Matching of 2D Laser Signatures based on Spatial and Spectral Analysis

A. Aboshosha, H. Tamimi and A. Zell
[aboshosha, tamimi, zell]@informatik.uni-tuebingen.de
http://www-ra.informatik.uni-tuebingen.de/

Rechnerarchitektur Abt., WSI, Universität Tübingen
Sand 1, D-72076, Tübingen, Germany.

Abstract. In this article we present a comparative study of three approaches for laser signature matching in indoor terrains. The first approach analyses the signature using spatial domain analysis, the second one relies on spectral domain analysis, and the third approach investigates the signature with a spatial-spectral analysis using wavelets. The main objective of this comparison is to explore the compression and identification capabilities of these approaches. Furthermore we study the possibility of pattern matching under some limited variations of the dynamic environments e.g. phase shift and scaling. Generally, matching and analysis of 2D laser scans underlies self localisation algorithms for mobile autonomous robots.

I. Introduction

Self-localization has been referred to as the most fundamental capability of an autonomous robot. Hence, it is considered as a key subject in robotics. Estimation of a mobile robot pose is the process of deducing the location relative to its environment from its sensor data. 2D laser signatures are highly precise compared with sonar [1]. Therefore, a variety of localization algorithms rely on laser signature matching and analysis to estimate the pose of robots, see figure (1).

A critical problem in localisation is the processing of a huge amount of data needed to model the environment and, consequently, large computational effort needed by the robot to match poses. This problem is exaggerated by real-time conditions. To overcome this problem we employ feature extraction/compression techniques. Then, we apply the comparison on the features rather than on the raw data.

Referring to the relevant research work, Lu and Milios proposed a solution for laser scan matching of points and tangents using least squares [6]. Mota and Ribeiro employed the maximum likelihood algorithm to match 2D laser scans in 3D reconstructed models [15]. Bengtsson and Baerveldt presented a scan matching algorithm, IDC-S, Iterative Dual Correspondence Sector, which deals with changes in the environment by dividing the scans in several sectors, which are matched separately [14]. Gutmann and Schlegel [8] combined the approach with the point to line matching of Cox [7, 9]. Both are iterative methods, i.e. they need a relatively large amount of processing time. Therefore, they are used as offline algorithms after all distance data was already acquired. In the method of Weiß et. al., histograms are used as a base of scan points matching [16]. Röfer (Bremen Autonomous Wheelchair) extended the method of Weiß et. al. to get faster matching [10].

Concerning the activities of the laboratory for autonomous robots at the University of Tübingen, several pattern matching algorithms have been investigated for robot self-localization. Feyrer and Zell employed the laser signature of human legs to underlie pursuing persons [4]. Mojaev and Zell [5] incorporated scan points into occupancy maps by which these local grids were matched to generate a global map. Aboshosha and Zell employed the spectral domain analysis to match laser and geomagnetic signatures [3]. Another technique has been introduced by Biber and Straßer to match 2D laser scans relying on the normal distribution transform [11].

In this paper we concentrate on the comparison of three approaches. The first approach is the spatial domain analysis using Euclidean distance (ED) and the cross correlation algorithm (CCA). The second one is the spectral domain analysis using discrete cosine transform (DCT). The third one is an integration of both domains under the Haar wavelet transform (HWT).

The remainder part of this paper is organized as follows; section **(II)** presents the use of spatial domain analysis to match laser signatures, in general laser data series. Section **(III)** illustrates applying spectral domain analysis to extract compressed features of signatures. Section **(IV)** focuses on the implementation of the Haar wavelet transform to compress and compare data series. Section **(V)** comprises the experimental results of pose tracking using the illustrated algorithms under rotation and limited translation. Section **(VI)**, demonstrates employing laser signatures (laser-milestones) in improving the vector mapping paradigm (VMP). Finally, section **(VII)** is the conclusion.

II. Spatial Analysis

Spatial domain analysis is an efficient method for data series matching. This method can be implemented by deducing the Euclidean difference of two series: x_i and y_i (equ.: 1) or the cross correlation of both of them (equ.: 2).

$$ED(x,y)=\sqrt{\sum_{i=1}^{N}(x_i-y_i)}^{\;2} \qquad (1)$$

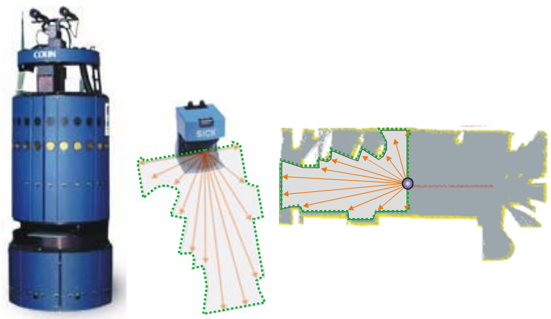

Figure 1. Deduction of robot poses using laser signatures.

The correlation between two series (cross correlation) is a standard approach to feature detection as well as a component of more sophisticated techniques. It is well known that cross correlation can be efficiently implemented in the transform domain, the cross correlation is preferred for feature matching applications that do not have a simple frequency expression. Cross correlation is a standard method for estimating the degree to which two series are correlated. Consider two series x_i and y_i where $i=1,2,...,N$. The cross correlation ρ at delay d (signature phase shift) is defined as:

$$\rho_d(x,y)=\frac{\sum_{i=1}^{N}(x_i-m_x)(y_{i-d}-m_y)}{\sqrt{\sum_{i=1}^{N}(x_i-m_x)^2}\sqrt{\sum_{i=1}^{N}(y_{i-d}-m_y)^2}}=\frac{\mathrm{cov}(x\ and\ y)}{\sqrt{Var(x)}\sqrt{Var(y)}} \qquad (2)$$

Where m_x and m_y are the means of the corresponding series. If the above is computed for all delays $d=1,2,...,N$ (phase shift) then it results in a cross correlation series of twice the length as the original series. The correlation coefficient is a normalized measure of the degree of correlation between two series, and the normalization is such that ρ always lies within the range $-1<\rho<1$. In figure (2) the best match is the global minimum of the Euclidean distance, while the best match as shown in figure (3) is the global maximum of the cross correlation.

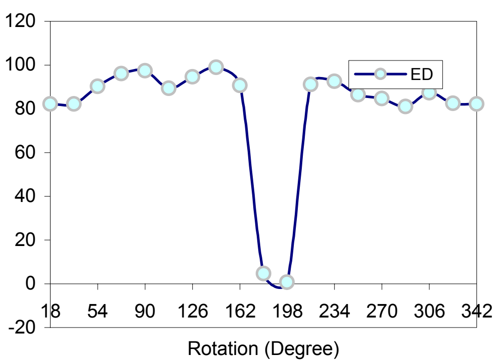

Figure 2. Euclidean Distance w.r.t. rotation.

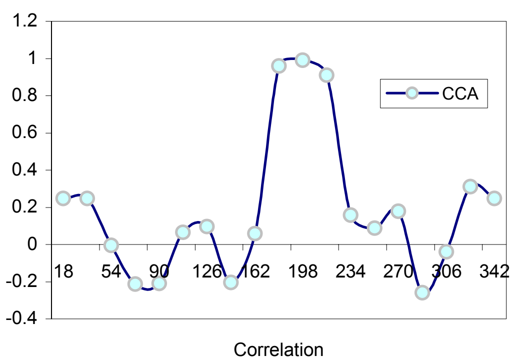

Figure 3. Correlation w.r.t. rotation.

III. Spectral Analysis of Signatures

The DCT transforms a signal from a spatial representation into a frequency representation. Lower frequencies contribute more to a signal than higher frequencies, so if we transform a signature into its frequency components and throw away data about higher frequencies we can reduce the amount of data needed to describe those signatures without sacrificing too much signature quality. The DCT transform can be computed as follows;

$$y_i = \Lambda_i \sum_{j=1}^{N} x_j \cos\frac{\pi(2j-1)(i-1)}{2N}, \quad i = 1,\ldots,F, \quad \Lambda_i = \begin{cases} \frac{1}{\sqrt{N}} & i=1 \\ \sqrt{\frac{2}{N}} & 2 \le i \le F \end{cases} \tag{3}$$

where, x_i is the data series, at time t_i, $x_i \in \mathbb{R}^n$, $i = 1,\ldots,N$, F is the No. of DCT coefficients, y_i are the DCT coefficients and N is the signature length. For all frequencies ($F=N$), i varies from 1 to N, there is no compression. To compress the signature (by omitting high frequencies), i varies from 1 to fl ($F=fl$), where fl is called the frequency limiter or the number of DCT coefficients, see figures (4 and 5). The inverse DCT can restore the original signature using a limited number of DCT coefficients, see figures (4, 5 and 6).

$$x_i = \sum_{j=1}^{F} \Lambda_j y_j \cos\frac{\pi(2i-1)(j-1)}{2N}, \quad i = 1,\ldots,N \ and \ \ j = 1,\ldots,F \tag{4}$$

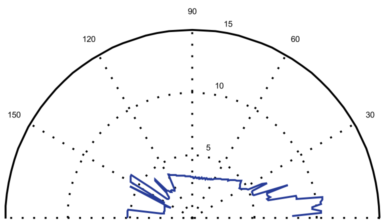

Figure 4. Original signature.

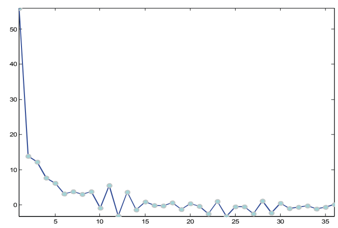

Figure 5. Low DCT coefficients.

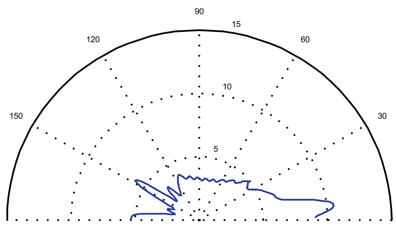

Figure 6. Restored signature.

Comparing DCT coefficients vectors instead of raw signatures is faster than the traditional matching techniques due to its compression capability. Hence, the elapsed time required to match signatures will be reduced.

1- Scaling property:

If $f(t) \Leftrightarrow F(\omega)$ then $f(at) \Leftrightarrow \frac{1}{|a|} F\left(\frac{\omega}{a}\right)$, see figure (7). The value $|a| > 1$ compresses the time axis and expands the frequency axis, ω is the frequency, the value $|a| < 1$ expands the time axis and compresses the frequency axis, t is the time and a, t_0 are constants. Hence, the spectral analysis can counteract the influence of scaling, see figure (7).

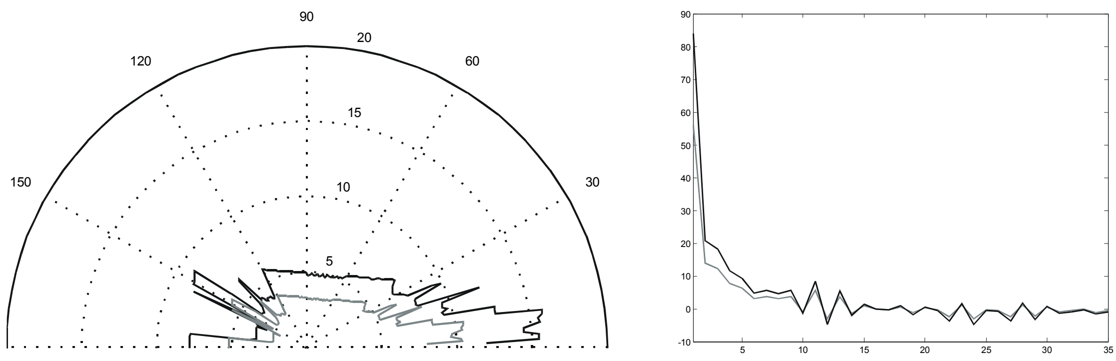

Figure 7. Signature scaling and its corresponding DCT coefficients.

2- Phase shift property:

If $f(t) \Leftrightarrow F(\omega)$ then $f(t-t_o) \Leftrightarrow e^{-j\omega t_o} F(\omega)$. Figure (8) shows the change of DCT characteristics due to rotation that indicate the capability of the spectral analysis to tolerate the rotation for a certain limit.

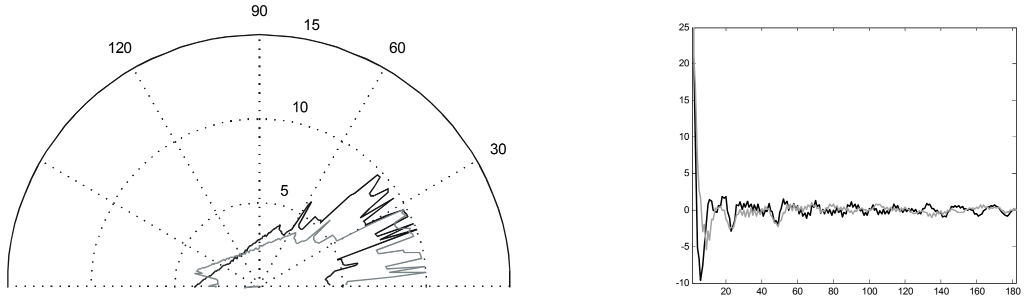

Figure 8. Signature phase shift and its corresponding DCT coefficients.

Figures (9 and 10) show the robustness of the DCT with respect to signature phase shift and translation, respectively. On the left we show how we can find the best match and heading of the robot at the global minimum although the robot is one meter apart from its home location. The right graph shows the change in match error due to translation.

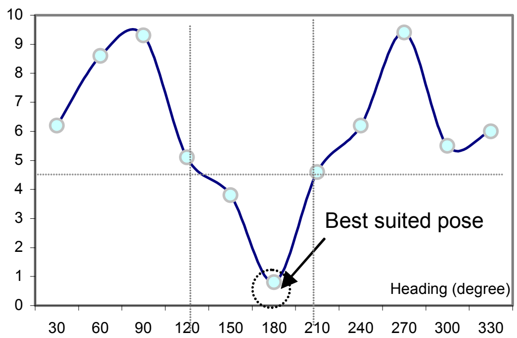

Figure 9. DCT matching error w.r.t. rotation.

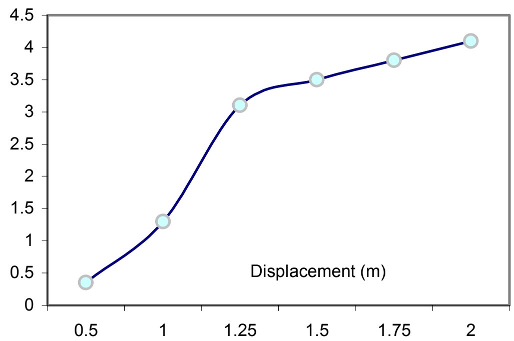

Figure 10. DCT matching error due to displacement.

IV. Haar Wavelet Transform (HWT)

Among many wavelet algorithms including Daubechies wavelets, Mexican Hat wavelets and Morlet wavelets, the Haar Wavelets are especially popular due to their simplicity and limited support. The HWT enable applying our approach in online mode on onboard computers of mobile robots.

We want to have a decomposition that is fast to compute and requires little storage for each sequence. The Haar wavelet is chosen for the following reasons: **(1)** it allows good approximation with a subset of coefficients, **(2)** it can be computed quickly and easily, requiring linear time in the length of the sequence and simple coding, and **(3)** it preserves Euclidean distance.

The most interesting dissimilarity between DCT and HWT transforms is that individual wavelet functions are localized in space, while DCT functions are not. This localization feature, along with wavelets' localization of frequency, makes many functions and operators using wavelets "sparse" when transformed into the wavelet domain. This sparseness, in turn, results in a number of useful applications such as data compression, detecting features in patterns, and removing noise from data series. One way to see the spatial-spectral resolution differences between the DCT and the HWT transforms is to look at the basis function coverage of the spatial-spectral domain. The Haar wavelet uses a rectangular window to sample the data series. The first pass over the time series uses a window width of two. The window width is doubled at each step until the window encompasses the entire data series.

In order to study the laser signature using HWT, we expose the signal to a recursive (multi-resolution) transform. Each time, we extract a set of coefficients, which deduce the data variation found in the signal at a given sub-band [12]. Figures (11, 12, 13 and 14) show a laser scan, the corresponding detail and approximation coefficients, and the reconstructed signature w.r.t the original one at wavelet decomposition level 3. The signal is entailed with the approximate coefficients found with the highest sub-band. In order to perform compression in the wavelet domain, a given number of the lower sub-bands is being neglected when defining our signature.

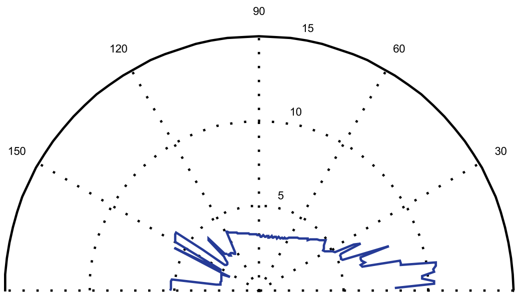

Figure 11. Original laser signature.

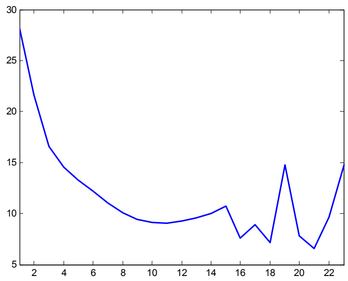

Figure 12. Approximation coefficients at wavelet decomposition levels 3.

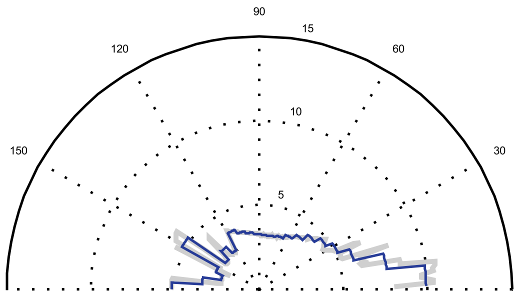

Figure 13. Reconstructed laser signature w.r.t. the original one at wavelet decomposition levels 3.

Figure 14. Detail coefficients at wavelet decomposition levels 3.

V. Experimental Results

To compare the presented approaches, we have performed some experiments using a Sick LMS 200 laser scanner mounted on our B21-RWI robot platform (Colin) in the laboratory for autonomous mobile robots. The laser signature of an arbitrary landmark has been registered and laser scan samples from four nearby locations have been stored. The stored samples comprise both translation and rotation. Then we apply HWT and DCT compression on the scans using equal compression factor. Finally we used the selected landmark and searched for it among all samples. To compare the results fairly we use mean square error in order to compare the spatial, DCT, and HWT signatures with the corresponding ones. Figures (15) shows the experimental results. It is worth mentioning that we use a compression factor of a high rate for DCT and HWT without sacrificing the nature of the signature.

These experiments show that both DCT and HWT are not superior to each other as their signatures are still capable of embracing the information even with high compression rates. Figure (15) clarifies that both DCT and spatial techniques comprise a unique global (reference pose) meanwhile they incorporated multiple local minima. Therefore, both DCT and HWT are considered partially invariant to translation and rotation.

VI. Laser-Milestones for VMP

Relying on the preceding analysis, the laser-landmarks can be precisely recognized in spatial, spectral or wavelet domains. We benefit from this idea in marking specific positions (nodes), locating on the mapping vector, as unique landmarks that label these positions, see figure (16). The set of these nodes and vectors constructs an accurate reference model of the workspace. This model is employed to correct the odometric errors associated with the VMP [1]. Laser-landmarks, locating on the mapping vector, are considered as milestones that describe the metric straightforward translation from the start point toward the goal.

Several mapping algorithms have been investigated to model the robot's working environment. The most widely used methods are the occupancy grid, the topological graph and maps integrating both. Each of these methods has its characteristics, advantages and disadvantages.

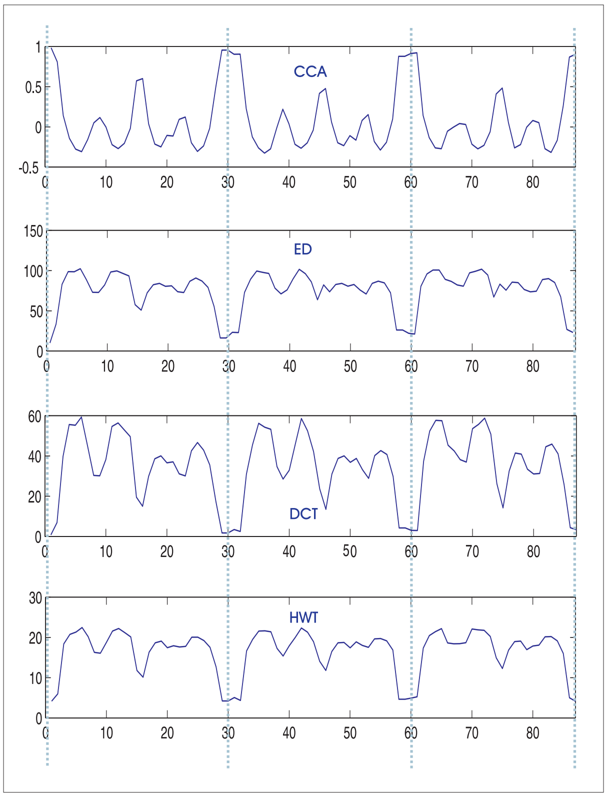

Figure 15. Pose tracking from 4 nearby locations under influence of rotation relying on CCA, ED, DCT and HWT algorithms.

Throughout this work the VMP has been used. This technique is suitable for robots equipped with a laser scanner. The VMP is originally based on the occupancy grid with a reduced map size. The main idea of the vector mapping is to determine an empty space as a region of cells between the laser scanner (robot's position) and the detected obstacles. In other words, these empty cells will be represented by end points of the laser rays (vectors) and the position of the laser scanner. The measurements of the VMP are given in a polar coordinate system whose origin is the position of the scanner (robot), while the end of the vectors is the obstacle boundaries. This map reduces both computer power and memory requirements. In this method, it is required to record just the start (once per scan) and the end of the vectors so the region in between is considered free space that will preserve the consistency of the maps. The laser scanner sends out 180 laser rays per scan with 1° angular resolution. The resolution of the VMP can be controlled using either hardware or software techniques. The VMP maps can be easily converted to the traditional forms. As example, the occupancy grid can be generated by marking all cells included in the vector region by null (empty) and the remainder cells by one (occupied). Also the topological graph and integrated form can be estimated through the occupancy grid. Based on vector mapping the contour-graph can be generated. This graph includes the contours of the existing obstacles. Figure (16) describes using laser milestones to deduce the metric straightforward translation from the start point. They are denoted from 1 to 5, while the first and the last points (1 and 5) are used to assembly the whole map-segments.

VII. Conclusion

The major contributions of this article arise from the formulation of new matching approaches, using the spatial and spectral domains to the modelling and identification of laser signatures, which provide improved computational efficiency in the positioning techniques. By manipulating the manner in which feature information of laser signatures is incorporated into the model, it can be shown that significant improvements in the performance of the algorithm can be realised. Moreover, the simplicity and the efficiency of dynamic pose tracking techniques succeeded to improve the robot pose estimation process. The experimental work shows that using either DCT or HWT can compress the laser scans up to 90% without sacrificing too much the features of the signature.

Acknowledgment

The first and the second authors would like to acknowledge the financial support by the German Academic Exchange Service (DAAD) of their PhD scholarships at the University of Tübingen.

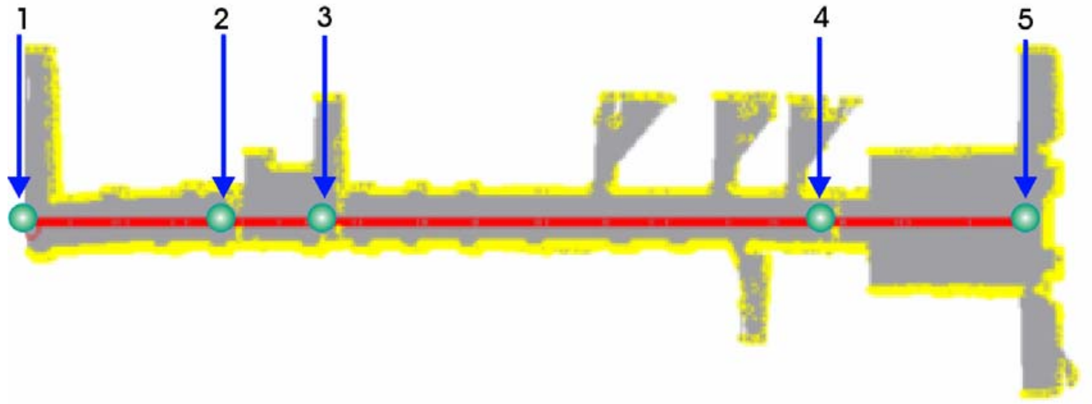

Figure 16. Description of metric translation using laser milestones.

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