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Radar Image Processing and AIS Target Fusion

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ABSTRACT: Collision avoidance is one of the high-level safety objectives and requires a complete and reliable description of maritime traffic situation. A combined use of data provided by independent data sources is an approach to improve the accuracy and integrity of traffic situation related information.
In this paper we study the usage of radar images for automatic identification system (AIS) and radar fusion. Therefore we simulate synthetic radar images and evaluate the tracking performance of the particle filter algorithm as the most promising filter approach. During the filter process the algorithm estimates the target position and velocity which we finally compare with the known position of the simulation. This approach allows the performance analysis of the particle filter for vessel tracking on radar images. In a second extended simulation we add the respective AIS information of the target vessel and study the gained level of improvement for the particle filter approach.
The work of this paper is integrated in the research and development activities of DLR Institute of Communications and Navigation dealing with the introduction of data and system integrity into the maritime traffic system. One of the aimed objectives is the automatic assessment of the traffic situation aboard a vessel including integrity information.

1 INTRODUCTION

One of the important carriers of the worldwide economy is the transport of goods and persons realized by vessels. The harmonization of the developments of electronic aids to navigation and dedicated systems and services aboard and ashore the International Maritime Organization (IMO) has initiated the e-Navigation strategy to integrate existing and new navigational tools, in particular electronic tools, in an all-embracing system.

The risk reduction of accidents between ships as well as ships and obstacles is the social goal associated to safe shipping from berth to berth. The technological goal covers the development of new tools and methods to support the ship-side and shore-side nautical staff during decision finding in complicated and complex navigational situations.

Related to the Safety of Life at Sea Convention [1] the primary source for collision avoidance and traffic situation awareness is the radar system with the opportunity to detect and track objects with the Radar Plotting Aid (ARPA) functionalities [2].

With the implementation of the automatic identification system (AIS) in 2004 an additional important step was done to deploy a second measure for ship-side and shore-side vessel tracking [3]. Like almost every technologies, neither ARPA nor AIS can be declared as an "altogether solution" and are subject to specific restrictions and limitations. Because of the cooperative character of AIS data (disengage able, dependent on the human initiated processes) and the dependency on other onboard devices (as for example the GPS receiver) there is still a margin for errors in the data. Insofar the possibility cannot be ruled out, that specific AIS data are wrong or not meaningful during important maneuvers of a vessel. An analysis of a comprehensive two month AIS data set (January and February 2010) describing the vessel traffic of the whole Baltic Sea [4,5] came to conclusion, that specific parameters like Rate of Turn (ROT) as well as Heading (HDG) deliver significantly defective or implausible results. The radar on the other side is an electromagnetic sensor used for object detection via reflected radio waves to determine the range, altitude, direction, or speed of objects. If the maritime radar is installed with ARPA functionalities the opportunity is given to derive tracks based on radar targets. ARPA systems are able to calculate the course and speed of tracked objects as well as the closest point of approach (CPA) and time to closest point of approach (TCPA) in relation to the own vessel. The majority of ARPA systems integrate the ARPA features with the radar display.

Previous studies of the maritime radar and the ARPA system found that the ARPA drawbacks [6,7] could be overcome with the use of the radar image instead of distance and bearing calculated from ARPA [8]. This paper propose and analyze the use of a sequential Monte Carlo algorithm also known as particle filter as a solution for radar target extraction and tracking as well as radar and AIS fusion.

The monitoring and assessment of vessel traffic is an important element of safe, secure and efficient shipping and the protection of environment. The collision and grounding avoidance at sea requires a reliable and comprehensive picture of the maritime traffic situation to enable an error-free decision making for the seafarers. A combined use of data provided by independent data sources is an approach to improve the accuracy and integrity of traffic situation related information. This paper focuses on the usage of two-dimensional radar image data for an improved target tracking in the frame of maritime traffic monitoring. More precisely, the aim of this paper is the analysis of a sequential Monte Carlo method for radar target detection and tracking as well as AIS and radar fusion. For this purpose the paper simulates radar images and AIS data to test the proposed filter algorithm.

The paper is structured in the following way: At first in section 2 the strategy of study is discussed. In the next part the scenarios and the generation of synthetic images is described in section 3. Section 4 gives a very brief introduction into the used sequential Monte Carlo method. In section 5 the results are presented and section 6 discusses and concludes the analysis of the results.

2 THE STRATEGY

Aim of this study is the performance analysis of the sequential Monte Carlo method for target detection and tracking in maritime radar image processing. The strategy of the study is illustrated in Fig. 1 and covers 4 steps.

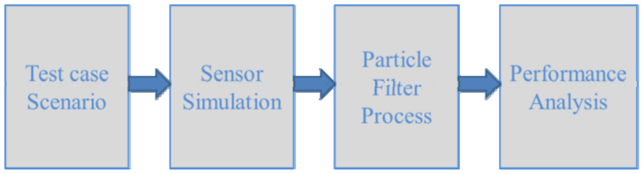

Figure 1. Systematic illustration of the strategy

The first step of the study is the definition of the test case scenarios. These scenarios are chosen such that the performance of the tracking position accuracy and the time to first detection of the target can be estimated. After the definition of the test cases the sensor data has to be simulated. This simulation generates error free radar images as well as error free AIS position data. After the data simulation the sequential Monte Carlo method was used to estimate the position of the target. The first position estimation was done in a radar only mode. In a second stage the method was used with radar and AIS data in a sensor fusion process. The simulation environment has the advantage that every parameter is precisely known and the comparison of estimated and simulated data is possible in order to determine the performance of the used method. The final step of the study is the analysis of results. During the analysis the accuracy of the target position, extracted from the radar image, and the time the algorithm needs to extract the first position are estimated.

3 TEST CASE AND SENSOR SIMULATION

In this section we describe the test case scenarios and the method used for radar image simulation. The purpose of the scenarios is the performance evaluation of the sequential Monte Carlo method for maritime radar image processing.

The scenarios were designed to estimate the position accuracy of the extracted target as well as the time the algorithm needs to calculate the first position. The simulations were done for static and dynamic echoes with and without AIS data. The first test case is a static radar echo without AIS position data. For this scenario different target echo sizes were simulated and the position accuracy as well the time to first position fix was estimated.

The second test case is a dynamic scenario. In this scenario the target echo moves with the velocity v on a straight line starting from position s_0 at time t=0 according the following equation.

$$s = s_0 + vt \qquad (1)$$

In the third scenario the AIS position as additional information is added to the static test case. The AIS position is simulated at the center of the radar echo without any additional position noise. In the last scenario the AIS position is as well added to the dynamic simulation.

The following part describes the generation of synthetic radar images, which are used as sensor input in the test case simulations.

The generation of synthetic radar image is based on data from a measurement campaign with the vessel BALTIC TAUCHER II in the area of Rostock. During this campaign the actual screen of the radar, as the officer of the watch uses it, was recorded. The radar images were extracted using a VGA to USB grabber and then stored as a series of uncompressed PNG-images. The use of the original image source solves the challenge of time synchronization and allows the simulation a realistic sensor performance.

One of these images from the BALTIC TAUCHER II radar screen (Sperry Marine VISIONMASTER FT) is shown in Fig. 2.

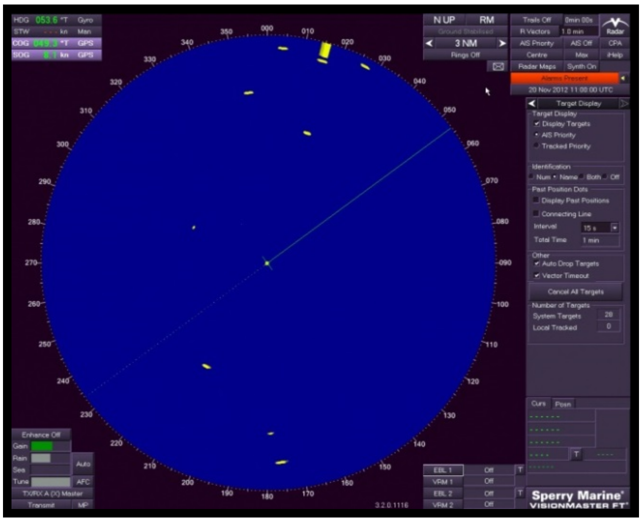

Figure 2. The original RADAR image as taken from Sperry Marine VISIONMASTER FT from BALTIC TAUCHER II.

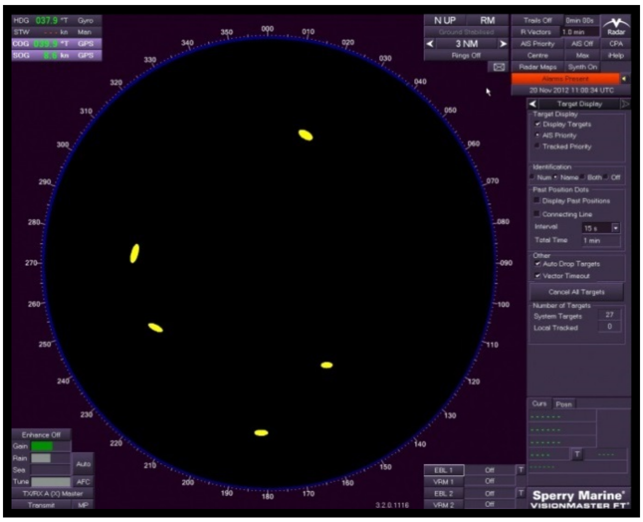

Figure 3. The simulated radar image with 5 elliptical targets of different size and orientation

The generation of synthetic images can be described as follows. The process starts with the removal of the part of the image which contains the radar echoes. After this process the synthetic image consists only of the user interface and a filled black circle. This was achieved by setting all pixel values within a radius of 468 pixels around the center pixel of (532,516) to zero. Note that this configuration is specific to the radar device from Sperry Marine. After the removal of the original data the synthetic radar echo is added to the image as a filled yellow ellipse. The use of ellipses for radar echoes is based on the suggestion of [4] that radar echoes are well described with elliptical parameters. The process is repeated for every image received from the data stream. While the removal of the original radar echoes is always identical the simulated target will be plotted at the position derived from the configured dynamic model. In principle, this allows the generation of any possible maritime scenario including near misses or even collisions of traffic participants. In addition to the simulation of radar echoes the software is possible to provide AIS data for all simulated vessels. Please note that the AIS dataset is derived from the simulated radar echoes without any additional error on position and velocity. Additionally we would like to point out that the software is able to simulate targets with elliptical shape, but the simulations were performed with circular echoes of different sizes in order to reduce the complexity of the interpretation of the results.

The simulated images are all based on data from the Sperry Marine VISIONMASTER FT RADAR, with a range set to 3 nautical miles. This configuration of the radar results in the Pixel size 11.87 meters.

4 SEQUENTIAL MONTE CARLO SAMPLING: PARTICLE FILTER

The paper studies the use of the sequential Monte Carlo method for the position estimation of a target vessel from radar images and AIS position data. The reason for choosing the particle filter as the algorithm of choice is based on previous analysis of AIS and radar sensors [8,9,10].

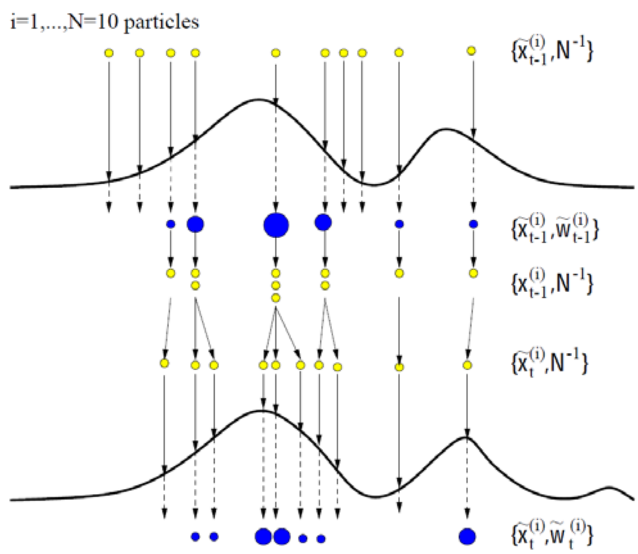

Figure 4. Illustration of the particle filter process taken from [11]

Figure 4 illustrates the concept of the sequential Monte Carlo method. A detailed description of the algorithm is given in [11]. The algorithm starts at time t-1 with an un-weighted distribution $\left\{\tilde{X}^{(i)}_{t-1}, N^{-1}\right\}$ of sampling particles (yellow circles in the first row of

Fig. 3). The next step is the calculation of the importance weights $\left\{\tilde{X}^{(i)}_{t-1}, \tilde{w}^{(i)}_{t-1}\right\}$ of each particle (blue circles 2nd row). The result is the approximation of $p(x_{t-1} \mid y_{1:t-1})$. During the next step, the resampling of the particles, only those particles are taken into account which reproduces the observation best. The result is an un-weighted distribution of sampling particles $\left\{\tilde{X}^{(i)}_{t-1}, N^{-1}\right\}$ (third row yellow circles). The final prediction step uses the filter model description including the model noise, which produces variety in the sampling distribution, for the approximation of $\left\{\tilde{X}^{(i)}_{t}, N^{-1}\right\}$ (4th row Fig. 3). The result is the approximation of $p(x_t \mid y_{1:t-1})$ (5th row Fig. 4), which is the posterior distribution of the estimated parameter. The process is repeated until the simulation is finished.

5 RESULTS

In this section the results of the simulations for the static and dynamic scenarios with and without AIS are presented.

As already discussed two main performance properties are of interest. The first is the convergence time, which is the time the method needs to estimate the position of the echo for the first time, and the second is the tracking error E_T, which can be interpreted as the position accuracy of the particle filter.

CONVERGENCE TIME

Initially the particles are spread randomly over the radar image. The filter has converged when the majority of the particles are close to the target. At this point the particles move with the target and adopt its shape. In this study we define convergence when the error, which is defined as the Euclidean distance between the simulated position of the target (Sx,Sy) and the estimated position of the particle filter (Px,Py), is smaller than 2 pixels. The distance is calculated with

$$E_j = \sqrt{\left(Px_j - Sx_j\right)^2 + \left(Py_j - Sy_j\right)^2}, \tag{2}$$

where j is the frame number and the position of the simulated target and the position of particle filter estimation is in radar coordinates.

TRACKING ERROR

The tracking error is a measure of the accuracy of the algorithm. In this paper the tracking error is defined, as the average over 400 images of the Euclidean distance between the real position of the target and the particle filter estimated position after the algorithm has converged. The tracking error E_T can be calculated with:

$$E_T = \frac{\sum_{j=N_C}^{N} \sqrt{\left(Px_j - Sx_j\right)^2 + \left(Py_j - Sy_j\right)^2}}{N - N_C}, \tag{3}$$

where Nc is the converge frame number as defined in the convergence subsection, N is the total number of images synthesized, (Px,Py) is position of the particle filter estimation and (Sx,Sy) is the position of the simulated target and j is the frame number

In the following part the results of the performed simulations are presented. The results of the particle filter process without the fusion of AIS data is shown first. Thereafter the results of the radar and AIS fusion are presented.

SIMULATION WITHOUT AIS

This part presents the results for the simulations without AIS. The first test scenario of a static radar echo is presented in Fig. 5.

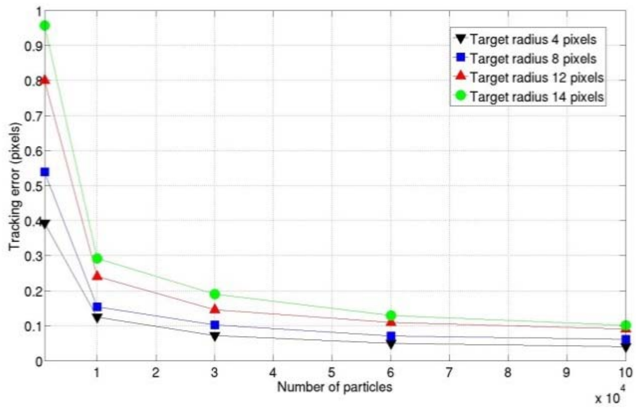

Figure 5. Tracking error as function of the number of particles for the static simulation of radar echo with four different sizes

This figure shows the tracking error in pixels as a function of the number of particles for four radar echo sizes: 4 (black triangle); 8 (blue square); 12 (red triangle) and 14 (green circle) pixels. The figure shows that a lower number of sampling particles results in a higher tracking error. In addition it can be seen that larger targets are more difficult to track, because they show larger tracking errors.

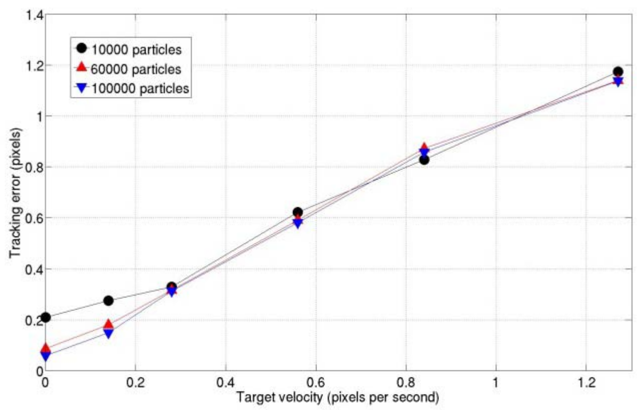

Figure 6. Tracking error as function of the number of target velocity for the dynamic simulation of radar echo for three different numbers of sampling particles

The results of the dynamic test scenario without AIS are shown in are shown in Fig. 6. The figure shows the tracking error as a function of target velocity for three different number of sampling particles: 10,000(black) 60,000(red) and 100,000(blue).

The figure shows that the tracking performance of the dynamic simulation can't be improved by increasing the number of sampling particles. Additionally it can be seen that radar target echoes with higher velocity show larger tracking errors.

SIMULATION WITH AIS

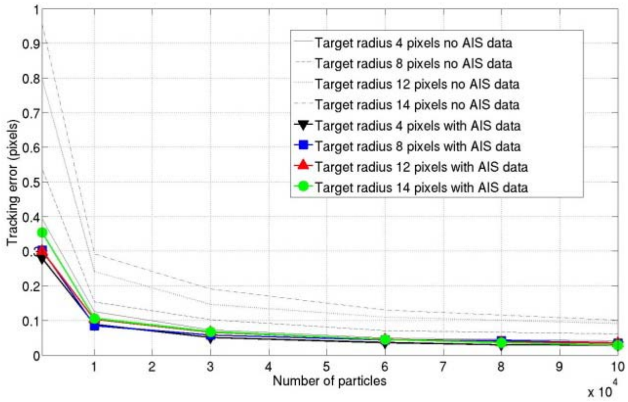

Figure 7. Tracking error as function of the number of particles for the static simulation with and without AIS for four different echo sizes

Fig. 7 shows the tracking error in pixels for particle filter configurations with different number of particles and radar echo sizes: 4 (black triangle); 8 (blue square); 12 (red triangle) and 14 (green circle) pixels. The figure compares the results of the static target with AIS (colored lines) with the results presented in Fig. 5 without AIS (gray lines). As shown in the figure the addition of AIS information improves the tracking performance by a factor of 2 for all target echo sizes. But the tracking error of larger objects is still larger than for smaller echoes.

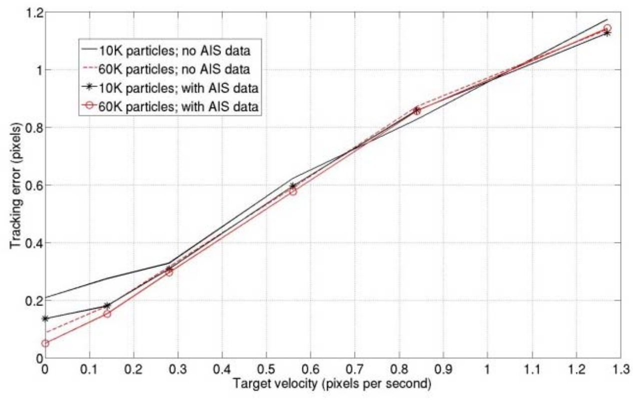

Figure 8. Tracking error as function of the number of target velocity for the dynamic simulation of radar echo for two different numbers of sampling particles

Fig. 8 shows the results of the dynamic test scenario with and without AIS. The figure shows that the tracking error as function of target velocity does not improve with the addition of AIS position data and does not depend on the number of sampling particles.

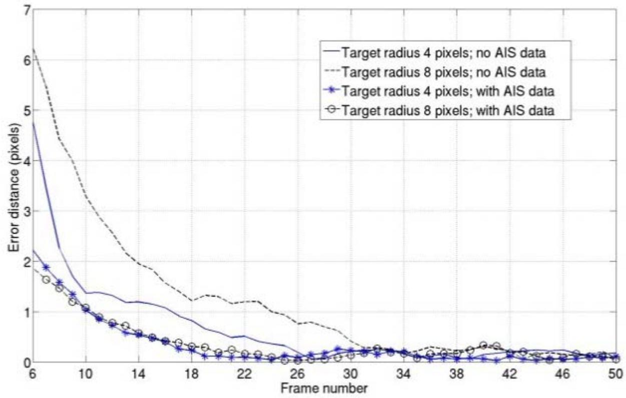

Figure 9. Error distance as function of the frame number for the dynamic simulation for two different veolcities with additional AIS information.

Fig. 9 shows the convergence time of the particle filter for a simulation with a static target of two sizes (4 and 8 pixel) with and without AIS data. It is clearly visible form this figure that the added AIS data reduces the convergence time from 17s to 10s and from 24s to 10s for the targets of sizes 4 and 8 pixels, respectively.

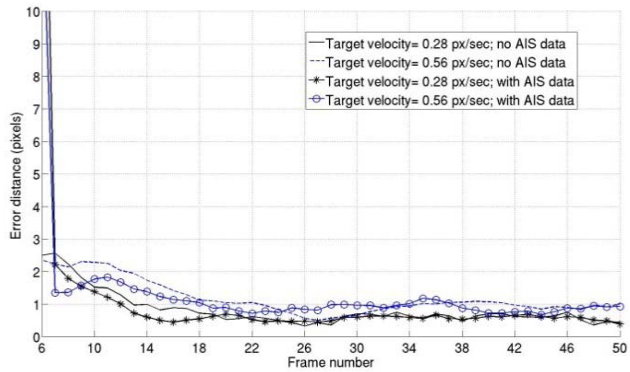

Figure 10. Error distance as function of the frame number for the dynamic simulation for two different veolcities.

Fig. 10 shows the convergence time of the particle filter for a simulation with a dynamic target with AIS data as solid lines and without AIS data as dashed lines. This figure shows that the added AIS data reduces the convergence time for the given scenario by 1s for the slow moving echo and 2s for the faster one.

6 DISCUSSION AND CONCLUSION

In this section the results of the previous section are discussed and concluding remarks are given.

This part discusses the results of the performed simulations. The results of the static target scenario show that the particle filter needs for the first detection of the target radar echo at least 10 frames, which is equivalent to 5 antenna rotations. The Addition of AIS data does reduce this detection time by a factor of 2.

The results of the dynamic target scenario show larger tracking errors in comparison to the static simulations. The explanation could be that the tracking performance, which is as accurate as 0.5 pixels in the static simulations, is smaller than the velocity of the vessel in the dynamic simulation. Therefore it is possible that the larger tracking error results from the movement of the target vessel instead of the position estimation. This would explain the result of a tracking error similar to the vessel speed of 1 pixel/second. This is consistent with the fact that the dynamic simulations with smaller velocities show smaller tracking errors. The results of very slow moving vessels show the same particle filter performance as the non-moving static targets.

Additionally we like to point out that the filter tuning is an important part of the overall performance of the filter.

In the following part we conclude the results of the study. In this paper we simulated scenarios of static and dynamic radar targets. The simulations were used to estimate the radar tracking performance of a sequential Monte Carlo filter to follow maritime radar echoes. The performed simulations cover situations with and without additional AIS sensor position data in the fusion process.

The results can be summarized as follows.

- The time to target vessel echo detection is smaller than 1 minute
- The resulting tracking accuracy of sequential Monte Carlo method is smaller than 1 pixel (~10 meters)
- The model assumption used in the particle filter has a strong impact on the resulting performance
- The addition of AIS data increase the performance the fusion process significantly

The in this paper performed simulations strongly suggest that the sequential Monte Carlo method is suitable for AIS and radar image fusion.

The next planned step is the improvement of the sequential Monte Carlo filter simulation to more realistic scenarios. This enhancement of the simulation will improve the performance evaluation of the fusion of radar image and AIS position. This step is necessary to gain integrity information from an AIS and radar fusion process with the final aim of the introduction of data and system integrity into the maritime traffic situation aboard a vessel as well as ashore.

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