Visual Recognition of Conspecifics by Swarm Robots

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Abstract

This paper examines the problem of giving very simple swarm robots the capability of recognizing and locating other swarm members. The ability to recognize conspecific robots will allow swarms of robots to adjust their mutual separation as required by any specific task. For instance, robots engaging in flocking behavior will need to maintain a fixed mutual separation. One of the perceived benefits of developing swarm robots is that the individual robots will be simpler than a single complex robot built for the same task. With this in mind it is essential that the robot recognition system be as simple as possible, otherwise part of the justification for using swarms is negated. For this project a visual recognition scheme based on considering the abilities of social insects has been developed. Hardware and processing capabilities are minimal making the scheme suitable for all but the simplest robot systems. In this paper details are given of the camera hardware, and image-processing steps required to determine the range and identity of robots carrying visual markings. Results of practical robot recognition experiments are also presented.

1 Introduction

Observers of social insect colonies have noted the efficient way that such groups of industrious creatures organize and coordinate their activities. A single ant, bee, wasp or termite is limited in the load that it can carry, structure that it can build, or invader that it can repel. However, the coordinated activities of a whole colony can source food for tens of thousands, build intricate dwellings meters tall and discourage intruders having thousands of times their body weight. The success of cooperating groups of insects is seen as a model for the development of robot swarms. It is suggested that multiple robots acting as part of a swarm have several advantages over a single, more complex and expensive robot [Liu and Wu, 2001]. A multiple robot system would tolerate the failure of one or even several system members. If all members of the robot swarm were not required for a single task they could split into smaller groups and perform several tasks in parallel. The system could cover a larger area in search operations and each individual would be simpler, easier to develop and cheaper than a single complex robot designed to perform the same function.

This paper proposes a method by which members of a robot swarm could recognize fellow swarm members and gauge their separation. Depending upon the task being undertaken by the swarm it may be necessary for individual robots to adjust their mutual separation. Robots performing a searching or other area coverage activity may be required to spread out evenly and increase their separation. Flocking behavior would allow a group of robots to operate in some ways as a single entity and this would involve the robots distributing themselves a fixed distance apart [Reynolds, 1987]. Very close proximity or physical contact would be necessary to allow robots to pass things to each other or to cooperate in some common task such as pushing, lifting, etc.

For members of a robot swarm recognition might be based on techniques practiced by insects such as:

- touch - antennation, mandibular contact or taste [Wigglesworth, 1965],
- close proximity - odor, audible buzzing [Dusenbery, 1992], or
- more distant - visual recognition (though visual recognition in most social insects has not been established).

Other non-biological recognition techniques would also be available to robots such as active radiation of coded light, radio waves or even nuclear radiation. From all of these possibilities it was decided to develop a visual scheme for robot recognition. Visual recognition provides identification at a distance that can also give useful range and bearing information. As a passive technique vision is energy efficient and also allows recognition of non-

functioning robots that would be important if damaged robots were to be identified and rescued.

2 Visual recognition

Some of the most intensively studied insect species are also of considerable economic importance. This is true of the honeybee. There is an obvious need for bees to recognize each other during feeding, communicating the source of food during the bee waggle dance and barring entry to the hive to outsiders. Many of these recognition situations take place within the hive where it is dark. Touch, smell and sound/vibration provide recognition cues in the darkness of the hive. There is no experimental confirmation that bees use visual cues to recognize conspecifics. However, it appears that they should be especially attuned to the striped pattern on their abdomen. The Austrian zoologist Karl von Frisch showed that bees could identify black and yellow, which are the colors of their abdomen, and are also able to distinguish patterns of linear stripes [von Frisch, 1950]. The evidence suggests that bees are able to detect the visual appearance of their abdomen and this information may be used to recognize conspecifics. Certainly, the markings on a bee's abdomen conform to the specifications given by Dusenbery for a visual signal [Dusenbery, 1992]. Such a signal should be easily recognized, simple, and distinctive. It is suggested that a bold pattern made up of a few colors, often black and a saturated color, would be appropriate. The bee abdomen fits this criterion and so a pattern of broad vertical black and white stripes was chosen for the robot pattern. Many research robots have a circular chassis. If the coding pattern has the same width all the way around the robot then it will present the same visual appearance to an external robot independent of the heading from which it is viewed. For this reason the robot markings were made the same width around the entire robot.

2.1 The robot

The mobile robot used in this project is based on the laboratory robot LABOT designed at Monash University. This 24cm diameter robot is formed from a stack of three disks. The lower disk carries two geared motors driving side-by-side wheels. Wheel motion is monitored by optical encoders attached to each wheel. Teflon skids provide stability for the robot by making a third point of contact with the ground. A printed circuit board containing power conditioning and interface electronics is attached to the middle disk and the top disk carries an Infineon C167 microcontroller for controlling all of the robot's systems including the visual recognition system.

2.2 Line-scan vision system

In this project, one of the underlying considerations was to develop a system that could be used on the simplest mobile robot. Minimal cost, size and processing requirements as selection criteria.

On grounds of cost it was decided to use a linear array oriented parallel to the ground to detect the vertical stripes chosen for the robot markings. The sensing element of the camera system is a Texas Instruments TLS214 64x1 linear array opto-sensor. This was directly interfaced to the C167 microcontroller using a minimum of additional components (Figure 1).

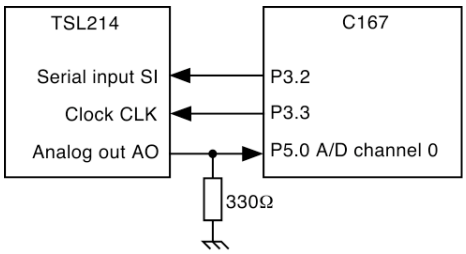

Figure 1. Connecting the TSL214 linear array sensor to the C167 microcontroller.

A 50 μs timer interrupt on the C167 was used to generate the clock signal for the TSL214 as well as to control the acquisition of a continual sequence of line images from the opto-sensor. This process also included automatic adjustment of the sensor integration time to allow for variations in the scene light level. Image update rate varied between 22Hz in low light levels to a maximum of 143Hz in bright illumination. Figure 2 shows the image of a repeated pattern of 2cm wide black and white stripes produced by the linear array sensor.

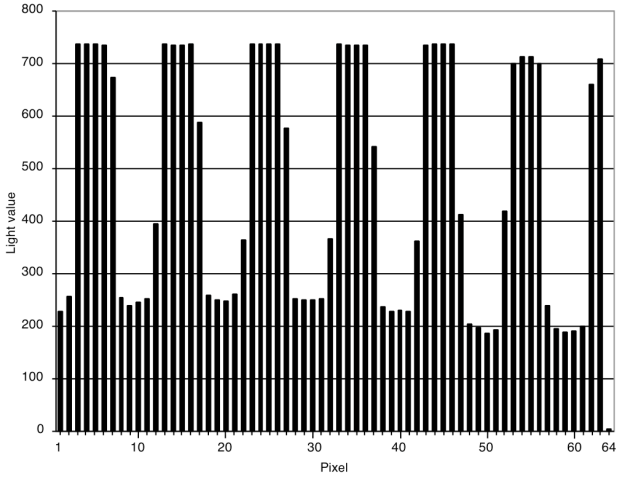

Figure 2. The line image of alternating vertical 2 cm wide black and white stripes.

2.3 Optical flow gives object range

The visual recognition system is required to provide the range, bearing, and positive identity of a conspecific robot. A moving observer can calculate its distance to a stationary object r given knowledge of its own linear velocity v, the bearing of the object θ and the object's apparent angular velocity θ' [Weber, *et al.*, 1997]:

$$r = \frac{v}{\theta'} \sin\theta \qquad (1)$$

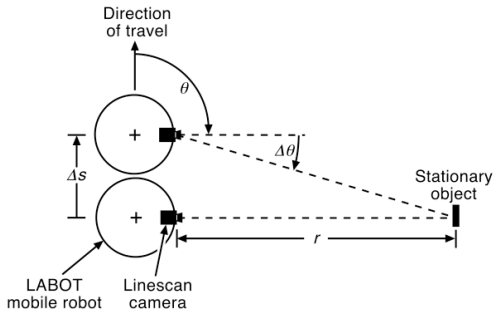

Figure 3. Measurement of object range using apparent motion.

and therefore:

$$r = \frac{\Delta s / \Delta t}{\Delta \theta / \Delta t} \sin\theta \qquad (2)$$

In order to simplify range calculation the camera optical axis was oriented at right angles to the direction of motion of the robot and thus the sine term in (2) becomes unity. The time between successive movements of the robot was made to be the same as the period between measurements of the angular motion of objects viewed by the camera leading to a further simplification of the range equation:

$$r = \frac{\Delta s}{\Delta \theta} \qquad (3)$$

In this experiment the focal length of the lens was 12.5mm and separation of pixels in the linear array sensor 0.125mm. Thus each image movement by one pixel corresponded to an approximate rotation of 0.01 radian. The motion of the robot is controlled via wheel odometry and is known. Therefore, if the movement of visual features recorded by the linear camera can be tracked as the robot travels a known distance, then the range of the environmental object corresponding to the visual feature can be calculated using (3). In the robot recognition system, tracking of image movement was controlled by a 50 ms interrupt. At the start of tracking a 16 pixel template was recorded from the center of the current line image and the position of the template *pos* was initialized to 24 (Figure 4). Every 50 ms the template was compared with the last recorded position of the template in the line image *pos* ±2 pixels.

$$Bestmatch = \underset{-2 \le j \le 2}{\mathrm{MIN}} \sum_{i=0}^{15} \mathrm{ABS}\left(template(i) - image(i + j + pos)\right) \qquad (4)$$

If the value of *j* that gave the best match (*Bestmatch*) was not equal to 0 then *pos* was updated appropriately. When *pos* moved below 8 or above 48 a new template was recorded from the center of the image and *pos* was reset to 24. To keep track of the total image movement recorded by the camera, a variable *postot* was updated by the same amount as *pos,* but was not changed when *pos* was reset to the center of the image. In order to accommodate sudden changes in light level or situations where the template tracking mechanism became completely lost a new template was recorded and *pos* reset to 24 every 10 seconds.

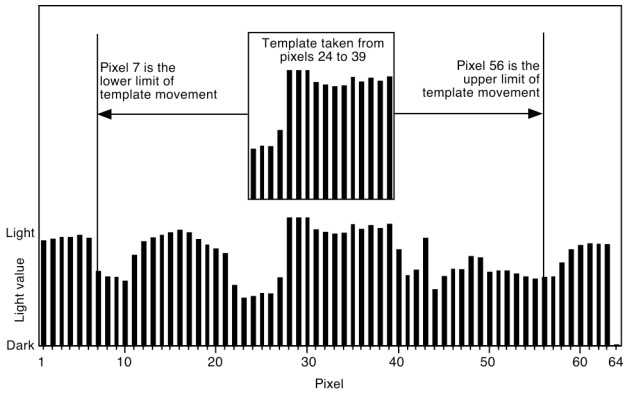

Figure 4. A 16 pixel template tracks movement of the camera image.

The LABOT robot moves at 6.25 cm/s. The maximum rate of image movement that can be tracked is 40 pixels/s (measuring movement 20 times a second and allowing a movement of up to ±2 pixels). Using a 12.5mm focal length lens the object range *r* must be greater than 62.5*12.5/(40*0.125) = 156mm.

A series of tests were performed to evaluate the template tracking scheme. The robot was moved a distance of 45mm parallel to a stripe pattern. The tests were repeated 10 times each at a distance of 250mm, 350mm and 450mm. Table 1 shows the results including calculated range.

TABLE I. RANGE MEASUREMENT USING APPARENT MOTION.

Range *r* (mm)	Average image movement in pixels when robot moves 45mm (10 trials)	Calculated range (mm)
250	21.8	229.4
350	15.1	331.1
450	11.7	427.4

Measurements of range were made to the body of the robot whereas the principle point of the camera lens was 25mm beyond the edge of the robot. The simplifying assumption is made that all of the pixels in the template correspond to points at the same range. If the template contains pixels that relate to objects at more than one range then there is a possibility that the template tracking scheme will fail.

2.4 Determining stripe width

Having calculated the range to an external object the next task for the visual recognition system is to find out if the object carries a regular stripe pattern and if it does, to determine the width of the stripes. What is required is a method that uses little computer resources in terms of data/program storage and processing time. Techniques for template matching and spectral analysis were considered but judged too resource intensive. As an alternative a heuristic stripe recognition system was developed.

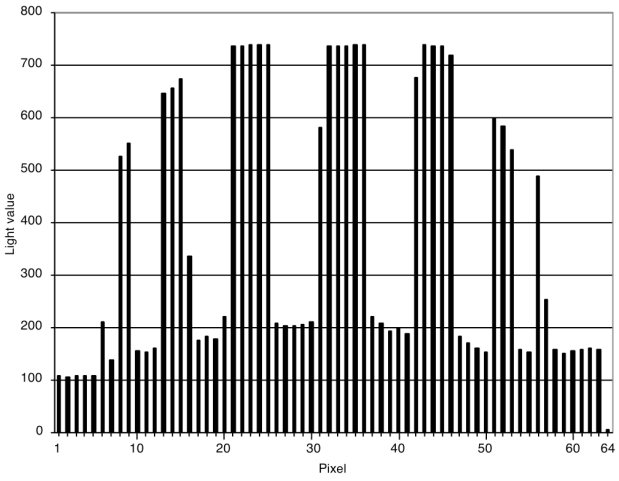

Figure 5. The line image of a 24cm diameter cylinder patterned with alternating 2 cm wide black and white stripes.

In order to locate the edges of each stripe in the camera image the mean pixel value was subtracted from each individual pixel value and the resulting zero-crossings identified the edges e_n of the stripe pattern (an edge was assumed to occur at the start of the image corresponding to pixel 1). The width of each stripe in the image (either black or white) was taken as the number of pixels between two successive edges:

$$\omega_v = \varepsilon_v - \varepsilon_{v-1} \tag{5}$$

In order to estimate stripe consistency the absolute change in stripe width between two adjacent stripes δ_n was calculated:

$$\delta_n = \left| w_n - w_{n-1} \right| \tag{6}$$

From successive values of the stripe width and change in its value, a smoothed estimate of the stripe width d_n and a confidence measure c_n were produced:

$$\begin{aligned} &\text{if}\left(\delta_n < 3\right) \text{ then} \\ &\quad d_n = \frac{\left(d_{n-1}c_{n-1} + w_n\right)}{\left(c_{n-1} + 1\right)} \\ &\text{else} \\ &\quad d_n = d_{n-1} \end{aligned} \tag{7}$$

and

$$\begin{aligned} &\text{if}\left(\delta_n < 3\right) \text{ then} \\ &\quad c_n = c_{n-1} + 1 \\ &\text{else} \\ &\quad c_n = c_{n-1} - 1 \quad \left(\text{until } c_n = 0\right) \end{aligned} \tag{8}$$

Finally, the maximum value of the smoothed stripe width m_n was found:

$$\begin{aligned} &\text{if}\left(c_n > 3\right) \text{ and } \left(m_{n\text{-}1} < d_n\right) \text{ then} \\ &\quad m_n = d_n \\ &\text{else} \\ &\quad m_n = m_{n-1} \end{aligned} \tag{9}$$

The stripe with the maximum width is located in the center of the robot image where the effects of robot curvature produce the least distortion. Initial values of w_n, c_n, d_n, δ_n, and m_n were taken to be zero.

From the apparent width of the stripes in the camera image and the distance to the stripes the next stage was to work out the true width of the stripes. Using the pinhole camera approximation [Horn, 1986]

$$Stripe\ width = \frac{m * pixel\ separation * r}{lens\ focal\ length} \tag{10}$$

where: m = maximum width estimate after scanning the entire image

TABLE II. RESULTS OF PROCESSING THE IMAGE SHOWN IN FIGURE5

e_n	w_n	c_n	d_n	δ_n	m_n
1	0	0	0	0	0
8	7	0	7	7	0
10	2	0	2	5	0
13	3	1	3	1	0
16	3	2	3	0	0
21	5	3	3.67	2	3.67
26	5	4	4	1.33	4
31	5	5	4.2	1	4.2
37	6	6	4.5	1.8	4.5
42	5	7	4.57	0.5	4.57
47	5	8	4.62	0.43	4.62
51	4	9	4.55	0.62	4.62
54	3	10	4.4	1.55	4.62
56	2	11	4.18	2.4	4.62
57	1	10	3.92	3.18	4.62

3 Results of robot recognition trials

For positive identification of a robot the calculated stripe width was required to lie between 15mm and 25mm with an associated confidence factor of greater than 4. In the first test an active robot moved in a straight path past a target robot. Figure 6 shows the measured stripe width and associated range plotted against the shortest distance between the robot's path and the target robot. At a range of 200mm the target robot was not recognised. Between 250mm and 1000mm the robot was recognised and the range returned had a maximum error of 35%. The true

error may be lower than this because the active robot detects the target robot before it arrives at the closest point between them.

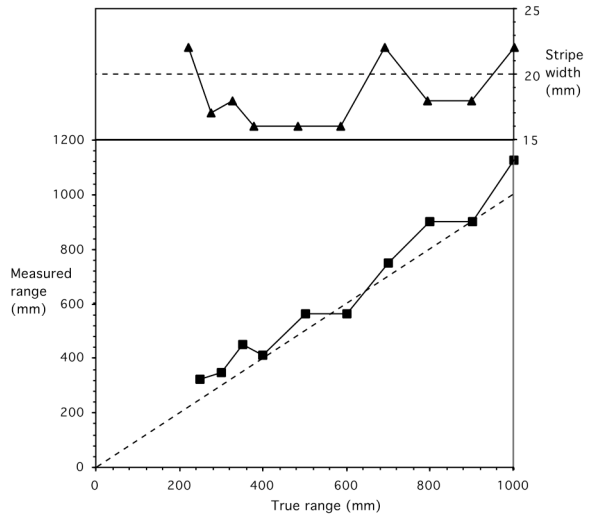

Figure 6. Values of range and stripe width produced by the recognition algorithms

For ranges beyond 1m the calculated range became very variable with errors greater than 100%. This is not surprising because the 2cm wide stripes correspond to less than 2 pixels at ranges greater than 1m. Inexpensive linear array opto-sensors are available with twice the number of pixels and using these would be a simple way of extending the range of the vision system.

An important requirement for the robot recognition system was the ability to discriminate between swarm members and other items that the swarm robots might come across, including other robots. To test the discrimination ability of the current algorithm the LABOT was run past an identity parade of small robots. The lineup consisted of a Sony Aibo, an imposter posing as a swarm member but having stripes of twice the normal width, a swarm robot, a Tandy Robie Junior and finally a II Walk humanoid robot. The robots were spaced 0.5 m apart. The active robot performed runs past the robot identity parade at three different separations.

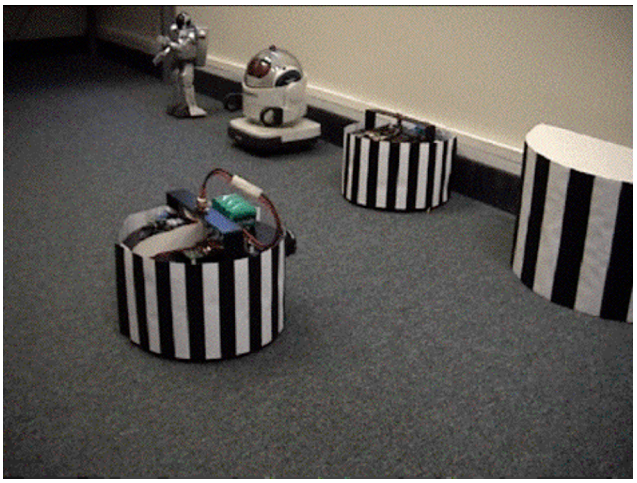

Figure 7. A robot identification parade (the usual suspects)

Figure 7 shows a photograph of some of the assembled robots and Fig 8 gives a plan view of the lineup with the positions of the active robot where it reported recognizing a conspecific robot. No false positive results were recorded and the swarm member was always in the camera receptive field when the active robot reported recognition by emitting a beep.

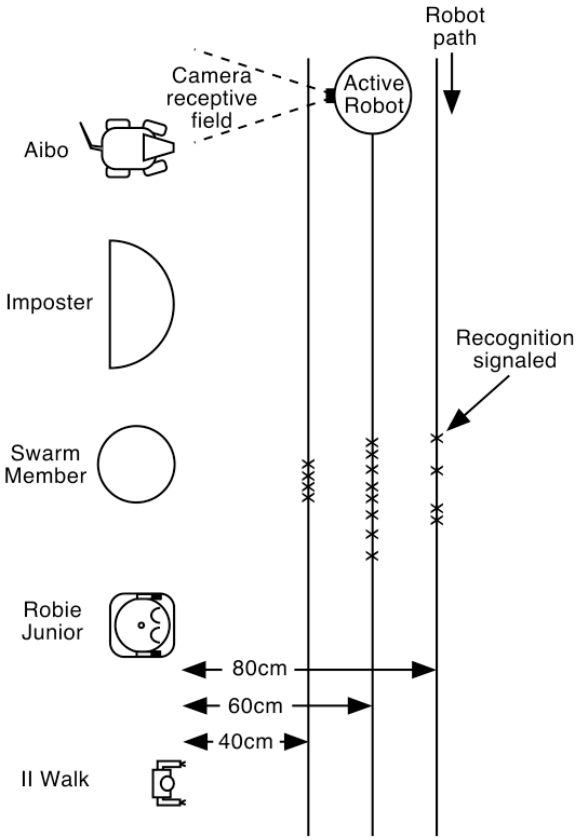

Figure 8. Positions where the active robot recognises the presence of a conspecific robot.

Similar results were obtained when experiments were conducted on vinyl and polished wood floors as well as the low pile carpet shown in Figure 7.

4 Conclusions

This project has demonstrated that a simple vision system can be used to recognize and locate swarm members coded by a pattern of regular vertical stripes. This technique is seen to have a number of advantages over other simple coding schemes such as those based purely on color. Stripe coding tolerates a wide range of illumination while also providing an estimate of robot range. In situations where several 'species' of swarm robot are mixing in the same workspace the recognition scheme could be extended to provide rejection of members of other swarms without compromising the simplicity of the scheme. This could be achieved by color coding the stripes and employing color filters to reject the markings of other robot 'species'.

Variation in stripe widths could also be used as a means of discriminating different markings. In its current form the recognition system can only recognize stationary robots. So, amongst other things the active robot cannot recognize its own reflection in a mirror. Techniques for extending the current recognition scheme to deal with moving robots are currently being investigated.

Acknowledgments

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