Perception for Autonomous Systems: A Measurement Perspective on Localisation and Positioning

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Autonomous systems are nowadays having an undisputed pervasiveness in the modern society. Autonomous driving cars as well as applications of service robots (e.g., cleaning robots, companion robots, intelligent healthcare solutions, tour guided systems) are becoming more and more popular and a general acceptance is now developing around such systems. Nonetheless, one of the major hurdles in building such applications relies on the capability of autonomous systems to understand their surroundings and then plan proper actions. The most popular solutions, which are gaining more and more attention, rely on artificial intelligence and deep learning as a means to perceive the structured and complex natural environment. Nonetheless, besides the importance of such powerful tools, classical concept of metrology, such as standard uncertainty, accuracy and precision, are still unavoidable for a clear and effective understanding of modern autonomous systems applications. In this paper, some fundamental measurement concepts will be revised in light of the autonomous systems domain, with an emphasis on localisation and positioning problems for mobile robots. In particular, we will discuss and present the main issues and concepts that build around the statistical approach to measurements and the main role of uncertainties.

A common class of Autonomous Systems: Mobile Robots

The term *Autonomous System* (AS) has different meaning depending on the research field considered, ranging from communication technology to mathematics. In this paper, we will consider the definition given in robotics: an AS is a *robot* that performs tasks (e.g., self-maintenance, moving in an unknown environment, handling objects) with a high degree of autonomy. Since autonomy is enforced by the connection of perception, control and actuation, a widely accepted definition of robotics is: "*the science studying the intelligent connection between perception and action*" [1]. In particular, perception is used both to understand the surroundings environment and to give feedback to specific controlled actions (i.e., actuation). From a measurement perspective, perception represents the most important component, since it comprises the description of the available *sensors* and the intelligent elaboration of the data they produce (i.e., *estimators*). A graphic representation of the different elements is offered in Figure 1.

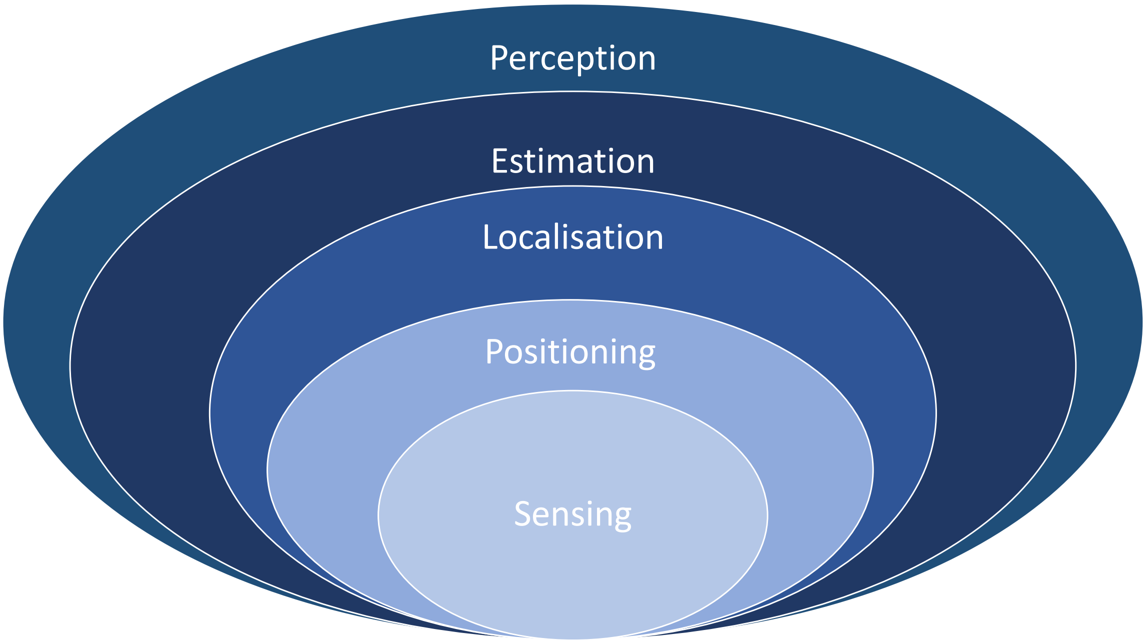

Figure 1: Graphical representation of perception for AS and its different components.

Perception is maybe the most fundamental component for *mobile robots*, i.e., robots that are able to move autonomously inside a (unknown) environment.

The main characteristic of a robot is its ability to interact with the environment, which asks for a model of the physical motion of the AS. In general, a robot is governed by a continuous time nonlinear dynamic that, for the practical implementation on a digital platform, is usually assumed to be discretised with a certain (possibly time varying) sampling time T_s. Denoting with $p_k \in \mathbb{R}^n$ the state vector of the system at time kT_s, the generic time-invariant discretised nonlinear dynamic can be expressed as

$$p_{k+1} = f(p_k, u_k, \eta_k), \quad (1)$$

where $u_k \in \mathbb{R}^q$ are the inputs (related to the number of actuators) and $\eta_k \in \mathbb{R}^l$ are the uncertainties related to the imperfect actuation or to the input measurements. It is usually assumed that the uncertainties are generated by a discrete time white stochastic process and being distributed as $\eta_k \sim \mathcal{N}(0, Q_k)$, where $Q_k \in \mathbb{R}^{l \times l}$ is the covariance matrix. When the dynamic is linear (that for a standard robot is usually a first order Taylor approximation of (*1*)), it is usually represented as

$$p_{k+1} = A_k p_k + B_k u_k + F_k \eta_k. \tag{2}$$

The model is then completed with the output function, which is usually a nonlinear function of the state variables, i.e.

$$z_k = h(p_k, \nu_k), \tag{3}$$

or in its linear (or linearised) version

$$z_k = C_k p_k + L_k \nu_k = C_k p_k + \varepsilon_k. \tag{4}$$

In this case, $z_k \in \mathbb{R}^m$ represents the vector of the m measurement results of the system outputs and $\nu_k \in \mathbb{R}^s$ are the related measurement uncertainty random effects (according to the GUM [2]) that are usually assumed generated by a discrete time white stochastic process with distribution $\nu_k \sim \mathcal{N}(0, E_k)$, where $E_k \in \mathbb{R}^{s \times s}$ is the covariance matrix. Therefore, for a first order Taylor approximation of (*3*) or exactly for (*4*), $z_k \sim \mathcal{N}(C_k p_k, R_k)$ where $R_k = L_k E_k L_k^T \in \mathbb{R}^{m \times m}$, which yields to the equivalent formulation of the measurement uncertainties by means of $\varepsilon_k = L_k \nu_k$ and $\varepsilon_k \sim \mathcal{N}(0, R_k)$ in (*4*).

The sensing system of an AS

From a measurement perspective, it is strictly needed to characterise the available sensors and the associated uncertainties, whose statistical description returns both the *process uncertainties* η_k in (*1*) and (*2*), and the *output uncertainties* ε_k in (*3*) and (*4*). Notice that in both cases, the systematic effects are supposed to be negligible (according to the GUM definition [2]).

In an AS, the sensors are divided into *proprioceptive* and *exteroceptive* sensors [3]. The former refers to sensors that are able to give information about relative motion quantities (e.g., measuring the instantaneous velocities, instantaneous accelerations or relative displacements). In this category fall odometers (including visual odometry), relative (joint) encoders, tachometers, gyroscopes, accelerometers or combination thereof (e.g., Inertial Measurement Units – IMUs).

The exteroceptive sensors, instead, return measurements about quantities that are external to the mobile AS (e.g., distances, orientations or Cartesian coordinates with respect to known or unknown environmental objects) and expressed either in a moving reference frame attached to the robot (generically expressed as $\langle M_k \rangle$, hence time varying) or in a fixed world reference frame (dubbed here $\langle W \rangle$). Examples of sensors in the first set are monocular, stereo or RGB-

D cameras, laser range finders and sonars measuring unknown objects or known objects in (partially) unknown locations. Sensing systems that intrinsically return measurements in $\langle W \rangle$ are the Global Positioning System (GPS), which is not available for indoor applications, or fingerprinting-based techniques using, e.g., radio signal strength intensity (RSSI). However, in this category also fall all the sensors that make use of a known set of environmental tags that are placed in known positions, e.g., Radio-Frequency Identification Tags (RFIDs), Ultra-Wide Band (UWB) anchors, 5G anchors, visual markers.

These two sensor categories play a fundamental role in determining the performance of the perception system of an AS in terms of uncertainties. At a very first step, it is most often assumed that proprioceptive sensors are responsible for the process uncertainties η_k in (*1*) or (*2*), while exteroceptive sensors are mapped into the output uncertainties ε_k in (*3*) or (*4*).

Estimators for ASs

The perception system can be identified with the characterisation of the sensing system and with the definition of a proper estimator. The objective of the estimator is to return both an estimate $\hat{p}_k$ of the state space variable and the associated uncertainty, which usually comes in the form of the covariance matrix $P_k = E(\tilde{p}_k \tilde{p}_k^T)$ of the estimation error $\tilde{p}_k = p_k - \hat{p}_k$, where $E(\cdot)$ represents the expected operator. It has to be noted that in order for the previous expression to be valid, the mean value $E(\tilde{p}_k) = 0$, $\forall k$, that is the estimator should be unbiased. The underlying assumption of using P_k to express the estimator uncertainties is that all the noises are Gaussian and their relation is linear, i.e., the models are (*2*) and (*4*). In the more probable case that the system is given in terms of (*1*) and (*3*), P_k should be regarded as just a first order Taylor approximation, which may lead to estimator inconsistency.

Due to the nonlinearity of the system dynamics (*1*) and of the output model (*3*), several different estimation approaches exist, such as particle filters, Monte Carlo-based filters and, more recently, machine learning-based approaches. However, the lion’s share is still played by those model-based solutions that make the most out of the given models, such as Bayesian filters. The success of such filters, that rely on the very essence of the Bayes Theorem as it has been explained by the mathematician and philosopher Richard Price, is that the more evidence is collected from the measurements, the lower will be the uncertainty. In particular, the analogy adopted by Price, who edited and published in “Philosophical Transactions” the work of Thomas Bayes [4], is the example of “a person that is brought forth in this world and left to collect from his observation" evidences about the natural phenomena (e.g., the sun rising). From a theoretical view-point, the Bayes Theorem relies on the following relation:

$$f_p(\hat{p}_k|z_k) = \frac{f_l(z_k|\hat{p}_k) f_p(\hat{p}_k)}{f_m(z_k)}, \tag{5}$$

where the *prior* probability density function (pdf) $f_p(\hat{p}_k)$ is combined with the *likelihood* pdf $f_l(z_k|\hat{p}_k)$, which expresses the evidence from measurement models (3) and (4), to obtain the *posterior* $f_p(\hat{p}_k|z_k)$ conditional pdf. Finally, the pdf $f_m(z_k)$ assumes the role of a normalisation factor.

Notice that, due to the Markovian property inherited by the dynamic system of a robot expressed as in (1) or (2), the prior $f_p(\hat{p}_k)$ is generated by the posterior $f_p(\hat{p}_{k-1}|z_{k-1})$ at the previous time instant. The nature of the uncertainties η_k and ε_k rules the choice and the attainable performance of the estimator:

- If they are generated by stochastic processes that are white and zero-mean, one solution from the Kalman Filter (KF) family turns to be a quite effective solution to implement a Bayesian filter [6];
- If, additionally, the system is described by the linear equations (2) and (4), the KF turns to be the Best Linear Unbiased Estimator (BLUE);
- If the uncertainties are also Gaussian (as assumed previously), the KF is optimal in the Mean Squared Error sense, i.e., it reaches the Cramer-Rao lower bound [6].

As a final remark, when the dynamic model is not explicitly considered in the estimator design, no prior is given and, hence, only the likelihood pdf $f_l(z_k|\hat{p}_k)$ can be used. In such a case, popular approaches such the Maximum Likelihood (ML) or the Least Squares (LS) can be effectively used [5].

Positioning and Localisation: Two Different Problems

A *localisation* problem deals with the estimates $\hat{p}_k$ representing the pose of the AS in a global and fixed reference frame $\langle W \rangle$. In such a case, the exteroceptive sensors are strictly needed. The measurement results should be expressed directly in $\langle W \rangle$ (such as wireless anchors in known positions or GPS) or local quantities that are matched against an available *map* (i.e., a metric representation of measurable quantities whose coordinates in $\langle W \rangle$ are given). Notice that localisation **is not** *positioning*, the latter having radically different characteristics in terms of feasible estimators, number of sensors and structural properties, as it will be evident in the next section. Localisation is probably the most important problem to solve to ensure autonomy for mobile robots, since with no knowledge of the pose, it is not possible to solve any task.

Observability: a necessary condition

The design of an estimator for $\hat{p}_k$ always requires a preliminary *observability* analysis to prove that the initial state p_0 of the robot can be reconstructed assuming the knowledge of both the sequence of input values $u_0, \dots, u_k$ and the sequence of measurements $z_0, \dots, z_k$. Since the observability is a *structural property* of the system [7], it just depends on the nominal dynamic and output functions, i.e., neglecting the presence of the uncertainties η_k and ε_k. It is then evident why observability refers to the initial state p_0: if the process uncertainties are neglected, knowing $u_0, \dots, u_k$ it is possible to reconstruct all the state sequence $p_1, \dots, p_k$ using (1) or (2). Furthermore, if the system is *unobservable*, it is not possible to design **any** estimator able to estimate $\hat{p}_k$, i.e., at least a subset of the eigenvalues of the estimation error covariance P_k (associated to the unobservable subspace) grows unbounded.

Example: let us consider a robot moving along a curvilinear path on a plane. Let us assume that $p_0 = [x_0, v_0]^T$ is the state of the robot, where x_0 is the initial position on the curvilinear path (expressed in $\langle W \rangle$), while v_0 is the initial velocity. We assume a (time invariant) linear dynamic as in (2), here reported explicitly

$$\begin{bmatrix} x_{k+1} \\ v_{k+1} \end{bmatrix} = \begin{bmatrix} 1 & T_s \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_k \\ v_k \end{bmatrix} + \begin{bmatrix} \frac{{T_s}^2}{2} \\ T_s \end{bmatrix} u_k = A p_k + B u_k, \tag{6}$$

where u_k represents the acceleration of the robot. Let us assume that the vehicle is equipped with odometers and uses an external reference system to collect a position measurement x_k in $\langle W \rangle$. It then follows that with odometers readings and knowing the sampling time T_s, it is possible to define an *indirect measurement* of the velocity v_k. Therefore, the output equation (4) turns to

$$z_k = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_k \\ v_k \end{bmatrix} = C p_k. \tag{7}$$

This is a very unusual situation since observability is ensured with just the first set of measurements, since $z_0 = p_0$. In other words, observability is ensured even without the need of the knowledge of the system dynamic (6), thus resulting in a *static observability* condition. Instead, if only the position x_k can be measured, i.e., if $C = [1, 0]^T$ in (7), static observability does not hold. However, after two consecutive measurements at time 0 and T_s (i.e., with $k = 0$ and $k = 1$), we have $z_0 = Cp_0 = x_0$ and

$$z_1 = Cp_1 = C(Ap_0 + Bu_0), \tag{8}$$

in which we have substituted explicitly the dynamic (6). Rearranging the terms, we can define the following linear system

$$\begin{bmatrix} z_0 \\ z_1 - CBu_0 \end{bmatrix} = \begin{bmatrix} C \\ CA \end{bmatrix} p_0 \Rightarrow p_0 = \begin{bmatrix} C \\ CA \end{bmatrix}^{-1} \begin{bmatrix} z_0 \\ z_1 - CBu_0 \end{bmatrix} = O^{-1} \begin{bmatrix} z_0 \\ z_1 - CBu_0 \end{bmatrix}. \tag{9}$$

The state p_0 can then be computed if and only if the *observability matrix* O in (*9*) is invertible, which is the case for the example at hand. It is now clear why the linear system observability is a structural property: it is based on the structure of the system expressed by the matrices C and A. Of course, this analysis can be extended to a linear system having a state variable $p_0 \in \mathbb{R}^n$, where the observability matrix should be computed up to order n [7], i.e.

$$O = \begin{bmatrix} C \\ CA \\ CA^2 \\ \vdots \\ CA^{n-1} \end{bmatrix}, \tag{10}$$

and then verifying that O is a of full column rank.

Notice that if only the velocity v_k can be measured, i.e., if $C = [0, 1]^T$ in (7), the resulting observability matrix is not invertible.

Notice that if the system is nonlinear and given by the equations (1) and (3) or when it is linear time variant, observability is no more a structural property, but instead depends on the particular trajectory followed. This is a remarkable difference, which is expressed by the fact that the nonlinear observability analysis, involving more complicated tools of differential geometry [7], is valid only *locally*. As a consequence, the state p_0 can be reconstructed only if there exists a prior knowledge available, i.e., the invertibility is ensured only in a neighbourhood of the actual state p_0. These concepts have been used recently for localisation using RFID [8] or for the definition of estimators stemming directly from a global observability analysis [9].

Estimators

If the system is observable, it is then possible to design an effective estimator. Let us first consider the case of localisation for a linear system. Under the hypothesis given previously about the whiteness of the stochastic processes related to η_k and to ε_k uncertainties, the most effective linear estimator is given by the KF, whose equations are subsumed in Figure 2.

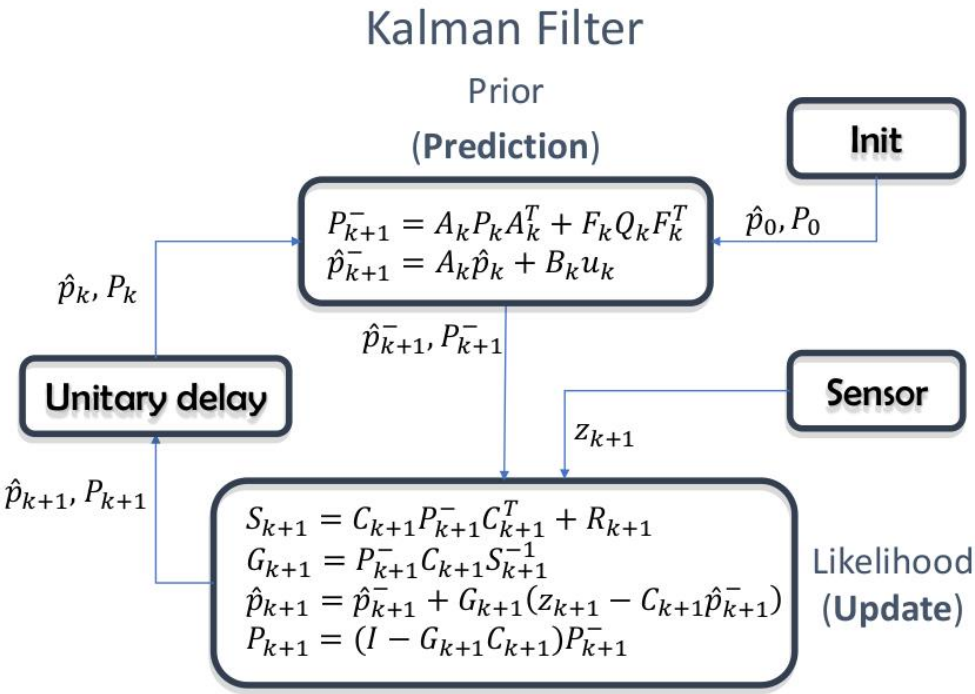

Figure 2: The Kalman Filter algorithm for a linear system localisation in which the two steps (Prediction and Update) are clearly visible.

The two steps comprising the KF, which are the *Prediction* and the *Update* steps, map on the prior and likelihood functions in (*5*). This algorithm is one of the most popular algorithms applied for robotics estimation problems and, in particular, to localisation [10].

As mentioned above, a positioning problem is basically a sub-class of a localisation problem and takes place whenever the system is *statically observable*, i.e., when it is sufficient just a set of (repeated) measurements to estimate the position, i.e., $p_k = (C_k^T C_k)^{-1} C_k^T z_k$. From a theoretical view-point, this implies that the state variable p_k is **not** treated as a random variable (as instead happens for localisation problems) but as a constant and unknown parameter. This marks a remarkable theoretical difference: the estimator that can be used does not consider the motion priors. In this case, one popular solution is to adopt a Weighted LS (WLS) [5], depicted in Figure 3.

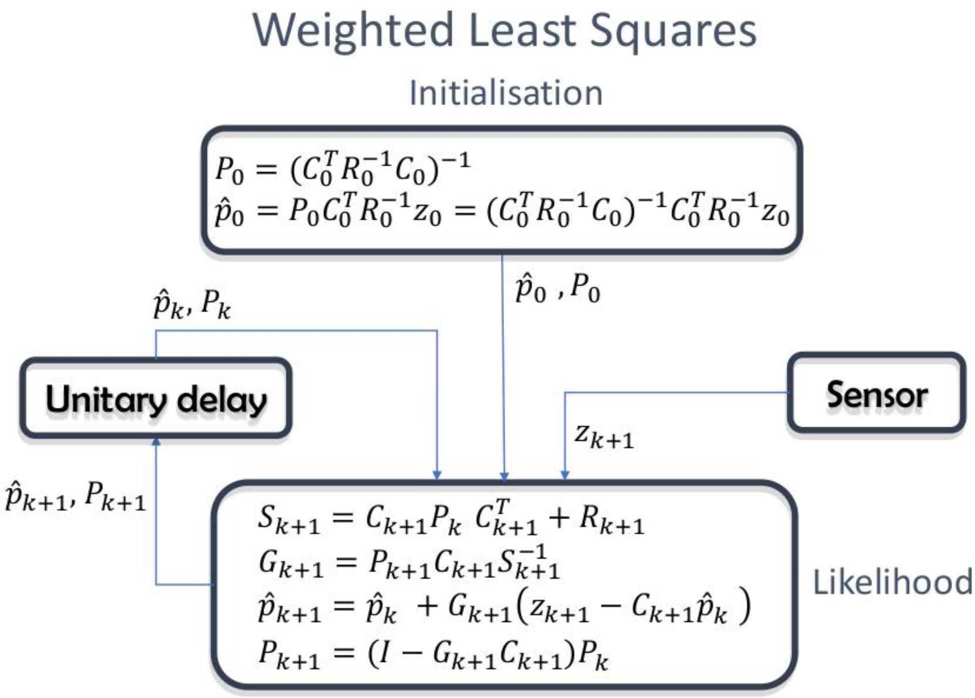

Figure 3: Weighted Least Squares algorithm for positioning problems.

In practice, since the measurement results are expressed as in (*4*), where p_k is the ideal true value of the measured quantity, the estimates are only related to the likelihood function obtained from a sampled distribution (in the frequentist sense) that is obtained by repeated measurements (Type A analysis [2]).

Notice how the WLS, here written in its recursive form, and the KF basically differ in the prior (e.g., process-based prediction) part. Furthermore, while the KF is optimal if the uncertainties are Gaussian, the WLS, which is solely based on the likelihood function, turns to be a disguised version of the ML for Gaussian uncertainties and optimal in its turn [5].

In the case of nonlinear dynamics (*1*) and/or of nonlinear output function (*3*), extension of both algorithms can be easily derived, such as the Extended KF, the Unscented KF or the Nonlinear WLS [6].

The dead-reckoning phenomenon

We have seen that a localisation problem involves both the dynamic and the output function of a system, while a positioning problem relies only on the output functions (*3*) or (*4*). However, it is also possible to use just the model (*1*) or (*2*) to estimate the position of a robot. This problem subsumes a lack of observability (being the output matrix $C = 0$), hence the initial position p_0 in the fixed reference frame $\langle W \rangle$ should be known a-priori, while the use of only proprioceptive sensors (e.g., odometers) or exteroceptive sensors measuring quantities in the mobile frame $\langle M_k \rangle$ only (e.g., visual odometry) is adopted. In such a case, only the prediction part of the KF in Figure 2 can be carried out. Since the covariance matrices P_k and Q_k involved in the prediction step are positive semi-definite and combined through a sum of quadratic forms, the eigenvalues of the covariance matrix P_k cannot asymptotically converge towards 0, even if an infinite number of measurements is collected, i.e., for $k \longrightarrow +\infty$. Moreover, a typical mobile agent moving on a plane is usually referred to as a *driftless system,* having an equilibrium (i.e., $p_{k+1} = p_k$) when $u_k = 0$ in (*1*) or (*2*). Hence, for a vehicle moving on a plane without output functions (*3*) or (*4*), the eigenvalues of the covariance matrix P_k grow unbounded when $k \longrightarrow +\infty$: the *dead-reckoning* phenomenon. This is somehow trivial since the system is unobservable.

Notice that this phenomenon is implicit in Simultaneous Localisation and Mapping (SLAM) problems, where the mobile agent is supposed to estimate a map of an unknown environment while simultaneously localising in the estimated map. Indeed, the measurement results can only be expressed in the moving reference frame $\langle M_k \rangle$. Nevertheless, with a loop closure, the uncertainty of a SLAM problem can be reduced [1].

Positioning and Localisation: final comments

The previously introduced concepts can be applied to any estimation problem for any AS. For example, the same ideas underlying the design of estimators for localisation or positioning problems can be applied to human tracking, provided that a model, e.g., [11], is given. Moreover, it is also affirming nowadays the idea of *active localisation*, for which the agent follows desired paths in order to control the uncertainty growth. Finally, it is worth to mention that a maximum *target uncertainty* can be always managed, either by instrumenting the environment with a suitable set of sensors [12] or by accessing on-demand to the available localisation infrastructure [13].

Distributed Localisation: The Role of Covariance

Consider a simple example: two robots X and Y are moving on the same curvilinear abscissa (e.g., a corridor), whose coordinates are x_k and y_k, respectively. Assuming known constant velocities $v_{x,k}$ and $v_{y,k}$, respectively, we have the following scalar linear systems derived from (*2*):

$$x_{k+1} = x_k + b_x v_{x,k} + f_x \eta_{x,k} \text{ and } y_{k+1} = y_k + b_y v_{y,k} + f_y \gamma_{y,k}, \quad (11)$$

where $\eta_{x,k} \sim \mathcal{N}(0, \sigma_{x,k}^2)$ and $\eta_{y,k} \sim \mathcal{N}(0, \sigma_{y,k}^2)$ are the two process uncertainties. Suppose that exteroceptive sensors measuring the actual locations in $\langle W \rangle$ are available and modelled from (4) as

$$z_{x,k} = x_k + \varepsilon_{x,k} \text{ and } z_{y,k} = y_k + \varepsilon_{y,k}, \quad (12)$$

with measurement uncertainties given by $\varepsilon_{x,k} \sim \mathcal{N}(0, \xi_{x,k}^2)$ and $\varepsilon_{y,k} \sim \mathcal{N}(0, \xi_{y,k}^2)$. Since all the uncertainties are white and mutually uncorrelated, each robot can implement a KF individually to estimate $\hat{x}_k$ and $\hat{y}_k$. However, let us assume that robot X can measure the relative distance to robot Y (e.g., using a laser scanner) in the moving frame $\langle M_{x,k} \rangle$. Hence there is an additional measure $\Delta_{xy,k} = x_k - y_k + \varepsilon_{xy,k}$ with uncertainty $\varepsilon_{xy,k} \sim \mathcal{N}(0, \xi_{xy,k}^2)$: if the robot Y sends its own estimated position to X, we have an indirect measurement of the position x_k in $\langle W \rangle$, i.e.

$$z_{xy,k} = \Delta_{xy,k} + \hat{y}_k + \varepsilon_{xy,k} = x_k + \tilde{y}_k + \varepsilon_{xy,k}, \quad (13)$$

where $\tilde{y}_k = y_k - \hat{y}_k$ is the estimation error of the KF executed on the robot Y with variance given by $P_{y,k}$ (see Figure 2). Assuming that $\varepsilon_{xy,k}$ is, again, generated by a white stochastic process and assuming that the robot Y sends the estimate $\hat{y}_k$ along with the variance $P_{y,k}$, the overall measurement uncertainty of $z_{xy,k}$ is available to the robot X and equals to $\xi_{xy,k}^2 + P_{y,k}$. If this measurement is additionally used in the KF of robot X, the estimation error variance $P_{x,k}$ certainly decreases [5]. Hence, it would be beneficial to do the same for robot Y if endowed with a similar relative sensor. Unfortunately, this is not working so straightforwardly: indeed, once X firstly uses $z_{xy,k}$, the estimate $\hat{x}_k$ becomes *correlated* with $\hat{y}_k$ by means of (13). Therefore, if the process is now repeated for Y, the measurements

$$z_{yx,k} = \Delta_{yx,k} + \hat{x}_k + \varepsilon_{yx,k} = y_k + \tilde{x}_k + \varepsilon_{yx,k}, \quad (14)$$

are now correlated with $\hat{y}_k$, which violates the KF assumption of model and measurement uncertainties to be uncorrelated. The problem can be circumvented by exchanging the mutual covariance quantity between X and Y. Indeed, by rewriting the problem as a single KF with state $p_k = [x_k, y_k]^T$ and applying the algorithm in Figure 2, it turns out that a relative measurement generates off-diagonal terms in P_k (covariance terms) that should be taken into account in the execution of the filter. Furthermore, it is also evident that using **only** relative measurements in $\langle M_{x,k} \rangle$ and $\langle M_{y,k} \rangle$ given by (13) and (14) for the mutual localisation problem leads to uncertainty growth with respect to the position in $\langle W \rangle$, as previously stated. This is immediately verified by the fact that p_k thus defined with the output functions (13) and (14) only is unobservable.

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