Laser-to-Radar Sensing Redundancy for Resilient Perception in Adverse Environmental Conditions

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Abstract
This paper presents an approach to promote the integrity of perception systems for outdoor unmanned ground vehicles (UGV) operating in challenging environmental conditions (presence of dust or smoke). The proposed technique automatically evaluates the consistency of the data provided by two sensing modalities: a 2D laser range finder and a millimetre-wave radar, allowing for perceptual failure mitigation. Experimental results, obtained with a UGV operating in rural environments, and an error analysis validate the approach.

1 Introduction
This work focuses on the development of reliable perception systems for outdoor unmanned ground vehicles (UGV), in particular in adverse environmental conditions (e.g. presence of airborne dust, smoke, thick fog or rain). The problem of modelling and mitigating systematic errors in perception models, such as sensor measurement errors or sensor misalignment, has been extensively studied by robotics researchers and thorough solutions have been proposed (e.g. [Underwood et al., 2010] for range sensors such as laser range finders (LRF) or radars). However, the main remaining challenge lies in interpretation errors. These errors can be random, are difficult to predict, and can often be orders of magnitude larger than the systematic errors mentioned above. Arguably, a reliable perception system should use different sensor modalities [C. Thorpe et al., 2001; C. Urmson et al., 2008], especially for outdoor operations. As these modalities sense the environment using different physical processes, they also respond differently to environmental conditions. For example, a mm-wave radar has excellent properties of penetration through heavy dust and smoke in contrast to a laser, and an infrared camera can see through smoke, contrary to a visual camera. Therefore, a more reliable perception system can be obtained by intelligently combining the data provided by such different sensing modalities [A. Kelly et al., 2006].

While the fusion of observations made by a laser and a radar in clear conditions, e.g. without the presence of challenging conditions such as dust or smoke, is straightforward when a good sensor error model is available [Underwood et al., 2010], it relies on the assumption (or precondition) that the two sensors actually detect the same targets in the environment. If, for example, a LRF does not see through a heavy dust cloud while a radar does, this assumption does not hold any more. Therefore, in such a situation data fusion should not be executed, at least not in its traditional form. Consequently, to be robust to adverse environmental conditions, the perception system should have the ability to verify this assumption of data consistency prior to fusion. Another advantage to this ability is that the data provided by a LRF can be conveniently filtered, separating points returned because of dust or smoke that a radar would hardly be affected by. The radar could then ensure that detection of actual obstacles and terrain modelling remains operational, albeit less accurate (since the radar accuracy is typically not comparable to the laser’s, as described in Table 1).

Recently, laser range finders capable of returning multiple echoes for each emitted pulse have been introduced commercially (e.g. the Sick LMS5xx series [SICK Inc., 2012b] or LD-MRS [SICK Inc., 2012a] for automotive applications). Although this ability has made such laser sensors more robust to adverse environmental conditions (e.g. compared to the LMS2xx series), they cannot provide a full solution of the problem. Because of the level of attenuation of the laser signal, a mm-wave radar will still be able to penetrate better through obscurants such as heavy dust that would eventually block laser signals [Brooker, 2009; Ryde and Hillier, 2009]. Moreover, an analysis of pre-conditions for laser-radar fusion and for separating dense objects from such obscurants would still be required to obtain a resilient navigation of the UGV.

The idea of using laser-radar data comparison for per-
2 Laser-Radar Redundancy

In order to compensate for the mis-alignment of the laser and radar sensors, we need to perform an extrinsic calibration of the relative transformation between the two sensors (or the transformation between each sensor and a frame linked to the body of the vehicle, which we will call the body frame). In this paper we use the calibration technique described in [Underwood et al., 2010], which can achieve a joint extrinsic calibration of multiple exteroceptive range-based sensors such as lasers and radar. Since the configurations of the sensors are different, only a (common) part of a synchronised pair of laser-radar scans contain points that can be considered consistent\(^1\).

This part can be seen as a “common footprint” (or “footprint overlap”) of the two scans and can be conveniently expressed as a range of bearing angles for each type of scan. Hereafter, all comparison of laser and radar points is made within this common part of the scans. Another important thing to consider during this comparison is the range resolution of the two sensors. As described in Table 1, radar resolution is much bigger than the laser resolution.

![](image.png)

**Figure 1:** The Argo UGV and its sensors.

The rest of the process can happen systematically online. Sec. 2.1 describes how target data points are extracted from the radar raw data (i.e. noise removal). Then, Sec. 2.2 shows how radar and laser points are effectively compared after their transformation into the body frame.

For each bearing angle the radar provides an FFT (Fast Fourier Transform) spectrum. Using the “radar equation” [Brooker, 2009] this spectrum can be mapped to a function of intensity vs. range. Most robotics applications only use the highest peak of that spectrum as a range value provided by the radar (such as in our prior work in [Peynot et al., 2009]). However, this leads to the loss of a significant amount of useful information contained in the rest of the spectrum. As an example, [Reina et al., 2011] exploited the shape of this spectrum to estimate a model of the ground. The resulting ground

\(^1\)The adjective consistent will be used to refer to the local agreement between laser and radar observations.

\(^2\)Note that radar and laser manufacturers use a different definition for resolution. The radar precision when observing a flat plate actually approaches that of the laser.
estimation was significantly more accurate than when using the highest peak of the spectrum only. However, this particular technique can only be used if a model of the spectrum profile obtained for a given target (such as a roughly flat piece of ground) is known a priori.

2.1 The Radar Data

In order to make a “fair” comparison of the radar points with observed laser points, in this paper we extract other peaks (local maxima) from the spectrum, in addition to the highest peaks (the global maxima), see Fig. 2(a). This will provide us with a better resolution in the discrimination of laser-radar data. First, for each radar bearing angle, all intensity peaks above a threshold of intensity are extracted from the radar spectrum (note that this includes the highest peak). This threshold is defined in order to minimise the radar noise. Then, given that:

- the laser actually detects dust, smoke or rain particles that the radar waves penetrate through,
- the perception is inconsistent because of the material the target is made of (e.g. the radar may detect the presence of a window that the laser sees through and therefore does not detect),
- the relative extrinsic calibration between the laser and the radar is wrong,
- the echo returned by the sensor is the result of a multi-path effect (see [Brooker, 2009; Ryde and Hillier, 2009]).

To determine an appropriate threshold on the 3D distance between comparable laser and radar points, we used a dataset in clear conditions in a rural environment (see Fig. 3), limiting the risks of multi-path or distinct reaction of the radar and the laser to particular materials. Since in these conditions a close match should always
be found, the dataset (containing about 1.7 million laser points) could be used as a reference.

Fig. 4 shows the number of inconsistent points for a varying value of distance threshold $\delta$ (i.e. number of laser points for which the closest radar peak was at a distance superior to $\delta$). A distance threshold of $\delta = 0.8m$ was found to be appropriate. With this threshold in the static environment used as reference, only about 0.5% of the points were inconsistent.

Section 3 and 4 show an experimental study to characterise the laser-radar distance and different examples of application of the laser-radar comparison.

3 Experimental Setup

The experiments were conducted with the Argo UGV, an 8-wheel skid-steering platform (see Fig. 1) equipped with a navigation system composed of a Novatel SPAN (Synchronised Position Attitude & Navigation) System and a Honeywell Inertial Measurement Unit. This unit usually provides a 2-cm accuracy localisation, with a constant update of the estimated uncertainties on this solution.

The following exteroceptive sensors were mounted on the vehicle (Fig. 1):

- 4 Sick LMS291/221 laser range scanners, with 180° field of view (FOV), 0.25° angular resolution, and a range resolution of 0.01m.
- a 94GHz Frequency Modulated Continuous Wave (FMCW) Radar, custom built at ACFR for environment imaging, with 360° FOV, 2° angular resolution and a range resolution of 0.2m,
- a visual camera and an infrared camera.

The Laser indicated in Fig. 1 was only roughly aligned with the Radar to have a similar perspective of the environment, therefore this laser was chosen to provide the data to be compared with the radar data. Fig. 5 shows an example of scans provided by these two sensors.

The experiments were conducted with the Marulan Datasets described in [Peynot et al., 2010]. We used various datasets with the vehicle driven around two different areas. Each dataset featured the presence of airborne dust (Fig. 8), smoke (Fig. 9), or none of the above (i.e. clear conditions). The environment was not known by the vehicle a priori.

4 Results

In these experiments, synchronised pairs of laser and radar scans were compared to separate consistent and inconsistent points. In practice, since the laser scanner has a higher scanning rate than the radar scanner (see Table 1), for each laser scan the closest radar data available in time was used for the comparison and the consistency check.

Fig. 8 shows an experiment realised in the same area as in Fig. 3 but with presence of heavy airborne dust. We can see that most dust points in the laser data have been well cleaned out from the dataset, after being found inconsistent with the radar data.

3Recall that only a rough physical alignment is sufficient, as mentioned earlier, as long as an extrinsic calibration between the two sensors is available.
Figure 5: Example of laser and radar scans displayed as range (m) vs. bearing angle (degree). Red points are laser returns while blue points are radar peaks (the highest peaks for each bearing angle are shown in dark blue). Note the laser returns due to dust at shorter range, which are clearly inconsistent with the radar measurements.

Figure 6: Experiments with adverse environmental conditions: presence of airborne dust.

However, some dust points returned by the laser have remained, as they were too close to the ground, which was still seen by the radar, to be called inconsistent.

Fig. 9 shows another experiment, conducted in a different area (a more natural and unstructured environment with surrounding trees), with presence of smoke. It shows how smoke also significantly affects the laser data and how the consistency test with the radar data allows for an effective separation of the smoke cloud.

5 Error Analysis

This section shows an analysis of results and errors obtained from the Laser-to-Radar consistency test described previously. In order to compare the errors in the consistency test we used static datasets where the platform and the objects detected are not moving (see Peynot et al., 2010)). A reference scan corresponding to data in clear conditions was compared against successive laser points. The inconsistencies found with this comparison were used as ground truth data. Fig. 10(b) shows a comparison between the reference scan (in blue) and a scan taken when dust is present. Note that dust is entering the scene from left to right, which is illustrated by the red points representing inconsistencies with the reference scan. The corresponding visual image is shown in Fig. 10(a).

One important aspect to consider for error measurements is the number of points classified as inconsistent for each laser scan ($e_n$), which can tell us the concentration of dust/smoke found. Fig. 11 shows the number of laser points labelled as inconsistent ($e_{ne}$) as estimated by the Laser-to-Radar consistency test, compared with the number of inconsistent points obtained based on the ground truth data in clear conditions ($e_{nr}$). Both scenarios started in clear conditions. Approximately at scan number 200 smoke (resp. dust) was released. Note that the estimation ($e_{ne}$) follows a very similar pattern compared with the ground truth ($e_{nr}$). Nevertheless, since we used a defined threshold, as explained in Sec. 2.1, differences with the ground truth inconsistency test are expected to be found, specially when dust/smoke particles are close to obstacles.

We computed the ratio $\lambda_n$ of the estimated number of inconsistent points $e_{ne}$ to the ground truth $e_{nr}$:

$$\lambda_n = \frac{\Sigma e_{ne}}{\Sigma e_{nr}}$$

We obtained $\lambda_n = 89\%$ for the dust scenario and $\lambda_n = 84\%$ for the smoke scenario. In addition to $e_n$, we also computed the number of points classified as consistent by the proposed approach: $a_{ne}$. We defined false positives ($f_p$) as the number of laser points found inconsistent by the test but not by the ground truth. Similarly, we defined false negatives ($f_n$) as the number of points found to be consistent by the test but not by the ground truth. The resulting precision rate of the inconsistency test ($\alpha$) was $97\%$ for the dust scenario and $95\%$.
Figure 8: Experiment with heavy airborne dust (see Fig. 6). Points are coloured by elevation. The laser points found to be consistent were coloured from green to red, while inconsistent points were coloured from yellow to white. The blue line shows the path followed by the platform while collecting this dataset.

Figure 9: Experiment with smoke, bird’s eye view. Points are coloured by elevation. The laser points found to be consistent were coloured from green to red, while inconsistent points were coloured from yellow to white.

for the smoke.

$$\alpha = \frac{\Sigma e_{ne} - \Sigma f_p}{\Sigma e_{ne}}$$  \hspace{1cm} (2)

The accuracy rate of the inconsistency test ($\beta$) was 88% and 84% for dust and smoke respectively.

$$\beta = \frac{\Sigma e_{ne} - \Sigma f_p + \Sigma a_{ne} - \Sigma f_n}{\Sigma e_{ne} + \Sigma a_{ne}}$$  \hspace{1cm} (3)

Similarly to $\lambda_n$, $\beta$ is expected to increase in cases where most of the inconsistencies are found in the proximities of obstacles or ground.

6 Discussion

The method presented in this paper enables to maintain the safe operation of a UGV in the presence of adverse environmental elements such as airborne dust or smoke, which are strong obscurants for common robotic sensing modalities such as a laser or a visual camera. When dust or smoke are present and block the laser perception, the UGV may still go through the obscurant cloud, with the radar allowing for persistent obstacle detection. On the other hand, when no obscurant cloud is present, laser perception will be preferred since it is...
more accurate compared with radar perception. In the experiments presented in this paper we have observed that some dust/smoke points may not be labelled as inconsistent when they are too close to dense obstacles, as their discrimination is limited by the resolution and the noise of the radar data.

Another situation that this method may not be able to identify is when airborne dust or smoke particles are detected by the laser in the immediate proximity of radar returns due to multi-path effect. In such situation the system will consider these radar returns as a confirmation that the target detected by the laser is in fact a dense object (therefore a potential obstacle for the UGV). To overcome this situation another sensing modality such as visual or infrared cameras could be used.

The proposed method relies on the availability of an accurate exteroceptive calibration between the laser and the radar. If the calibration is jeopardised during a mission of the UGV (for example one of the sensors is accidentally displaced), the consistency test might reject a large part of the laser data even in clear conditions. Consequently, the UGV would have to rely entirely and systematically on the radar data (which is typically less accurate). However, such situations could be recognised over time since the inconsistency between the laser and radar data would then be very stable and geometrically constant. This could let the system distinguish this case from the presence of dust or smoke for example. A sensor model that accounts for uncertainties will be introduced in future work. Uncertainties in the comparison test will also be accounted for.

Acknowledgements

This work was supported in part by the Australian Centre for Field Robotics (ACFR) and the NSW State Government. This material is based on research sponsored by the Air Force Research Laboratory, under agreement number FA2386-10-1-4153. The U.S. Government is authorized to reproduce and distribute reprints for Governmental purposes notwithstanding any copyright notation thereon.

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