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Driving assistance system based on the detection of head-on collisions

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***Abstract* – An artificial vision system for vehicles is proposed in this article to alert drivers of potential head-on collisions. It is capable of detecting any type of frontal collision from any type of obstacle that may present itself in a vehicle's path. The system operates based on a sequence of algorithms whose images are recorded on a camera located in the moving vehicle, resulting in the calculation of *Time-to-Contact* taken from an analysis of the optical flow, which allows the vehicle's movement to be studied from a sequence of images.**

I. INTRODUCTION

Traffic accidents are currently a health problem of epidemic proportion. Because of the high mortality rate, there is more and more interest in the development of systems aimed at increasing driver security, efficiency and comfort. Among these, this proposal focuses on the early detection of head-on collisions.

Current systems already in use are sensor-based technologies such as ultrasound and laser [9]. With these systems, the data registered is based on *distances* measured between vehicle and obstacle. Depending on the type of system used, obstacles may be detected within a broad or narrow range, and costs vary accordingly. In contrast to these options, the method proposed herewith calculates *time-to-contact* rather than *distance.* This method is based on artificial vision, but without requiring any type of 3D reconstruction of the subject field under study. Artificial vision technology based on the calculation of *time-to-contact* has already been applied in various disciplines. It is already in use in the field of robotics for the detection of obstacles, the manipulation of objects, and the navigation of the robots themselves [3] [4]. *Time-to-contact* technology has been studied for traffic-related application, but limited to pedestrians rather than vehicles [6]. Others have used the technology as inspiration for the calculation of optical-flow expansion patterns related to translatable movement approximation [1]. To date, *time-to-contact* calculation technology based on artificial vision has not yet been proposed for traffic-related collision avoidance detection systems as described in this present work.

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This paper proposes an algorithm capable of detecting potential head-on collisions. The system (see figure 1) consists of 6 phases: acquisition of images, pre-processing, features extraction, calculation of optical flow, calculation of *Time-to-Contact* (TTC), and the interpretation of the results.

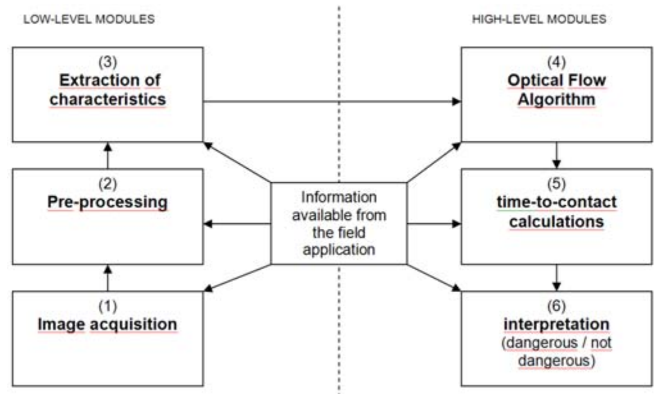

Fig. 1. Head-on collision detection system using artificial vision

Image acquisition is one of the most important phases, as any type of improvement that can be applied to this phase facilitates the work that follows in the subsequent phases. Pre-processing involves improving the contrast of the image in preparation for the extraction of characteristics phase, where distinctive points of the image are selected for further treatment. This process makes possible the linking together of images through the selection of corresponding features from frame to frame of the optical flow calculation sequence. Once the optical flow calculations have been made, the *time-to-contact* calculations are drawn from the results of this data. Lastly, according to the results of this data, the final phase involves the interpretation of the results, where depending on the outcome of the TTC calculations, a distinction may be made indicating when we are in a situation of potential danger, and when we are not.
Recent studies demonstrate that obstacle avoidance is controlled by time-to-contact instead of distance [5]. It is commonly known that time to contact can be computed from an image sequence recorded while approaching an object, as

long as the camera will continue its approach without changing speed. This calculation can be done without knowing anything about the size or distance of the object or the speed of the camera. Thus it has been pointed out as a quantity likely to be highly relevant to control navigating robots.

II. PROPOSED METHOD

A. Acquisition of the images

In this first stage, tests have been carried out using synthetic sequences and real sequences (see Fig.2). The synthetic recordings, which simulate potential real-life situations, have made it possible to carry out tests with greater freedom. These images have made it easier to make recordings of all kinds of sequences. They also have allowed for the camera to be positioned on the exterior of the vehicle and centered along the front, which is the ideal camera placement location. At the same time, the synthetic images have allowed for a pure image translation of the camera. Obtaining a pure image translation in the real-life sequences would have made the tests much more complicated. For the real-life sequences, the focus of expansion of the image does not coincide exactly with the center of the image. The camera was located inside the vehicle, in the front behind the windshield, for the making of the different recordings.

Fig. 2. The image on the left belongs to a real-life sequence; the image on the right belongs to a synthetic one.

Once the images have been acquired, we pass to the following phase of the process.

B. Pre-processing of the images

Once the images have been obtained, they are converted to a grey-scale and their contrast is accentuated. For this, an equalization of the image is carried out. This pre-processing will be important especially for those images for which it is difficult to find distinguishing points.

C. Extraction of characteristics

Once we have the equalized images their important characteristics are sought out. In this case distinguishable points are identified, as they facilitate the correspondence between a frame and the one that follows. The search of correspondences between frames is not always easy. Looking for correspondences of points that belong to a homogeneous region is more difficult and costlier, as there is a certain degree of ambiguity and uncertainty. On the other hand, if we look for points of interest of an image, for example the corners of an object, it will be easier to look for its correspondences in the following frame (see Fig 3).

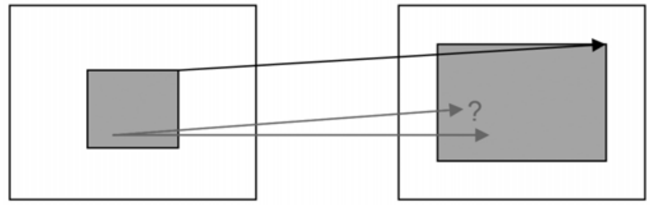

Fig. 3. Ambiguities and uncertainties in the correspondences of points that belong to homogeneous regions.

When put to practice, this search of correspondences is carried out by means of Harris Corner's Detector algorithm [7], which looks for pixels of the image that have a gradient raised in two orthogonal directions (see Fig 4).

Fig. 4. Points distinguished by means of Harris Corner Detector

D. Calculation of the Optical Flow

Once we have found the distinguishing points from the images, these same points have to be located on the following frame. It is precisely these that will later allow us to perform the calculation of the optical flow [2]. This is defined as the apparent movement of the levels of intensity of the image. It allows us to calculate a field of vectors that describes the apparent movement between two consecutive frames. It is important to speak about apparent movement, because it is necessary not to forget that the images are the projection in a flat surface of three-dimensional scenes, supposing a loss of information.

To calculate the optical flow we start from a sequence of images. Once the sequence is obtained the conservation of the information is assumed.

$$\frac{dI(x,y,t)}{dt} = 0 \quad (1)$$

That is to say, it is assumed that the levels of intensity of the image I, are kept constant throughout the time. Therefore, the movement will be identified by the changes of location of the levels of grey of the image. In deriving this expression, the equation of the optical flow is obtained as

$$I_x . v_x + I_y . v_y + I_t = 0 \quad (2),$$

where I_x, I_y and I_t are the spatial and temporary derivatives of the image, v_x and v_y is the vector displacement, and the vector of optical flow is the end result we are looking for. There are analyzed different algorithms based on the calculation of the optical flow [1], [2] and finally the pyramidal method of Lucas and Kanade is applied [2]. In working with a pyramidal technique, what is done is to work with images of different resolutions so that one finds the optical flow in the image of minor resolution and from this one on, the calculation of the optical flow moves on to the top levels. This method is more solid since in the image of minor resolution a movement affects far fewer pixels.

Using this algorithm for the calculation of the optical flow, we will locate the distinguishable points between one frame and the next (see Fig 5).

E. Calculation of the TTC

The TTC is the time that remains prior to contact with a potential obstacle. That is to say, as the vehicle approaches the danger, the TTC diminishes. The TTC can be expressed depending on the distance that separates the vehicle from the possible obstacle and the speed of the vehicle with the built-in camera.

$$TTC = \frac{Z(t)}{V(t)} \quad (3)$$

Fig. 5. Representation of the vectors of optical flow of the frame 'i' to the frame 'i+1'.

As can be seen in equation (3), acceleration is not taken into account: that is to say, a constant speed is assumed for putting this method into practice. But both parameters of the equation are information that we do not know. For this reason, the TTC is calculated from information that is extracted from the image. That is to say, the TTC is calculated from the found optical flow. To relate these two concepts, we use the camera Pinhole model as a reference (see Fig 6), which allows us to associate the 3D space with the plane of the image.

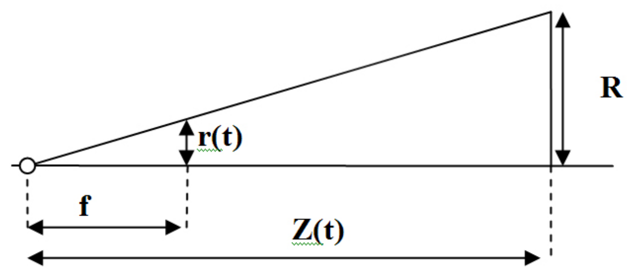

Fig. 6. Pinhole camera model.

Without loss of generality, one can assume a known focal distance, equal to 1, therefore:

$$|Z(t)| = \left|\frac{R}{r(t)}\right| \quad (4)$$

Deriving expression (4) one obtains:

$$V(t) = \frac{dZ(t)}{dt} = R\frac{\frac{-dr(t)}{dt}}{r^2(t)} = -Z(t)\frac{v(t)}{r(t)} \quad (5)$$

Reordering the terms of equation (5):

$$\frac{V(t)}{Z(t)} = \frac{-v(t)}{r(t)} \quad (6)$$

Therefore, relating (6) to (3) the TTC can now be expressed from the information extracted from the image (r (t) and v (t)), and it is not necessary to know neither the speed of the vehicle nor the distance that separates it from the obstacle:

$$TTC = \left|\frac{Z(t)}{V(t)}\right| = \left|\frac{r(t)}{v(t)}\right| \quad (7)$$

v (t) is the speed of a point from one frame to the following one. This information is known from the optical flow calculated in the previous phase. The parameter r (t) is the distance that exists from each of these points to the Focus of Expansion of the image (FOE). The FOE is the point of the image to which the optical flow vectors converge for translational motions.

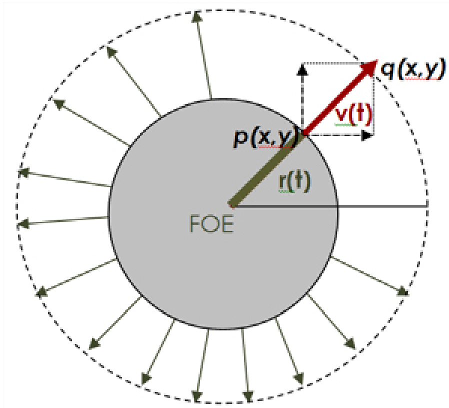

Fig. 7. Example showing the parameters for calculating the TTC with the camera approaching a sphere.

In Fig 7 we can see by means of a simple example that as the camera comes closer to a sphere, the parameters mentioned have moved from the point p (x, y) to the position q (x, y).

In the circumstances of work of the treated application, it can be considered that the situations of risk will be given for pure movements towards the obstacle. That is why we are concentrating on the detection of situations in which the FOE practically coincides with the centre of the image.

The calculation of the TTC occurs for every distinctive point from the image that has a corresponding point detected on the following frame. In this way, when possible frontal obstacles are encountered, the TTC diminishes as we approach the object. This is so because it is possible to demonstrate that the objects nearest to the camera have greater movement than those that are more remote. Consequently, as the vehicle approaches the possible obstacle the TTC diminishes because the parameter v (t) is increasing.

F. *Interpretation of the results.*

Once the TTC has been calculated from the optical flow, the system is then capable of distinguishing when one is facing a situation of potential danger and when one is not. From there it must analyze the number of pixels that have a small TTC and if the number of pixels goes beyond a certain established threshold, the system will indicate that one is facing a dangerous situation. If the opposite occurs, then the scenario will not be identified as dangerous. One must emphasize that the TTC calculation is valid only when the computed optical flow corresponds with the pattern of a possible collision. To calculate equation (7) in other circumstances does not result in a real TTC.

III. TESTS

Once the method is put into practice, a series of problems arise that must be taken into account when implementing the algorithm.

A. *Distinguishing movements unrelated to the scene*

One of the things that must be taken into account when putting into practice the previously-described method, is that in the sequences with which we are working, there is movement which is significant to the task at hand, but there may also be movement in the scene from other un-related objects, such as that from other vehicles passing by laterally, the images of which become incorporated into the camera's field of view (see Fig 8). These outside movements complicate the work, since they must be distinguished and separated from the main subject.

In order that the unrelated movement does not interfere, it is discarded from the scenario when calculating the TTC. For this to happen, it is assumed that all the objects within the scenario that are of significance will have optical flow vectors that converge towards the FOE of the image. Those that do not converge on the FOE mean that they do not correspond to the collision pattern. There are however movements that are not unrelated, but that still are not part of the expansion pattern. On the other hand, there are movements that do correspond to the expansion pattern, but are still unrelated. However, the system does not take these into account.

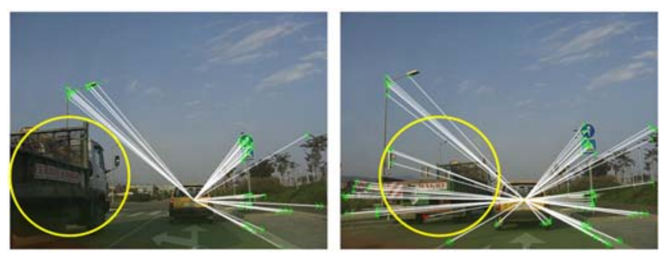

Fig. 8. Example of a scene with movement that is significant for the camera and another that is unrelated, in the form of a vehicle that passes by laterally.

To put this into practice, the scalar sum of the vectors r (t) and v (t) seen in (7), is calculated. From this calculation, the vector angles can then be determined. Thus, if the angle between both is zero or very near to zero, it is considered that the optical flow vector being analyzed converges towards the FOE and therefore is defined as having points that do not have unrelated movement. In the opposite case, the points are discarded because they are defined as being unrelated.

B. *Identification of the expansion pattern*

The following problem arises when it is understood that in many cases the pixels that have small TTC values in the recorded sequences do not form a part of the potential obstacles. There are even big quantities of pixels with small TTC values when the obstacle is not yet present in the image. This is due to the fact that although they are not points with unrelated movement, they are not part of the collision pattern. This problem makes it necessary to distinguish between two types of situations (see Fig 9): when the pixels with small TTC values form part of the objects that really are expanding from the FOE, and therefore, would be possible objects with which one could collide; and when the pixels with small TTC values form part of the objects that do not expand from the FOE and therefore, would not be possible obstacles.

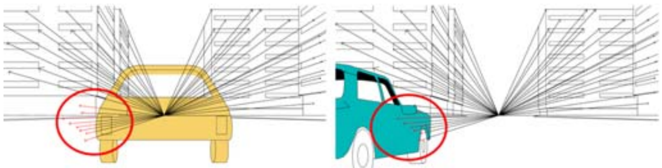

Fig. 9. In the image on the left, the objects expand from the FOE (real situation of danger) and in the image on the right, the objects do not expand from the FOE (false situation of danger).

To distinguish between the two situations, a series of methods are discussed:

1) Using mathematical morphology, the pixels with small TTC values can be used like seeds in a process of geodesic expansion. It is used in a way that, depending on the reconstructed region, it is possible to distinguish if it is a dangerous situation or not. The system assumes that if the zone is close to the FOE, it constitutes a dangerous situation (see Fig 10) and if it is far away, the threat of danger is false (see Fig.11). The problem with this type of solution using mathematical morphology is the high computational cost.

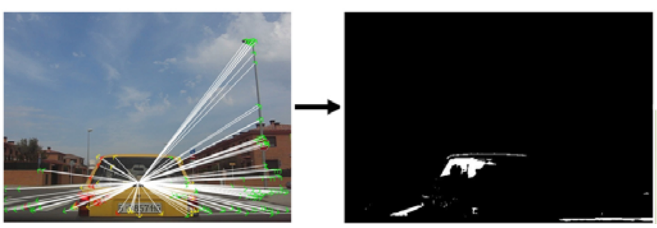

Fig. 10. Real situation of danger.

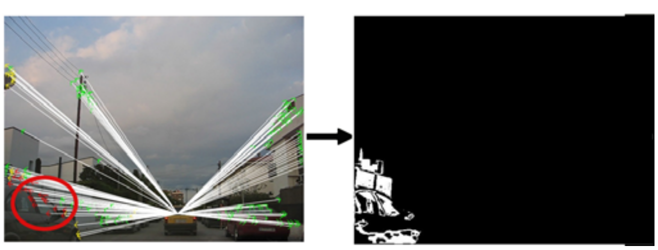

Fig. 11. False situation of danger.

2) The next method discussed does not use mathematical morphology, and therefore the computational costs are considerably reduced. This method consists of analyzing the location of pixels with small TTC values. Under this system, if the pixels really belong to a potential obstacle, - and given the steady stream of pixels with small TTC values flowing from the image to the FOE - then small TTC pixels should continue to appear. But if pixels reappear again with big TTC values as we approach the FOE, it signifies a false collision. This is because the appearance of large TTC-value pixels signifies that they belong to objects that are far away from the camera, because they do not demonstrate much apparent movement and therefore do not constitute a dangerous situation. Based on this, a problem can arise in the case of an obstacle that is very far from the camera (or has not yet appeared in the scene), while at the same time, on the sides of the field of vision, other objects appear in close range of the camera. This results in small TTC values, but without being obstacles within the vehicle's trajectory. This presents a problem because if the obstacle is far away, the movement might not be detected in the zone close to the FOE, but the system might on the other hand detect as a dangerous situation the case we just described above (see Fig 12).

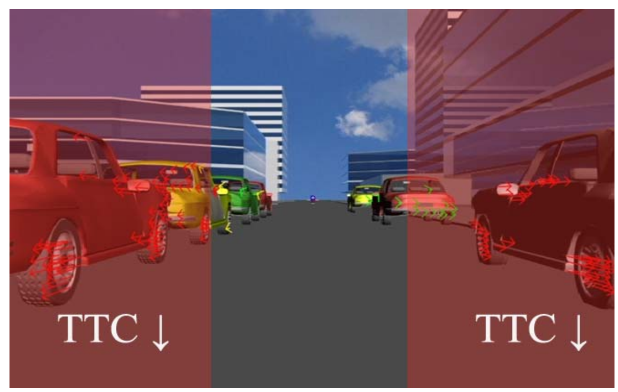

Fig. 12. False situation of danger, where the vectors of red color indicate small TTC values.

3) Lastly, after analysis of these problems, a new restriction can be put into practice. This consists of delimiting the zone of interest of the image. That is, only those pixels that belong to the area close to the FOE are taken into account. This is done because that is the region where the potential obstacles appear (see Fig 13). The other zones are discarded because as we have demonstrated, they have shown to be the cause of erroneous danger readings such as those marked with a circle on the images. These regions are omitted because they do not form a part of the area of interest. To delimit the region of interest, other driving assistance systems may be taken into account, such as those that detect the outer edges of the roadway [8]. In this way, one can take into account a certain perspective of the image when delimiting the zone of interest, and this allows us to locate the area within the path of the vehicle, within the lane in which the vehicle carrying the camera is being driven.

Fig. 13. Region of interest around the FOE

IV. RESULTS

The method under consideration allows for the detection of potential collisions with all types of obstacles - not only with vehicles - that may find themselves in the path of the vehicle (see Fig 14). In the images, the optical flow vectors take on the colours of red, yellow or green, depending on whether the TTC is small, medium or large.

The method detects obstacles depending on the TTC and not based on the distances that separate vehicle from obstacle, so that if the former circulates faster or slower, the potential collisions will be detected with greater or lesser braking distance.

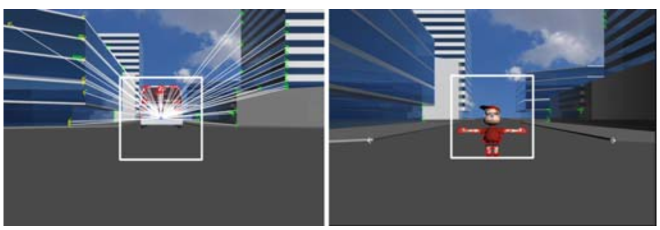

Fig. 14. Synthetic examples of obstacles detected by the algorithm.

In Fig. 15, a frame is shown detecting the collision in two sequences. The image on the left is part of a sequence that has been recorded at a slow speed; the sequence on the right has been recorded at a high speed.

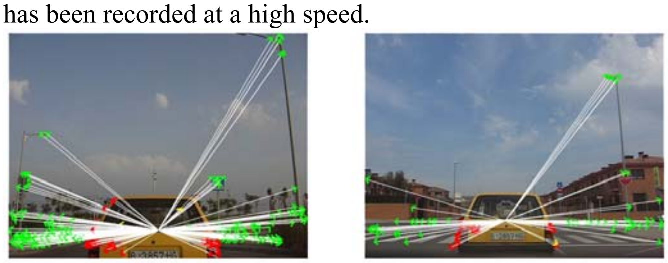

Fig. 15. Real examples of obstacles detected by the algorithm.

V. CONCLUSIONS

We have presented herewith a driving assistance system for the detection of head-on collisions. For this, a single and simple camera has been used to carry out the data recording. TTC calculations have been made for collision detection based on the computation of optical flow. This system detects potential collisions based on the *time* separating a vehicle from an obstacle, instead of the *distance*. In this way, the algorithm allows for a greater or lesser braking distance depending on the speed of the vehicle.

In the tests carried out, working with both synthetic and real sequences, the position of the camera was seen to be an important factor. With the correct camera location, a pure translational movement is obtained between the subject and obstacle, which in turn permits the establishment of the FOE as a given workable factor, coincidental with the center of the image. The fact that the work is carried out using synthetic sequences has allowed us to verify that the system is capable of detecting any type of obstacle, and not limited just to vehicles. This type of verification was more difficult to carry out in real-life situations.

The method implemented herewith is based on an algorithm which is sensitive to the vehicle's movements. Future improvements can be added by using algorithms which compensate for the movement by stabilizing the recorded sequences and in this way ensuring the algorithm is less sensitive to movement. It also needs to be pointed out that the method is also sensitive to changes in lighting, because when working with optical flow it is assumed that the levels of intensity of the images are kept constant throughout the duration of the sequence, whereas changes of intensity of the image are in fact attributable to the movements. To resolve this possible problem, infrared-sensitive cameras could be used in future simulations. Finally, TTC is only computed when an expansion pattern is detected in the optical flow computation. It is related to the case in which the vehicle is frontally approaching an obstacle. As mentioned in section II.E, acceleration is not taken into account in the TTC equation. Hence, as it assumes constant speed, the proposed TTC measure is intended to be a qualitative help for the driver, not a precise measure of time.

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