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SIMULATION-BASED SENSING-SYSTEM CONFIGURATION FOR DYNAMIC DISPATCHING

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Abstract

This paper presents a methodology for determining the initial configuration of a set of sensors for a surveillance task. It serves to complement a dynamic dispatching methodology, which selects and maneuvers subsets of sensors to achieve optimal data acquisition in real-time. Specifically, given *a priori* information about the expected object trajectory, the initial sensor poses are determined such that the sensing-system effectiveness is maximized. This is achieved using the a constrained, non-linear, direct search method in combination with simulations of the sensing-system performance. (i.e., dynamic dispatching to adjust the sensor poses in response to the object motion.)

1 Introduction

Many autonomous robotic tasks require sensory data collected in real-time. As discussed in [1], dynamic dispatching can be effectively utilized to adjust a sensor set on-line to provide the best information possible. This involves both selecting an appropriate subset of sensors to be used in a sensor fusion process (thereby reducing measurement uncertainty [2]) and maneuvering all sensors in response to the motion of the object. Namely, the sensors provide information of sufficient quality for the task at hand while ensuring adequate response to object maneuvers (keeping all sensors "in the game").

The goal of sensor dispatching, as considered herein, is to select and position groups of sensors in a coordinated manner for the surveillance of a maneuvering target in real-time. The methodology employed considers the principles of dispatching, as used for the effective operation of service vehicles (e.g., taxicabs), to ensure the effectiveness of the sensing-system.

For surveillance, the object trajectory is discretized into a number of demand instants (data acquisition times) to which groups of sensors are assigned, respectively. Heuristic rules are used to evaluate the suitability of each sensor for servicing (observing) a demand instant, determine the composition of the sensor group, and, in the case of dynamic sensors, specify the position of each sensor with respect to the target. This approach aims to improve the quality of the surveillance data in three ways: (1) the assigned sensors are maneuvered into "optimal" sensing positions, (2) the uncertainty of the measured data is mitigated through sensor fusion, and (3) the poses of the unassigned sensors are adjusted to ensure that sensing-system can react to object maneuvers. For a detailed discussion of this approach and a review of the related literature, the interested reader is referred to [1, 3]

The effectiveness of the sensing-system may depend on the initial pose of each sensor within the workspace. This is especially true in the case of slow-speed or fixed sensors. It is, therefore, desirable to search for an optimal initial pose for each sensor based on the requirements of the task at hand. Zhang [4] proposed a method for sensing a 2-D static object which minimizes the magnitude of the sensor measurement covariances by optimally placing multiple sensors to be used for sensor fusion. The system proposed in [5] uses a "generate-and-test" method to determine the best sensor position to optimize both feature visibility and measurement reliability. Matsuyama *et al.* [6] use a simulation method to optimize layouts for fixed cameras observing 2-D, static objects. This paper aims to present a simulation-based approach to the problem of initial sensing-system configuration, suitable for surveying moving objects with dynamic sensors.

2 Sensor Model

Herein, non-contact proximity sensors are modelled and utilized for illustrative purposes. A three-dimensional proximity measurement is defined as the range, bearing, and elevation to the object from a known sensor sensor pose. For the sensor shown in Figure 1, the range, r, is the linear distance between the object and the sensor frame. The bearing, θ, is the radial difference between the orientation of the sensor axis with respect to the x-z plane, α_s, and the object position. The elevation, ϕ, is the angular difference between the orientation of the sensor axis with respect to the x-y plane, β_s, and the object position.

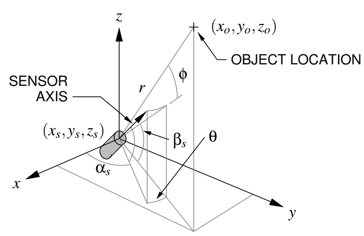


Figure 1: Proximity sensor measurement variables.

2.1 Quality Assessment

A visibility metric can be used to evaluate the quality of information that a sensor, or a group of sensors, can provide about a demand point. We propose the following visibility measure for a single proximity sensor:

$$v_s = \begin{cases} \dfrac{1}{\|R\|} & \text{if demand point is unoccluded,} \\ 0 & \text{otherwise,} \end{cases} \tag{1}$$

where $\|R\|$ is the Euclidean norm of the covariance matrix associated with the sensor measurement. For the proximity sensor in Figure 1, the variance in r, θ, and ϕ may be expressed as:

$$\sigma_r^2 = \begin{cases} a + b_1(r - r^*)^2 & \text{if } r < r^*,\ r \in \mathcal{R}^+, \\ a + b_2(r) & \text{otherwise,} \end{cases} \tag{2}$$

$$\sigma_\theta^2 = \begin{cases} c + d\,\theta^2 & \text{if } |\theta| < \theta_{\max},\ \theta \in \mathcal{R}, \\ \infty & \text{otherwise,} \end{cases} \tag{3}$$

$$\sigma_\phi^2 = \begin{cases} e + f\,\phi^2 & \text{if } |\phi| < \phi_{\max},\ \phi \in \mathcal{R}, \\ \infty & \text{otherwise,} \end{cases} \tag{4}$$

where $a, b_1, b_2, c, d, e,$ and f are characteristic constants. r^* is the range between the sensor and the object at which the variance is minimal; here, the variance is equal to the constant error a. If the range is small, the variance increases proportional to b_1; if the range is large, the variance increases proportional to b_2. Similarly, for the variance in bearing and elevation, c and e are the constant measurement errors, while d and f represent the increase in variance incurred by deviations of the object position from the sensor axis. $\theta_{\max}$ and $\phi_{\max}$ limit the field of view of the sensor. Assuming that σ_r^2, σ_θ^2, and σ_ϕ^2 are uncorrelated, the covariance matrix R may be expressed in Cartesian coordinates as follows:

$$R = \begin{bmatrix} \sigma_x^2 & \sigma_{xy} & \sigma_{xz} \\ \sigma_{xy} & \sigma_y^2 & \sigma_{yz} \\ \sigma_{xz} & \sigma_{yz} & \sigma_z^2 \end{bmatrix}, \tag{5}$$

where σ_x^2, σ_y^2, σ_z^2, σ_{xy}, and σ_{yz} are functions of σ_r^2, σ_θ^2, σ_ϕ^2, r, θ, and ϕ.

The visibility measure for a fusion subset comprising k sensors, whose measurements are combined using sensor fusion, is defined as:

$$v_f = \frac{1}{\|P\|}, \tag{6a}$$

where P represents the fused covariance matrix,

$$P = \left[\sum_{i=1}^{k} {R'}_i^{-1}\right]^{-1}, \tag{6a}$$

and

$$R'_i = \begin{cases} R_i & \text{if demand point is unoccluded,} \\ \emptyset & \text{otherwise.} \end{cases} \tag{6b}$$

2.2 Best-Achievable Pose

The best-achievable pose is one that maximizes the visibility of the object at the demand instant, constrained by the dynamic limitations of the sensor. As may be ascertained from the variance Equations (2)–(4), the object visibility is maximal when $r = r^*$, $\theta = 0$, and $\phi = 0$. In other words, the "best-possible" pose consists of the sensor at the optimal range (or as close to it as the workspace constraints will allow), with the sensor axis aligned with the object. If the dynamic capabilities of the sensor are insufficient to attain the best-possible pose before sensing must occur, the best-achievable pose is utilized. Here, the sensor is positioned as close as possible to the object and the error between the sensor axis and the object is minimized. It is from this pose that the visibility measures discussed above are usually assessed.

3 Initial Configuration Determination

The initial surveillance-system configuration specifies the initial poses of the set of sensors that will be available during surveillance. Determined off-line, it serves to initially distribute and position the sensors within the workspace in an optimal manner based on *a priori* information available for the target motion over the entire workspace. The objective in determining this initial configuration could be to maximize a visibility criterion over the entire object motion. This section first presents a methodology suitable for a single (expected) object trajectory. The single trajectory approach is then extended to accommodate the more general case of multiple object trajectories.

3.1 Single Object Trajectory

The overall visibility measure of a single object over its "entire motion" v_c, may be stated as,

$$\max v_c = w_1 \min_{i=1}^{m} (v_b)_i + w_2 (v_b)_1. \tag{7}$$

The objective function value to be maximized, v_c, in Equation (7) above, consists of two parts: The first part chooses the minimum of all the individual best-achievable visibilities ($v_b \equiv \max v_f$) at the i = 1 to m demand instants as the representative (best-achievable) overall visibility of the moving object by the surveillance system, if it were to have the initial configuration under consideration. The second part places additional emphasis on the visibility of the object at the first demand instant (to ensure adequate detection). w_1 and w_2 are user-chosen weighting factors, which serve to balance between these two objectives.

Equation (7) is utilized as follows: First, a guess of the object trajectory is discretized and used to define a set of demand instants. Typically, these demand instants would correspond to the required sensing intervals of a particular task. Then, for a set of initial sensor poses chosen by a search technique, a comprehensive sensor dispatching simulation is conducted to survey the object at all of the demand instants. For each demand instant, sensors are dispatched to poses that will result in the best-achievable visibility as described in [1]. The best-achievable visibility, v_b, is then determined using Equation (6a), i.e., ($\max v_f$), with the assigned sensors in these "best" poses. The overall object visibility for the entire motion is subsequently determined using Equation (7). Having determined v_c, the search technique is invoked again to vary the initial sensor poses. This process is repeated until the "best" initial configuration is found within a desired convergence value.

The specific search technique utilized in our simulations was the Flexible Tolerance Method (FTM). This is a constrained non-linear direct search method, introduced by Paviani and Himmelblau [7] and discussed in detail by Himmelblau in [8]. Note that, the simulation-based nature of the search and the topography of the search space may result in solutions that are not globally optimal; however, this approach provides near-optimal solutions that are suitable for the heuristic dispatching approach used for sensing-system reconfiguration.

3.2 Multiple Object Trajectories

The approach utilized for a single object trajectory discussed above may be extended to determine an initial sensing-system configuration that is suited to the surveillance of two or more different object trajectories. These trajectories may be a single object with multiple possible trajectories or multiple objects, each with a unique trajectory. Since there can be only one initial configuration, it must be determined such that the probability of successfully surveying the object is maximized—regardless of the actual trajectory. To facilitate this, the *a priori* probability of encountering each trajectory is used in addition to the target motion estimates. These probabilities serve to weight the initial configuration, skewing its performance towards those trajectories with the highest probability of occurring.

Normalized Visibility Measure

The visibility measures discussed in Section 2.1 for a particular demand point are dependent on the constraints of the workspace. To better understand the ramifications of this, consider a sensor that is fixed in the workspace, i.e., its pose is static. Now, if an object (demand) is placed such that it is in-line with the sensor axis, it will have a particular visibility measure, say v_1. If the object is then moved along the sensor axis, away from the sensor, the visibility, say v_2, will drop (i.e., $v_1 < v_2$). Maintaining the distance between the object and the sensor while moving the object away from the sensor axis (i.e., the object follows an arc of constant radius) would produce a similar effect.

This same effect may be observed with dynamic sensors constrained to rails (linear motion is limited to a single axis). The closer the trajectory happens to be to the rails, the higher the visibility measure will be from the best achievable pose. Thus, to compare the performance of the sensing system for different trajectories, it is necessary to normalize the visibility measure, thereby reducing the degree to which the sensing system is affected by the (uncontrollable) distance of the trajectory to the rails. Using this normalized visibility, the performance of the sensing-system configuration can be evaluated equally for trajectories that pass close to the sensors and those that do not. For a given demand instant, the normalized visibility of the object is as follows:

$$v_n = \frac{v_b}{v_p} \tag{8}$$

where v_b is the best-achievable visibility, determined as discussed in Section 3.1. v_p is the best-possible combined visibility. Here, each sensor is positioned such that each is in its best-possible pose, as defined in Section 2.2. This requires that the sensor pose be adjusted such that $r = r^*$ if the closest possible position results in r being less than r^*. Since v_p is a fused visibility measure, it must also consider what the best possible fusion subset is (which may differ from that chosen by the dispatching algorithm). This is accomplished by considering each sensor in its best-possible pose (adhering to any workspace constraints). From these individual poses, the combination of k sensors (the fusion subset size) that maximize the combined visibility measure, v_f, (as determined by Equation (6a)) is selected.

Objective Function

To determine the optimal initial sensing-system configuration for multiple object trajectories, the following objective function is maximized:

$$\max \sum_{j=1}^{q} P_j (v_c)_j \tag{9}$$

where P_j is the probability that trajectory j will be observed (of q trajectories in total). Note that, $\sum_{i=j}^{q} P_j$ must equal 1. $(v_c)_j$ is the overall configuration visibility of the sensing system for the jth trajectory. v_c is evaluated as:

$$v_c = w_1 \min_{i=1}^{m} (v_n)_i + w_2 (v_n)_1. \tag{10}$$

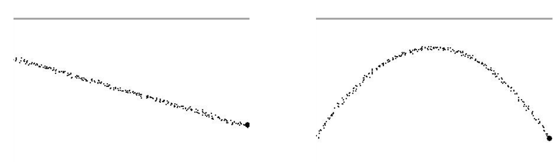
Evaluation of Equation (9) is similar to that for a single trajectory. First, each object trajectory is discretized into a number of demand points. A single set of initial sensor poses is then chosen by a search technique. For each trajectory, a comprehensive dispatching simulation is conducted, determining the best-achievable visibility for each demand instant and evaluating the configuration visibility, v_c. The i configuration visibilities are then combined using Equation (9), i.e., $\sum_{j=1}^{q} P_j (v_c)_j$. The initial sensor poses are then adjusted by the search technique and the process is repeated until the "best" initial configuration is found within a desired convergence value.

4 Examples

In these illustrative examples, a 2-D workspace and four dynamic sensors having identical characteristics are considered. The workspace is 1.0 m by 0.875 m in area. Sensors are constrained to rails at the edge of the workspace, but are free to assume any position and orientation along the rail. Thus, each sensor has two degrees of freedom: rotation, α, and horizontal translation, x. The resulting initial sensing-system optimization problem, thus, solves the objective function (Equation (7) or (9)) for eight parameters: the initial (horizontal) position and orientation for each of the four sensors. (The vertical position of each sensor is fixed by the rail to which it is constrained.)

4.1 Single Trajectory

For the straight-line trajectory shown in Figure 2(a) (the object is translating at approximately 0.2 m/sec), a number of optimal initial configurations were by varying the dynamic characteristics of the sensors, Figure 3. The configuration visibilities for each of these cases are presented in Table 1.



(a) Straight-line (b) Parabolic

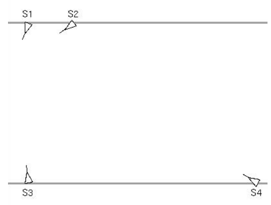
Figure 2: Object trajectories considered.

$\dot{x}$ [m/sec]	$\dot{\alpha}$ [rad/sec]	v_c	v_n
2.5	2π	0.88888	1.00000
0.2	$\frac{\pi}{2}$	0.88837	0.99943
0.1	$\frac{\pi}{3}$	0.65450	0.72507
0.0	$\frac{\pi}{3}$	0.55119	0.62009
0.0	0	0.09358	0.10528

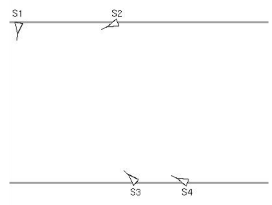
Table 1: Configuration visibilities, v_c, for various optimal initial configurations.

(a) $\dot{x} = 2.5$ m/sec, $\dot{\alpha} = 2\pi$ rad/sec

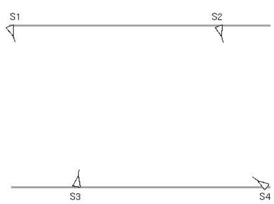
(b) $\dot{x} = 0.2$ m/sec, $\dot{\alpha} = \frac{\pi}{2}$ rad/sec



(c) $\dot{x} = 0.1$ m/sec, $\dot{\alpha} = \frac{\pi}{3}$ rad/sec



(d) $\dot{x} = 0.0$ m/sec, $\dot{\alpha} = \frac{\pi}{3}$ rad/sec



(e) $\dot{x} = 0.0$ m/sec, $\dot{\alpha} = 0$ rad/sec

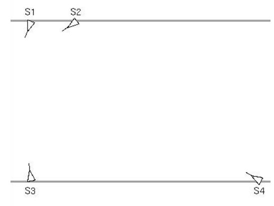
Figure 3: Optimal initial surveillance-system configurations for varying sensor dynamics.

Clearly, as the dynamic characteristics of the sensors change, so too does the initial configuration. The general trend is: as the dynamic capabilities decrease, the sensors become more widely distributed in the workspace. This is logical. If the sensors are fast enough to "keep up" with the object, maximum visibility can be obtained at all times. Slower sensors must compromise visibility for workspace coverage.

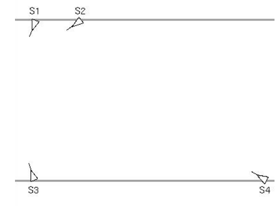
4.2 Multiple Trajectories

Considering both the straight-line and parabolic object trajectories in Figure 2, optimal initial configurations may be determined using the method outlined in Section 3.2. Figure 4 presents a number of optimal initial configurations for different probabilities of observing each trajectory. P_1 represents the probability of observing the straight-line trajectory, P_2 the parabolic. Here, all of the sensors have identical characteristics: $\dot{x} = 0.1$ m/sec and $\dot{\alpha} = \frac{\pi}{3}$ rad/sec.

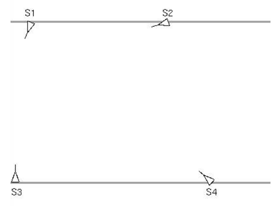
The performance of selected initial sensing-system



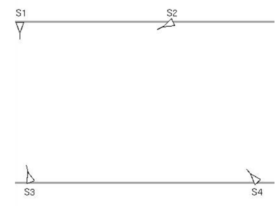
(a) $P_1 = 1.0$, $P_2 = 0.0$



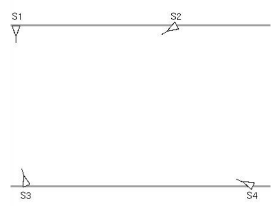
(b) $P_1 = 0.9$, $P_2 = 0.1$



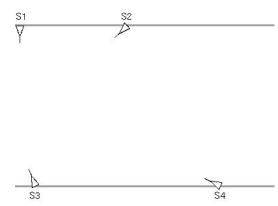
(c) $P_1 = 0.8$, $P_2 = 0.2$



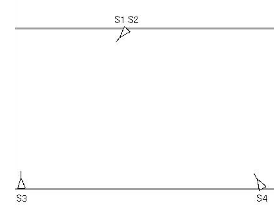
(d) $P_1 = 0.5$, $P_2 = 0.5$



(e) $P_1 = 0.2$, $P_2 = 0.8$



(f) $P_1 = 0.1$, $P_2 = 0.9$



(g) $P_1 = 0.0$, $P_2 = 1.0$

Figure 4: Optimal initial surveillance-system configurations for varying trajectory occurrence probabilities.

configurations, when utilized as the starting point for dispatching, is presented in Figure 5.

As expected, the configurations optimized for only one trajectory (i.e., $P_1 = 1.0$ for straight-line and $P_2 = 1.0$ for parabolic) outperformed all other configurations (considering only first and worst demand) when applied to their respective trajectories, and faired the worst when presented with the other (unexpected) trajectory. The initial sensing-system configuration that considered both trajectories with equal probability (i.e., $P_1 = 0.5$ and $P_2 = 0.5$) managed proved capable of adequately observing both trajectories. The performance of the configuration expecting the parabolic trajectory with probability of only $P_2 = 0.1$ is interest-

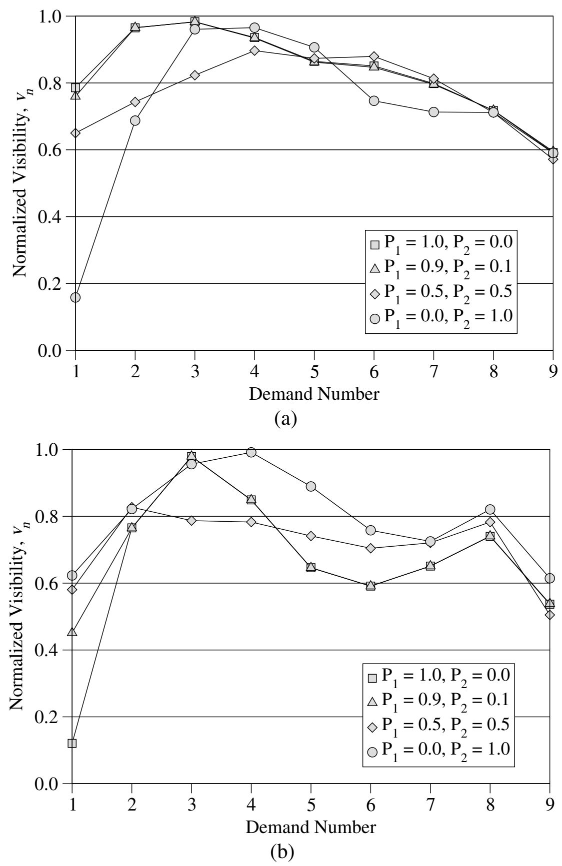


Figure 5: Dispatching performance of initial configurations for (a) straight-line and (b) parabolic object trajectories.

ing. By considering this small probability, the initial configuration is adjusted enough to significantly improve performance with the parabolic trajectory, with little impact on performance for the (expected) straight object trajectory.

It is worth noting that as the speed of the sensors increases, the need for a suitable initial configuration diminishes. If fast sensors are placed reasonably near the object's entry point, they can adapt to whatever maneuvers the object may demonstrate. Conversely, as relatively slow sensors are less able to adapt to different object motion, they require a carefully chosen initial configuration to ensure adequate performance.

5 Conclusions

A method for determining a near-optimal initial sensing-system configuration for moving-object surveillance is presented in this paper. The goal of the method is to provide a suitable starting point for real-time dynamic dispatching (reconfiguration) of the sensing system, maximizing its effectiveness. The proposed solution combines a constrained direct search method with simulations of the sensing-system under dispatcher control. This approach is shown to be suitable to one or more trajectories.

Acknowledgements

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