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To cite this article: Emidio DiGiampaolo and Francesco Martinelli 2020 *IOP Conf. Ser.: Mater. Sci. Eng.* **922** 012010

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# An algorithm for automatic grasping an UHF RFID passive tag

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**Abstract.** This paper proposes an automatic system which allows a mobile robot to reach a tagged object in an unknown environment, exploiting the Radio Frequency IDentification (RFID) technology. It is assumed that the robot has an odometry system (e.g., wheel encoders) and an RFID reader which provides it with phase-shift measurements of the RFID signal backscattered by the tagged object. Since phases are ambiguous measurements of the tag-reader distance, a Multi-Hypothesis Extended Kalman Filter is proposed to on-line extract, by fusing phase measurements with odometry readings, the range and the bearing of the unknown tag. Once the relative position of the tag is known, a control algorithm is applied to drive the robot toward the desired destination. Numerical results are reported to illustrate the approach.

## 1. Introduction

Localization of tagged objects is of interest in several application domains, from robotics to inventory operations in warehouses or factories. Due to the low cost and size, the absence of batteries, together with the virtual absence of maintenance, passive UHF RFID tags have attracted the research attention as a promising candidate technological solution in many contexts. Due to the low complexity of off-the-shelf hardware, only non-cooperative localization techniques based on the received signal strength indicator (RSSI) or on the phase of the backscattered signal [1] are considered. RSS-based techniques offer poor performances, since RSS suffers from noise and has low resolution and low dynamic if using off-the-shelf hardware. Phase-based techniques, instead, suffer from narrow bandwidth of RFID signal leading to ambiguities in distance evaluation. However, in dynamic environments, where either the tag or the reader is moving, it is possible to collect multiple phase measurements to overcome the lack of bandwidth [1]: this is the kind of RFID measurements considered in this paper.

In inventory contexts, it can be of interest, like in [2], to automatically map tagged objects on shelves in absolute coordinates. In these cases, the mobile unit performing the recognition should be always localized in the environment. In other applications, however, it could be of interest simply to localize a tagged object with respect to a mobile unit, in order, e.g., to reach and grasp it. This is the case, for example, of [3], which uses a Particle Filter based on an unwrapped transformation of the measured phase, to drive a human operator toward a tagged object. Unwrapping algorithms, however, may become not very effective under moderate noise situations, especially if the path of the robot is generic and quite complex, as it happens in the case of a wandering mobile unit.

The localization of a tagged object through RFID phase measurements can be faced through different approaches: fingerprinting, e.g., [4], localizes tagged objects by exploiting the similarity of phase readings with a database of measurements preliminary collected in the environment with respect to anchor tags; Synthetic Aperture Radar (SAR) methods like, e.g., [5] and [6], exploit a set of measurements from a given number of known locations to localize the unknown tag. A survey on possible localization approaches is given in [7].



In this paper, we propose a recursive, computationally efficient approach, based on a Multi-Hypothesis Extended Kalman Filter, which feeds a motion control algorithm to drive the robot to a desired objective. In order to reach a tagged object, only the relative position of the tag with respect to the reader on the mobile unit must be estimated. The relative position is captured by the tag-reader distance (range) and the bearing. The mobile unit is equipped with an odometry system (e.g., encoder on the wheels), but the robot does not have the necessity of localizing itself in an absolute frame. The key-features of the proposed strategy are, mainly, the online nature of the estimation (i.e. a range and bearing estimation is available from the first steps of the algorithm and is continuously updated as new measurements arrive, allowing the robot to immediately move toward the objective) and the fact that any robot path is suitable for the estimation (unlike other approaches, like, e.g., [2]), except possibly for straight paths, which may not allow in some situations to resolve ambiguities.

## 2. Notation and problem formulation

We consider a unicycle mobile robot with the pose denoted by  $x_r = (x, y, \theta)$ , where  $(x, y)$  is the position and  $\theta$  the robot orientation. The dynamics of the robot pose can be written as:

$$\dot{x} = v_1 \cos \theta, \quad \dot{y} = v_1 \sin \theta, \quad \dot{\theta} = v_2 \quad (1)$$

where  $v_1$  and  $v_2$  are, respectively, the linear and angular velocity of the robot and can be evaluated through, e.g., the encoders mounted on the actuated wheels of the unicycle.

A RFID tag is located in an unknown position of the environment and the robot, equipped with an RFID reader and antenna, has the objective of localizing and reaching it. The unique external measurement available to the robot is the phase-shift of the RFID signal backscattered by the tag:

$$\varphi = \text{mod}(-2K\rho + \varphi_0 + n_\varphi, 2\pi) \quad (2)$$

where  $K = 2\pi/\lambda$  (with  $\lambda$  the wavelength of the electromagnetic signal),  $\rho$  is the (unknown) tag-reader distance,  $\varphi_0$  is an unknown offset and  $n_\varphi$  is a 0-mean Gaussian noise, with standard deviation  $\sigma_\varphi = 10^\circ$  in our numerical investigations. The 2 multiplying  $K$  in (2) depends on the roundtrip travel of the electromagnetic wave. For simplicity,  $\varphi_0$  will be assumed 0 but the proposed algorithm can be easily adapted to handle the estimation of an unknown offset: by including  $\varphi_0$  in the state of the EKF instances, the performance of the approach is not significantly different from the case  $\varphi_0 = 0$ .

## 3. Solution approach

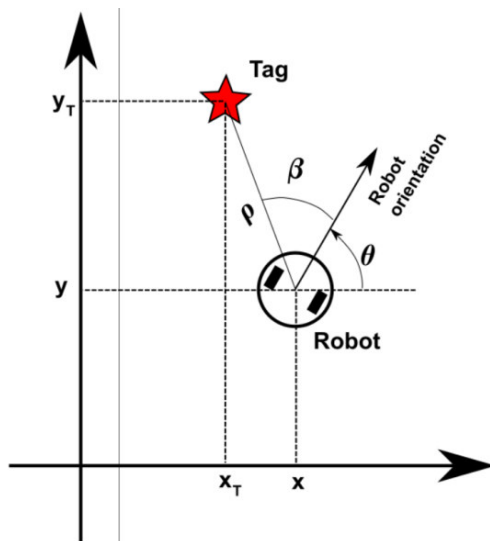
To reach the tagged object, the robot has, first, to estimate the position of the tag and, then, to apply a control strategy which drives it toward the objective. If  $(x_T, y_T)$  denotes the position of the tagged object, assumed known for a moment, we adopt the control law in [8], which assigns

$$v_1 = K_{v1} \rho \cos(\beta), \quad v_2 = -K_{v2} \beta, \quad (3)$$

where  $K_{v1}$  and  $K_{v2}$  are two positive constants, while  $\rho = \sqrt{(x - x_T)^2 + (y - y_T)^2}$  and  $\beta = \theta - \text{atan2}(y_T - y, x_T - x)$  are, respectively, the range and the bearing of the tag with respect to the robot, (see figure 1). This control law is proved to ensure the convergence of the unicycle to the tagged object (see [8]) for any positive value of  $K_{v1}$  and  $K_{v2}$ , even if the value of these constants strongly characterizes the transient behavior of the motion.

Since the tag (and the robot) position is unknown, the range and the bearing of the tag must be estimated. The control law (3) will then be applied on the estimates  $\hat{\rho}$  and  $\hat{\beta}$ , i.e.

$$v_1 = K_{v1} \hat{\rho} \cos(\hat{\beta}), \quad v_2 = -K_{v2} \hat{\beta}. \quad (4)$$



**Figure 1.** The robot, located in position  $(x, y)$ , with orientation  $\theta$ , detects the tag, located in  $(x_T, y_T)$ , at a distance (range)  $\rho$  with a bearing  $\beta$ . The bearing is assumed positive if the tag is on the right-hand side of the robot (it is negative in the figure). Hence  $\theta + |\beta| = \theta - \beta = \text{atan2}(y_T - y, x_T - x)$ .

The estimation of  $\rho$  and  $\beta$  will be realized through an Extended Kalman Filter. For this reason we have to derive the dynamics of these variables. Now, from the definition of  $\rho$ , assuming that the tag is not moving, we have  $\dot{\rho} = \frac{v_1}{\rho} [(x - x_T) \cos(\theta) + (y - y_T) \sin(\theta)]$ , where we have used (1). The quantity  $[(x_T - x) \cos(\theta) + (y_T - y) \sin(\theta)]$  is the scalar product of vectors  $[x_T - x, y_T - y]$  and  $[\cos(\theta), \sin(\theta)]$  and is then equal to the product of the norm of these vectors with the cosine of the angle between them, which is in fact  $\beta$ . But the norm of  $[x_T - x, y_T - y]$  is by definition  $\rho$ . Hence we have  $\dot{\rho} = -v_1 \cos(\beta)$ . In a similar way, it is possible to derive the dynamics of  $\beta$ . Overall we have:

$$\dot{\rho} = -v_1 \cos(\beta), \quad \dot{\beta} = v_2 + \frac{v_1}{\rho} \sin(\beta). \tag{5}$$

The phase measurement (2) is related to the range  $\rho$ . If this quantity was directly measured by the robot, the system was observable (as long as the robot moves over a non straight line) and an Extended Kalman Filter, initialized with the first measurement of  $\rho$  and with an arbitrary value of  $\beta$ , e.g.  $\beta = 0$ , was able to provide a reliable estimate of  $\rho$  and  $\beta$ . The system remains observable even if the phase is measured. However, in view of the modulus function in (2), which represents a periodic (and hence ambiguous) measure of the range  $\rho$ , the estimation becomes more difficult and an Extended Kalman Filter is not able to solve the problem. In fact, a phase measurement gives rise to a multimodal probability distribution over the  $\rho$  values: this will make the  $\rho$  estimate of the EKF converge to the best value of the cycle where the filter has been initialized. To handle this multimodal situation, one possible solution is to use a multi-hypotheses Extended Kalman filter, that is a certain number of EKF instances, each one initialized on a different cycle corresponding to the initial phase measurement. Given the spatial periodicity of the phases (about 17cm at 867MHz, taking into account the roundtrip travel of the signal) and the usual detection range of RFID antennas in indoor environments (a few meters), 10-20 EKF instances are usually enough to cover the set of all possible cycles. The EKF instances evolve in parallel and, at each time step, they are weighed to detect which one of them is more likely to be in the correct cycle. The weight of each EKF instance is computed according to the agreement between the last, say,  $N_s$  phase measurements and the ones obtained if the tag was in the position estimated by that particular instance. The overall algorithm is as follows.

**Initialization.** Let  $k=0$  and let  $\varphi_0$  be the first phase measurement available. Initialize  $n_M$  EKF instances

$$\ell = 1, 2, \dots, n_M, \text{ with } \hat{\rho}_0^\ell = -\frac{1}{2K} \varphi_0 + \ell \frac{\lambda}{2}, \hat{\beta}_0^\ell = 0 \text{ and covariance matrix } P_0^\ell = \begin{bmatrix} \sigma_D^2 & 0 \\ 0 & (\frac{\pi}{3})^2 \end{bmatrix}, \text{ where}$$

$\sigma_D = \frac{\sigma_\varphi}{2K}$  is the standard deviation of the spatial counterpart of the phase measurement noise.

**Prediction step.** The prediction step is applied independently in each EKF instance  $\ell$ , by computing the discretized version of the dynamics (5) with the estimated quantities and using the encoder readings available, to obtain the a priori estimate  $(\hat{p}_{k+1}^{-,\ell}, \hat{\beta}_{k+1}^{-,\ell})$  and its covariance matrix  $P_{k+1}^{-,\ell}$ .

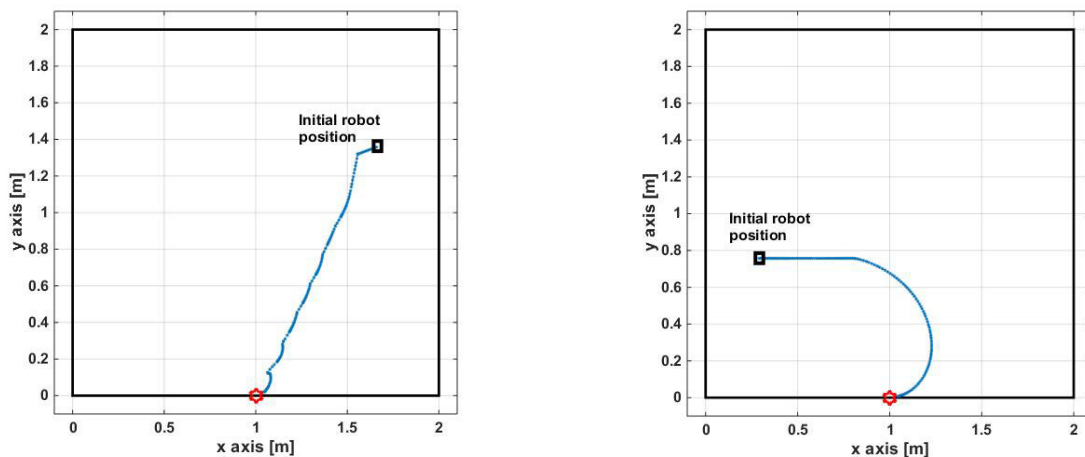
**Correction step.** Let  $\varphi_{k+1}^{\ell} = \text{mod}(-2K\hat{p}_{k+1}^{-,\ell}, 2\pi)$  be the expected phase in instance  $\ell$ . The correction step, applied independently in each EKF instance, exploits the innovation  $\varphi_{k+1} - \varphi_{k+1}^{\ell}$ .

**Weighing and control step.** The EKF instances are weighed according to the agreement between the last  $N_s$  phase measurements and their expected values. Take as final estimates  $\hat{p}_{k+1}^{\ell^*}$  and  $\hat{\beta}_{k+1}^{\ell^*}$  the ones provided by the EKF instance  $\ell^*$  with the largest weight and apply the control law (4).

#### 4. Numerical results

The numerical results refer to a differential drive kinematics unicycle with a distance between the actuated wheels of 26cm. The wheel displacements are measured through encoders, characterized by a 0 mean Gaussian error, with variance proportional (through a factor  $10^{-4}$ m) to the wheel displacement. The control is applied starting from step 50. Before this step, the robot moves on a random path, generated by randomly selecting the initial position and orientation of the robot and by performing random turns when the distance to the walls of the environment becomes less than a threshold. In each step, the maximum wheel displacement is forced to be not larger than 2cm per time step, by saturating the control requests on  $v_1$  and  $v_2$ . The control law constants are  $K_{v1} = 0.1s^{-1}$  and  $K_{v2} = 0.2s^{-1}$ . The window to evaluate the weight of the different EKF instances comprises  $N_s = 50$  steps. Figure 2 reports two trajectories generated by the proposed approach: it is possible to see, in particular on the right plot of figure 2, the part of the trajectory where the control is not active.

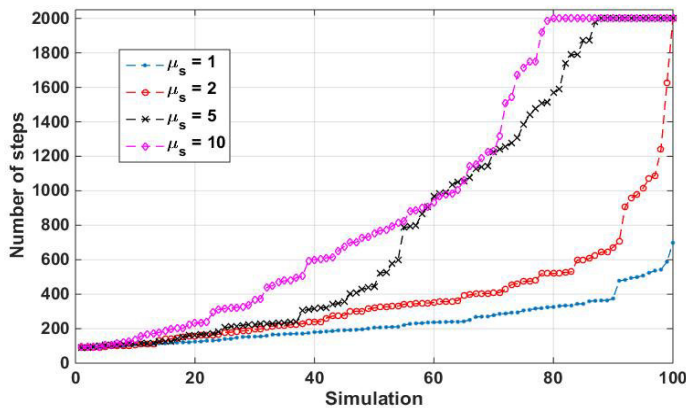
**Figure 2.** The tag, located in position (1, 0), is reached by the robot, initialized in two random positions with a random orientation, in 213 (left) and 126 (right) steps.



An important parameter is the frequency of measurements. Encoder readings are assumed available at all steps. The maximum displacement of the wheels in each step, as mentioned, is 2cm. Phase measurements are assumed available only every  $\mu_s$  discretization steps ( $\mu_s = 1$  in figure 2).

When  $\mu_s$  increases, the performance deteriorates, as illustrated in figure 3, which reports, for different values of  $\mu_s$ , the number of steps required to reach the tag in each execution of the algorithm over 100 different simulations (each one with a different initial robot pose and noise realization).

The performance significantly worsens starting with  $\mu_s = 5$ , which corresponds roughly to a sample about every 10cm. This is due to aliasing, being the spatial periodicity of the signal 17.3cm.



**Figure 3.** Number of steps necessary to reach the tag in 100 independent simulations, sorted according to the required number of steps: 2000 steps (which is the total duration of the simulations) means that the robot was not able to reach the tag in that simulation.

## 5. Conclusions

An automatic system to drive a mobile robot unit toward a tagged object in an unknown environment is proposed in this paper. The only external sensor used by the robot is based on the RFID technology and provides the phase-shift measurements of the RFID signal backscattered by the tagged object. The robot has also an odometry system (e.g., the wheel encoders) which allows it to know local displacements. This information is fused with phase measurements to compute an estimate of the relative position (range and bearing) of the tagged object with respect to the robot. Since the phases are ambiguous measurements of the tag-reader distance, a Multi-Hypothesis Extended Kalman Filter is necessary to solve the estimation problem. Once the relative position of the tag is known, a control motion algorithm is applied to drive the robot toward the desired destination. The proposed approach allows the robot to reach the target in an effective way, even if the interaction of the control and the estimation modules of the algorithm remains a challenging problem to be further investigated.

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