Mobile Robot Trajectory Analysis with the Help of Vision System

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Abstract. We present a vision-based motion analysis method for single and multiple mobile robots which allows quantifying the robot's behaviour. The method defines how often and for how much each of the robots turn and move straight. The motion analysis relies on the robot trajectories acquired online or offline by an external camera and the algorithm is based on iteratively performed a linear regression to detect straight and curved paths for each robot. The method is experimentally validated with the indoor mobile robotic system. Potential applications include remote robot inspection, rescue robotics and multi-robotic system coordination.

Keywords: mobile robot · motion analysis · visual tracking

1 Introduction

Multi mobile robotic systems can be efficiently used in exploration and inspection tasks [1–3]. Successful task completion in such applications depends on careful multi-robot control and coordination [4]. However, due to limited communication, computing and human-operator resources it is often difficult to ensure safe and reliable operation of such robotic systems. For example, in common applications it is required to know the current state of each individual robot to ensure that it follows the exploration tasks. Understanding the actual movement patterns of a group of robots is important for many reasons. Comparing the actual motion with pre-programmed behaviour can reveal potential deviations from the expected task. It can also be helpful to identify whether the remotely observed robots are teleoperated [5] or controlled autonomously [6], as well as to detect and indicate the mobile robots' operation faults, such as reduced speed due the low battery charge or mechanism jamming.

Vision-based tracking has been widely investigated and deployed for mobile robots motion analysis [7]. Video surveillance systems are used for real-time tracking and can classify certain activities to detect unusual events of people and vehicles [8]. On-board sensory systems can also be used to measure the effectiveness of the operation of multi-robot and multi-sensors networks to estimate the robot's locations in hazardous environments [2]. Other studies have explored the trajectory tracking with adaptive vision control systems to guide mobile robots towards a desired location [10]. Camera-based environment tracking was used for obstacle avoidance in mobile robot navigation [12]. A graph-based modelling approach was used for motion analysis of a multi-robotic system [13]. Similarly, point distribution modelling trajectories analysis and comparison between several mobile robots [14]. An on-board vision based tracking system was used together with a UAV to track moving objects during the flight [15, 16].

In this work, we propose to use an external visual tracking system to continuously monitor a multi-mobile robotics system and to quantify each robot's behaviour. An algorithm which analyses the trajectories of the mobile robots based on the captured top view from a video camera is the core component of the proposed methodology.

2 Motion tracking and analysis

Our method analyses a mobile robot's movement trajectories and classifies them into elementary motion patterns such as straight movements and turns. The proposed method assumes that the position of the mobile robot, $p(k)$, is available through an external visual tracking system. The position of the robot is defined as

$$p(k) = [x(k),\ y(k)] \in \mathcal{R}^2, \quad \text{for discrete time points} : k = \{1...M\}\,,\ M \in \mathcal{N}, \tag{1}$$

where $x(k)$ and $y(k)$ are planar coordinates in the camera frame at discrete time, $t = k$, and, M - the number of recorded points. These coordinates are estimated through visual tracking and recorded for online (on-fly) or offline analysis. In the following we describe the motion analysis steps for the online case and a similar approach can be used for the off-line analysis. Our algorithm runs simultaneously with visual tracking and at every iteration (frame) a series of recorded robot position points $\{p(k)...p(k-N)\}$, $N \in \mathcal{N}$ and $N < M$, is used to test whether the robot's trajectory can be expressed with a straight line. In other words, a linear regression analysis is done for the points $\{p(k)...p(k-N)\}$ to define straight paths of the trajectory leading to a linear fit, Y_k, at time $t = k$:

$$Y_k :\ y = \hat{\beta}_{0,k} + \hat{\beta}_{1,k}x, \quad \text{for}\ \{p(k)...p(k-N)\}\,, \tag{2}$$

with constant parameters, $\hat{\beta}_0$ and $\hat{\beta}_1$, to be identified. For each obtained fit Y_k, the coefficient of determination (R^2, *R-squared*) was calculated to define the goodness of estimation for the robot's straight movements. This is conveniently scaled between 0 and 1, where a coefficient closer to 1 indicates a straight line movement. Subsequent fits Y_k and Y_{k-1} were compared to detect turns in the robot's trajectories:

$$\textbf{turning detected if :} \ \varphi_k > \delta, \tag{3}$$
$$\text{where } \varphi_k = \operatorname{atan}\beta_{1,k} - \operatorname{atan}\beta_{1,k-1},$$
$$\text{or } \varphi_k = \operatorname{atan}\frac{\beta_{1,k} - \beta_{1,k-1}}{1 - \beta_{1,k}\beta_{1,k-1}},$$

where constant design parameter δ defines the turning detection threshold and the sign of the angle φ_k defines the direction of turning at time t_k. For example, clockwise turning (right turn) corresponds to $\varphi_k < 0$. Then, the coefficients of determinations for each fit (2) are compared at each iteration to define when turning starts and ends:

$$\textbf{turning motion : if} \ {R^2}_k < \delta_R, \tag{4}$$
$$\textbf{straight motion : otherwise},$$

where δ_R is the design parameter defining the threshold to discriminate between straight motion (linear trajectories) and turning motion (curved trajectories). In our algorithm, δ_R was set to be 0.999. Conditions (3) and (4) were used together to define the transitions between the straight motion paths and the turnings, and total turning angle was computed for each turning action as follows

$$\Theta = \sum_{i=l}^{k} \varphi_i, \tag{5}$$
$$\text{where } \textbf{turning started} \text{ at time } t = l,$$
$$\text{and } \textbf{turning completed} \text{ at time } t = k.$$

The calculated turning angle, Θ, was recorded for each turning action in addition to the total number of turning actions for a robot. Then, the final outcome of the motion analysis described above is the turning statistics expressed as the turning frequency (distribution) function $F(\Theta)$ which specifies the turning behaviour patterns for a given mobile robot.

The proposed motion analysis method is scalable to a multi-robot case when an external vision system would track several mobile robots and the proposed motion analysis will apply to each of the robots. The statistics collected through our tracking and analysis algorithm can provide useful information about the behavioural and control patterns of the observed robots. Next section presents the experimental validation of our method.

3 Experimental setup

We validated the proposed motion analysis algorithm in an indoor environment using three miniature mobile robots (Elisa 3 [17]) and an RGB camera-based visual tracking system (SwisTrack [18]).

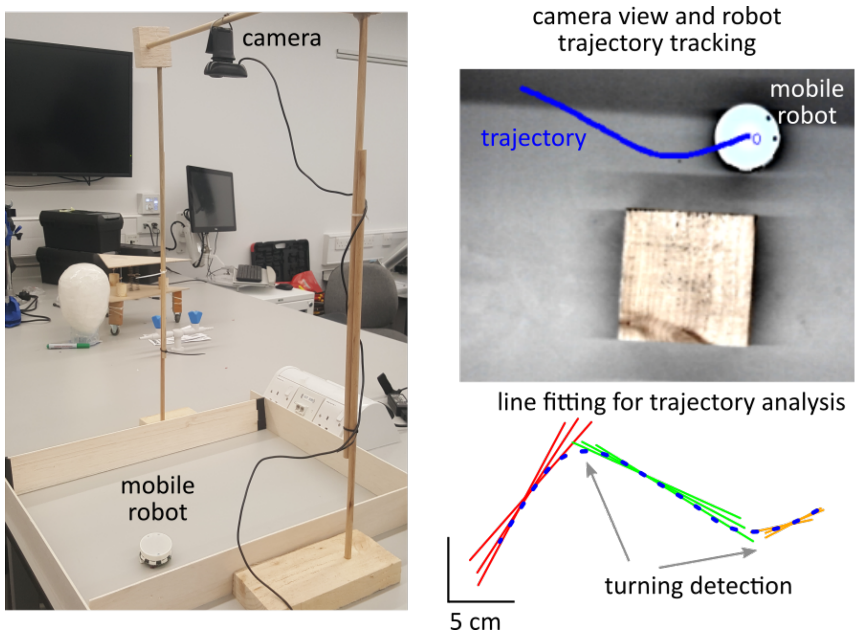

Fig. 1. General view of the experimental setup (left) and mobile robot trajectory tracking and analysis (right).

Elisa 3 miniature mobile robots are small (⌀5 cm) wheeled autonomous robots. Each robot is equipped with Atmel-Arduino compatible micro-controller, central RGB LEDs, eight infra-red obstacle range sensors, four terrain detection sensors, three infra-red emitters, accelerometers and two DC motors to actuate the wheels. The robots were pre-programmed to follow straight trajectories and navigate around the obstacles detected with the infra-red sensors. The same obstacle avoidance programme was uploaded to the controller of each robot. For testing the robots were placed on a table top (size 1 by 1 meter) surrounded by a 10 cm high protection barrier as shown in Figure 1. As a result, the robots normally moved straight and avoided collisions with the protective barrier during the tests.

Visual tracking was performed with a simple RGB-camera connected to a laptop through the USB port. The camera was fixed one meter above the robot arena to perform tracking using the top view. The robot's positions on the desktop were obtained with the help of an open-source visual tracking library SwisTrack [18]. In the experiments, the position of the robot (1) was sent by SwisTrack via a TCP/IP protocol to our motion analysis algorithm described in the previous section. The algorithm was implemented as Matlab-script. The analysis was performed online at 25 Hz.

The test involved motion analysis of a single Elisa mobile robot. 5000 data points (frames) were recorded in the test. The goal of the test was to quantify the motion of the robot.

4 Results

Figure 2A shows an example of trajectory tracking for a robot. It shows the data points acquired during visual tracking of a single robot's motion. Figure 2B shows the results of straight movement detection experiment. By detecting straight movements and turns with the proposed algorithm we could quantify the movement of the robot. For example, in this particular test there were 80 straight movements, 53 left turns and 26 right turns.

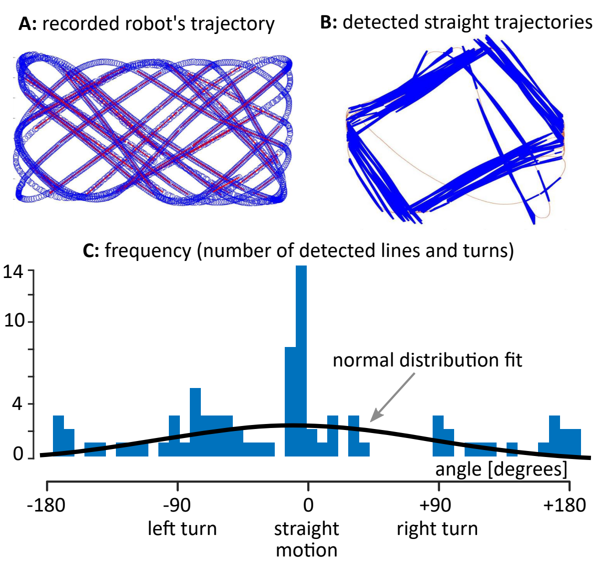

Fig. 2. Experimental results. **A:** an example of recorded robot's trajectory; **B:** linear fitting to detect straight movements; **C:** distribution of turning and straight movements for one robot.

The proposed motion analysis algorithm enabled us to describe the movement patterns for the tested robot. Figure 2C shows the results of motion analysis as frequency (distribution) plot in which the height of the bars corresponds to the number of straight movements (around angle 0°) and turning left or right (around angles ±90°) or half turns (around angles ±180°).

The frequency plot of Figure 2C can be used to quantitatively characterise the robots' behaviour. Furthermore, the data characterising the robot's behaviour can be modelled statistically by fitting the data points to normal distribution.

For example, the behaviour of the robot can be modelled with the normal distribution with mean 14.47° and the standard deviation is 92.48°. This normal distribution fit is shown in Figure 2C. It is easily noticed that these fits do not fully capture the behaviour of the robots but they can indicate how much each robot deviates from the straight movements and the range of the turning angles. Alternatively, the frequency plots can be modelled by a combination of several normal distribution fits. For example, separate normal distribution models can be found for the data points for straight motion (around 0°) and left/right turns to form a kernel density estimate of behaviour for each robot.

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