Low-cost Autonomous Navigation System Based on Optical Flow Classification

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Abstract. This work presents a low-cost robot, controlled by a Raspberry Pi, whose navigation system is based on vision. The strategy used consisted of identifying obstacles via optical flow pattern recognition. Its estimation was done using the Lucas-Kanade algorithm, which can be executed by the Raspberry Pi without harming its performance. Finally, an SVM-based classifier was used to identify patterns of this signal associated with obstacles movement. The developed system was evaluated considering its execution over an optical flow pattern dataset extracted from a real navigation environment. In the end, it was verified that the acquisition cost of the system was inferior to that presented by most of the cited works, while its performance was similar to theirs.

1. Introduction

The development of robots capable of locomoting in an autonomous manner can be considered one of the most promising research topics in robotics [Bekey 2005]. Such importance is due to the almost unlimited amount of relevant and innovative applications provided by the use of those instruments [Kim et al. 2012, Wang et al. 2015, Kadir et al. 2015, Chaiyasoonthorn et al. 2015]. In general, its navigation consists of four subprocesses: modeling of the environment where the robot is inserted in; localization of the robot inside that model; planning of the path to be followed by the robot; control of the robot’s actuators in order to ensure the accomplishment of the planned path [Siegwart and Nourbakhsh 2004].

In contexts where the robot must present full autonomy, one can notice that the problem of perception and modeling of the environment becomes significantly relevant for the other subprocesses related to the navigation. This autonomy does not only refer to the complete independence of human intervention during the navigation but also to the non-utilization of any external auxiliary system species (such as radars or geolocation systems). In fact, in these situations, the only source of information about the environment used by the other subprocesses corresponds to the model built by the robot. Consequently, the detail level of this model defines the complexity and the limitations involved in the other navigation subprocesses. Among the principal sensing methods, there are those based on vision.

Sensing through vision uses cameras to obtain both dimensional and visual information, such as textures, color, luminosity, etc. In many situations these features present vital importance to the correct modeling of the environment. Moreover, monocular vision techniques demand low computational cost, especially when compared to those based on stereo vision. That is why this kind of sensing is appropriate for small, low-cost and fast
robotic systems. These systems can be implemented, for instance, through a Raspberry Pi [Foundation 2016], which presents hardware and software specifications that are suitable for the context of autonomous navigation.

Therefore, the principal objective of this work is to develop a robotic system which is capable of locomoting in an autonomous manner through monocular vision and which is based on the low-cost Raspberry Pi platform. This paper is organized as follows: section 2 consists of a bibliographic review related to autonomous navigation systems based on monocular vision; section 3 discusses the obstacle detection based on optical flow recognition; section 4 presents the details of the navigation system proposed by this work; section 5 describes the methodology used to evaluate the developed system and discusses the obtained results.

2. Related Work

Multiple autonomous navigation strategies based on monocular vision are proposed in recent publications. Table 1 presents the main parameters of the navigation systems suggested in some of those works. It is important to mention that since each of those papers used its own evaluation methodology, the accuracy and processing rate should not be individually taken into account to establish superiority relations. By analyzing them, it becomes clear that those techniques based on floor detection demand platforms which present higher processing power. On the other hand, those techniques which considered optical flow as their input signal presented shorter processing time and lower acquisition cost. Then, the use of this signal seems more suitable for systems which have the same low-cost requirements as that intended by this work.

| Strategy                                        | Accuracy | FPS | Cost of the Platform (US$) |
|-------------------------------------------------|----------|-----|---------------------------|
| Floor detection by homography                   | 99,60%   | -   | 7.142,82                  |
| [Conrad and DeSouza 2010]                       |          |     |                           |
| Floor detection by line segmentation            | 89,10%   | 5   | 10.612,82                 |
| [Li and Birchfield 2010]                        |          |     |                           |
| Optical flow segmentation                       | -        | 7,41| 4.080,00                  |
| [Caldeira et al. 2007]                          |          |     |                           |
| Optical flow classification                     | 88,80%   | 7   | 50,00                     |
| [Shankar et al. 2014]                           |          |     |                           |

3. Obstacle Detection by Optical Flow Classification

Let \( t \), defined by the function \( I(\vec{x}, t) \), be the brightness intensity of an image, where \( \vec{x} = (x, y)^T \) corresponds to the position of each pixel. Considering that at \( t + 1 \) such intensity is translated and holds, it follows that:
\[ I(\vec{x}, t) = I(\vec{x} + \vec{u}, t + 1), \]  

(1)

where \( \vec{u} = (u_1, u_2)^T \) denotes the displacement on the 2D plan. Such a vector equals to the optical flow, which describes the apparent motion of an image intensity pattern. This motion is generally associated with the relative displacement between objects included in an image sequence and the camera. Consequently, it is possible to measure such movement through this flow [Horn and Schunck 1981]. For the problem of autonomous navigation, this kind of information is extremely relevant since it is directly related to the motion realized by the robot about the other elements included in the environment. Among the principal applications of this knowledge, there is the obstacle detection. Obstacles have as central feature their accent relative motion. Such movement is contrasting to that presented by the remaining elements in the scene, once these are further from the agent (Figure 1 and Figure 2).

Therefore, it follows that by optical flow samples extracted from many scenes with and without obstacles it is possible to build a model which is capable of separating such patterns. In other words, it is possible to train a classifier from motion patterns already labeled and to apply it to indicate if a new scene presents or not an obstacle. Thus, obstacle detection based on optical flow recognition can be performed by a classifier machine, whose supervised learning is achieved based on the following definitions:

- \( \vec{x}_i = (F_1, ... F_n) \) corresponds to the feature vector associated with the \( i \)-th image in the considered sequence;
- \( F_n \) corresponds to the pair \((v_1, v_2)\), where \( v_1 \) and \( v_2 \) are the amplitude and the phase of the optical flow vector associated with the \( n \)-th image point, respectively;
- Each \( \vec{x}_i \) is related to a value \( y_i \in \{-1, +1\} \), where the labels \(-1\) and \(+1\) indicate the absence and the presence of an obstacle in the image, respectively.

4. Developed System

The navigation system developed in this work is based on obstacle detection by optical flow classification. The whole system was built on the low-cost Raspberry Pi platform. The following sections describe both hardware and software of the developed robot.
4.1. Hardware

The components that constitute the hardware of the designed platform correspond to a Raspberry Pi computer, a sustain chassis which contains two actuators, a power supply, and two sensors: a monocular camera and an ultrasonic sensor. Figure 3 presents the final built platform. Its financial cost is described in Table 2.

![Figure 3. Perspective view of the built robotics platform.](image)

| Component               | Cost (US$) |
|-------------------------|------------|
| Raspberry Pi 3          | 30.00      |
| LG AN-VC500 Camera      | 89.99      |
| Chassis                 | 21.55      |
| HC-SR04 Sensor          | 2.00       |
| L293D                   | 1.90       |
| Power Bank APC M5WH     | 25.38      |
| **Total**               | **170.82** |

4.2. Software

The proposed navigation system was developed based on the computer vision and machine learning libraries OpenCV [Team 2017] and Scikit-Learn [Pedregosa et al. 2011], respectively. Its work cycle is shortly described in Figure 4. According to that flowchart, the system initially catches a referential image and starts the navigation cycle. Then, another image is acquired and the optical flow from those two images is estimated. This flow is presented to an SVM classifier [Chih-Wei Hsu, Chih-Chung Chang and Lin 2008] with RBF kernel, which indicates if there is an obstacle on the path to be followed. Based on that indication, a decision related to the update of the robot’s direction is made. In the cases where obstacles are detected, a deflection to the direction with lower optical flow intensity is made, since this direction presents less relative motion and, hence, has a lower probability of containing new obstacles.

The Lucas-Kanade algorithm [Lucas and Kanade 1981] was used to estimate the optical flow from two environment images taken in a row. In order to apply it, a circular
Figure 4. Flowchart of the proposed navigation system.

symmetrical observation points distribution was considered (Figure 5). This distribution consists of 1 central point surrounded by 5 concentric rings, each one formed by 20 equally spaced points. The distance between each of these rings and the central point increases exponentially. Figure 6 illustrates the flow estimated from a scene registered during the robot's navigation.

5. System Evaluation

5.1. Off-line Evaluation

The off-line evaluation considered only the quality of the SVM classifier. The following sections describe its details.

5.1.1. Methodology

The off-line methodology consisted of the k-fold cross validation [Kohavi et al. 1995] where $k = 8$. The correct and incorrect indications of the classifier during all the process were registered for both classes, in order to fill out its confusion matrix. By using this, it was possible to extract measures which clearly express the quality of the classifier’s performance. Such measures correspond to the precision, the recall, the F measure and the accuracy.
5.1.2. Dataset

The dataset used during the classifier’s validation process was built in this work since no repositories containing optical flow patterns labeled according to the presence of obstacles were found. Therefore, that dataset was built through optical flow patterns extracted from 8 videos whose resolution equals to $320 \times 240$ pixels. Those videos were recorded by the robotic platform developed in this work. In order to accomplish this, the robot was remotely guided by a human controller throughout a circuit which contained different obstacles. Moreover, the features of the environment were changed as long as new videos were recorded. Finally, the labels of the built dataset were created by measures obtained through the ultrasonic sensor HC-SR04, which was already set up on the platform. Figure 7 shows the environment run by the robot.

5.1.3. Baseline

The same methodology which was used to evaluate the SVM classifier was also applied to other two learning models: a Perceptron [Rosenblatt 1958] and an SVR classifier (Support Vector Regressor) with RBF kernel [Drucker et al. 1997]. The first one consisted of a
linear classification model whose training parameters corresponded to a maximum limit of 100 iterations and balanced weight of examples of each class. On the other hand, the second model consisted of a regression model, through which it is possible to estimate the distance associated with each flow pattern.

5.1.4. Results

Table 3 presents both the performance measures extracted from the SVM classifier and those associated with the baseline models. One can notice that the SVM classifier’s recall value was relatively low. However, in a real situation, it is only necessary to recognize one flow sample as related to an obstacle in order to apply an avoidance maneuver. In other words, the recall value does not necessarily equal the collision rate. On the other hand, the classifier’s precision is more relevant since the lower this measure is the higher the number of mistaken deflections tends to be. By analyzing the mean measured precision it is possible to notice that its value is relatively superior to the recall, which was expected.

| Model       | Precision | Recall    | F Measure | Accuracy   |
|-------------|-----------|-----------|-----------|------------|
| SVM         | 75, 46 ± 6, 21% | 61, 71 ± 4, 75% | 68, 00 ± 3, 75% | 89, 00 ± 1, 36% |
| Perceptron  | 16, 37 ± 2, 36% | 45, 92 ± 9, 89% | 24, 08 ± 3, 81% | 50, 83 ± 3, 09% |
| SVR         | -         | 0, 00 ± 0, 00% | -         | 82, 84 ± 1, 08% |

Nevertheless, the processing frequency presented by the system, without considering the time to catch the images, was equal to 14,88FPS. When considering the average system’s capture frequency as equal to 25,28FPS (assessed experimentally), it can be concluded that its average full processing rate was equal to 9,4FPS.

Table 4 shows a final comparison between the developed system and those suggested by those works cited in section 2. Based on the comparative parameters presented, it can be concluded that the developed navigation system has a low cost, a high processing frequency, and a satisfactory accuracy.

| System                                      | Accuracy | Frames Per Second | Cost of the Platform (US$) |
|---------------------------------------------|----------|-------------------|----------------------------|
| Floor detection by homography [Conrad and DeSouza 2010] | 99,60%   | -                 | 7142,82                    |
| Floor detection by line segmentation [Li and Birchfield 2010] | 89,10%   | 5                 | 10612,82                   |
| Optical flow segmentation [Caldeira et al. 2007] | -        | 7,41              | 4080,00                    |
| Optical flow classification [Shankar et al. 2014] | 88,80%   | 7                 | 50                         |
| Developed                                   | 89,90%   | 9,4               | 170,82                     |
5.2. On-line Evaluation

The on-line evaluation consisted of inserting the robot into a specific environment and watching its autonomous navigation. Then, the circuit showed in Figure 8 was considered. In order to allow the robot to recognize obstacles, the SVM trained during the off-line experiment (subsection 5.1) was embedded into the platform. Finally, it is import to highlight that some of the obstacles present in the on-line test circuit were not used to build the classifier training dataset.

The video provided at [http://www.youtube.com/v/hzyKAGhQExg?rel=0](http://www.youtube.com/v/hzyKAGhQExg?rel=0) shows the robot’s navigation throughout the test circuit (Figure 9). By analyzing it, one can highlight that at no moment the robot had collided with any of the obstacles inserted into the circuit. Moreover, it can be observed that every avoidance maneuver was made to the right direction. Finally, it is realized that the actuators control allowed the precise execution of the maneuvers, through which the robot could place itself in the correct direction to the subsequent obstacles.

6. Conclusion

This work had explored the definition of optical flow and its application in obstacle recognition. Based on the performed investigation, an autonomous robot capable of identifying obstacles by optical flow classification was developed. This navigation system was based on the Lucas-Kanade algorithm and in an SVM classifier. This system had been evaluated based on its off-line and on-line performance. In the end, it could be verified that the built system had exhibited a higher accuracy and a lower cost than the majority of the cited works. Also, its processing frequency had overcome those shown by the related works. Finally, it was possible to prove the successful behavior of the whole system in a real navigation circuit.

For future works, one could exploit the use of probability classification models by which would be possible to develop a navigation system capable of predicting obstacles based on optical flow patterns estimated in the past [Lipton et al. 2015]. Also, one could experiment new strategies to extract the features of the optical flow assessed from a scene, in a way that the number of dimensions analyzed by the classifier would be reduced.
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