Maastricht University
Department of Knowledge Engineering

Technical Report
No.: 101.2013.05.02

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You can cite this report via following reference:

Sjriek Alers, Bijan Ranjbar-Sahraei, Stefan May, Karl Tuyls, and Gerhard Weiss (2013).
An Experimental Framework for Exploiting Vision in Swarm Robotics
In Proceedings of ADAPTIVE 2013. 6 pages.

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An Experimental Framework for Exploiting Vision in Swarm Robotics

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***Abstract*—This paper studies the requirements of a successful vision-based approach in swarm robotic settings. Required features such as landmarks and different patterns are introduced, and appropriate feature detection algorithms are described in detail. The features are designed to be very simple, and providing enough information, while the proposed detection algorithms have considered the very limited resources (i.e. limited storage memory, and limited computational power) of swarm robots. In order to evaluate the performance of the proposed vision approaches and the defined features for the environment, the whole approach is verified by implementation on e-puck robots in a real-world setting.**

I. Introduction

Natural phenomena has always fascinated and inspired scientists, not only the biologists but also others such as computer scientists. One of the interesting phenomena in nature is the behavior seen in colonies of social insects such as ants and bees. These insects have evolved over a long period of time and display a behavior that is highly suitable for addressing the complex tasks that they face. Therefore, over the recent years an increasing interest is seen among researchers for creating artificial systems that mimic such behavior for accomplishing the complex tasks that human face in their life [5, 6, 7].

The best known example for emergence of Swarm Intelligence (SI) among social insects is the ant foraging behavior. In ant foraging, ants deposit pheromones on their path during traveling. Using this path they are able to navigate between the nest and food [4]. A slightly different behavior can be seen among Honeybees, in which instead of using pheromones to navigate through an unknown environment, they use a strategy called *Path Integration*, in combination with landmark navigation [2]. The foraging task can be seen as an abstract representation for many other advanced tasks, such as patrolling and routing. Therefore, a successful embodied implementation of distributed foraging can result in promising applications in e.g. security patrolling, monitoring of environments, exploration of hazardous environments, search and rescue, and crisis management situations.

Getting motivation from the mentioned potential applications of distributed coordination and following the previous work [2], in which we mainly relied on random exploration methods and infrared sensor data for obstacle detection, this paper is focusing on using vision for detecting the key environmental features. These features then can be used as waypoints to navigate in an unknown environment, locate other entities, and detect modifications made in the environment.

For this purpose, we explored several visual features that can be used for acquiring information from the environment by a robot with limited computation abilities, and equipped with a simple camera. For detecting key locations in the environment (e.g. corners in a maze), we investigate the usage of specific landmarks for these locations. Each landmark consists of an upper ring with a solid color, so that it can be detected from a far distance, and on the lower part a unique barcode for keeping track of the landmark numbers. Furthermore we explored the possibility to detect markers with an even higher data density: QR-codes. The challenge in the detection of these 2-dimensional codes, lies in analyzing and processing the camera data with the limited processing and memory resources that are available in a robotic platform. Finally, the most common feature already available in every robotic swarm setting is the robot itself. It's always favorable to detect the relative location and orientation of other robots in respect of one's position. Therefore, the available LEDs on the robot provide a very good feature for robot detection from a far distance. Moreover, we have designed specific gradient patterns for robot detection from a closer distance, which can conclude to a very accurate orientation detection.

Authors believe the proposed environmental features defined in this paper, in combination with the detection algorithms which are included as well, can provide an experimental framework for any kind of swarm robotic experiment with simple robots (e.g. [10, 2, 11, 12]) as illustrated in Fig. 1.

The remainder of the paper is structured as follows: The physical setup and designed software are described in Section II. The main features used in this paper are defined in Section III, and the techniques for detection of each feature is described in Section IV. A real-world demonstration of this work is described in Section V and also can be found in http://swarmlab.unimaas.nl/papers/adaptive-2013-demo/. Finally, in Section VI we will give the concluding remarks.

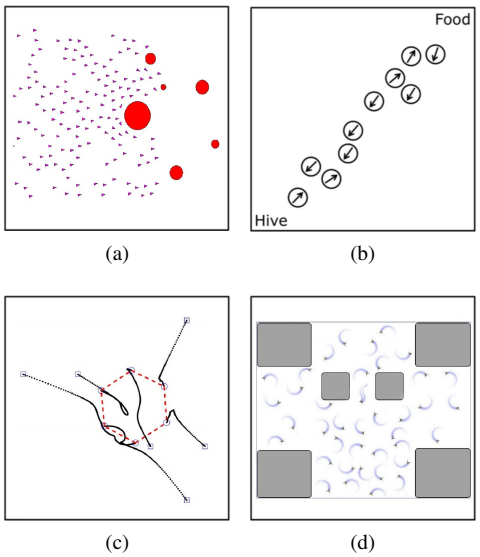

Fig. 1: Different swarm robotic applications which require visual feature detection: (a) Flocking in multi-agent systems [10]. (b) Bee-inspire foraging [2]. (c) Formation control in multi-agent systems [11]. (d) StiCo: Stigmergic coverage in complex environments [12]

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II. Physical Setup and Designed Software

The e-puck robot is a small platform for educational and research purposes, developed by the EPFL University [9]. This robot is efficiently used in numerous projects in the domain of swarm robotics and swarm intelligence (e.g. [2, 3, 9]).

The main features of e-puck robot include but are not limited to, a robust design, flexibility for a large spectrum of educational activities, compact size, and rich on-board accessibilities (e.g. microphones, accelerometer, camera).

In this section, the hardware specifications of e-puck are briefly introduced, and then the developed software which is designed for monitoring the e-puck camera during its image processing and feature detection tasks is described.

A. Hardware Specifications

The e-puck hardware consists of different sensor types for detecting visible/IR light, sound, acceleration, etc. The motors are the only actuators which are available in e-puck. A microprocessor of PIC family with 8 KB RAM memory, assist the robot to get data from it's sensors, analyze it, and perform actions. The main hardware elements, which are involved in our experiments are listed in Table I.

As listed in the table, the on-board camera of the e-puck has a resolution of 640×480 pixels. It is placed at the front of e-puck, 2.7 cm above the ground. With this camera we can detect objects on the floor at a minimum distance of 7.4 cm. At this distance objects of 5.1 cm width can be fully seen. The camera angle is approximately $40°$.

Remark 1: *Although, we have a VGA camera, the on-board processing and storage of the e-puck robot is not adequate for dealing with all of the camera data. A gray-scale image of size* 640×480 *needs at least* 307.2 *KB to store the image. However, based on the technical details of Table I, e-puck robot has a RAM of size* 8 *KB. Analysis, and storage of sub-parts of the image helps to overcome this limitation. In following sections of this paper, we address the issue of how to split an image into informative sub-parts.*

TABLE I: E-puck technical specification

Element	Technical information
Processor	dsPIC30F6014A @ 60 MHz (15 MIPS), 16-bit microcontroller with DSP core
Memory	RAM: 8KB Flash: 144 KB
Motors	2 stepper motors with a 50:1 reduction gear
Camera	VGA color camera with resolution of 640x480
LEDs	8 red LEDs on the ring, green LEDs around the body, 1 high intensity red LED in the front
Wireless Communication	Bluetooth for robot-computer and robot-robot communications Infrared for robot-robot communication

B. Software

In order to monitor the e-puck in real-time and for debugging the image processing algorithms, a Java-based software application is developed. This software, shown in Fig. 2, communicates with the e-puck via Bluetooth. It receives text messages from the e-puck which are reports of immediate status of the e-puck (e.g. "found something", "driving to the landmark", "code read", "searching"). At the same time, it also receives the captured image from the robot. Logging all of the data, storing the text messages and captured images, as well as the filtered and segmented images, makes both real-time and offline debugging very easy. Finally, it should be mentioned that time stamps are always attached both to the captured images, and stored text messages.

Fig. 2: Developed software for monitoring e-puck: (1) The required controls to establish the connection with e-puck. (2) The real-time captured image. (3) Log statements (4) The last 20 captured pictures are archived.

III. Feature Definition

Due to the limited resources of a simple robot, defining a collection of detectable features is an important task, which is a part of the main scope in this paper. Different objects in the environment (e.g. pieces of wood, balls, walls, floor, and robots) and many available patterns (e.g. different colors, checkerboard and barcodes) can be considered as environmental features, however their detection via a robot with limited capabilities might be computationally complex, and or not adequately robust to environmental disturbances (e.g. light variations and distance variations).

Generally, we define required environmental features into two main categories: *far features*, and *close features*. For the far features bright lights (e.g. from a red LED) or specific relative large areas with solid colors, should be considered. Moreover, these features should be recognizable from different directions, which makes cylindrical shapes more favorable. However, for close features, the patterns which can store higher amount of information are required (e.g. a QR-code which can store digital codes). By considering the mentioned constraints, a collection of the most appropriate environmental features will be introduced in this section.

A. Landmark

Most important features for an environment are the landmarks. Robot can use landmarks in many various missions, like localization, mapping, exploration, etc cetera. These features should be recognizable from different directions, and also from a distance. Landmarks should provide useful information to the robots (e.g. their exact location), therefore, we introduce a cylindrical tube which is a combination of a colored ring and an barcode, as shown in Fig. 3.

At the top of the cylinder a colored ring is denoted which is easily detectable form a distance. For our setup purple is chosen for coloring this ring, which does not exist in any other objects in our environment. To differentiate the landmarks, an EAN-8 (European Article Number) barcode was selected, containing an ID consisting of 8 digits, including a control number. The EAN-8 barcode is printed vertically below the purple block, surrounding the whole cylinder.

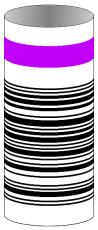


Fig. 3: Example for a landmark

B. QR-Code

Although, landmarks are very useful in terms of being detectable from a distance, we need a smaller pattern which can be mounted on walls, and also directly on robots for providing more information (e.g. specific ID of a robot, wall orders). Therefore, we use a 2-dimensional Quick Response code (QR) which is developed as a universal data storage standard. These QR-codes can store a higher data density, then the EAN-8 barcode.

The only disadvantage of the QR-code is the complexity of its pattern. In general, the pattern is comprised of several parts: At the top left, the top right and the lower left corner an orientation pattern is placed. It is a square of size 9×9 modules. The fourth corner does not contain this pattern, which makes detection of QR-code angle easier. In most swarm robotic applications, the orientation of the QR-code can be fixed, so the orientation check can be ignored during image-processing, decreasing the computational complexity drastically.

Different versions of QR-codes have different sizes. The smallest size is Version 1, which has a size of 21×21 modules. For each version, the size is increased by 4 modules in each direction. Between the three orientation patterns there are timing pattern lines with strict changing modules of black and white at row 6 and column 6. Every QR-code from Version 2 and higher, contain position adjustment patterns at specific points. In Fig. 4 the structure for QR-code Version 3 is given, in which the black and white parts are fixed.

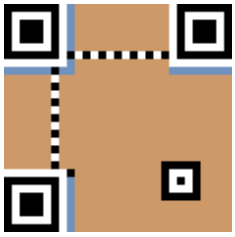


Fig. 4: Structure of a QR-code Version 3, displaying orientation and timing patterns

C. Robot Detection

A very important feature which will be available in the environment of any swarm robotic application, is the robot itself. Inherently, robots contain various information like their position, orientation, and their ID which can be very useful for the other individuals to know. Therefore, detection of other robot relative orientation and location is very convenient for implementation of many complex swarm algorithms (e.g. [2]).

In practice, the best way for detecting the robots with a camera, is using light sources (e.g. on-board LEDs). As such a light source has a good contrast to the other parts of the environment, it can be detected from a far distance even on low resolution captured images.

To determine the orientation of the robots, based on it's own visual features (e.g. the wheels and body of the robots) is a really complex task. Therefore, we propose a black-white pattern comprised of two slopes as shown in Fig. 5. Computing the exact orientation of a robot by using this pattern is easily implementable.

Fig. 5: Body pattern of e-puck for orientation detection

Based on the standard size of an e-puck robot, the pattern should have a total height of 33 mm and consists of two black bars separated by a white bar on top. All the bars are 3 mm in height. A sloped pattern, in the form of a black triangle is added to the bottom of the pattern.

Finally it should be mentioned that, in addition to orientation measurement, the distance measurement also becomes possible by using this specific pattern.

IV. Feature Detection

In the previous section, we introduced four main features: *landmark*, *QR-code*, *Robot LED*, and *Robot body pattern*. The main approach for detection of these features is to first use basic filters for highlighting the required information (e.g. purple color or edges in the image) and then zooming into the informative part of the image for reading it in more details. The most important factor in designing each detection algorithm, is to use the least possible memory and computation power. In the following subsections, these techniques for detection of each feature will be described.

Remark 2: *It should be mentioned that all of the required thresholds which will be used in following subsections are computed based on practical experiments and with real-time calibrations. However, describing these experiments in detail is beyond the scope of this paper.*

A. Landmark

The landmark contains a purple ring and an EAN-8 code. The landmarks are designed to be taller than robots. Therefore, finding the purple ring of each landmark, limits the scanning area of the image to the upper half of the camera view.

Detection of an area with a specific color is a basic task. In the first step a color filter with the specific color is applied on the image. Resulting in a grayscale image with bright values for the colors which match the color the best. To avoid errors where single pixels fit to the color, the image is blurred with a Gaussian algorithm [8]. Afterward the image is split into a binary black/white image with a fixed threshold. This procedure is illustrated in Fig. 6.

After this pre-processing phase, a group-finding algorithm [8] is applied on the image, and the largest group, is considered as the purple ring.

Consequently, the exact position of purple ring in the image can help to estimate its distance to the robot. The higher the purple ring is, the further the distance should be. This estimated distance is basically used to find the appropriate distance to start reading the barcode. As soon as the required distance, in which the barcode is readable is reached, the required scanning area is already determined (i.e. the area under the purple ring).

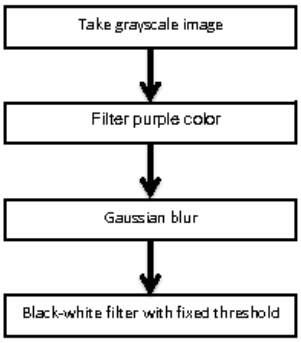


Fig. 6: The required pre-processing procedure for detection of a specific color (e.g. purple).

Barcodes are 1-dimensional, this simplifies the scanning process and makes the whole procedure faster. Therefore, addressing the issue described in Remark 1, the robot prepares a grayscale image with low resolution in width but high resolution in height (i.e. zooming into an area of 4 pixels in width and 80 pixels in height).

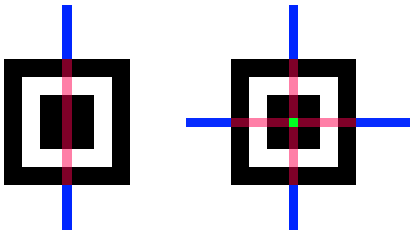
The pre-processing for the EAN-8 barcode is done by using a halftone filter [8] with a threshold calculated by an average of the pixels intensity. Afterward, all patterns of form black-white-black, as shown in Fig. 7 are located. Based on the EAN-8 standards, at least three occurrences should be detected for the start, center and end of barcode.

Fig. 7: Structure of EAN-8 barcode, with the black-white-black pattern in the beginning, middle, and end.

After this validation check, the part of the image containing the code is transformed into the 67 bits representing the barcode. Each bit is defined by the average of the pixels it represented. For each seven bits the best corresponding match to a data character is determined. As the last step, the control-character is calculated out of the seven data-characters.

B. QR-Code

Detection of QR-codes is more complex than detection of one-dimensional barcodes. We assume that the QR-code is fully visible in the camera frame, as a partial QR-code cannot be decoded. As the QR-code needs a resolution as high as possible, first a black-white image is filtered out of the initial captured image. For finding the three orientation markers of the QR-code, a pattern finding algorithm is used, which looks for a black-white-3$\times$black-white-black on each column.The detectable pattern looks like the center line in Fig. 8a. As soon as the pattern is found, the same pattern is located in the rows. The results should be similar to Fig. 8b. The orientation marker validation is passed, if both found regions have nearly the same size and center.



(a) (b)

Fig. 8: Detection of QR-code orientation markers: (a) pattern detected in vertical alignment. (b) pattern detected in horizontal alignment.

A QR-code is comprised of a collection of modules, each black or white. In order to determine the number of pixels which construct a single module, the size of orientation modules, and their distance to each other can be used. For example, the pattern shown in Fig. 8 consists of 7 modules, so we can divide the number of pixels in this pattern by 7 to compute the size of a single module. Moreover, to improve the estimation of the module size, the distance between each two patterns can also be used. Each version has a size of $21+n\cdot 4$ modules, where n is the version of QR-code. Therefore we can calculate the version and get a more exact value for the module size. The decoding process of the QR-code after its structure has been extracted is described in [1].

The most challenging problem with QR-code image has to be stored in a high enough resolution at once for being decodable. However, addressing the issue mentioned in Remark 1, the memory on the e-puck is limited to 4 KB for which each bit can store one pixel, and to have some error tolerance, there should be at least four pixels describing one module. Therefore, we can find the biggest detectable size for QR-code with following equation:

$$4000 \times 8 = modules^2 + (4 \cdot modules)^2 \qquad (1)$$

in which the left side shows number of available bits, and on the right side, the first and second terms show the number of required bits for storing the QR-code and image itself. This equation concludes to the fact that width and height of the QR-code should not exceed 43×43 modules. The QR-code version which fits into 43×43 modules is Version 6, which is 41×41. In practice we also need memory for the detection algorithms and internal calculations, so the QR-code Version 5 which contains 37×37 modules, is used in our experiments.

C. Robot Detection

An other robot is generally detected in two different steps. First, the detection from far distance is done by searching for the red LEDS, and second the body pattern (Fig. 5), which consists of two black ramps around the robot, is scanned for measuring the exact orientation of robot.

1) LED Detection: The LEDs are mounted above the camera on the e-puck. Therefore only the upper half of the image has to be scanned, which results in a higher resolution of the relevant parts of 20×80 gray-scale pixels. First, a black-white filter with a fixed threshold is used. The threshold is chosen to be higher that ambient light, and less that the brightness of an LED.The next filter is a Gaussian blur filter, which is used to combine light groups which are very close to each other, and dismisses the single pixels which were falsely recognized. Afterwards, a black-filter is used, this time with an average threshold. All LEDs are now highlighted.

As with this simple detection technique it is not possible to really determine between a red LED from other color LED sources some improvements should be applied to this technique. Therefore, after finding the light sources, the camera zooms in on each group center (zooming is a built-in feature of e-puck camera). The size of the zoom depends on how many pixels belong to each group. In Fig. 9 an image of a zoomed in LED is shown. There is a bright center visible with red at the left and the right, but not at top or bottom. This is a result of the surrounding border of the e-puck. To verify that the LED is a red one or another color, both sides of the detected light source starting from the center are searched for red color. The color is checked by converting it into the HSL color space and only comparing the Hue value, as the lightness and saturation are very unstable. We consider a light source as an LED, if more than 50% of the height of the bright center contains a red surrounding.

(a) (b) (c) (d) (e) (f)

Fig. 9: Different steps of pre-processing for LED detection.

2) Body Pattern Detection: If the robot is located close enough to the camera, the body pattern detection can be activated. To get the highest probability to detect the e-puck, the image should have a high resolution, but still work fast. The maximum image size which fits into memory and leaves enough space for the other required operations, is 80×40 pixels in gray-scale. As pre-processing step, a black-white filter with average threshold is applied on the image.

Subsequently, for each column of the image a pattern with one white, and one black module is located. For all found locations where the pattern fits it is checked if the repetitive white and black modules have approximately a size of 5. If this holds, the column is stored as a part of pattern. Fig. 10a shows a captured image from an epuck, and Fig. 10b highlights the parts of image which are extracted as body pattern according to this technique.

For rejecting the wrong detections, only modules with at least three detected neighboring results are accepted. Afterward, the center of the e-puck is determined by searching the location where most left and right results are found and dividing their x-coordinates by 2. The orientation of robot can be easily measured by computing the length of middle white module, and comparing this size, with the size of the whole pattern.

(a) (b)

Fig. 10: Body patter detection (a) Initial image. (b) the detected pattern is highlighted.

V. Real World Demonstration

To examine the proposed approach in a real scenario, an environment as shown in Fig. 11 is set up: A white floor of 40×40 cm^2 is surrounded with white walls. Three landmarks are placed in three corners, and in the fourth corner a QR-Code is attached to the wall. Two e-pucks are placed in this environment. One is stationary, with all of the red LEDs on, and a body pattern around it. The second robot uses the vision-based detection algorithms for detecting the features of the environment.

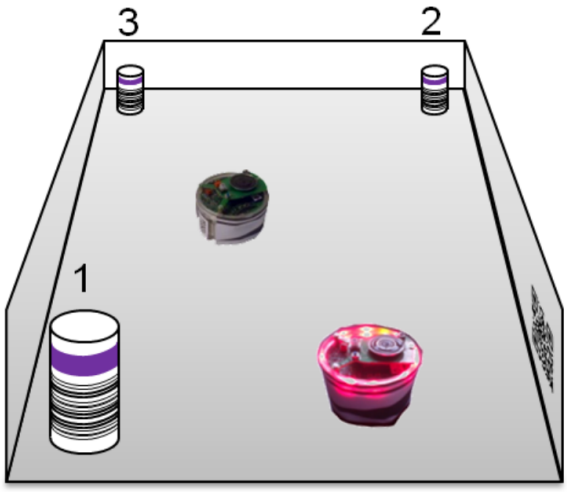


Fig. 11: Designed scenario for validation of proposed approach

In this scenario, the robot has to first located landmark #1, continue to #2 and then drive to #3 in the correct order. For each landmark it has to approach it, read the barcode and after validating the number find the other robot. By using the other robot orientation, it should move in the environment till both robots are facing each other from the front. Finally, the QR-code mounted on the wall is detected, and the code will be extracted.

A video of this performed experiment can be found in http://swarmlab.unimaas.nl/papers/adaptive-2013-demo/, including the prepossessed image data sent from the robot.

VI. Conclusions

In this paper we proposed a feature detection approach based on robot vision which can be useful for swarm robotic experiments. The e-puck robot was chosen as the main platform for doing experiments. The e-puck is equipped with a VGA camera, but has limited resources for storing data, and also in performing computations. Different possible environmental features were introduced, and described accurately. Afterward, required image processing techniques for detection of each feature was described in detail. Finally, a general demonstration was set up to show the applicability of proposed approach in real-world robotic experiments.

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