A New Landmark and Sensor Selection Method for Vehicle Localization and Guidance

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Abstract-Markov localization is one of the effective techniques for determining the physical locations of an autonomous vehicle whose the perceptions of the environment are limited. To improve the localization, a multi-sensor approach is used. A landmark selection process is usually employed. The aim of this selection strategy is to select the landmark that answers at best to a criterion. In general, the selected landmark is the one that improve the most the vehicle's location. In this paper, we extend the landmark selection problem into a resource selection (i.e. sensor and feature detection algorithm) problem. This selection is also based on a criterion. However, this criterion is defined in function of the application's objectives. Here, the application concerns vehicle's guidance. This last one requires an accurate and reliable estimation. Thus, we propose a novel selection strategy of the landmark, the sensor, and the feature detection algorithm to offer an accurate and reliable localization. We demonstrate the practicality of this approach by guiding an experimental vehicle in real outdoor environment.

I. INTRODUCTION

Recent years have witnessed a growing interest towards autonomous robots: several industrial and scientific research projects are aimed at obtaining increased autonomy of mobile robots, in order to reduce the intervention of human operators. For instance, such systems are used for touristic courses, cleaning vehicles, farm vehicles guidance,... Several guidance devices have already been developed (e.g. CLAAS [1], John Deere [2], see also [3]). However, these systems have been designed to perform specific tasks (harvesting [1], achieving perfectly straight runs [2], and so on).

In this work, we are interesting in vehicle localization dedicated to a vehicle guidance system. The development of this autonomous robot relies on a Map Aided Localization (MAL) approach. It is obvious that environment perception is the key point for an efficient localization system. Several works have been addressed using a range-finder (see, e.g., [4], [5], [6], [7]), others using camera (see, e.g., [8], [9], [10]) or both ([11]). However, only one sensor can perceive a small part of the environment and most of the case, it measures a single physical component (eg. luminance for a camera). A multi-sensor approach is a way to improve environment perception: a larger and more complete area can be perceived from a given position. Consequently, it

A video of this work is available at the following address: http://tessiercedric.free.fr/manip.wmv

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will be possible to observe a greater diversity of landmarks along the trajectory to follow. This permits to use the localization system in larger environments having a better accuracy. As the goal of the system is to guide accurately the vehicle, an accurate localization is necessary but most of all a reliable position estimation is required. Effectively, the system is based on a MAL approach and thus is susceptible to make wrong data associations [12], [13]. A solution to this problem is to use a Multi-Hypothesis Tracking filter [7], [14]. However, we have decided to not use such a system, too time consuming, which didn't permit us to control the vehicle every 100ms. Rather than propagating all matching hypothesis at a particular time, the system propagates the most probable one. To deal with wrong data association, it can undo a previously made data association.

This paper mainly deals with the landmark and sensor selection problems in Markov localization. A good selection strategy has to optimize the use of the set of sensors fixed on the vehicle and observable landmarks, to answer system's objectives. One of the popularly used strategies is based on the expected information gain, as first proposed in [15]. This information gain was also introduced in [10], [16] and proven to be effective in landmark selection. The mutual information between predicted sensor observation and the current robot location was used to calculate the expected information gain about the robot location attributable to the landmark detection. A novel entropy-based heuristic for landmark selection was proposed in [16] which is computationally more efficient than those relying on the use of a grid-map [15]. Given (a) prior probability distribution of robot location and (b) the location of a set of candidate landmarks, the entropy based approach selects the most informative landmark such that the resulting posterior distribution of robot location has maximal reduction in the entropy compared with the prior distribution. However, this approach answers partially to this problem since it doesn't take into account the reliability notion of the estimation. In Zhang's target tracking system [17], a simple criterion is proposed for sensor selection to maximally increase the probability that a target is at its actual location. We propose here to develop a selection strategy which permits to select not only a landmark but also a sensor and able to take into account guidance process requirements (i.e. accuracy and reliability).

II. VEHICLE LOCALIZATION PRINCIPLE

The autonomous vehicle guidance system proposed estimates periodically the vehicle's pose with a confidence level (e.g. see [18]) associated to this estimation. After this task, it steers the front wheel and fine-tunes the vehicle's speed in order to track the trajectory previously recorded or defined.

This localization system takes part in the Map Aided Localization family and uses a geographical information system (GIS) to identify all landmarks of the environment. From the vehicle's pose, the localization system chooses a landmark to observe. Then, it realizes a data association between the selected landmark and the detection, which permits to locate the vehicle. The landmarks' detection is made using exteroceptive sensors fixed on the vehicle (camera and rangefinder). A multi-sensor approach is used that permits to increase the number and variety of the visible landmarks at a particular time. Consequently, the system should be able to locate itself accurately in a larger area. In some cases, a landmark is susceptible to be detected by several sensors, with an appropriate feature detection algorithm associated to each of them. Generally, the couple sensor/feature detection algorithm has not the same landmark recognition performance as another. For instance, some are accurate, others are reliable with a fast detection. In addition, because of the geometric position of landmarks, all landmarks don't improve the estimated vehicle state in the same manner. For instance, at a particular moment, a landmark will be useful to estimate the vehicle's heading and at another time, it will be only useful to correct the position. The proposed system takes explicitly into account this way to detect a landmark thanks to the use of the perceptive triplet concept. A perceptive triplet is the association of a landmark, a sensor and a detector in a same entity. Thus, the system's goal is no longer to select a landmark to detect but to select a perceptive triplet to use that defines accurately all the steps to recognize the landmark.

Furthermore, due to outdoor considerations, an active search approach ([16], [10], [15]) is used to improve the perceptive triplets observation process. This approach consists in searching the landmark in a small area of the sensor data. This region of interest (ROI) takes into account all the geometrical information of the landmark. It is built using the estimated vehicle position, its uncertainty area and the landmark position in the map (Figure 1). This approach has been extended to our multi-sensor system enabling the use of the focusing concept for each sensor data. For instance, detecting a perceptive triplet in camera image will lead to a focusing on landmarks existing in camera image but also on those existing in range finder space. As the system's objective is to guide the vehicle, an accurate estimation of the vehicle's pose with a high confidence level is necessary. When these two constraints (accuracy and confidence) are not satisfied, the localization system uses perceptive triplets: it means a way to sense and recognize a particular landmark of the environment. Although many such triplets may be observable in a given view of the vehicle's environment,



Fig. 1. Illustration of the active search method representing the ROI of a tree landmark in the range-finder data.

only a few such triplets are necessary to estimate the robot's position and orientation with a high confidence level. One objective of our system: triplets selection strategy, is to iteratively select when it's necessary, the minimum (optimal) set of triplets from the entire set of triplets observable in the robot's environment to satisfy vehicle process requirements. Unfortunately, the whole system is still susceptible to realize a wrong matching hypothesis. The final objective of our system is to manage the confidence level over the estimated vehicle's pose. After each landmark detection or detection failure, this probability is modified function of triplet's performance. When it drops below a threshold, the system is able to revise a previous matching hypothesis in order to recover an uncorrupted vehicle estimation.

III. A PROBABILISTIC FRAMEWORK

A. System's objectives

The objective of our system is to guide the vehicle from an estimated vehicle's pose. This last one is represented by the state vector X associated with its covariance matrix \mathbf{Q} . This vector is estimated by a Bayesian approach through the use of an Extended Kalman filter.

$$X = (x, y, \theta, v, \omega)^T \tag{1}$$

with:

- x abscissa of the position in the world reference,
- y ordinate of the position in the world reference,
- θ vehicle orientation angle in the world reference,
- v linear velocity
- w angular velocity,

We define the event **H**: the true vehicle's position belongs to the uncertainty area (the ellipsis of equiprobability defined by one standard deviation around the estimated position). In the following of the document, we will use the expression "the state is valid" when the event **H** is true.

In summary, the proposed localization system estimates periodically the vehicle's state, it means:

- the state vector X, the associated covariance matrix Q using an active search with an EKF and
- the probability of the event **H** using our probabilistic framework detailed in the next parts.

B. Confidence level evolution

The estimated confidence level over the estimated vehicle's state is function of data associations realized, i.e. the matching hypothesis made between the searched landmark and its detection. Using our focusing system, the landmark detection is made in a ROI. Thus, when the system looks for a landmark in a ROI and no result is returned, the confidence decreases. Conversely, if a result is returned, the confidence increases. This confidence level takes into account not only positive information but also negative ones. Positive information pertains to the detection of a landmark whereas negative information pertains to the detection failure of a landmark. In general, localization systems don't take into account those negative information. Clearly, not seeing a feature when one expects to see it carries relevant information. For example, not seeing the Eiffel Tower in Paris implies that it is unlikely that we are right next to it. We propose now several propositions about ROI's characteristics.

Proposition 1: If the searched landmark doesn't belong to its ROI, then the current vehicle's state is invalid.

Proposition 2: The negation of the proposition 1 is wrong. Effectively, if the current vehicle state is invalid, the searched landmark can yet be present in its ROI. This comes from the fact that the projection function of the landmark from the GIS frame to the sensor data is sometimes surjective. Thus several vehicle's positions can lead to the same ROI for the same landmark.

In our case, the localization system uses a feature detection algorithm to recognize the landmark in its ROI. When the vehicle's state is valid, this algorithm can:

- succeed in detecting the searched landmark,
- detect an information (another landmark or noise) thinking it is the searched landmark,
- fail in recognizing the landmark (no result is returned) whereas the system's state is valid.

When the vehicle's state is invalid, this algorithm can:

- return no result,
- detect an information (noise).

When the feature detection algorithm returns a result, it does not mean that the searched landmark belongs to its ROI. This comes from the fact that the result could be a spurious measurement. In the same way, when it returns no result, it does not mean that the system's state is invalid like it has been explained in *proposition 1* because such a result can be obtained from a valid state. That's why we suggest to modify the confidence level in a stochastic manner. This sums it up:

 Detecting a landmark strengthens the current estimation of the vehicle's state. It means that the landmark is assumed to belong to the ROI and therefore the vehicle uncertainty area contains the true vehicle's position. Thus the confidence level of the current state increases. Then, a new vehicle's state is created with a new position, a new covariance matrix and a new confidence level. This last one is function of the confidence level of the current state and the probability the system has made a right data association.

Detection success:
$$P(H)_{current state}$$
: increases $P(H)_{new state}$: $f(P(H)_{current state})$

2) Not detecting a landmark weakens the current estimation of the vehicle's state because the landmark is assumed to belong to the ROI and the detector returns nothing. Thus the confidence level decreases.

Detection failure:
$$P(H)_{\text{current state}}$$
: decreases (3)

When a detection fails, this notices that maybe the system has made a previously wrong data association. Effectively, after having made a wrong data association, the estimated path doesn't correspond anymore to the true path. Thus, all attempted detections will fail. Consequently, the system can detect a wrong data association by monitoring this confidence level. To recover a correct estimation, it has to undo the last matching.

Detection failure:if
$$P(H)_{\text{current state}}$$
 is too lowundo the last matching

The recognition and detection performances of a landmark depend on the type of the searched landmark, the sensor used and the feature detection algorithm employed. However, the perceptive triplet concept presented in this work is used here to define a way to perceive the environment. By characterising accurately triplets' performance in terms of detection and robustness face to noisy sensor data, the system is able to offer a good estimation of this confidence level.

C. Confidence level calculation

1) Notation: We denote the discrete time index by the variable k, the vector describing an odometry measurement from time k - 1 to time k by the variable u[k], a detector's result at time k by the variable y[k] and the state vector describing the true location of the vehicle at time k by the variable x[k]. A discrete random variable h[k], corresponding to the event H at time step k, is associated to the estimated vehicle's state x[k].

2) Theory: The problem of confidence level calculation can be formulated by a dynamic Bayesian network where the goal is to compute the probability: $P(h[k] \mid y[1:k])$. As we have seen in Equations (2) and (3), the confidence level updating is function of the probability that the feature detection algorithm returns a result. Thus, we define for each perceptive triplet, two terms:

- P(y[k]|h[k]) ($P(\overline{y}[k]|h[k])$): represents the probability that the detector returns (or not) a result when the vehicle localization is valid.
- $P(y[k]|\overline{h}[k])$ $(P(\overline{y}[k]|\overline{h}[k]))$: represents the probability that the detector returns (or not) a result when the vehicle localization at time step k is invalid.

These two probabilities must be computed taking into account the sensor, the feature detection algorithm, the landmark used and most of all of the shape of the ROI. It means that when the focusing is important (small ROI), P(y[k]|h[k]) is far superior over $P(y[k]|\overline{h}[k])$ because of the presence of the searched landmark in the ROI. Thus, thanks to a Bayesian inference, the confidence level is updated in the following manner:

• when the system succeeds in detecting a landmark (i.e.: a result, not necessarily recognizing the searched landmark):

$$P(h[k]|y[k]) = \frac{P(y[k]|h[k]) \cdot P(h[k])}{P(y[k])}$$
(5)

with:

 $P(y[k]) = P(y[k]|h[k])P(h[k]) + P(y[k]|\overline{h}[k])P(\overline{h}[k])$ • when the system fails in detecting a landmark (i.e.: no

• when the system rans in detecting a randmark (i.e., no result is returned):

$$P(h[k]|\overline{y}[k]) = \frac{P(\overline{y}[k]|h[k]) \cdot P(h[k])}{P(\overline{y}[k])}$$
(6)

with:

$$P(\overline{y}[k]) = P(\overline{y}[k]|h[k])P(h[k]) + P(\overline{y}[k]|\overline{h}[k])P(\overline{h}[k])$$

When the system succeeds in detecting a landmark (event y[k] occurs), a new vehicle's position estimation is created like it is represented in Figure 2). After having updated the confidence level of the current state, the system computes the new vehicle's state using the Extended Kalman Filter. It must also calculate the confidence level of this new state. This last one (P(h[k+1])) is function of the probability of the current state and the probability to have made a right data association.



Fig. 2. Presentation of the two steps that occur after a detection success. The first step consists in updating the confidence level of the current step (Eq 5). The final step is the creation of the new vehicle's state with its own confidence level.

Actually, this new probability corresponds to the joint probability of all the matching hypothesis:

$$P(h[k+1]) = P(h[k+1], h[k], ..., h[1])$$

= $P(h[k+1]|h[k]) \cdot P(h[k])$ (7)

where

• P(h[k + 1]|h[k]) is the probability that the vehicle localization at time step k + 1 is correct, it means the probability to have detected the searched landmark. (a right data association)

• P(h[k]) is a hidden state of the dynamic Bayesian network. Thus, it will be replaced by P(h[k]|y[k]), computed by the previous Bayesian inference.

The final term to express is P(h[k + 1]|h[k]). If there are several landmarks of the same type than the searched landmark in the ROI of the searched landmark, the detector will have a low probability to return the correct landmark. The idea is to take into account the fact that other landmarks of the same type than the searched landmark, recorded in the GIS, can belong to the ROI of the searched landmark. Moreover, bigger is the size of the ROI, greater is the probability that some noise is returned. Thus, we suggest to divide this probability into two terms:

$$P(h[k+1]|h[k]) = P(h[k+1]|z[k]) \cdot P(z[k]|y[k], h[k])$$
(8)

where

- P(z[k]|y[k], h[k]) is the probability that the detector returns a registered landmark of the same type than the searched landmark. Thus, this probability corresponds to the capability of the detector to be robust against noise.
- P(h[k + 1]|z[k]) is the probability that the detector returns the searched landmark among all landmarks of the same type existing in the ROI. This probability can be easily computed since it is a combinatorial problem.

In summary, the probability P(h[k+1]) is: $P(h[k+1]) = P(h[k+1]|z[k]) \cdot P(z[k]|z[k]) \cdot P(h[k+1]) \cdot P(h[k+1])$

$$P(h[k+1]) = P(h[k+1]|z[k]) \cdot P(z[k]|y[k], h[k]) \cdot P(h[k])$$
(9)

and each perceptive triplet is defined by these probabilities:

- probability to have a result: P(y[k]|h[k]) and $P(y[k]|\overline{h}[k])$
- probability to detect a landmark (not noise): P(z[k]|y[k], h[k])
- probability to detect the searched landmark: P(h[k+1]|z[k])

IV. A TRIPLET SELECTION STRATEGY

In the section II, the perceptive triplet concept has been presented. This concept permits to the localization system to efficiently select the resources to employ and the landmark to look. The part of the system in charge of this selection is the supervisor that has two objectives:

- determine when it is necessary to sense the environment. The localization system is entirely devoted to the guidance process. When the guidance process requirements aren't satisfied, the localization system will have to use some perceptive triplets. It means that the system only runs some perception algorithms when needed and doesn't process all measurement.
- 2) determine what perceptive triplet, the system must use to answer at best to the vehicle process requirements.

There are three main steps in the localization process. At first, this is a **monitoring** of the vehicle process requirements. Then, the second step is a **decision** step to select a perceptive triplet. And finally, this is an **action** step where the detection of the perceptive triplet is realized.

A. When to look ?

The localization system proposed computes every 100ms an estimated vehicle's state in order to achieve the vehicle control. This estimation is used by the guidance process that controls the vehicle's heading so that it reproduces faithfully the prerecorded path. It is generally admitted that an accurate and reliable position is a necessary condition to control accurately the vehicle. In this part, we defined these conditions. The problem is to know the link between the accuracy of the estimated state at input of the guidance process (computed by our localization system) with the accuracy at output (the lateral deviation with the real path). To answer this question, we have used a simulator based on the control law proposed by [19]. The vehicle used in this simulation is a vehicle with a wheel base of 2.75m moving at 4.1m/s (Fig. 3) and the trajectory to replay is a straight line. As input, the simulator takes the true position and heading of the vehicle affected with a white Gaussian noise with standard deviation respectively $\sigma_{position}$ and $\sigma_{heading}$. As output, the simulator gives the true guidance precision: it means the lateral deviation with the path. In our case, we are interesting in an accuracy of $\pm 0.15m$ that implies a standard deviation on the estimated pose about 0.25m and 0.052rad for the heading. In the following, we will call the volume defined by 0.25m around the estimated vehicle's pose and 0.052radaround the estimated vehicle's heading, the guidance area. Thus, the estimation is sufficiently accurate when the current estimation is inside this guidance area. As the system uses an extended Kalman filter, the vehicle's state is estimated by a Gaussian probability law. However, what is important, is to have a sufficient probability (Pmin) that the estimation is inside the guidance area. We suggest to define a criterion to represent the system's accuracy compared with the guidance area. This criterion is:

$$ACCURACY = max(1.0, \frac{P(x \in [\mu_x \pm 0.25])}{Pmin}) \times max(1.0, \frac{P(y \in [\mu_y \pm 0.25])}{Pmin}) \times max(1.0, \frac{P(\theta \in [\mu_\theta \pm 0.052])}{Pmin})$$
(10)

When this criterion is below 1.0, the estimation is not enough accurate to guide efficiently the vehicle.

In the same way, a criterion is defined to represent the reliability of the current estimation. This criterion is: P(h[k]). When this criterion is below a particular threshold, it means that the estimation is not enough reliable.

As a conclusion, the system has to detect some perceptive triplets when the current estimation is not enough accurate or reliable.

B. What and how to look?

The perceptive triplet concept was introduced in the system to permit a selection of resources to use to locate the vehicle. Contrary to other works [15], [10], [20], [16], the resources to select doesn't correspond only to the choice of landmarks but consists in determining landmarks, sensors and detectors in a coherent manner. Effectively, all detectors are not able to recognize all landmarks: some combinations landmark/sensor/detector are not possible. The aim of this selection process: determine "What and how to look?", is to compute the best location accuracy for the vehicle with a high probability.

When selecting appropriate landmarks, it is essential to maximize the perceptual distinctiveness of landmarks. The further apart landmarks are, the smaller the chance to accidentally confuse them. It is therefore common practice to choose landmarks that are sufficiently far away from each other so that the probability of confusing one with another becomes small. It can also be interesting to select landmarks that cannot be recognize with the same couple sensor/detector.

1) The selection procedure: An important issue is how to define a meaningful metric that can be used to optimize the performance of the entire system. A specific criterion must be associated to each perceptive triplet evaluating the appropriateness in estimating the robot location. This criterion can be either static of dynamic. In Markov localization, it is dynamic; i.e. data dependent. This means that past measurements together with past choice of triplets will affect which triplet to choose at present. However, when dealing with the triplet selection problem, it faces a combinatorial explosion in the search space. The optimal solution requires to exhaustively explore the triplet list which has exponential complexity. For this reason, we decide to adopt a greedy heuristic method.

Fox [15] and Davison [16] suggest to use a payoff function. The payoff, denoted r, is a function of the state and the perceptive triplet and can be divided into two terms:

- the *utility*: U, that indicates how a triplet participates to system's objectives,
- and the *cost*: C.

Given the utility and cost of all observable perceptive triplets, the system chooses the triplet "*triplet**" to detect that maximizes:

$$triplet* = \operatorname{argmax}_{triplet}(U(x, triplet) - \delta \cdot C(x, triplet))$$
(11)
Here δ determines the relative importance of utility versus

Here δ determines the relative importance of utility versus cost. The choice of δ depends on the application.

2) *Perceptive triplet description:* It's necessary to define the utility and the cost for each perceptive triplet. When a perceptive triplet is detected, the detection leads to:

- a rise of the **confidence level of the current estimation**. We define the variable CONFIRMATION as the updated confidence level.
- a rise of the vehicle location accuracy.
- the creation of a **new estimation with a confidence level** function of the probability to have made a right data association. We define the variable BELIEF as this new confidence level.

and the detection requires:

• a detection time.

Thus, the utility and the cost of a triplet are:

$$U(x, triplet) = \alpha \cdot \text{CONFIRMATION}(x, triplet) + \beta \cdot \text{ACCURACY}(x, triplet) + \gamma \cdot \text{BELIEF}(x, triplet) + \gamma \cdot \text{BELIEF}(x, triplet) \\ C(x, triplet) = \frac{\text{detection time}(x, triplet)}{\text{system's period}}$$
(12)

Here, α , β , γ determine the relative importance of each term of utility. The terms CONFIRMATION, ACCURACY and BELIEF correspond here to expected value.

V. EXPERIMENTATIONS

A. OVERVIEW

The following section describes experimentations that were carried out to validate our approach. A terrestrial vehicle was used for the experiments. This research platform, called "Arocco" (Figure 3), was initially equipped with odometers, a wheel direction angle sensor and an on-board PC running Linux RTAI. A video camera (Sony VL500) giving 7.5 640x480 YUV422 images per second and a rangefinder was added to the robot.



Fig. 3. "Arocco" with the camera and the range-finder

B. PROBABILISTIC FRAMEWORK

The aim of this part is to illustrate the probabilistic framework used. The figure 4 presents the scene seen on the top. On this map, we can distinguish five tree landmarks and the true vehicle's pose in green. The system is first initialized using a magnetometer and a low cost GPS. This initial position is represented by the red circle and the red ellipsis represents the uncertainty area.

At the end of the experiment, we have built the matching hypothesis tree represented on Figure 5. Figure 6 shows the probability curve and Figure 7 the system's accuracy. What we can notice is that the initial state is reliable but not accurate. A fist matching is realized with landmark (a) that permits to increase the accuracy and a new state is created with a probability of 0.23. Then, the system fails in detecting landmark (b). This detection failure and the low confidence level indicates that the previous data association is wrong. Then other detections are realized and all ones succeed in detecting a result. It permits to increase the system's accuracy and to strengthen the current state.



Fig. 4. The map seen on the top with 5 tree landmarks, the true vehicle's pose in green and the estimated initial vehicle's pose in red with its uncertainty area.



Fig. 5. The hypothesis matching tree.



Fig. 6. Probability of the a posteriori state during the experiment.



Fig. 7. Accuracy of the localization during the experiment.

By using focusing system characteristic, the proposed probabilistic framework is able to offer an estimation of the confidence level. When the system fails in detecting a landmark, this probability is used to detect wrong data association and recover a valid vehicle's state.

C. TRIPLET SELECTION STRATEGY

The triplet selection strategy is integrated in our system to better answer application's objectives. The aimed application concerns vehicle's guidance. It requires an accurate localization. As we have seen it in Section IV, the estimated position must have an accuracy of $\pm 25cm$ and the estimated heading must have an accuracy of $\pm 3^{\circ}$. This permits to define a guidance area. For this first experiment, we have chosen to set the minimum probability to belong to this area to Pmin = 0.7. In addition, the application also requires a reliable localization. We have chosen the criterion P(H) > 0.8.

TABLE IComparison of system's results.

	with strategy	without strategy
number of wrong matchings	1	2
nb steps to be accurate	6	8
nb steps to be reliable	5	8

From the previous experiment, we have compared localization's results using our strategy in the first case and without it in the second case. The second case means that the observable perceptive triplets list is built but it is not sorted using a specific criterion like the payoff function. Thus, triplets are selected randomly. Table I summarizes these results. For this experiment, the strategy permit not only to answer quickly to accuracy criterion and reliability criterion but also to reduce the number of wrong matchings. In summary, the triplet selection strategy is a way to improve the vehicle localization system in relation with the application.

VI. CONCLUSION

This paper presents a landmark and sensor selection strategy for multi-sensor perception systems. It fits very well into the proposed system. This last one uses a probabilistic framework to compute a confidence level on the system's state estimation. The suggested strategy uses the set of probabilities defined in this framework and the accuracy of the estimation. In addition, application's goals were formulated that permits to the strategy to launches detections when it's necessary and useful. In our case, we have used this strategy in a vehicle localization application. This multisensor application was able to guide a vehicle in an outdoor environment on a 300m length path. The vehicle followed faithfully this trajectory ten times (without stopping). The max lateral deviation with the reference path was below 10cm.

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