LADAR SCAN PREPROCESSING FOR ROBUST MOTION ESTIMATION

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ABSTRACT

Two-dimensional laser radars (2D-ladars) are sensors extensively used in mobile robotics for map building, self-localization, and obstacle detection due to their accuracy and reliability. Due to their fast sampling of the environment they also perfectly suit incremental ego-motion estimation, that is, to find how the position of the vehicle changes in short periods of time only by comparing sensor readings. Some of the most accurate methods dealing with this problem rely on a consistent computation of derivatives of range scans provided by the ladar. In practice, edges in the environment and sensor noise lead to inconsistencies in this computation. In this work we introduce an approach in the frequency domain, which robustly detects the continuous contour patches in the scan and then filters out the noise in those sections. In contrast with other methods based on batches of filters and heuristic rules, our approach employs spectral information to automatically select the filter parameters. We validate our method with experimental results on real environments.

1. INTRODUCTION

One of the fundamental requisites for truly autonomous vehicle navigation is the ability to perform self-localization into its environment. Many of the works for dealing with this problem rely on *ladar* sensors (also known as *laser range finders*) on board of the vehicle [1]. These sensors have gained a huge popularity due to their high accuracy, small beam aperture, and short acquisition time. A typical *2D-ladar* supplies *radial range scans* of the environment contour comprised into a certain field-of-view and depth, typically 180º or 360º, and up to a range of 50m.

Given the range scans at two instants of time, the estimation of the ladar motion between them is a problem commonly addressed by scan matching, or *registration* [5]. We focus on those registration methods that match scans on the basis of contour derivatives. Examples of them are the so-called *differential methods* [3], [4], but also some variations of the popular *iterative closed point* (ICP) method [2], which outperform the precision of the original proposal, as shown in [8]. Regarding derivative-based registration methods, they usually are of limited applicability, because of *sensor noise* and *edges in the contour of the environment.*

In this paper we propose a two-stage method to preprocess range scans, in order to robustly estimate the environment contour derivatives from scans. Firstly, the range scan is segmented into *continuous contour patches* by applying a unique frequency-selective filter, designed according to the scan features in the frequency domain. Thus, unlike other approaches that operate upon a battery of scaled filters [7], our method performs more efficiency by using a single adaptive filter. In a second stage, the range readings within each patch are filtered out to

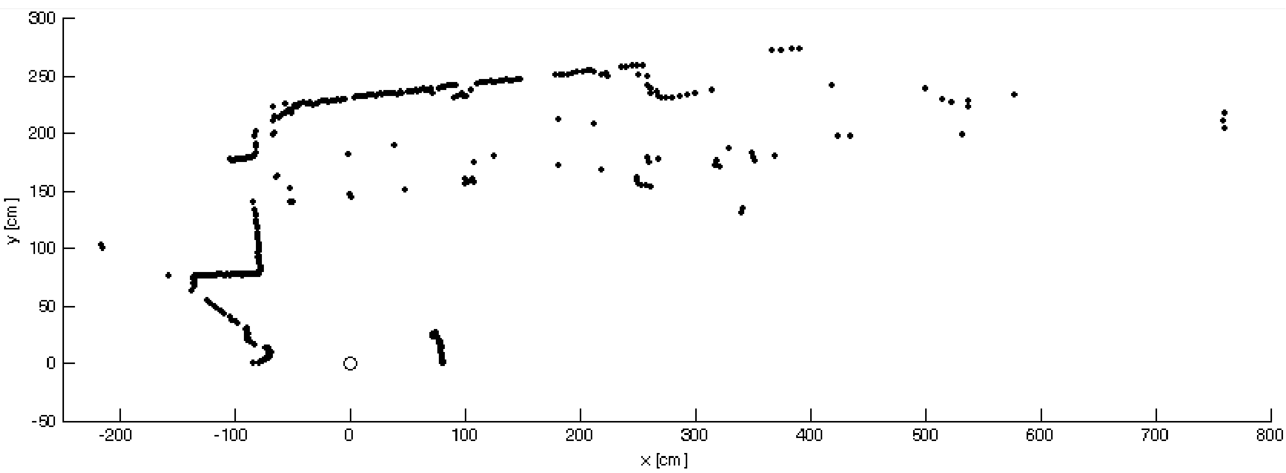

Figure 1. (a) A 2D range scan of a real scenario for $n = 361$ samples. (b) The 1D range sequence.

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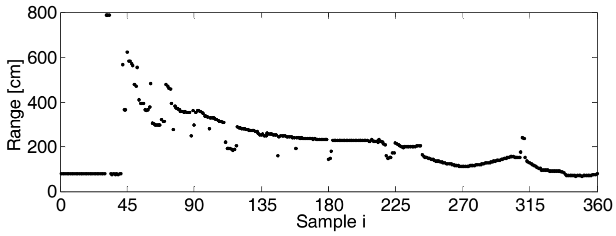

Figure 2. 1D range sequence of the scan in Figure 1.

attenuate noise by analyzing its frequency components. The resulting patches are now suitable for the numerical estimation of the derivatives.

The rest of this paper is outlined as follows. In sections 2 and 3 we introduce the methods for edge detection and noise filtering, respectively. Next, we present experimental results or a real environment, and, finally, we provide some discussion about the results.

2. EDGE DETECTION

We firstly introduce the notation required for the statement of the problem. Let the *range function* $r(\theta)$ be the range from the ladar to the closest obstacle in the direction θ. A ladar scan is a sequence of ranges $r[i] = r(\theta[i])$ taken for a discrete set of directions $\theta[i] = i\Delta\theta$, where $i = 0,\ldots,n-1$ and $\Delta\theta$ is the angular sampling interval (see Figure 1 and Figure 2).

Derivative-based registration methods operate on the range function derivatives $r^{\theta}(\theta) = dr(\theta)/d\theta$, but provided the discrete nature of ladar scans we can only obtain approximations at the scanning directions. These numeric approximations, denoted by $r^{\theta}[i] = r^{\theta}(i\Delta\theta)$, involve samples in the neighborhood of $r[i]$ in the same continuous contour patch than $r(i\Delta\theta)$. Consequently, it is of crucial importance to detect the contour edges as well as spurious samples *(outliers)*, since they do not belong to any continuous patch. After edge detection the scan is divided into *segments,* i.e. sets of ranges sampled from the same continuous patch of the contour.

An edge between two contour patches can be a discontinuity either in the range function (called *occlusion border*, or *step*), or in its derivative (*corner*, or *roof*), as illustrated in Figure 3. On the other hand, there are two kinds of outliers in scans: those associated to non-reflected laser rays (maximum ranges), and isolated points (typically originated by small obstacles).

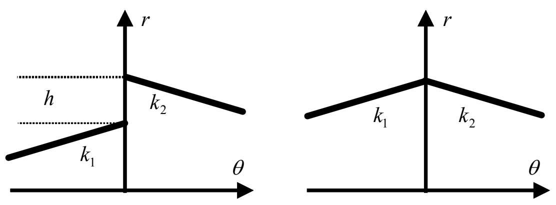

Figure 3. Edge models: step (left) and roof (right).

A method to detect steps and roofs from 3D range functions is established in [7]. They are respectively identified through the zero crossings and local extrema of some directional curvatures of the range function. In the case of a 2D range function, its curvature $\kappa(\theta)$ can be obtained as [9]:

$$\kappa = \left(r^2 + 2r^{\theta 2} - r^{\theta\theta} r\right)\left(r^2 + 2r^{\theta 2}\right)^{-\frac{3}{2}}, \qquad (1)$$

where the first and second derivatives of the range function are needed. Preliminary approximations of these derivatives at the scanning directions can be found from the scan samples by means of convolutions: $r_0^{\theta} = r * D_{\theta}$ and $r_0^{\theta\theta} = r * D_{\theta\theta}$, where the kernels are:

$$D_{\theta} = (2\Delta\theta)^{-1}[-1,0,1] \quad D_{\theta\theta} = \Delta\theta^{-2}[1,-2,1].$$

Thus, a sequence of approximate contour curvature at the scanning directions $\kappa[i]$ can be obtained from (1). Then, scan ranges $r_e[j]$ corresponding to zero-crossings or extrema of $\kappa[i]$ are samples *close to* a contour step or roof, respectively. The exact location of the edges is not obtained due to the approximations assumed in the computation of $\kappa[i]$. Hence we propose a finer edge localization method, implemented through a low-pass filtering of the scan, which smoothes the edges. In [7] a batch of filters and a coarse-to-fine strategy is proposed for this aim. Alike this technique, our approach employs a single filter that adapts to the spectral features of scan, as described next.

Let $r_{DFT}[i]$ be the discrete Fourier transform (DFT) of the range scan $r[i]$, whose *power spectral density* (PSD) is given by $P[i] = |r_{DFT}[i]|^2 / 2\pi n$ (see Figure 4). A range scan can be seen as a base-band signal, thus the relevant information is contained in a given low-pass bandwidth $Bw = [0, i_p]$. Hence we propose an adapted low-pass filter to filter out frequencies above a given frequency $\Omega_p = 2\pi\, i_p / n$. Here i_p is the highest index such as $P[i_p] > P_{\max} - P_p$, where $P_{\max}$ is the largest power component and P_p is a threshold set that controls how much spectral information to preserve. In this work we

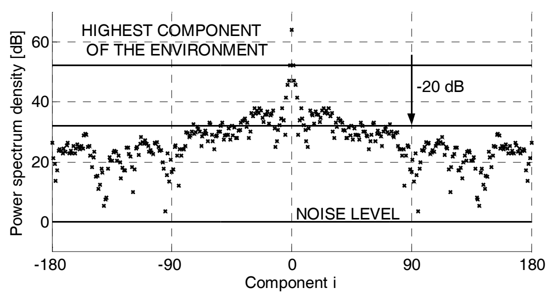

Figure 4. PSD of the range scan of Figure 1, which is affected by an additive Gaussian noise with $\sigma = 1\,\mathrm{cm}$.

have implemented this filter by a low-pass FIR Gaussian filter [6]:

$$\mathrm{G}[i] = \left(\sigma_G \sqrt{2\pi}\right)^{-1} e^{-\frac{i^2}{2\sigma_G^2}} .$$

Therefore, the smoothed scan is computed by convolving it with the Gaussian filter: $r_G = r * \mathrm{G}$. The free parameter σ_G in the above filter is computed from $10 \log e(\sigma_G \Omega_p)^2 = \alpha_p$ to achieve a negligible attenuation, e.g. $\alpha_p = 0.1\mathrm{dB}$, at the highest desired frequency Ω_p .

We illustrate the above process with an example in Figure 4: There, $P_{\max} = 52.11\mathrm{dB}$ for $i = 1$ and, if we want to keep the spectral components within a margin of $P_p = 20\mathrm{dB}$, it is found that $i_p = 74$, for a power of $P[74] = 32.55\mathrm{dB}$.

Now, two sequences computed from the smoothed scan allow us to locate steps and roofs, respectively: the *range increments,* $\Delta r[i] = r_G[i+1] - r_G[i]$, and the *range differences,* $\delta r[i] = r[i] - r_G[i]$. Therefore, the exact location of the edges $r_e[i]$ are the extrema of the former sequences closest to the candidates $r_e[j]$.

In practice, some detected edges may be false-positives because a number of reasons: noise, obstacles that are oriented nearly parallel to a laser ray, etc. This problem can be overcome by considering only the most salient edges, according to the following criterion. Let us denote by $\langle \mu_{\Delta r}, \sigma_{\Delta r} \rangle$ and $\langle \mu_{\delta r}, \sigma_{\delta r} \rangle$ the means and standard deviations of the range increment and range difference sequences, respectively. Then a point $r_e[i]$ is definitively considered to be a step or a roof only if it fulfills $|\Delta r_e[i] - \mu_{\Delta r}| > k_{\Delta r}\, \sigma_{\Delta r}$ or $|\delta r_e[i] - \mu_{\delta r}| > k_{\delta r}\, \sigma_{\delta r}$, respectively, where $k_{\Delta r}$ and $k_{\delta r}$ are non-critical parameters determined experimentally.

Finally, outliers can be easily detected as those ranges either having a value of $r_{\max}$ (the sensor maximum measurable value), or being isolated, namely, those ones in single-range segments.

3. NOISE FILTERING

Noise filtering removes as much noise as possible from each scan segment while preserving its important features. The ladar measurement noise can be thoroughly modeled as *additive white Gaussian noise* (AWGN), whose only parameter is the standard deviation σ . For this kind of noise the PSD is given by $P_r = 20 \log \sigma$.

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The denser the sampling rate of a continuous contour patch is, the narrower becomes its PSD. Consequently, for a sufficiently large sampling rate, some high frequency components of the PSD must be under the noise level P_r , i.e. that part of the information is lost, as illustrated in Figure 5. This leads to the conclusion that by low-pass filtering components below P_r , we only remove noise. Thus, if $P[i]$ is the PSD of the m ranges in a segment, we are interested in the information within a bandwidth $Bw = [0, i_n]$, where i_n is the largest component fulfilling both $P[i_n] > P_r$ and $i_n \le \mu_n + 2\sigma_n$. Here μ_n and σ_n are the mean and standard deviation of the indexes in the bandwidth, respectively. The second condition prevents the selection of spurious values of i_n by forcing the bandwidth to be sufficiently clustered. As a illustrative example, the bandwidth for the PDS in Figure 5 spans up to $i_n = 9$ only.

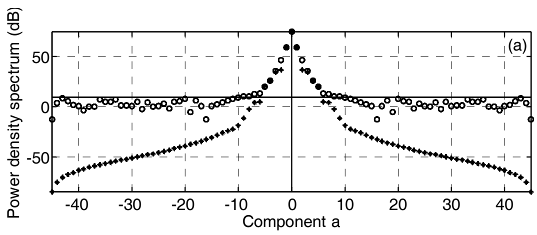

Figure 5. PSD of an ellipse-shaped patch with $n = 91$ samples. Results for measurements without noise (∗) and corrupted with AWGN of $\sigma = 3\,\mathrm{cm}$ (○). The horizontal line is the noise level at $20 \log(\sigma) = 9.54\mathrm{dB}$.

Therefore, at the corresponding frequency in the discrete filter, $\Omega_n = 2\pi\, i_n / m$, the maximum attenuation α_n must be still negligible, e.g. $\alpha_n = 0.1\mathrm{dB}$. Since a scan segment may have a low number of ranges, the filter is implemented by a low-pass IIR Butterworth filter [6], due to the small number of required coefficients in comparison to an equivalent FIR filter. The number of coefficients is related to the filter order N , which must be a tradeoff between high attenuation and a low number of coefficients. Experimentally, we have verified that a filter order $N = 4$ produces good results.

Finally, we obtain the filtered scan $r_B[i]$ and estimate the angular derivative of the scan through the formulas in Table 1. The 3 points formulas are preferred due to its smaller approximation error, thus the 2 points formulas are used only for segments of just 2 elements.

Table 1. Approximations to the angular derivative.

Label	Formula
Outlier	$r^\theta[i]$ is indeterminable
First point of a patch	$r^\theta[i] = \frac{-r_B[i+2] + 4r_B[i+1] - 3r_B[i]}{2\Delta\theta}$
Interior point of a patch	$r^\theta[i] = \frac{r_B[i+1] - r_B[i-1]}{2\Delta\theta}$
Last point of a patch	$r^\theta[i] = \frac{3r_B[i] - 4r_B[i-1] + r_B[i-2]}{2\Delta\theta}$
First point of a 2 point patch	$r^\theta[i] = \frac{r_B[i+1] - r_B[i]}{\Delta\theta}$
Last point of a 2 point patch	$r^\theta[i] = \frac{r_B[i] - r_B[i-1]}{\Delta\theta}$

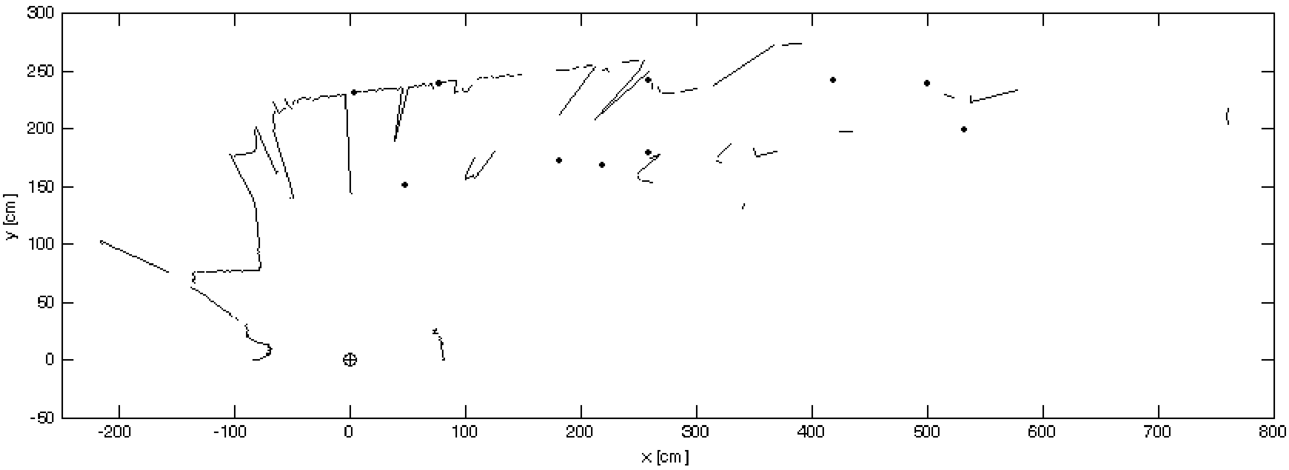

Figure 6. Results for edge detection for the environment of Figure 1. The obtained patches are represented by continuous lines, while outliers are represented by isolated points.

4. EXPERIMENTAL RESULTS

In Figure 6 we illustrate the edge detection process for data gathered at a complex real environment. It can be seen that the main patches are successfully detected, despite of their variety in length and orientation, and perfectly located through the adjusted Gaussian filter. Outliers have also being effectively isolated from the scan. Although there are a few roofs not labeled as edges, they are sufficiently flat as to lead to negligible errors in the computation of derivatives.

Additionally, we illustrate in Figure 7 how the noise reduction successes in reducing errors in derivative approximations. It can be seen that the derivatives of the filtered scan are a smoothed version of those ones of the original scan without discarding meaningful contour information. The main justification for this remarkable performance is because the applied Butterworth filters are tuned to each segment.

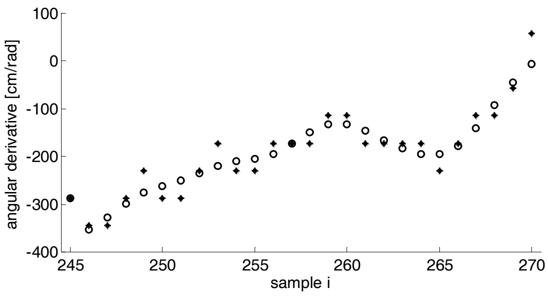

Figure 7. Angular derivatives for a patch of the environment in Figure 1. Results include the derivative approximations using the original (∗) and filtered (○) range scans. Noise of $\sigma = 1\,\text{cm}$.

5. CONCLUSIONS

In this paper, we have described a range scan processing method to robustly compute scan derivatives. This becomes a critical issue when scan registration for motion estimation is based on contour derivatives.

The first step in our method detects edges from the contour curvature and properly positions them using just a Gaussian filter that is adjusted to preserve the range scan main characteristics. In the second step, noise contained in the measurement of each contour patch is attenuated by a Butterworth filter whose bandwidth is adapted according to the noise power in the scan.

Experimental results from a real and cluttered scenario are shown that validate our approach.

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