

Timed Trajectory Generation for a Vision-based Autonomous Mobile Robot in Cluttered Environments

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Abstract: An autonomous mobile robot should find feasible trajectories in order to avoid collisions with obstacles in its environment. This ability to plan collision-free trajectories requires two major aspects: modulation and generation of trajectories. This is especially important if temporal stabilization of the generated trajectories is considered. Temporal stabilization means to conform to the planned movement time, in spite of diversified environmental conditions or perturbations. This timing problem applied for wheeled vehicles has not been addressed in most current robotic systems. Herein, we extend our previous work by integrating an architecture able to generate timed trajectories for a wheeled mobile robot, whose goal is to reach a target location within a specified time, independently of the world complexity.

1 INTRODUCTION

An autonomous mobile robot should find feasible trajectories in order to avoid collisions with obstacles in its environment. This ability to plan collision-free trajectories requires the combination of generation and modulation techniques. Moreover, a more relevant issue arises in the path planning problem if temporal stabilization of the generated trajectories is considered, in particular when discrete movements are considered.

Temporal stabilization means to conform to the planned movement time, in spite of diversified environmental conditions or perturbations. Controlling the time of a concrete action requires involving stable temporal relationships. Moreover, several robotic tasks have the necessity of temporal stabilization of actions since they are initiated only once previous actions have terminated.

To the best of our knowledge, the generation of timed trajectories embedded in feedback structures remains an open problem, who has received attention both in robotics and in neuroscience. Typical approaches in literature for generating timed controls are based on nonlinear dynamical systems due to several advantages to address the temporal stabilization problem. Herein, related research concerning to timed trajectories has been verified in several scopes such as: learning by demonstration, (Ijspeert

et al., 2002), generation of synchronized movement for biped and quadruped autonomous adaptive locomotion (Santos and Matos, 2011), drumming (Ijspeert et al., 2002), rehabilitation (Ronsse et al., 2010) and modular robotics (Cui et al., 2010) for instance. The proposed systems are robust against disturbances but temporal stabilization is not effectively attempted.

Other works including a dynamical system architecture (Schöner, 1994) to generate timed trajectories were implemented in a real vehicle, with a temporal stabilization mechanism (Santos, 2004). These works have achieved an online linkage to noisy sensorial information by coupling these dynamical systems to time-varying sensory information. The framework proposed in (Schöner and Santos, 2001) has suffered some changes introduced by (Tuma et al., 2009), arguing that the mechanism of temporal stabilization was not able to preserve the temporal constraint. Additionally, they proposed to use the dynamical solution to control the velocity of the robot.

Later, this challenge of controlling the velocity of a mobile robot has suffered some novel adaptations when in (Silva et al., 2010a), it was proposed to explore the intrinsic properties of the used oscillator. However, the target was defined geographically and using vision to detect targets makes the application more realistic. Thus, in (Silva et al., 2010b) the sensory loop was closed by online acquiring the location of the target.

However, when the localization of a target is visually achieved, there might be situations where the visual system is unable to detect the target. Then, in this contribution we extend our previous work to deal with these localization problems by using an Extended Kalman Filter (EKF) to estimate the location of the target. However, the inclusion of an EKF could affect the temporal nature of architecture. Several comparative examples of temporal solutions with and without the EKF are presented to show the intrinsic robustness of the system.

Additionally, to verify that our proposed architecture can be used in cluttered environments, we validated it in a hospital environment.

2 SYSTEM OVERVIEW

The overall architecture of our system (fig. 1) is hierarchically divided into two functional layers according to their level of abstraction.

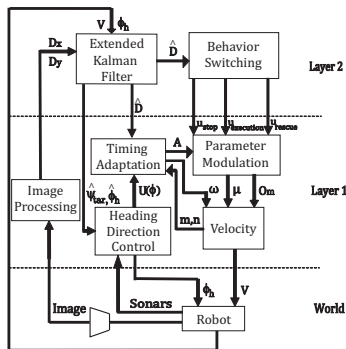


Figure 1: Schematic of the overall architecture.

The second layer is responsible for mimicking the role of supra-spinal structures in biological systems. In other words, it selects the most adequate robot motor behavior according to external conditions and send them to the first layer at the right timing. Also, an EKF is used to estimate the localization of the target relatively to the robot’s position.

The first layer is responsible for controlling the 2D motion of the robot according to the dynamics of two behavioral variables: the heading direction ϕ_h and the velocity v . The generated trajectories are modulated in a simple and straightforward manner through sets of parameters that are received from the second layer at the right timing. For a complete explanation please see (Silva et al., 2010a).

3 EXTENDED KALMAN FILTER FORMULATION

The EKF operation requires a state space model of the dynamic system describing the time evolution of the state to be estimated. Herein, the state to be estimated is the target position in the robot coordinate system, which is expressed by the system state discrete variable $x_k = [Dx_k, Dy_k, \phi_{h_k}]^T$.

To calculate the localization of a target relative to the robot’s position, it is necessary to calculate the Euclidean distance between the robot and the target D , as well as the angle from the robot Y-axes to the target around the robot’s Z-axes ψ_{tar} . Both variables are detailed in fig. 2, in which it is represented the motion of the robot relative to the target’s position in two different instants of time. All variables are defined in the robot coordinate system.

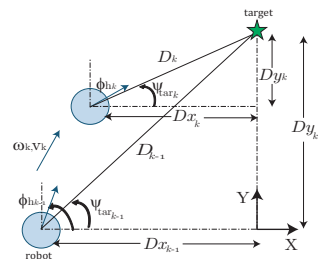


Figure 2: Representation of the variables involved in the motion of the robot relative to the target. Variables are described in the robot coordinate system.

The following relationships may be established among these variables:

$$Dx_k = Dx_{k-1} - v_k \cos(\phi_{h_k})dt, \quad (1)$$

$$Dy_k = Dy_{k-1} - v_k \sin(\phi_{h_k})dt, \quad (2)$$

$$\phi_{h_k} = \phi_{h_{k-1}} + \omega_k dt, \quad (3)$$

where Dx_k, Dy_k are respectively the projections onto the robot X and Y-axes of the distance between the robot and the target, ϕ_{h_k} is the current heading direction of the robot, v_k is the robot forward velocity and ω_k is the robot angular velocity. The time step between two different instants of time is defined by dt

From equations (1),(2) and observing fig. 2 we can derive the angle ψ_{tar_k} that the robot has to follow in order to reach the target, and the distance D_k that it has to travel to reach the target at instant of time k :

$$\psi_{tar_k} = \arctan\left(\frac{Dy_k}{Dx_k}\right), \quad (4)$$

$$D_k = \sqrt{Dx_k^2 + Dy_k^2}. \quad (5)$$

To estimate our process, we have adopted an EKF since the next state of the process follows a nonlinear function of the previous state.

4 PERFORMANCE OF EXTENDED KALMAN FILTER

In order to verify if by adding the EKF to the system we do not degrade the temporal nature, comparative examples of the robot moving towards to a target with and without the EKF are evaluated. Table I shows the obtained results for several performance indexes defined in the following.

The robot's visual system perceives the target as if it is moving inside an hypothetical circumference, whose radius is varied in the different experiments, simulating a noisy target perception.

ΔT indicates if the robot satisfied the time constraints. It is calculated as the ratio between the time needed by the robot to reach the target and the specified movement time. If this value is smaller than 1 the timing properties are verified.

Table 1: Performance of the system resulting from different perceptions of the target noise. Averaged over 10 runs for each noise level.

Radius	Version	$\Delta P_f(m)$	ΔT	E
5 cm	non-EKF	0.034	0.970	0.1155
5 cm	EKF	0.023	0.957	0.1148
10 cm	non-EKF	0.036	0.966	0.1163
10 cm	EKF	0.011	0.93	0.1140
20 cm	non-EKF	0.039	0.960	0.1166
20 cm	EKF	0.007	0.921	0.1104
30 cm	non-EKF	0.040	0.957	0.1166
30 cm	EKF	0.031	0.939	0.1105

From table I, when the EKF is used the error in the distance between the final position of the robot and the target position, ΔP_f , is smaller. Thus, the inclusion of the EKF has reduced the error caused by the noise perception. We verify that in both modes (with and without the EKF) ΔT is smaller than 1. This means that the inclusion of the EKF did not compromise the timing properties.

These results show that the average energy, calculated as $E = \sqrt{v^2 + \omega^2}$, required for the robot to successfully complete the missions is lower when the EKF is used. Also, the inclusion of an EKF does not destroy the good properties of the architecture provided that the EKF converges.

5 SIMULATION RESULTS

This simulation demonstrates the reliability of the architecture to integrate nonlinear dynamical systems and an EKF, and simultaneously to preserve the temporal nature of the approach.

At each sensorial cycle, information is acquired, dynamic equations are calculated and integrated using an Euler method with a time step of $0.2 s$. The robot is able to reach a maximum velocity of approximately $0.75 m/s$.

In this simulation the robot has to deal with both dynamic and static obstacles. Initially, the robot is stopped and starts moving towards the red mark and having 20 s to reach it. However, a first person starts to move in the robot direction obstructing partially its trajectory, $t = 8 s$. Another person moves towards the robot at $t = 14 s$. The setup for this experiment is depicted in fig. 3. In fig. 4 (top) it is depicted the velocity

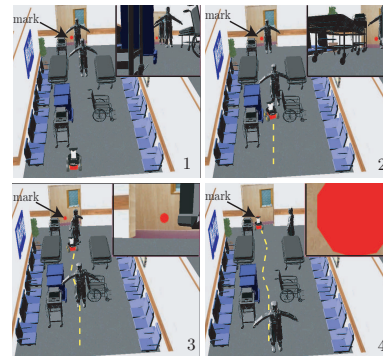


Figure 3: Snapshots of the robot motion.

profile of the robot for this experiment. The amplitude of the oscillator (black dashed-dotted line) remains practically constant during the task until the robot has detected the first person, $t = 8 s$. At this instant of time, the amplitude of the oscillator decreases and the velocity of the robot decreases accordingly. Then, the velocity of the robot is increased to compensate this delay. When the second person is detected, a significant reduction of the velocity in order to ensure a safe circumnavigation is required. After the circumnavigation the velocity of the robot increases to compensate for this provoked delay.

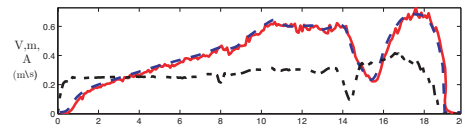


Figure 4: Velocity performed by the robot (continuous red line), generated velocity by the oscillator (dashed blue line) and amplitude of the oscillator (black dashed-dotted).

We can verify in fig. 5 that in this experiment, the robot loses the visual contact with the mark during several intervals of time, and as expected the EKF filters the measurements and provides reliable estimations when no measurements are available (shadow areas).

In the bottom panel, we can note that the direction of the robot, $\hat{\phi}_h$, (green continuous line) changes when obstacles in the trajectory are detected (shadow areas). These changes are required for obstacle circumnavigation. However, as soon as the obstacles were circumnavigated, the heading direction converges to the goal direction $\hat{\psi}_{tar}$. This experiment demonstrated

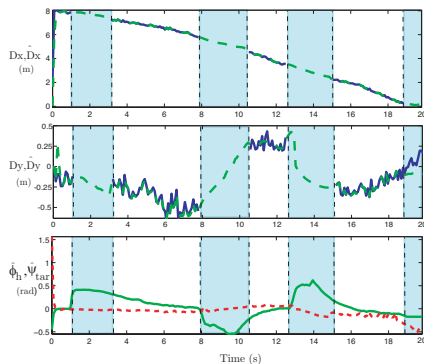


Figure 5: Top panel (Middle): Measured D_x (D_y) by the robot's visual system (blue continuous line), and estimated \hat{D}_x (\hat{D}_y) by the EKF (continuous green line). Bottom: Estimated robot's heading direction $\hat{\phi}_h$ (green continuous line), and the angle $\hat{\psi}_{tar}$ (red dashed line) that the robot has to follow.

that the EKF is able to filter and to estimate sensorial information, in this case visual information about the goal, and simultaneously, to ensure that the temporal nature of the nonlinear dynamical system approach is not degraded, even when the robot has to deal with dynamical obstacles in a cluttered environment.

6 CONCLUSIONS

The purpose of this paper was to address the problem of generating timed trajectories for an autonomous mobile robot equipped with noisy and low-level sensory information, while simultaneously has to estimate the goal location using an EKF.

We have successfully demonstrated that the integration of a standard EKF and a nonlinear dynamical system to robotics in the same approach without degrading the temporal nature of the proposed architecture. Moreover, the inclusion of the EKF has allowed to reduce the error between the final position of the robot and the position of the goal.

For future work, we intend to address other more complex and cluttered environments, as well as to operate in a real hospital environment.

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