Fusion of active detections for outdoor vehicle guidance

Cédric Tessier, Christophe Debain
CEMAGREF
24, avenue des Landais
BP 50085, 63172 Aubière, France
cedric.tessier@cemagref.fr

Roland Chapuis, Frédéric Chausse
LASMEA - UMR 6602
24, avenue des Landais
63177 Aubière, France
chapuis@lasmea.univ-bpclermont.fr

Abstract - One of the major current developments in outdoor robotic aims at providing vehicles with automatic guidance capabilities. Such systems need a localization module to work. However, indoor localization methods are not directly usable in outdoor due to noise and the dynamic aspect of these environments. In this paper, we propose an original active localization system relying on sensors fusion able to supply an accurate position with a high confidence level. The main contributions of this work are: 1) The introduction of the “perceptive triplet” notion that associates landmarks, sensors and detectors to supervise the detections. 2) The use of a supervisor that determines at each time which landmark, with which sensor and detector, should be used to detect this landmark in order to improve the localization. The supervisor constitutes the intelligent part of this localization system. It decides when it’s necessary to detect a landmark. 3) The integration of a confidence level over the vehicle’s pose estimation that permits to take wrong matching hypothesis into account. Our system was tested in an outdoor environment, where it succeeded in accurately localizing the vehicle.

Keywords: active detection, perceptive triplets, confidence level, supervised localization

1 Introduction

The autonomous guidance of an outdoor vehicle requires its localization. A process able to estimate the vehicle’s pose (position and orientation) has to be set up. Vehicle guidance in an outdoor environment mainly makes use of a GPS-RTK (Real Time Kinematics) system, sometimes coupled with odometers. Thus, some researchers suggest an accurate path tracking algorithm in outdoor requiring an accurate localization system such as in [1]. In this particular case, only a GPS-RTK is used, which is not always adequate. On one hand, the position alone is not sufficient for path tracking in outdoor environment (other parameters must be estimated during vehicle guidance: roll, pitch, …). On the other hand, these systems are expensive and not robust enough because of GPS signal losses: accuracy to within 2 centimeters, the main advantage of GPS-RTK, is not always available. However, these systems are reliable. It means the probability that the real vehicle position belongs to the GPS uncertainty area (the area defined by three standard deviations around position given by GPS) is 99%. We want to build a localization system for vehicle control task, providing an accurate position (most of the time below 25 cm) with a high confidence level (most of the time about 70%) but without GPS-RTK drawbacks. The solution, proposed in this paper, is based on the perception of the environment by exteroceptive sensors. Such methods make matchings between environment landmarks and features detected in sensor data. A landmark detection provides a clue about the vehicle’s pose. In general, several matchings are necessary to reach a good precision. However, the presence of a wrong matching can generate a wrong position estimation. As a result, it’s impossible to have a whole confidence in the vehicle pose estimated by the system.

Precision and confidence are two notions explicitly taken into account in the suggested localization method. Before describing it, let’s analyze the main localization approaches based on the perception of the environment. The main problem of those systems concern the recognition of landmarks. It means detecting the landmark and making a matching hypothesis between the detection and the searched landmark. Two distinct and well-known solutions then arise: 1) landmarks global search, and 2) landmarks local search (also called active detection). In the first way, it consists in building a local map of the landmarks around the vehicle and then realizing a map-matching [2], [3], [4]. Contrary to this approach, active detection aims at searching the landmark in the sensor data where it supposed to be. This is done by taking into account the vehicle position uncertainty and by projecting landmark position into the sensor data [5], [6], [7]. In our case, we must localize the vehicle in outdoor environment, which leads to two difficulties:

- the noise. In a landmark detection system, a detector is an algorithm responsible for landmark detection, working on sensor data. Apply it on the whole sensor data takes a long time and risks to not detect the landmark but noises (robot evolves in outdoor).
- the dynamic aspect of environment. To avoid detecting other objects than the searched landmark, it’s possible to improve the landmark’s model. However, if this model describes very well an environment area at a particular time, it will be inadequate at another time. This is due to the dynamic aspect of outdoor en-
environment. Thus, localization systems have to allow some deviations between the landmark’s model and the landmark, to work. Unfortunately, those deviations cause the detection of other landmarks than the searched one.

Landmark active detection constitutes a solution to these problems. Thus, the algorithm proposed in this paper is based on active detection method, using a landmark bank. This bank can be obtained beforehand by a SLAM process (Simultaneous Localization and Mapping). Let’s remark that SLAM processes are useless for the vehicle automatic guidance we are looking for here.

This paper is organized as follows: the mechanism of landmark active detection is first recalled. Through a state of the art, we underline limitations of this classical approach. The new notion of perceptive triplets is then presented to improve landmarks detection. Next a confidence level is integrated in the localization system in order to answer classical approach drawbacks. Section 3.3.3 describes the localization framework that manages perceptive triplets and confidence level. Finally, full scale experiments in outdoor environment are reported. Localization accuracy and confidence level progress are analysed in details.

2 General active detection framework

2.1 Landmark detection components

A landmark active detection system needs three components to work:

1. a landmarks bank. Several kinds of bank can be defined: Fox [8] proposes to use a probability grid while other researchers [9] and [10] suggest to use a metric map. Each landmark, recorded in the data bank, possesses its position in the absolute reference (the one used for vehicle localization). Other characteristics can be added to improve the landmark recognition.

2. some exteroceptive sensors. In a landmark detection system, the robot must be equipped with exteroceptive sensors able to perceive detectable features of landmarks. For instance, landmark active detection systems have been realized from ultrasound sensor or telemeter [8] or camera [10], [11] and [9]. If range finders provide a distance from robot to landmark, a camera doesn’t provide directly a clue about landmark position. The detector, explained in the next paragraph, permits to solve this problem.

3. some detectors. Detectors are algorithms working on sensor data able to recognize a particular landmark. When the system tries to detect a landmark, it uses an exteroceptive sensor that provides a perception of the environment, not directly the landmark position. The purpose of the detector is to provide this information.

2.2 Classical active detection principle

Draper [10] introduces a detection system able to select a landmark and recognize it at a given time. The estimated pose of the vehicle is used to select a landmark on the map. Then the color of this landmark is used to focus the system attention on a specific region of interest of the camera image. Nevertheless, the window-of-interest is built from landmark features and not from vehicle position. It means that the detector works on the entire image to built a window and then it detects the landmark in this window. Yoon [11] and Davison [9] suggest to use the vehicle position to built the regions of interest of the searched landmark. It permits to improve drastically landmark detection and reduce wrong matching hypothesis (i.e. noise detection). In the same manner as [10], Fox [8] and Davison [9] select a landmark according to a criterion to improve the vehicle localization system. This selection criterion is computed from the vehicle state (vehicle position and position covariance).

Figure 1 summarizes this process. Each number represents a step in the localization process.

Figure 1 summarizes this process where the red bold arrows represent the active notion. We can divide the process of active detection in three steps. The first consists in selecting a landmark. Then an area is created in the sensor data, thanks to vehicle state (vehicle position and position covariance) and landmark position supposed to be (the one defined in the landmarks bank). Thus, the searched landmark might belong to this area. Finally, a matching hypothesis is made between the landmark to detect and the detection: detector’s results applied to searching area.

2.3 Limitations of this classical approach and suggested improvements

In the landmark detection system proposed by [9], Davison explains it will be necessary to built a more realistic system to take into account wrong matching hypothesis. Only Yoon [11] suggests a manner to avoid such problems. Unfortunately, the module proposed
works after detecting all landmarks and not during the localization process.

In this paper, we suggest two improvements of the classical active detection process to answer this drawback. The first consists in the use of a new concept, called hereafter “perceptive triplet”, to reduce the probability of wrong matching hypothesis. The second improvement permits to avoid taking into account wrong hypothesis, by the integration of a confidence level over the vehicle’s state estimation. Finally, a framework is proposed to manage all these detections.

3 Enhanced active detection

3.1 Perceptive triplets

Because of outdoor considerations, it is necessary to use several sensors. Thus, a landmark is susceptible to be perceived by various types of sensors. Moreover, for a given sensor, several detectors are ready to extract the features corresponding to a particular landmark. One of the sensor/detector couples will detect the landmark differently from another (precision, reliability, detection speed). The association of the 3 elements:

- landmark (type, position, position covariance),
- sensors able to perceive the landmark,
- detectors able to extract the features of the landmark from the sensor data,

is called hereafter a “perceptive triplet”. Thus a landmark can belong to several perceptive triplets. The introduction of this new concept is motivated by the use of several sensors and several detection algorithms. Figure 2 shows the interaction of the triplet in the classical scheme.

The first step of the landmark detection system becomes a perceptive triplet selection. The choosing triplet obliges the system to use a specific sensor and detector to recognize the landmark. The triplet selection step will be detailed in Section 3.3.

3.1.1 Landmarks bank

The landmarks bank used in our localization system registers several landmark information:

- Name
- Type: dot, line segment or poly-line (these 3 types are used in Geographical Information Systems)

We add to each type the coordinates of its position in the absolute reference (the one used for vehicle localization) and the covariance matrix of these coordinates. This last matrix makes possible to take the uncertainty on the position of landmarks into account in the active detection process.

3.2 Confidence level

The second new notion introduced in this paper is the confidence level. The aim of this confidence level is to provide to vehicle control process not only an estimated vehicle position but also a probability that the real position is inside the vehicle uncertainty area (computed thanks to the vehicle position covariance).

The use of this confidence level over vehicle position estimation is motivated by the problem of wrong matching. Actually, when the system tries to detect a landmark, it applies a detector in the region of interest defined in the sensor data. If this detector succeeds in recognizing the landmark feature, a matching hypothesis is made between the detection and the searched landmark. We can distinguish three kinds of matching hypothesis:

- a correct hypothesis: the detection corresponds to the searched landmark,
- a wrong hypothesis: the detection corresponds to another landmark,
- a wrong hypothesis: the detector returns noise as a landmark.

However, the system has not any information to decide if the matching is correct or not. The problem is that a wrong matching might generate a wrong position estimation (the real vehicle position is outside vehicle uncertainty). In this case, the next active detections have a high probability to fail because regions of interest are built from a wrong robot’s position. In [9], Davison has not this problem because he uses landmarks very easy to detect in indoor environment. Yoon [11] suggests a method to detect wrong hypothesis. Unfortunately, this detection is made after the localization process and not during it.

The part of the system responsible for the confidence level progress is the supervisor explained in details hereafter.

3.3 Supervisor

3.3.1 Description

The supervisor: the intelligent part of the localization system, has three objectives:

Figure 2: Introduction of the perceptive triplet selection in the active landmark detection based localization system. Each number represents a step in the localization process.
check some criteria to know when it’s necessary to detect a landmark,
select the “best” perceptive triplet according to a criterion,
monitor the confidence level. A low confidence level indicates that localization system is making a wrong estimation of the robot’s pose due to a wrong matching (or erroneous data in the data bank, not considered here).

Figure 3 describes the localization system mechanism.

![Figure 3: Synopsis of localization algorithm.](image)

### 3.3.2 Perceptive triplet active detection

Our localization system is based on a technique of iterative pose updating. It means, after each perceptive triplet detection, vehicle state is updated. It consists in computing the new vehicle pose estimated and the new vehicle position covariance. Moreover, the regions of interest of other triplets have to be recalculated as vehicle uncertainty area was reduced. Then, the system can detect another triplet in an optimal manner.

All this algorithm is based on the use of an extended Kalman Filter. This section aims to explain the perceptive triplet active detection principle. To illustrate the triplet detection effect over the other triplets, we take an example with a single kind of triplet: a white line landmark, a camera and a line detector.

The first step of active landmark detection consists in defining a region of interest by taking into account the vehicle’s position \( X \), the covariance of this position \( C_X \), and the landmark’s position \( A \).

\[ A_{EstimatedSensor} = f(X, A) \]

\[ C_{ASensor} = J_f \cdot \begin{pmatrix} C_X & 0 \\ 0 & C_A \end{pmatrix} \cdot J_f^t \]  

where:
- \( A_{EstimatedSensor} \) is the landmark position in sensor data (here the image),
- \( C_{ASensor} \) is the landmark position covariance in sensor data,
- \( f \) is the projection function in sensor data,
- \( J_f \) is the Jacobian matrix of partial derivate of \( f \),
- \( C_X \) and \( C_A \) are the landmark position covariance in the absolute reference.
- \( Q_{Detector} \) is the measurement noise covariance.

Finally, vehicle’s position and position covariance are updated using a Kalman filter, taking as measurements the output of the detection.

\[ K = C_X \cdot J_f^t \cdot (J_f^t \cdot C_X \cdot J_f^t + Q_{Detector} + Q_L)^{-1} \]
\[ X = X + K \cdot (A_{DetectedSensor} - f(X, A)) \]

- \( C_A \) is the landmark position covariance in the absolute reference.

Then, the detector tries to recognize the landmark in this area. For this kind of landmark: line landmark, a slope test is made during the recognition process in order to take into account only the data compatible with the information indexed in the landmark bank.

\[ Detector’s results: \]
- \( A_{DetectedSensor} \): landmark position detected in image,
- \( Q_{Detector} \): measurement noise covariance.

\[ Vehicle state updating: \]

\[ K = C_X \cdot J_f^t \cdot (J_f^t \cdot C_X \cdot J_f^t + Q_{Detector} + Q_L)^{-1} \]
\[ X = X + K \cdot (A_{DetectedSensor} - f(X, A)) \]
\[ C_X = (1 - K \cdot J f_1) \cdot C_X \] (5)

where:
- \( K \) is the Kalman gain,
- \( J f_1 \) is the Jacobian matrix of partial derivatives of \( f \) with respect to \( X \),
- \( Q_L \) is the landmark position covariance in sensor data induced by \( C_A \).

A real scenario (Figure 4) illustrates this stage. As we can see, after each detection, the vehicle position uncertainty is reduced, that decreases the size of the regions of interest of other triplets.

3.3.3 Confidence level progress

A method is here proposed to avoid to take into account wrong hypothesis by defining a probability on vehicle state estimation. The probability theory was chosen for the fusion method since a bayesian formalism is used by the Kalman filter. Actually, our localization system is based on the fact that all the detections must be coherent each other:
- recognizing a landmark permits to focus on seeking on another landmark (reduction of regions of interest),
- detecting a landmark increases the confidence level. It means that the landmark belongs to the region of interest and therefore the vehicle uncertainty area contains the real vehicle position,
- not detecting a landmark reduces the confidence level.

To integrate this probability in our system, we define two events:
- event H: the real vehicle’s position belongs to the ellipsoid of equal density function of \( \bar{X} \) defined by one standard deviation around updated \( \bar{X} \),
- event O: the detector returned a result when it actively searched for a particular landmark.

Only “one standard deviation” is used in the definition of the event H because active detection process uses also only one standard deviation to build landmarks’ searching areas. Moreover, in the definition of the event O, we define a result returned by a detector. In most cases, this result corresponds to the searched landmark but sometimes, it corresponds to another information (another landmark or noise). In the next formulas, we’ll make the assumption that future data are independent of past data given knowledge of the current state (an assumption typically referred to as the Markov assumption).

The objective is to compute \( P(H) \) probability for each vehicle position estimation. When the system succeeds in detecting a landmark (event O occurs), it updates this probability by replacing it with:

\[
P(H/O) = \frac{P(O/H) \cdot P(H)}{P(O/H) \cdot P(H) + P(O/\overline{O}) \cdot P(\overline{O})} \tag{6}
\]

In the same way, when the system fails in detecting a landmark (event \( \overline{O} \) occurs), it updates this probability by replacing it with:

\[
P(H/\overline{O}) = \frac{P(\overline{O}/H) \cdot P(H)}{P(\overline{O}/H) \cdot P(H) + P(\overline{O}/\overline{H}) \cdot P(\overline{H})} \tag{7}
\]

- \( P(O/H) \) \((P(\overline{O}/H))\): represents the probability that the detector returns (or not) a result when the vehicle localization is correct.
- \( P(O/\overline{O}) \) \((P(\overline{O}/\overline{H}))\): represents the probability that the detector returns (or not) a result when the vehicle localization is improper.

When the system succeeds in detecting a landmark, a new vehicle position estimation is created. It’s necessary to define a probability for this estimation.

- event \( \text{Ho} \): the real vehicle’s position belongs to the ellipsoid of equal density function of \( \bar{X} \) defined by one standard deviation around updated \( \bar{X} \).

And the confidence level for this new estimation is:

\[
P(\text{Ho}/O) = \frac{P(O/\text{Ho}) \cdot P(\text{Ho})}{P(O/\text{Ho}) \cdot P(\text{Ho}) + P(O/\overline{\text{Ho}}) \cdot P(\overline{\text{Ho}})} \tag{8}
\]

- \( P(\text{Ho}) \): represents the volume ratio of vehicle position uncertainty areas before and after the detection.

Figure 5 summarize the probability evolution after some detections.

When the system fails in detecting a landmark, supervisor updates \( P(H) \) by computing \( P(H/\overline{O}) \). This update drops down \( P(H) \). If this probability becomes lower than a threshold, it means that the system made a wrong matching hypothesis and the supervisor deletes the final matching (erasing the effect of the last detection).

3.3.4 Supervisor’s conditions

In this section, we explain supervisor’s conditions. By now, we implemented two conditions: a condition about accuracy of localization and another about the confidence level.

The condition about confidence level consists in verifying that \( P(H) \) is above a particular threshold. About accuracy condition, it consists in checking that the accuracy provided by the localization system is sufficient to control the vehicle. This is realized by comparing the standard deviation of longitude and latitude with 10 cm value. This one represents the localization accuracy needed for an accurate vehicle control such as in [1].

3.3.5 Perceptive triplet selection

To improve the localization system, it’s necessary to choose the landmark to detect, or best, to choose the perceptive triplet. Davison [9] suggests to choose the landmark that improves the localization. However, it uses ideal detectors that can’t make mistakes (detect noise). In our case, we prefer to choose the triplet that maximizes the probability to do a correct matching. This criterion is defined by choosing the perceptive triplet that has the lowest probability \( P(O/\overline{O}) \). When vehicle is badly localized, this low probability ensures the system has little chance to return a detection. In other words, this criterion permits to detect wrong matching hypothesis as soon as possible.
4 Experimentation and results

4.1 Description

A terrestrial robot was used for the experiments. This research platform, called “Robucar TT” from Robosoft company (Figure 6), was initially equipped with odometers, a wheel direction angle sensor and an onboard PC running Linux RTAI. A video camera (Sony VL500) giving 7.5 640x480 YUV422 images per second, a low cost GPS and two inclinometers was added to the robot.

4.1.1 Perceptive triplets

For this experiment, the system works with four types of perceptive triplet. Each type is described in Table 1. As we can see, there’s only one perceptive triplet associated to the single exteroceptive sensor (camera): country path sides. This decision comes from the fact that we want to use natural landmarks and not to create artificial landmarks for improving the localization process. Moreover, we must remember that all these kinds of perceptive triplets are actively detected.

As we explain in Section 3.3.3, it’s necessary to define some values to the probability for each kind of perceptive triplet. By now, these probabilities have been estimated by our knowledge (Table 2). We plan to realize a statistical survey, though.

<p>| Table 1: Four types of perceptive triplet are used in experimentations |</p>
<table>
<thead>
<tr>
<th>Sensor</th>
<th>Detector</th>
<th>Landmark</th>
</tr>
</thead>
<tbody>
<tr>
<td>low cost GPS</td>
<td>–</td>
<td>vehicle’s pose (longitude, latitude)</td>
</tr>
<tr>
<td>inclinometer 1</td>
<td>–</td>
<td>vehicle’s rolling</td>
</tr>
<tr>
<td>inclinometer 2</td>
<td>–</td>
<td>vehicle’s pitching</td>
</tr>
<tr>
<td>camera</td>
<td>path side detector</td>
<td>path side landmark</td>
</tr>
</tbody>
</table>

<p>| Table 2: Probability values for perceptive triplets |</p>
<table>
<thead>
<tr>
<th>Triplet</th>
<th>$P(O/H)$</th>
<th>$P(H/O)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.8</td>
<td></td>
</tr>
<tr>
<td>2, 3</td>
<td>0.5</td>
<td>0.3</td>
</tr>
<tr>
<td>4</td>
<td>0.75 (small windows*)</td>
<td>0.5 (medium windows*)</td>
</tr>
<tr>
<td></td>
<td>0.5 (medium windows*)</td>
<td>0.3 (large windows*)</td>
</tr>
<tr>
<td></td>
<td>0.2</td>
<td></td>
</tr>
</tbody>
</table>

*: the region of interest defined by the active detection method.

4.1.2 Scenario

The scenario (Figure 7) shows the environment where we test the performance of our localization system. The experimentation’s goal is to localize the vehicle in the red area. A real application of such a localization could be for instance a road tracking. We decide to test our method in a complex scenario in order to study this behavior: wrong matching hypothesis detection, confidence level value during wrong vehicle pose estimation and accuracy. The complex scenario comes...
from lot of pitch and roll angles perturbations and low-cost GPS signal losses.

Figure 7: Evaluation of vehicle localization system in the red area

During the experiment, vehicle position estimated by our localization system is recorded, while vehicle is driven by human. A GPS RTK (THALES Navigation) giving the absolute position of the robot with $2\text{cm}$ accuracy at a frequency $10\text{Hz}$ is used as a reference position sensor.

4.2 Localization system valuation

To analyse our system during localization process, we made two studies: an accuracy analysis and a study of the confidence level.

4.2.1 Accuracy

To analyse the accuracy of our system, we represent on the Figure 8 two standard deviations. $\sigma_\parallel$ represents the standard deviation of vehicle position along the vector parallel to lane limits whereas $\sigma_\perp$ is the standard deviation of vehicle position along the vector perpendicular to lane limits. As we can see on the following figure, $\sigma_\perp$ is very low whereas $\sigma_\parallel$ is close to $0.8m$. This important value does not indicate a weakness of our system because it’s due to landmarks distribution in environment. An accurate localization system need a landmarks’ distribution more appropriated.

Figure 8: Evolution of $\sigma_\parallel$ (blue) and $\sigma_\perp$ (black) over detection attempts

4.2.2 Confidence level analysis

The position estimated by our method is compared each time with the GPS-RTK reference by computing the difference (error) between them. Moreover, we define $\sigma_{error}$ as the standard deviation along the error vector. It permits to know when the vehicle uncertainty area contains the real vehicle position. To conclude we can say that our localization system fails to localize the vehicle when $\sigma_{error}$ is lower than error because the real vehicle position is outside the uncertainty area. Figure 9 summarizes symbols used.

Figure 9: Definition of error and $\sigma_{error}$

(a) Evolution of localization error (red) and $\sigma_{error}$ (blue) over detection attempts

(b) Evolution of confidence level over detection attempts

Figure 10: Localization error and confidence level progress

Figure 10(a) shows the absolute position error changes along detection attempts while Figure 10(b) shows the confidence level evolution. At first, we can notice that the confidence level is, in general, at a high level. This is due to localization system succeeds in detecting perceptive triplets.
• From detection 0 to 200, system manages to localize correctly the vehicle.
• From detection 200 to 300, system fails in localizing the vehicle. The $P(H)$ drop-off indicates that several landmark detections failed. The low value of this confidence level informs system from a wrong matching hypothesis have been made. Next, system succeeds in detecting landmarks as we can notice by the increase of $P(H)$.
• From detection 300 to 550, $\sigma_{\text{error}}$ is greater than error and $P(H)$ is close to 1. The localization system works perfectly.

5 Conclusion and future work

This paper has proposed a fusion strategy of landmarks active detection to localize a vehicle in outdoor environment. A new active detection mechanism has first been designed. This system includes two new notions. First the perceptive triplet concept has been added in the classical active detection scheme, to improve vehicle localization in outdoor environment. Then a confidence level over vehicle state estimation has been integrated, in order to avoid to take into account wrong matching hypothesis. Finally, an active detection framework has been presented to manage these two new notions during the landmark detection process.

Capabilities of the proposed localization system have been studied via experiments, demonstrating important improvements. Confidence level, provided by our localization system, permits to monitor vehicle pose estimated, and most of all, to detect wrong vehicle pose.

Improvement in active localization system can be achieved by integrating mobile sensors. We are currently working on the use of a telemeter to focus the sensor on the searched landmark. Another benefit can be gained by improving perceptive triplet selection. A more elaborate triplet selection strategy (taking into account the precision, the reliability, the detection speed of each perceptive triplet) should be able to localize vehicle with a great confidence.

References


