Combination of Active Sensing and Sensor Fusion for Collision Avoidance in Mobile Robots

Terence Chek Hion Heng, Yoshinori Kuno and Yoshiaki Shirai

Osaka University, Suita, Osaka 565, Japan

Abstract. Presently, mobile robots are navigated by means of a number of methods, using navigating systems such as the sonar-sensing system or the visual-sensing system. These systems each have their strengths and weaknesses. To fully utilise the strengths of both the sonar and visual sensing systems, this paper proposes a fusion of navigating methods involving both the sonar and visual systems as primary sources to produce a fast, efficient and reliable obstacle-avoiding and navigating system. Furthermore, to further enhance a better perception of the surroundings and to improve the navigation capabilities of the mobile robot, active sensing modules are also included. The result is an active sensor fusion system for the collision avoiding behaviour of mobile robots. This behaviour can then be incorporated into other purposive behaviours (e.g. Object Seeking, Path Finding etc.). The validity of this system is also shown in real robot experiments.

1 Introduction

For robots to operate efficiently in a human environment, they need to be able to navigate efficiently and to avoid collisions. Therefore, taking the safety factor into consideration, "Collision Avoidance" would essentially form the basic behaviour of all behaviour-based autonomous robots.

The sonar sensing system has traditionally been used for collision avoidance in mobile robots. It is cost effective and relatively quick in response. Processing is not time consuming either. Recently, however, with the reduction in size of video cameras and the increase in computing speed of computers, the use of visual sensing has become popular too.

Sonar systems can cover a wide horizontal range, depending on the number of sonar sensors attached around the mobile robot. Many conventional methods use sonar data to generate two or three dimensional maps of the environment for robot navigation (e.g. [1], [2]). These maps are usually difficult to construct and often incomplete. This is basically due to the fact that most commercial sonar sensors are very "uni-directional", in the sense that only sonar reflections from surfaces that are of a certain level of perpendicularity to the sensors can be picked up. Furthermore, once the height of the sonar sensors are fixed, the vertical readable range can be very restrictive. This will mean that obstacles at an angle to the sonar sensors or obstacles that are not of the same height as the sonar sensors will not be correctly represented in the generated maps. Nakamura et al. [3] proposed a statistical map representation method that is robust to sensor noise. Still, it does not solve the problems mentioned above, which is basically due to the low-levelness of sonar data.

On the other hand, although the visual sensing system supplies a rich input of data about the surrounding environment which can enable mobile robots to navigate competently (e.g. [4], [5]), processing of images is invariably time-consuming, and the horizontal range is fairly limited too. Calculation of optical flows is effective in getting an accurate understanding of the environment [6]. However, as it is time-consuming and error-prone due to noise, it cannot be applied efficiently to the navigation of a mobile robot in an environment with moving objects. Liu et al. [7] proposed the Image Gradient Evolution (IGE) for a faster processing of images over the conventional methods of computing optical flows. Still, it might not be fast enough for the mobile robot to avoid moving obstacles during real-time running in a constantly changing environment. Cheng and Zelinsky [8] experimented obstacle-avoidance successfully with their Yamabico robot by locating free space using template matching of the floor. This would mean that in an office environment where the floor might be cluttered with pieces of paper or where the carpet might not be of a uniform design, this method would lose its practicality and efficiency. Simple single-camera (monocular) set-ups are further restricted due to the fact that the depth of the environment could not be calculated efficiently. I.R.Nourbakhsh et al. [9] experimented successfully with their Nomad 150 robot by getting depth information about the environment and navigating accordingly. They did so by varying the foci of their cameras. Though simple, four cameras were needed for their set-up. Thus, in a constantly changing environment, the visual system alone may not be sufficient.

Hence, a combination of both sonar and visual systems might improve the overall navigating capabilities of the mobile robot. Still, there might be situations whereby conclusive data do not exist. For example, a flat piece of object (which the robot can safely run over) might be interpreted as an obstacle, or a thin rod protruding from the ground might be mistaken for a line drawn on the floor. Here, we introduce active sensing modules, whereby if the mobile robot encounters such situations, it will do an active sensing of the surrounding area using both the sonar and visual systems. In this way, through active sensor fusion [10], the robot will be able to navigate more intelligently in a real-life situation.

This paper presents this active senor fusion system and shows its validity in real robot experiments.

2 Active Sensor Fusion System

A block diagram of the active sensor fusion system is shown in Fig. 1. Basically, there are four modules: the sonar sensor module, the visual module, the situation assessment module and the movement module. These modules are individually sub-divided into sub-modules.

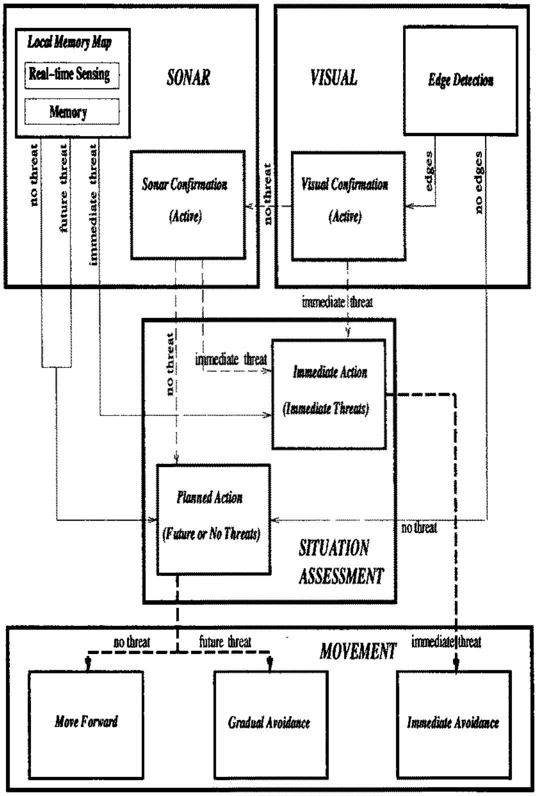


Fig. 1. Active sensor fusion system

The first two main modules are "sensing modules" and all the data collected by these two modules are relayed to the situation assessment module, which will decide on an appropriate action or reaction (based on past and present data) and which will in turn, pass an order to the movement module. In our system, there are three possible situations: a no-threat situation, a future-threat situation and an immediate-threat situation. If at any point of time, an immediate threat is detected by any one of the modules(sub-modules), priority will be given to the situation assessment module to take immediate evasive measures. A future-threat situation would mean that although there are obstacles detected, they pose no immediate danger to the robot and so they can be avoided gradually or be ignored (if they do not lie in the robot's path of motion). These data can also be used to avoid obstacles more efficiently. For example, we would want the robot to avoid in the direction away from a crowded area and not towards it. In a no-threat situation, the robot is free to move forward. Furthermore, considering the fact that the mobile robot can safely run over flat objects like paper and carpets in an office or laboratory environment, once edges near to the mobile robot are detected, active visual and sonar sensing will be carried out respectively to further assess the situation. If the active visual sensing fails to confirm the existence of a real threat (i.e. the detected object could be flat on the floor), active sonar sensing will then be carried out to further ensure that the path is clear, and the appropriate actions can then be made. On the other hand, if the existence of a real threat is confirmed at any point of time, immediate avoiding actions will be taken. The robot will proceed forward only when a clear path is confirmed. Both visual and sonar data are combined with active sensing to ensure safe navigation of the mobile robot.

3 Visual Sensing

The camera is normally set at a horizontal position to enhance its usage by other modules of behaviour like for example "Object Seeking". Images taken are tested for edges and as the lower part of the images corresponds to the immediate front floor space of the robot, any edges detected in this region will be interpreted as possible threats. In such cases, visual confirmation will be carried out to verify the situation.

3.1 Edge Detection

Images taken are processed as follows: First, using a Sobel operator, edges are detected and an "edge" image is obtained. Then, through a process of labelling, continuous line segments are labelled. Finally, line segments that are shorter than a certain threshold length are removed, leaving only the long edges behind. This is to remove background noises and noises caused by small debris on the floor. Scanning is then carried out on the bottom part of the processed images, which corresponds to the floor space immediately in front of the mobile robot. If any edges are detected in this region, they will be considered as possible threats.

3.2 Visual Confirmation (Active)

In this process, the robot stops, tilts the camera to face the immediate front floor space, takes an image, moves slightly forward (about 200mm) to take another image and then tilts the camera back to the original horizontal position. The two images that were taken are then transformed to plan view (bird's eye view) using the following transformation [8] (see Fig. 2).

$$y = max_y + blind_y - \frac{height}{tan[\theta + \frac{pixel_y}{screen_y}(\alpha - \theta)]}$$

$$x = \frac{max_x}{2} - (max_y + blind_y - y)tan((\frac{1}{2} - \frac{pixel_x}{screen_x})\beta)$$

The two transformed images are then each divided into an appropriate number of vertical sections and the sizes (vertical lengths) of the contents of each section are compared. By applying the principle of "Focus Of Expansion"(FOE), a big change in size (length) would imply a relatively big expansion factor, which in turn, would imply that the object in question would most likely be an obstacle. When this happens, the obstacle will be taken as an immediate threat, because the robot had already moved nearer to the obstacle to take the second image. On the other hand, a small change in expansion factor would imply that there is a likelihood that the object in question might be a part of the floor. When this happens, sonar confirmation (which will be mentioned later) will be carried out.

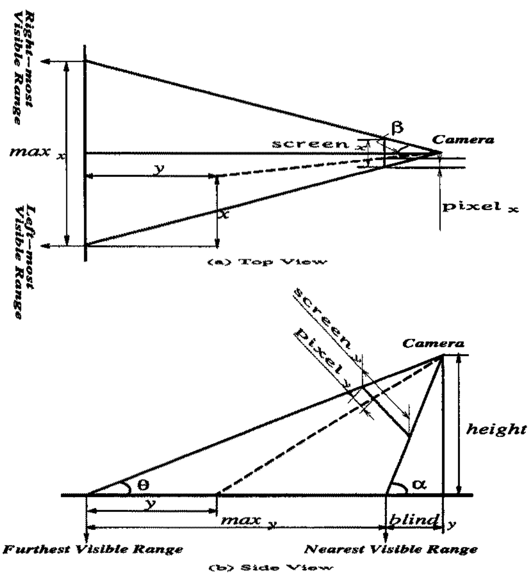
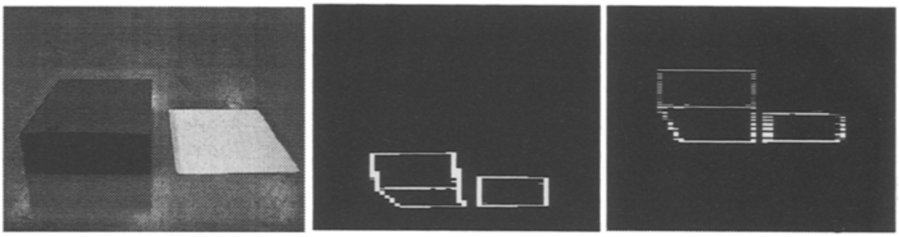


Fig. 2. Transformation to plan view

This process is applied to the situation shown in Fig. 3 (a) in which a piece of paper is lying on the floor beside a box, which is too low for sonar detection. The results are shown in Figs. 3 (b) and (c), and as can be seen by comparing the two images taken from two differing distances, the box has a distinctively greater change in size than the piece of paper.

4 Sonar Sensing

The real-time sonar sensing module and the memory module can be grouped into a "Local Memory Map" sub-module, where rather than trying to build a global map of the surrounding, only relative distances of detected threats are recorded. The sonar active confirmation sub-module is used for the confirmation of visual data when ambiguous situations arise.



(a) Camera view (near) (b) Plan view (far) (c) Plan view (near)

Fig. 3. Visual confirmation

4.1 Local Memory Map (Real-time & Memory)

When objects at a distance that is closer than an appropriate "near" threshold range are detected, they are classified as "immediate threats". If they are beyond an appropriate "far" threshold range, they are "no threats". Any obstacles detected in between those two threshold ranges are classified as "future threats". Whenever an immediate threat is sensed by any of the sonar sensors through real-time sensing, immediate action is taken. This is effective for fast moving obstacles like humans and other mobile robots. However, sonar sensing is not consistently accurate. A previously detected obstacle might evade detection as the mobile robot moves nearer towards it, due to the change in orientation of the reflecting surfaces. To counter this problem, even when objects not presenting any immediate danger are detected, their distances are recorded. This set of data can then be used later to avoid threats not detected by real-time sonar sensing. This memory is also useful in the planning of the direction to avoid during avoidance. For example, when caught in a crowded spot, we would want the robot to avoid efficiently in the direction of a less crowded area in one smooth turn rather than in an unplanned trial-and-error series of turns, which eventually might land the robot in an even tighter spot.

4.2 Sonar Confirmation (Active)

In the situation presented in Fig. 4, a long thin rod-like structure protruding from the floor is placed beside a line-partition of the flooring. If the thin rod were short, it will be detected by the visual confirmation module. In this particular situation, however, both will appear as long straight lines in the two processed images taken during visual confirmation. As there are little or no apparent changes in lengths, the rod might not be interpreted as a threat. Furthermore, as the reflecting surface of the thin rod is small, it might avoid detection by the Local Memory Map of the Sonar module.

In a situation like this, active sonar confirmation will be carried out for a fail-safe verification. In this process, the robot will rotate (left and right) on the

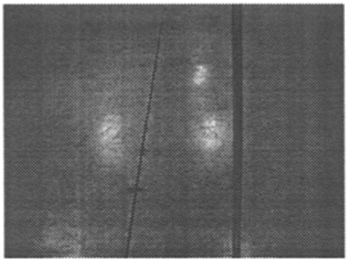


Fig. 4. An ambiguous situation

spot to confirm if there is ample space ahead for forward movement or if there are any obstacles. The rotation is necessary to ensure a wider angle of collected data and to improve reliability. In this way, the chances of detecting the thin rod (or any other similar structures) will be higher. If any obstacles are detected here, they will be taken as immediate threats, because the robot had already moved closer to the obstacle during the active visual confirmation process. On the other hand, if no threats are detected, the robot will proceed forward.

5 Experiments

We installed the active sensor fusion system in a small mobile robot, experimenting with the collision avoidance behaviour of the robot. Figure 5 shows an experimental setup consisting of (from left to right) a low-lying box, a length of wire, a long thin rod and a piece of paper enclosed by two big boxes (on the extreme left and right ends of Fig. 5) serving as walls.

Our robot was made to move randomly within the confines of the above setup, and collision avoidance was successful. The low-lying box, together with the length of wire, were detected visually, and active visual sensing confirmed them to be obstacles. Although the long thin rod was detected visually, visual confirmation was not successful. This was covered by sonar confirmation, which managed to detect it. The piece of paper was detected and successfully confirmed as a no-threat by visual and the robot was able to run over it. The walls were avoided by the direct sensing and memory of sonar. The results of this experiment are tabulated in Table 1.

6 Conclusions

Although we have tried using the sonar system and the visual system separately for collision avoidance, the results from the above experiments clearly show that by utilising both systems and applying active sensing to adapt to differing situations, a high level of competent collision avoidance behaviour can be achieved. This behaviour can then be incorporated into other behaviours to achieve a higher level of intelligence in behaviour-based robots.

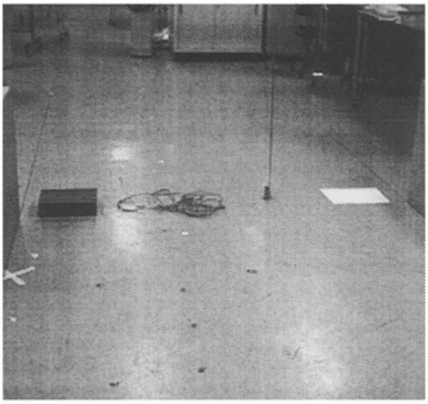


Fig. 5. Experimental setup

Table 1. Effectiveness of the various sensing modules

	Visual	Visual (Active)	Sonar	Sonar (Active)
Small box	⊙	⊗	-	-
Wires	⊙	⊗	-	-
Thin Rod	⊙	-	-	⊗
Paper	⊙	⊗	-	-
Walls	-	-	⊙	-

⊙ : detection
⊗ : confirmation
- : not effective

References

1. Reeve, S., Durrant-Whyte, H.: A qualitative approach to sensor data fusion for mobile robot navigation. Proc. 14th Int. Joint Conf. on Artificial Intelligence (1995) 36-41
2. Kröse, B.J.A., Eecen, M.: A self-organizing representation of sensor space for mobile robot navigation. Proc. 1994 IEEE/RSJ/GI Int. Conf. on Intelligent Robots and Systems (1994) 9-14
3. Nakamura, T., Takamura, S., Asada, M.: Behaviour-based map representation for a sonar-based mobile robot by statistical methods. Proc. 1996 IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (1996) 276-283
4. Horswill, I.: Visual collision avoidance by segmentation. Proc. 1994 IEEE/RSJ/GI Int. Conf. on Intelligent Robots and Systems (1994) 902-909
5. Ohno, T., Ohya, A., Yuta, S.: Autonomous navigation for mobile robots referring pre-recorded image sequence. Proc. 1994 IEEE/RSJ/GI Int. Conf. on Intelligent Robots and Systems (1994) 902-909
6. Kuniyoshi, Y., Riekki, J., Ishii, M., Rougeaux, S., Kita, N., Sakane, S., Kakikura, M.: Vision-based behaviors for multi-robot cooperation. Proc. 1994 IEEE/RSJ/GI Int. Conf. on Intelligent Robots and Systems (1994) 925-932
7. Liu, H.C., Hong, T.H., Herman, M., Chellappa, R.: Image gradient evolution - a visual cue for collision avoidance. Proc. 13th Int. Conf. on Pattern Recognition, Volume I, Track A: Computer Vision (1996) 446-450
8. Cheng, G., Zelinsky, A.: Real-time visual behaviours for navigating a mobile robot. Proc. 1996 IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (1996) 973-980
9. Nourbakhsh, I.R., Andre, D., Tomasi, C., Genesereth, M.R.: Obstacle avoidance via depth from focus. Proc. 1996 Image Understanding Workshop (1996) 1339-1344
10. Kweon, I.S., Kuno, Y., Watanabe, M., Onoguchi, K.: Behaviour-based mobile robot using active sensor fusion. Proc. 1992 IEEE Int. Conf. on Robotics and Automation (1992) 1675-1682