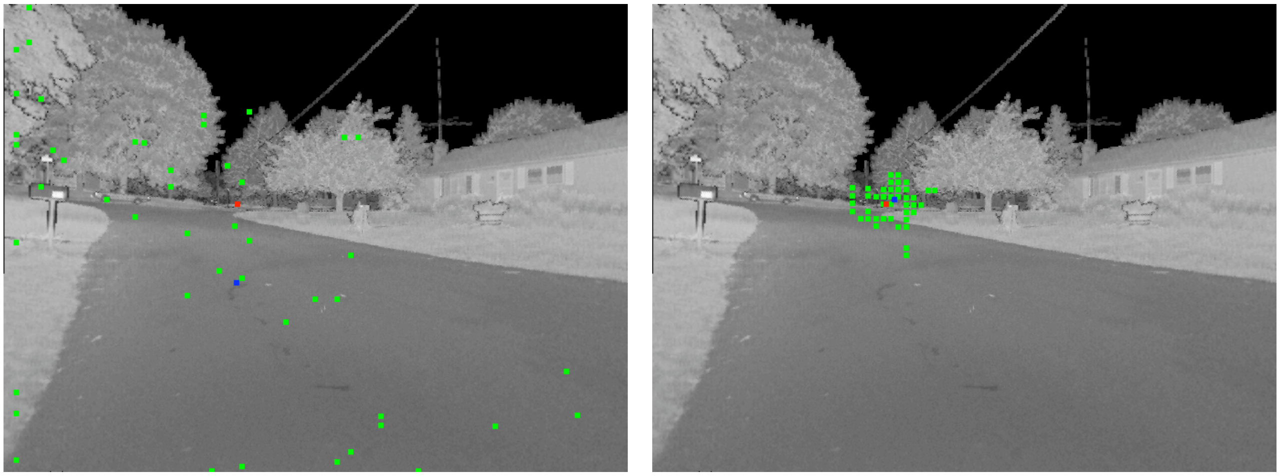

Figure 3: Individual results of heading estimation, left: unfiltered flow, right: space-variant filtered flow

The left image of figure 4 shows the flow field after the space variant filtering. The noise is decreased, outliers are removed, and the effect of the aperture problem is somewhat rectified. Compatible to a mainly forward motion with less rotation the filtered flow field has a basically radial structure starting from a "focus of expansion".

Examples of the results of the Heeger-Jepson algorithm applied to the unfiltered and the space-variant filtered flow are showed in figure 5. The black cross marks the center of view. The white points show the individual results of single runs. The black point near the center is the mean. The black circle arranged around the middle black point marks the standard deviation of the distribution of the results.

In contrast to the unfiltered flow the heading detection algorithm applied on the space-variant filtered flow leads to more stable results. In the unfiltered case the standard deviation of the distributions of the results range between 8 and 12 degree and the single results are spread over the entire view field. The space-variant filtering leads to results which lie much closer together with standard deviations ranging between 1 and 4 degree. The heading estimates after filtering appear compatible with the specific driving situation. For instance, during the braking that takes place because of the stopping of the foregoing car the estimated heading of the camera car shifts downward according to the dip in the trajectory of the car. In the sample of figure 5 the overtaking procedure leads to a rightward shift of the estimated heading.

4 Discussion

Our results clearly demonstrate that space-variant filtering is a reasonable strategy to decrease noise in optical flow fields and to improve heading detection. The method works well on optical flow fields based on natural scenes affected by strong noise and the aperture problem. The stability

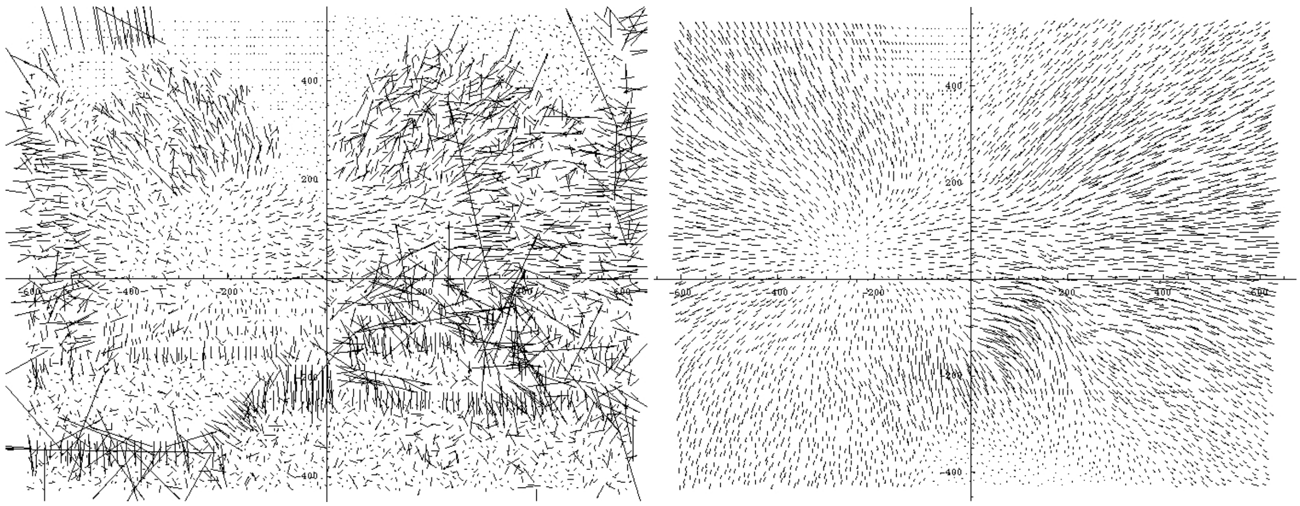

Figure 4: Flow fields obtained from real camera recorded image sequences. Left : flow field obtained from the Nagel-algorithm. Right: space-variant filtered flow.

of the heading detection algorithm is increased, the spread of the resulting heading directions is dramatically decreased and the mean is more reliable than in the unfiltered case. Especially in the cases where we operate with the brid-database, the correct heading-direction are well reflected by the results.

Although the stability of the heading estimates is clearly improved, we do not claim that the filtering method generates the locally correct flow field according to the self motion and the scene structure. We think the smoothing properties of the method are to strong to accomplish this. We rather believe that the space-variant filtering method reproduces the global structure of the correct flow and therefore it allows to estimate the correct components of self motion from the filtered flow. Hence, our method is a task specific optimization that enhances the applicability of the flow field to the task of heading detection but not for other task. For instance, the segmentation of objects in depth would rather become more difficult after the space-variant filtering.

The filtering method easily lends itself to further improvements by adding for instance disparity information from a second camera [9]. Therefore, the successful performance of heading estimation on the filtered flow should only be the first step of a larger agenda. Certainly, the next step is to estimate the rotational component of the self motion from the filtered flow. Further, although the filtered flow is not applicable to extract grouping information, to perform background-foreground segregation, or to identify moving external objects, the knowledge of the global parameters of self motion from the filtered flow gives the possibility, supposing one has the disparity information of the scene, to reconstruct the correct flow. Thus, apart from the relevance for the reliable estimation of the global motion parameters from noisy flow, the space-variant filtering method could be used as a part of an improved future optic flow algorithm.

Figure 5: Individual results of heading estimation on flow fields obtained from real camera recorded image sequences. Left: unfiltered flow, right: space-variant filtered flow

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