VELOCITY ESTIMATION OF A MOBILE MAPPING VEHICLE USING FILTERED MONOCULAR OPTICAL FLOW

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ABSTRACT:

Generally, a road image sequence acquired by a mobile mapping system (MMS) is oriented by integrating the Global Positioning System (GPS) and an inertial navigation system (INS) data. Alternatively, this article presents a methodology completely based only on data derived from a road image sequence acquired by a low cost land based MMS as an alternative to orient the images without any auxiliary data so that the derived information comes from the internal image motion through the optical flow. The vehicle velocity computation is based on the monocular optical flow of an image sequence captured by a video camera mounted on the top of a vehicle that travels in a flat urban road without any auxiliary data. With the estimated velocity and the constant image sequence time interval the mobile's relative position can be computed. No matter the technique, the optical flow computation is very sensible to the noise caused by the image acquisition process under real conditions. The noise sources such as high variation of illumination and camera vibration, among others, can affect the velocity estimation if the dense optical flow is used. In order to avoid such drawbacks the translational velocity is computed from a reduced amount of optical flow vectors, exactly those that represent the effective displacement. These vectors are taken in certain portions of the images – the region of interest (ROI) – and they are supposed to be detected by the Canny edge detector algorithm, which means they come from edges and consequently they have intensity variation in the images. The optical flow computation is based on Horn and Schunck method because it is simple and easy to implement. The technique based on the detected vectors reveals a potential to be developed. The best result shows that the estimated velocity is as good as 1% less than the one determined in the control surveying mission. Additionally, the amount of vectors is only 560 instead of 720 x 480 of the dense flow (original image size) or about 230,000 vectors of a reduced quadrilateral image. These results indicate that the implemented technique contributes to reach a better translational velocity estimation and therefore to the vehicle displacement which lets one know the relative position of the MMS from a road image sequence without any auxiliary data.

1. INTRODUCTION

Generally, a mobile mapping system (MMS) has a few sensors to provide full orientation (position and attitude) for the stereo image pair sequence. Integrating GPS (Global Positioning System) and INS (Inertial Navigation System) data a solution to the image orientation problem is guaranteed. With the outer orientation given by the sensors, the object points, along and aside the roads, selected in the image pairs, can be mapped by photogrammetric intersection (Silva et al., 2003).

Although there is a few research institutions that have been developing this methodology in order to provide both an alternative and a complement to the GPS/INS integration system (Ayman, 1998; Tao et al., 2001; Roncella et al., 2005), distinctly, there is another way to work out the image orientation problem completely based only on data extracted from the road image sequence. Simply, the problem can be put in two parts: image translational displacement and image angular orientation. Considering that a pair of cameras is mounted on the roof of the vehicle pointing forward with the optical axes approximately horizontal and parallel to each other, it is necessary to compute the translational displacement of both image perspective centers, which can be done by considering the constant time interval of the frames in the road image sequence and the vehicle velocity estimated from the optical flow. The image angular orientation can be computed by phototriangulation (Silva; Oliveira, 1998; Silva et al., 2000).

This article presents the first part of the problem solution, the velocity estimation fully based on the optical flow extracted from an image sequence acquired on a flat urban road. The optical flow vectors are filtered by means of points detected by the Canny algorithm (Canny, 1986) and their centrifugal radial behavior considering the image perspective resulting from the translational displacement. The vectors are taken in a reduced quadrilateral image; most of them in the lower half of the images as the upper half represents a lot of the sky, as shown in figure 2, section 4.

Either external or internal data, the improvement of the mobile mapping technology for road surveying and mapping is highly interesting for the public and private organizations that are responsible for the maintenance or need information about the equipment installed along the road network.

2. OPTICAL FLOW

Optical flow is a 2D distribution of the apparent velocity of the intensity value movement on the image plane. The optical flow field consists of a dense velocity field where each pixel on the image plane is associated with only one velocity vector. If the time interval between two consecutive images is known, the

velocity vectors may be converted into displacement vectors and vice versa (Shi; Shun, 2000).
Computing both the optical flow and the image velocity is a fundamental issue on the image sequence processing and it may help in various tasks, such as the scene interpretation, exploratory navigation, video coding, robot vision, etc. (Tekalp, 1995).
The methods for computing the optical flow may be classified into three main groups: differential techniques, correlation techniques and techniques based on frequency/energy (Barron et al., 1994; Beauchemin; Barron, 1995). For differential techniques, the initial hypothesis for the optical flow computation is that the inter-frame intensities of an image sequence are approximately constant on a short time interval, which is equivalent to understand that the displacement is minimum.
The image velocity is computed from the temporal spatial derivatives on the image. The intensity on the image (domain) is taken as continuous (or differentiable) on space and time (Horn; Schunck, 1981).
The differential technique accuracy depends mainly on the estimation of the partial derivatives of the intensity function. Despite being simple, the finite difference method does not make any distinction between the original data and the noise. In order to eliminate or reduce such a problem, a pre-smoothing of the image by the use of a Gaussian filter must be carried out (Barron et al., 1994; Brandt, 1997).
The process which determines the 2D movement is complex because, besides involving the movement of the sensor, there is also the movement of the objects on the scene which may cause occlusions, and then the optical flow estimation more difficult. Another important aspect on real world projects is the camera vibration, caused by shocks and holes on the surface of the displacement. The illumination condition must also be considered because shadows and clouds may modify the intensity of images.

3. MONOCULAR VELOCITY ESTIMATION

Assuming the vehicle translational velocity as parallel to the optical axis of the camera, the optical flow (u, v) is given by (Giachetti et al., 1998):

$$\begin{aligned} u &= \frac{\omega}{f}x^2 + \frac{V}{hf}xy + \omega f \\ v &= \frac{\omega}{f}xy + \frac{V}{hf}y^2 \end{aligned} \quad (1)$$

where f is the camera focal length, h is the height of the camera from the ground, ω is the angular velocity and x and y are coordinates on the image plane. The equations (1) describe the 2D movement when the vehicle runs a long flat surface with a static scenario, that is, only the movement of the camera, which is fixed on the top of the vehicle, is taken into account. This kind of movement is known as passive navigation and the estimated velocity may strongly differ from the actual one (Giachetti et al., 1998).
The computation of the angular and translational velocity is carried out by the least square method, thus the use of the dense flow is not advisable, either for the computational effort (too much points) or for the noise which affects the precision. In order to reduce the amount of vectors used in the translational velocity estimation and to improve the velocity precision, each vector is filtered as in the following procedure: (i) it has to belong to a quadrilateral region of interest (ROI); (ii) it has to have a centrifugal radial behavior expected in accordance to the forward and planar displacement; and (iii) it has to have its origin coincident with a point detected by the Canny algorithm (edge point).
Besides this filtering procedure, it is also recommendable to reduce the outliers influence on the translational velocity estimation. This can be done by carrying out the estimation in two steps: the first with all the filtered vectors as shown above; the second with those vectors whose residuals (computed at the end of the first step) fall into the following intervals:

$$\bar{u} \pm s_u \; ; \; \bar{v} \pm s_v \quad (2)$$

where $\bar{u}$ and s_u are the average and the standard deviation of the u-component residuals of the optical flow, respectively. Accordingly, $\bar{v}$ and s_v refer to the average and the standard deviation for the v-component. Of course, the velocity estimation given by the second step is quite better than the first one, as it is presented in the next section.

4. RESULTS

The sequential images were acquired by a MMS stereo camera while traveling on a flat urban road with little illumination. The digital cameras (Sony DSR 200A) have 30 fps sample rate and 720 x 480 pixel resolution. The color images were converted into gray tones and smoothed by a Gaussian filter. The optical flow was computed with the Horn and Schunck sequential algorithm (1981). In every image, Canny algorithm was applied for the edge detection. Each optical flow vector was filtered and classified according to the filtering procedure. Figure 1 shows an example of a dense optical flow using a 10 x 10 spacing needle map.

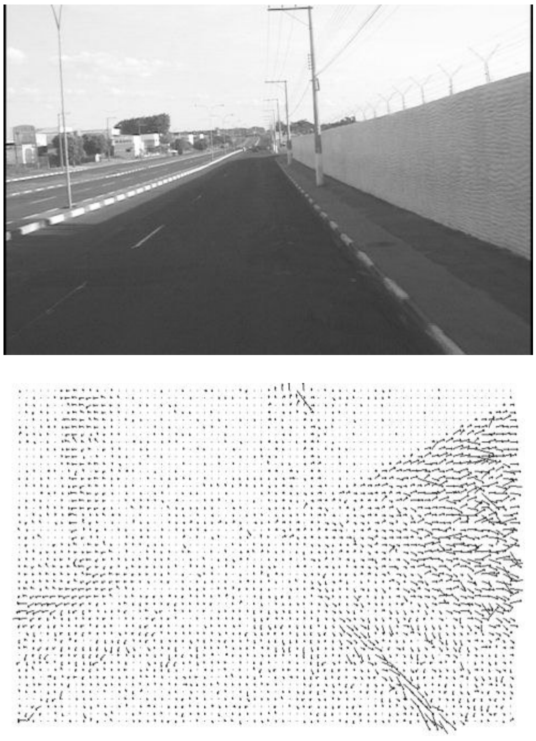


Figure 1. Original image (upper) and optical flow (below)

Although the radial pattern is dominant, a great amount of vectors with no centrifugal radial orientation is seen. The presence of these vectors can deteriorate the velocity estimation, which is improved with the filtered flow vectors.

In the experiments, two pairs of the road image sequence were used, and each sequence had 30 frames for the left (L) and other 30 frames for the right camera (R). The first sequence was named s_1 and the second s_2. Following the sequential method to compute the optical flow, each sequence had 29 calculated flows. Tables 1-4 show the average velocity (vel), the velocity standard deviation (sd), the amount of vectors (vet(n)), and the respective standard deviation (sd(n)).

Step 1 means that the velocity estimation was carried out with all filtered optical flow vectors. In the step 2 the estimation was done after eliminating the outliers, as defined by the equations (2).

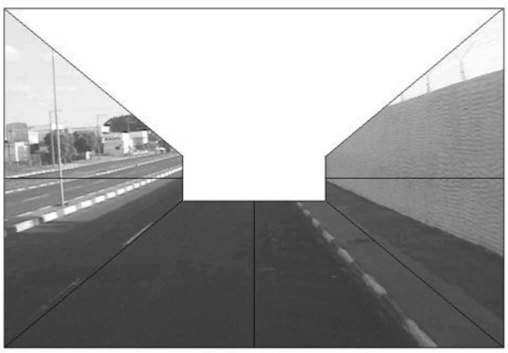
The quality control of the experiments was based on the velocity computed from the two GPS sequence data, namely 19.83 km/h for the sequence s_1 (t=1s), and 19.75 km/h for the sequence s_2 (t=2s).

Table 1. Estimated velocity from vectors in the quadrilateral regions of interest

vel	sd	vet(n)	sd(n)	seq.	t	step
1.57	0.54	230,186	0	L	1	1
2.15	0.37	230,186	0	R	1	1
1.83	0.76	230,186	0	L	2	1
2.07	0.82	230,186	0	R	2	1
12.48	7.83	489.59	145.15	L	1	2
9.13	5.19	411.17	129.68	R	1	2
8.02	2.35	697.03	202.56	L	2	2
9.65	3.84	443.72	130.18	R	2	2

Table 1 shows the results of the velocity estimation by using all vectors that lie in the quadrilateral regions of interest, regardless if they were detected by Canny algorithm and presented centrifugal pattern.

Although the quantity of vector is very large (230,186), the velocity estimation is far from the correct value because there are also low quality vectors (no centrifugal radial orientation) in the data set. In the first step, the standard deviation was zero because the dense flow of all quadrilateral image vectors was considered (figure 2). In the second step, the estimated velocity approaches the correct value as a reduction of vector amount occurs (outlier elimination), but the velocity is still lower than the actual one given by the GPS.



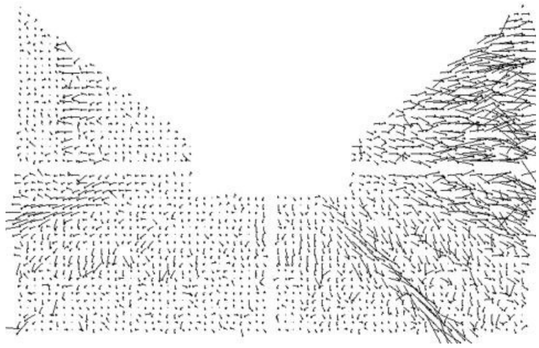


Figure 2. The quadrilateral portions of the original image (upper) and optical flow (below).

The results shown on table 2 are a little better than those referred in table 1 because the velocity estimation was based on the radial pattern vectors of the ROI. In the first step, the velocity was estimated as practically the double better than the first experiment, but it remains lower than the actual value. The estimated velocity in the second step is about the same as those of the first experiment.

Table 2. Estimated velocity in the ROI with the radial pattern vectors.

vel	sd	vet(n)	sd(n)	seq.	t	step
3.34	0.59	110,367	25,972	L	1	1
4.07	0.36	107,169	22,780	R	1	1
3.54	0.57	113,889	27,590	L	2	1
3.81	0.82	107,726	24,595	R	2	1
12.39	7.46	485.66	142.82	L	1	2
9.29	5.04	412.90	129.78	R	1	2
8.13	2.18	705.38	210.07	L	2	2
9.91	3.85	447.17	128.70	R	2	2

The third experiment was carried out with the vectors detected by the Canny algorithm in the ROI, regardless the vectors had or not the radial pattern (table 3).

Table 3. Estimated velocity in the ROI and Canny algorithm

vel.	sd	vet(n)	sd(n)	seq	t	step
17.72	4.77	1,190.55	120.12	L	1	1
16.10	3.20	1,093.66	77.72	R	1	1
12.87	3.64	1,694.07	195.19	L	2	1
13.08	3.31	1,260.41	55.55	R	2	1
18.19	4.67	511.52	154.67	L	1	2
17.83	3.65	480.07	161.78	R	1	2
13.67	4.42	735.52	221.31	L	2	2
15.00	3.02	524.62	152.01	R	2	2

The use of these vectors improved the results, both in the first and the second steps, although the results remained underestimated: 92% for the best case (s_1-L) and 70% for the worst one (s_2-L).

Table 4 shows the results obtained with the filtering procedure proposed in this work, which is the velocity computation with the vectors that showed the centrifugal radial pattern in the lower half of the images and that were detected by the Canny algorithm.

The amount of vectors in the first step presents a significant reduction regarding prior experiments and the first column shows better velocity estimation. In the second step an evident improvement is noticed. In the worst case (s_2-L) the velocity is 80% of that accepted as correct, and in the best case (s_1-R) the velocity is slower than 1% of the true one.
The low quality estimation of the velocity related to the sequence s_2 (L and R) may be due to the fact that there is a great variation on the image intensity, which generated noise on the sequential optical flow calculation.

Table 4. Estimated velocity with the proposed methodology.

vel	sd	vet(n)	sd(n)	seq.	t	step
19.06	3.26	949.17	290.94	L	1	1
18.78	1.95	809.59	263.71	R	1	1
14.53	3.27	1,243.86	376.10	L	2	1
14.34	2.83	839.24	252.34	R	2	1
19.67	2.96	510.83	153.35	L	1	2
19.90	1.96	482.14	162.35	R	1	2
15.88	3.96	735.31	222.83	L	2	2
16.51	1.68	520.10	152.77	R	2	2

Figure 3 shows the resulting image related to the optical flow whose vectors were filtered by the proposed methodology. The results shown on table 4 were based on these optical flow vectors.

Figure 3. Filtered optical flow image.

5. CONCLUSION

This work aimed to estimate the velocity of a vehicle considering only on a pair of image sequence without using any external sensor data. The method was based on a monocular optical flow computation from road images taken on an external environment without any scene control. The proposed filtering procedure was able to select those vectors with centrifugal radial pattern in the quadrilateral portions of the images with the aid of Canny algorithm and this procedure provided a good estimation for the vehicle velocity. The worst result is 80% below the true value and the best estimate is only 1% below.
The estimated velocity can be used to compute the vehicle displacement and, consequently, to provide data to orient the images without using any external sensors.

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