GPS-Free Operation of Ships and Aircraft Utilizing Terrestrial Satellites

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***Abstract*—Modern aerial and naval navigation systems utilize the GPS technology extensively to retrieve the own position infor-mation automatically, which in turn is fed into other navigation and warfare systems through a serial link. A failure of the GPS system would result in a significant loss in speed and accuracy of any navigational calculation, making it nearly impossible to maintain a reliable and automated operation in air or at sea. This paper investigates the feasibility of utilizing the long range radar transmissions incident on vehicle's electronic support system measures (ESM) that is composed of direction finders. By simple triangulation of the Radars uncertain directions and adaptive filtering, an alternative automated local positioning system (LPS) would be very useful in case of a GPS-free operation. In this paper, we evaluate the operation of the proposed LPS technique by simulation. A certain number of terrestrial Radars were randomly located on land and a ship is simulated to navigate on the open seas. The islands and land structures that would prevent the Radar beams to reach the ship were taken into account and the blockage of such rays were calculated using image processing of the Navigation maps pixel values. The triangulation and positioning errors were calculated and the noise was cancelled by adaptive filtering using linear Kalman filter. With the simulation experiments, we show that such an LPS system is feasible and could be integrated to the ships ESM systems to provide an automated and reliable own ship position information in case of a GPS failure.**

Keywords*—*Kalman Filtering, triangulation, localization

I. INTRODUCTION

This paper presents an automated methodology of navigation and positioning for ships and aircraft in case of a GPS failure. The work primarily depends making another use of the on board ESM system to locate on ship position from terrestrial target emissions. This methodology is no different from the GPS system itself, except the usage of space satellites. One other alternative to GPS, used by ships and aircraft, the Long Range Navigation (LORAN) system exploits medium range hyperbolic radio emissions by a fixed, land-based radio beacons. The working principle depends on comparing the difference in reception time of the signals, just like GPS [1].

The crux of this work is to utilize the (possibly faulty) ESM bearings incident on the ship/aircraft's direction finder and automatically feed the war and navigation systems by estimated location obtained by the triangulation and adaptive filtering process. In the next subsection we briefly introduce the related work for alternative location systems. In Section-II, we provide the main elements of the proposed methodol-ogy along with the implementation details. In Section-III we present the simulation results draw our conclusions.

A. Related Work

Triangulation method dates back to thousands of years ago, and was used by the ancient Greek and Egyptian civilizations [2]. All current Global Navigation Satellite Systems (GNSS) systems; Navstar GPS, GLONASS, Galileo, Beidou and others, use the corresponding mid range satellites that orbit around the Earth such that there are always a certain number of satellites that are used calculate the temporal difference of the signals on the receiver. These differences are then converted into range by taking into account the speed of light. Several range information from known locations in space are then used to calculate the receiver's position by triangulation.

Du and Lee studied utilizing Radar emissions and their Time-Difference-Of-Arrival (TDOA) along with Unmanned Aerial Vehicles (UAVs) to geolocate the passive radar emitter locations [3]. In addition to this work's and GPS' timing-based approach, signal strength-based and angle of arrival-based (AoA) approaches have also be investigated in the literature [4], [5]. Cost effective alternative GPS systems, based on local transmitters appear predominantly for indoor scenarios where the accuracy of GPS is seriously diminished by the physical factors. For indoor operations several sensors like radio cameras, ultrasonic and infrared sensors are used for localization by comparison of the incoming signal strength [2], [6]–[8]. Likewise, in an indoor localization system radio and ultrasound signals are used to estimate Euclidean distances to fixed source locations to conduct triangulation [9]. Besides the satellite-based approaches described above, GPS-free operation methodologies have been proposed in the network literature as network-based methods [10]. Čapkun et al. proposed a GPS-free relative positioning system by deciding the origin of the coordinate system by voting as collection of nodes [11]. In [12] Monte Carlo methods and adaptive filtering were used for bearing-only positioning while

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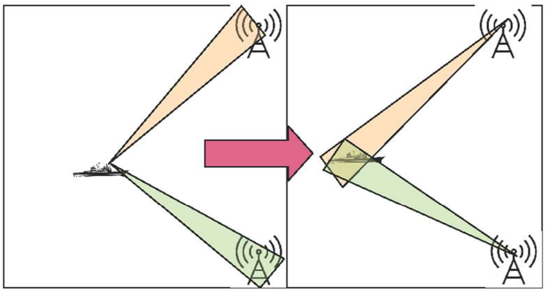

Fig. 1. The ESM systems are now used to detect the unknown own location by using the noisy incoming ray angles.

[13] addressed the bearing-only multi-target tracking problem.

This paper, like [12], can be categorized under the angle-of-arrival-based methods. The measured bearings will be noisy and their triangulation will yield a bi-variate random number. The best explanation of the bearing error is generally done by the zero mean Gaussian distrubution [2], [14], [15]. Over this bi-variate noisy location estimates, we apply Kalman filtering, which was also proposed by [6].

II. System Description

The goal of this study is to investigate and quantify the feasibility of utilizing the existing ESM systems for automatic positioning and navigation. We aim to employ this feasibility study with no additional cost of ship/aircraft/UAV operation, instead, by solely simulation of real application. Therefore, one gained outcome of this study is a user interface that shows the navigation of the ship/aircraft.

The application of ship and aircraft differ in two aspects. In the case of ship applications, the blind sectors of Radar beams that are caused by islands or land between the receiver and the signal source effect the positioning and navigation performance. Whereas the aircraft is not effected by such peculiarities, the processing speed of corrective filtering should be designed to match the speed of the aircraft operation. The actual ESM problem is to locate and decide the identity/position of the Radar sources using the direction finders and the electronic signature libraries of the system. In this paper, however, we change this problem of finding locations of the incoming signal sources, into finding the own ship location by making use of the fixed terrestrial satellite locations. The problem change can be illustrated in Figure 1.

In this paper, we studied the operation at sea, as the blind-spot-handling required particular discretion. Furthermore we chose the Aegean sea that is famous for its more than 6000 islands and islets, bays and peninsulas. The system consists of 4 main phases:

1) Image processing and simulation
2) Triangulation
3) Error estimation
4) Adaptive filtering

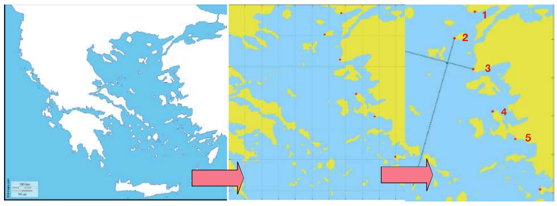

Fig. 2. An illustration of the image processing and simulation phase. The left image shows the original map image obtained from [16]. The middle image is the resolution increased and pre-processed image. On the right figure, we see how the blind spot ruling automatically hides the rays incident from Radar-1 and Radar-4 that are in range yet blocked by land/island.

A. Image Processing and Simulation

This phase consists of building up an interface-like system such that the navigation is simulated. For this, we obtained an image of the sea of interest from an open source webpage, d-maps [16]. We first increased the resolution of the image by interpolation and converted the color spectra to match the graphical user interface of the widely used electronic chart display systems. We then located 7 Radars to randomly selected locations on the map. This, pre-processing operations can be seen in Figure 2. The simulation of the incident ray angle calculation to the (unknown) ship location from the fixed terrestrial satellite (Radars) is also employed in this phase. This ray angle is calculated as follows:

$$\theta_{Rad} = \tan^{-1}(\frac{y_{own} - y_{Rad}}{x_{own} - x_{Rad}}) + \epsilon \qquad (1)$$

If there is a large area of land, either an island or another landmark, the Radar is automatically marked as 'blind' and omitted in the location calculation. This process is done solely using image processing techniques by deciding using the pixel values of the map. The summation of the pixel values on the line segment between the radar and the ship is checked to detect any landmark that blocks the ray. This trick was made possible by binarizing the map. The range and the blind spots of the Radars are taken into account and the incoming rays are plotted on the map interface. This procedure can be seen in Figure 2 on the right. All Radars are in range for the current ships location on the right figure. However, the rays from only the Radars 2 and 3 reach the ship since others are blocked by land. This phenomenon is simulated in the program and illustrated in the figure.

B. Triangulation

In the triangulation process, we calculate the intersections of the incoming rays, which do not cross own location due to the bearing error. Each incoming signal bearing that is calculated from the Radar location and the (unknown) actual location as in Equation (1). A zero-mean Gaussian noise, at each iteration in run time, is then added to this bearing to provide the simulation for the ESM operation.

$$\theta_{ESM} = \theta_{Rad} = +\epsilon \qquad (2)$$

where,

$$\epsilon \sim \mathcal{N}(0, \sigma^2) \tag{3}$$

Several incoming ray locations are used to calculate the estimated ray locations. If there is no incoming ray, i.e the ship is at a blind location for all of the random Radars, or if there is only one incoming ray, we estimate the location by dead reckoning the previously estimated location and then adding a drifting noise. If there are two rays, we calculate the intersection of the rays and use it as the estimation. Calculating the linear equations of the two incoming rays to be

$$y_1 = ax + c \tag{4}$$

and

$$y_2 = bx + d \tag{5}$$

The estimates are found at

$$\begin{aligned} \hat{x} &= \frac{d-c}{a-b} \\ \hat{y} &= a\frac{d-c}{a-b} + c \end{aligned} \tag{6}$$

If there are more than three incoming rays in a given location, we produce the triangle by the closest three Radars and calculate the centroid (center of gravity) to use the initial location estimate. This procedure is illustrated in Figure 3. If we denote the incoming ray equations to be

$$\begin{aligned} y_1 &= m_1 x + a \\ y_2 &= m_2 x + b \\ y_3 &= m_3 x + c \end{aligned} \tag{7}$$

Then the corners of the triangle and the centroid as the new location estimate is calculated as follows:

$$\begin{aligned} x_{12} &= \frac{b-a}{m_1 - m_2} \\ x_{13} &= \frac{c-a}{m_1 - m_3} \\ x_{23} &= \frac{b-c}{m_3 - m_2} \\ y_{12} &= \frac{m_1 b - m_2 a}{m_1 - m_2} \\ y_{13} &= \frac{m_1 c - m_3 a}{m_1 - m_3} \\ y_{23} &= \frac{m_3 b - m_2 c}{m_3 - m_2} \\ \hat{x} &= \text{median}(x_{12}, x_{13}, x_{23}) \\ \hat{y} &= \text{median}(y_{12}, y_{13}, y_{23}) \end{aligned} \tag{8}$$

C. Error Estimation

Naturally, the navigation for aircraft takes place on the three-dimensional space. Therefore, in aircraft operation, we consider the true location as a three-dimensional array, (x, y, z), and the ESM estimation yielding not only the horizontal AoA by also the vertical AoA. However, as stated earlier, in this paper we approach the problem of blind spots

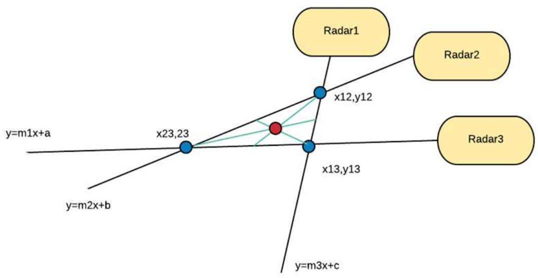

Fig. 3. An illustration of the triangulation for location estimation.

and treat the vehicle as a ship. The uni-variate Gaussian noise apparent on the incoming rays causes a noisy location estimation. The probability distribution of location estimate

$$\mathbf{L} = [\hat{x}, \hat{y}] \tag{9}$$

is assumed to conform a bi-variate Gaussian density with mean vector as the own ship location

$$\mathbf{O} = [x_{own}, y_{own}] \tag{10}$$

and a diagonal covariance matrix ($\mathbf{\Sigma}$):

$$\mathbf{L} \sim \mathcal{N}(\mathbf{O}, \mathbf{\Sigma}) \tag{11}$$

The maximum-likelihood estimates for the covariance matrix and the mean are calculated for all pixels (locations) on the map, using K samples of noisy bearings and calculating triangulation. We see that our mean assumption of the true location holds and the covariance matrix is not far from diagonal. Naturally, due to the blind areas and the distance from the Radar beams, the accuracy of the location estimation differs per location and the noise distribution differs across various locations. Hence it would be too naive to expect a perfectly non-stationary process over the map. However, we kept the stationarity assumption for the sake of simplicity in the first implementation, while keeping this intricacy in mind. The estimated diagonal covariance matrix ($\hat{\mathbf{\Sigma}}$) is obtained thus:

$$\sigma_x^2 = \frac{1}{KN_x - 1} \sum_{i=1}^{N_x} \sum_{k=1}^{K} (i - \hat{x}_k)^2 \tag{12}$$

$$\sigma_y^2 = \frac{1}{KN_y - 1} \sum_{j=1}^{N_y} \sum_{k=1}^{K} (j - \hat{y}_k)^2 \tag{13}$$

$$\hat{\mathbf{\Sigma}} = \begin{bmatrix} \sigma_x^2 & 0 \\ 0 & \sigma_x^2 \end{bmatrix}, \tag{14}$$

where $(\hat{x}_k, \hat{y}_k)$ and (N_x, N_y) are the k^{th} estimation and the dimensions of the error estimation map, respectively. We took $K = 1000$ in our implementation.

D. Adaptive Filtering

The final part of the study is the adaptive filtering of the noisy estimates. We implement Kalman filtering [17] on the noisy estimates, which has long been studied for tracking and location estimation purposes [6]. The noisy estimates ($\hat{\mathbf{L}}$)

are considered to be the observation and the unknown ship location becomes the transient state.

$$x_k = Ax_{k-1} + Bu_k + w_k \qquad (15)$$
$$z_k = Cx_k + v_k$$

The A, B, and C matrices are simply identity matrices since the observation and the hidden states are in the same space. The state transition is obtained by the impulse signal (u_k) that is fed from the gyro. That is, the step is pointing at the direction of the course of the ship, obtained by only the ships gyro repeater, sticking loyal to the GPS-free assumption.

The transition noise w is introduced by the drift inherent in the operation area. For the application in the Aegean sea, we added a random drift with no assumed direction of up to $3NM$. Namely, we took w to be distributed with a zero mean and identity covariance matrix Gaussian. This measurement noise v, on the other hand, is the direct output of the *Error estimation phase*. Hence, the ultimate positioning problem can be defined in terms of (9) and (10) as

where the impulse is implemented to come from the previous location estimates

$$u_k = \hat{\mathbf{O}}_{k-1} - \hat{\mathbf{O}}_{k-2} \qquad (16)$$

and

$$v \sim \mathcal{N}(0, \mathbf{\Sigma}) \qquad (17)$$
$$w \sim \mathcal{N}(0, \mathbf{\Sigma}_{drift})$$

where

$$\mathbf{\Sigma}_{drift} = \sigma_{drift} I \qquad (18)$$

The observation (measurement) covariance matrix is estimated as explained in Equation (12). The estimated covariance matrix can be seen below:

$$\hat{\mathbf{\Sigma}} = \begin{bmatrix} 100 & 0 \\ 0 & 150 \end{bmatrix} \qquad (19)$$

The state transition error covariance matrix is chosen to be consistent with the drift value applied during simulation and this value is taken to be $\sigma_{drift} = 10^{-3}$.

The Kalman filter process is employed in the following steps:

- In the *prediction* step, we iterate the location estimation with the route information and update the estimate covariance matrix ($\mathbf{P}$) with it

$$\hat{\mathbf{O}}_{k|k-1} = \hat{\mathbf{O}}_{k-1|k-1} + u_k$$
$$\hat{\mathbf{P}} = \mathbf{P} + \mathbf{\Sigma}_{drift} \qquad (20)$$

- In the *update* step, we use the current triangulation location estimate and the predicted statistical properties of the model and update the state estimate. The Kalman gain value (K) and the location estimate is also updated in this step:

$$\mathbf{K} = \hat{\mathbf{P}}(\hat{\mathbf{P}} + \mathbf{\Sigma}_{drift})^{-1}$$
$$\hat{\mathbf{O}}_{k|k} = \hat{\mathbf{O}}_{k|k-1} + \mathbf{K}(\mathbf{L}_k - \hat{\mathbf{O}}_{k|k-1}) \qquad (21)$$
$$\mathbf{P} = (I - \mathbf{K})\hat{\mathbf{P}}$$

These two steps are repeated every time an ESM location is taken on the ships/aircraft's route. The algorithm for the position estimation system can be summarized as follows:

Algorithm 1 GPS-free Navigation Algorithm

Require: Initial location estimates $\hat{\mathbf{O}}_{0|0}, \mathbf{K}$ and $\mathbf{P}$
```
k = 0
repeat
    N = total number of active Radars that reaches ship
    predict Ô_{k|k-1} and P̂ using (20)
    if N < 2 then
        Ô_k = Ô_{k|k-1} and P = P̂
    else if N = 2 then
        Calculate L using (6)
        update prediction and Kalman gains using (21)
    else if N ≥ 3 then
        Find the nearest 3 radars using Euclidean distance
        Calculate L using (8)
        update prediction and Kalman gains using (21)
    end if
until O is available (GPS comes back)
```

The operation of the proposed algorithm can be observed in Figure 4, which is a snapshot from the GUI we developed for this task. The blue line is the actual course of the ship. Black dots are location estimates obtained by triangulation. The green rays are incident from the terrestrial satellites. The red curve is the Kalman filtered versions of the noisy (black) location estimates. In terms of the algorithm and the mathematical formulae described above, the blue is $\mathbf{O}$, black is $\mathbf{L}$ and the red is $\hat{\mathbf{O}}$. It can be seen how $\hat{\mathbf{O}}$ tracks $\mathbf{O}$ even though $\mathbf{L}$ can get very noisy at times.

III. Discussion and Conclusion

In this paper, we proposed and implemented a system that enables ships and aircraft to utilize their ESM systems to retrieve their own ship location in case of a GPS failure. The importance of this system is that it automatically feeds the other warfare and navigation systems. We have also conducted a feasibility experiment with no cost, but just utilizing simulation using image processing, statistical signal processing, and trigonometric rules. With only 7 random Radars, not optimally or particularly located, the positioning error of the system becomes average $300 yards$ of Euclidean distance on a ship coarse from the Marmara Sea to the

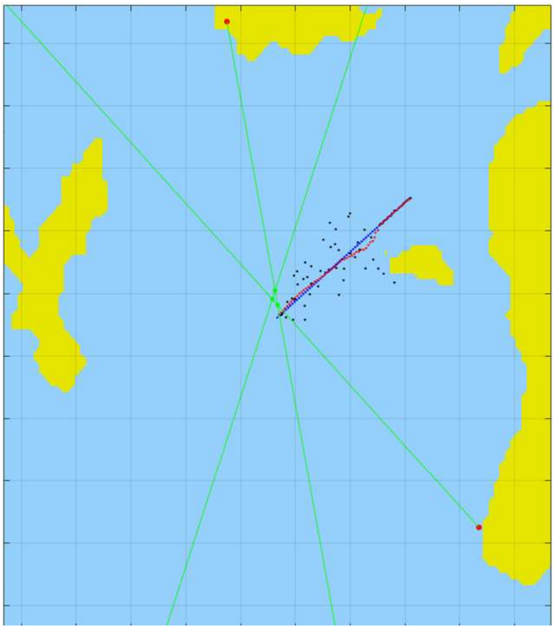

Fig. 4. An illustration of the GPS-free operation, from the software

Mediterranean.

As future work, optimal locations of the Radars can be studied which would yield the best operation performed using the same error values of the ESM system. Also, the third dimension can also be estimated for aircraft, relaxing the blind sector constraints we pushed for ships in this paper.

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REFERENCES

[1] J. V. Carroll and J. A. Weitzen, "Gps and loran-c: A great approach navigation system for general aviation aircraft," *GPS Solutions*, vol. 1, no. 1, pp. 11–12, 1995.

[2] T. Roos, P. Myllymaki, and H. Tirri, "A statistical modeling approach to location estimation," *IEEE Transactions on Mobile computing*, vol. 99, no. 1, pp. 59–69, 2002.

[3] H.-J. Du and J. Lee, "Radar emitter localization using tdoa measurements from uavs and shipborne/land-based platforms," in *NATO RTA SCI-116 Symposium on Multi-Platform Integration of Sensors and Weapon Systems for Maritime Applications*, 2002.

[4] S. Tomic, M. Beko, R. Dinis, and L. Bernardo, "On target localization using combined rss and aoa measurements," *Sensors*, vol. 18, no. 4, p. 1266, 2018.

[5] G. Kumar, R. Saha, M. K. Rai, R. Thomas, T.-H. Kim, S.-J. Lim, and J. S. P. Singh, "Improved location estimation in wireless sensor networks using a vector-based swarm optimized connected dominating set," *Sensors*, vol. 19, no. 2, p. 376, 2019.

[6] D. Fox, J. Hightower, L. Liao, D. Schulz, and G. Borriello, "Bayesian filtering for location estimation," *IEEE pervasive computing*, no. 3, pp. 24–33, 2003.

[7] J. Yin, Q. Yang, and L. M. Ni, "Learning adaptive temporal radio maps for signal-strength-based location estimation," *IEEE transactions on mobile computing*, vol. 7, no. 7, pp. 869–883, 2008.

[8] K. Pahlavan, *Indoor Geolocation Science and Technology: at the Emergence of Smart World and IoT*. Stylus Publishing, LLC, 2019.

[9] W. Wang and B.-H. Soong, "A distributed heuristics of localization in wireless sensor network," in *2006 International Conference on Wireless Communications, Networking and Mobile Computing*. IEEE, 2006, pp. 1–4.

[10] D. Niculescu and B. Nath, "Ad hoc positioning system (aps)," in *GLOBECOM'01. IEEE Global Telecommunications Conference (Cat. No. 01CH37270)*, vol. 5. IEEE, 2001, pp. 2926–2931.

[11] S. Čapkun, M. Hamdi, and J.-P. Hubaux, "Gps-free positioning in mobile ad hoc networks," *Cluster Computing*, vol. 5, no. 2, pp. 157–167, 2002.

[12] S. Särkkä, A. Vehtari, and J. Lampinen, "Rao-blackwellized monte carlo data association for multiple target tracking," in *Proceedings of the seventh international conference on information fusion*, vol. 1. I, 2004, pp. 583–590.

[13] E. Taghavi, R. Tharmarasa, T. Kirubarajan, and M. Mcdonald, "Multisensor-multitarget bearing-only sensor registration," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 52, no. 4, pp. 1654–1666, 2016.

[14] B. F. La Scala and M. R. Morelande, "An analysis of the single sensor bearings-only tracking problem." in *FUSION*, 2008, pp. 1–6.

[15] B. F. D. Hähnel and D. Fox, "Gaussian processes for signal strength-based location estimation," in *Proceeding of Robotics: Science and Systems*. Citeseer, 2006.

[16] "D maps," http://d-maps.com, accessed: 2019-04-04.

[17] B. Ristic, S. Arulampalam, and N. Gordon, "Beyond the kalman filter," *IEEE Aerospace and Electronic Systems Magazine*, vol. 19, no. 7, pp. 37–38, 2004.