Evaluation of the probability of correct positioning of the beacon and its motion parameters in passive search and rescue systems

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Abstract In this article, the approach to evaluate the probability of estimating the range of the beacon with a given accuracy is proposed. To determine the range to the beacon, a set of Kalman filters is applied to the beacon bearing measurements according to the given hypotheses about its motion parameters. The calculation of the probability of the correct choice of a hypothesis is presented. The hypothesis with the minimum sum of squared residuals is considered without prediction errors, its expectation and standard deviation, respectively, are. The time, required to determine the range with the probability 0.9-0.95 is calculated according to the proposed method agrees with the results obtained by statistical analysis, performed over multiple data sets. The results of the simulation of the “frequency” graph are shown.

1. Introduction
The recent developments of passive or semi-active radars have increased their application for target positioning, together with active radars [1, 26].

To determine the location of the target, the existing methods requires either two passive radars placed at different positions or the presence of the external signal (GSM or broadcast signal). However, if the target radiates, it is possible to determine its range by measuring the bearing of the target and its radiation parameters using only one mobile passive locator [23-25]. In these methods, the acceptable accuracy of the location is achieved not after one measurement, but after a while, and therefore it is unknown at what time instant the estimated target location is accurate with the predefined accuracy [3-6]. This article derives the probability of correct target (emitting beacon) location using the algorithm described below.

2. Model and Method
To determine the location of a mobile beacon using only one mobile direction finder, the hypothesis testing algorithm is proposed [13]. The task is to determine the location of the target: the direction finder begins to move with the speed V₁ and course Ψ₁ when the radiation of the beacon is detected. After the time T㎝ the finder changes the course of the motion to Ψ₂ and moves with the speed V₂ [7-9]. Multilevel prognosis of logistics chains in case of uncertainty: Journal of Open Innovation: Technology, Market, and Complexity, 4(1) doi:10.1186/s40852-018-0081-8. The beacon during the operation of the algorithm moves rectilinearly with a constant speed. It is required to determine the range to the beacon with the required relative accuracy δD [10-12]. The geometry of the problem is shown in figure 1. The notations on the figure are the following: V₁, V₂ – the speed of the finder, Ψ₁, Ψ₂ – the course of the finder movement, V, Ψ – speed and heading of the beacon, D₀, φ₀ – range and bearing to the beacon at the moment of its detection, Di, φᵢ – the distance and bearing to the beacon in time i. Oy, Ox – axes of coordinates, the axe Oy directed to the North, the axe Ox – directed to the East [18-22].
Figure 1. The geometry of the mutual motion of the direction finder and beacon

To determine the range to the beacon, a set of one-dimensional Kalman filters is formed, each filter is determined by a set of hypotheses about the initial range to the beacon, the speed and the course of its movement. Kalman filter will be denoted by three indices abc (a – a number of hypotheses about the initial range, b – a number of hypotheses about the speed, c – a number of hypotheses about the course).

The Kalman filter with indices abc is given by:

1) Prediction of the bearing of the beacon:

\[
\phi_{i,i-1}^{abc} = \hat{\phi}_{i-1}^{abc} + \frac{V^b \cdot dt \cdot \sin(\Psi^c - \hat{\phi}_{i-1}^{abc}) - \sqrt{(\Delta x_i)^2 + (\Delta y_i)^2} \cdot \sin \left( \frac{\Delta x_i}{\Delta y_i} - \hat{\phi}_{i-1}^{abc} \right)}{\hat{D}_{i-1}^{abc} + V^b \cdot dt \cdot \cos(\Psi^c - \hat{\phi}_{i-1}^{abc}) - \sqrt{(\Delta x_i)^2 + (\Delta y_i)^2} \cdot \cos \left( \frac{\Delta x_i}{\Delta y_i} - \hat{\phi}_{i-1}^{abc} \right)}
\]

2) Predicted MSE error: \( p_{i,i-1} = p_{i-1} \)

3) Kalman Gain: \( K_i = \frac{p_{i,i-1}}{p_{i,i-1} + \sigma_\phi^2} \)

4) Correction of the beacon bearing: \( \hat{\phi}_i^{abc} = \phi_{i,i-1}^{abc} + K_i \cdot (\phi_i - \phi_{i,i-1}^{abc}) \)

5) MSE: \( P_i = (1 - K_i) \cdot p_{i,i-1} \)

\( V_b \) – the hypothesis on the beacon speed, \( \Psi_c \) – the hypothesis on the beacon course, \( \hat{D}_{0}^{abc} = D^a \) – the hypothesis on the initial range to the beacon, \( V \) – the speed of the beacon, \( \Psi \) – the rate of motion of the beacon, \( dt \) – the time between measurements of bearing, \( \Delta x_i \) – movement of the direction finder along the
Ox axis during the time dt at step i, $\Delta y_i$ – movement of the direction finder along the Oy axis during the time dt at step i.

$$S_i = \sum_{k=1}^{i} (\hat{\phi}_j - \phi_j)^2$$

For each filter, the sum of the squares of the residuals is calculated.

The estimation of the beacon range and motion parameters corresponds to the Kalman filter with the smallest sum of squares of residuals [14-17].

3. Determination of the probability of correct choice of the hypothesis of determining the range with a given relative accuracy $\delta D$.

The parameter that determines the choice of the hypothesis with the current range to the target and the parameters of the target movement is the sum of squares of residuals $S_i$ at time i. Thus, the probability of the correct choice of the hypothesis on i step algorithm is the probability that the sum of the squares of the residuals $S^0_i$ for the hypothesis with indices abc with the value of the current range up to a beacon with the minimum sum of squares of residuals at the step i will be less than the sum of squares of residuals $S^1_i$ for the hypothesis with indices ’b’c’, which have a minimum sum of squares of residuals from the range of hypotheses that have a current estimate of the range to the target outside the range

$$[D_i^{abc} \cdot (1 - 2 \cdot \delta D), D_i^{abc} \cdot (1 + 2 \cdot \delta D)]$$

The probability of the correct choice of the hypothesis can be calculated with:

$$p(S^0_i < S^1_i) = \int_{-\infty}^{+\infty} f_0(x) \cdot dx \cdot f_i(h) \cdot dh = \int_{-\infty}^{+\infty} F_0(h) \cdot f_i(h) \cdot dh$$

$f_0(x)$ – probability density of the sum of squares of residuals $S^0_i$, $f_i(h)$ – probability density of the sum of squares of residuals $S^1_i$, $F_0(h)$ – probability distribution function of the sum of squares of residuals $S^0_i$.

Sum of squared residuals at the i-th step of the algorithm is

$$S_i = \sum_{j=1}^{i} (\hat{\phi}_j - \phi_j)^2 = \sum_{j=1}^{i} (\phi_j + \Delta \phi_j - \phi_j - \Delta \phi_j)^2 = \sum_{k=1}^{i} (\Delta \phi_j - \Delta \phi_j)^2$$

$\hat{\phi}_j$ – the measured bearing of the beacon, $\phi_j$ – the estimated bearing of the beacon, $\Delta \phi_j$ – the measurement error in the bearing of the radio beacon, $\Delta \hat{\phi}_j$ – estimation error of the bearing to the beacon.

The sum of the squares of residuals for the i-th reference is a random value in the form

$$S_i = \sum_{k=1}^{i} (D \Delta \phi_k \cdot \Delta \phi_k)^2 = \sum_{k=1}^{i} (D \Delta \phi_k \cdot \Delta \phi_k)^2 \cdot N(0,1)^2 = \sum_{k=1}^{i} (D \Delta \phi_k \cdot \Delta \phi_k)^2 \cdot \chi^2(1)$$

$N(0,1)$ - random variable with standard normal distribution, $\chi^2(1)$ - a random variable distributed by the Chi-square law with the degree of freedom equal to 1.

To solve the problem of determining the location of the radio beacon, it is necessary to collect more than 100 measurements of the direction finder. Then, according to the Central limit theorem, the sum of the squares of residuals can be considered a normally distributed random variable (Petinov, S. V., 2018) (Zegzhda, P., et al., 2017).
The probability density of the normal distribution is determined by the parameters of expectation and variance. We derive the expectation and variance of the sum of squares of residuals with the minimum sum of squares of residuals $S_i^0$ (no prediction errors) and prediction errors $S_i^1$.

Because the estimation of bearing is used, the algorithm of Kalman filter, the estimate of the bearing at the time i can be expressed in the form:

$$\hat{\phi}_i = K_i \cdot \hat{\phi}_i + (1 - K_i) \cdot \hat{\phi}_{i-1} = K_i \cdot \phi_i + K_i \cdot \Delta \phi_i + (1 - K_i) \cdot (\hat{\phi}_{i-1} + \hat{u}_i) =$$

$$= K_i \cdot \phi_i + K_i \cdot \Delta \phi_i + (1 - K_i) \cdot (\phi_{i-1} + \Delta \phi_{i-1} + \phi_i - \phi_{i-1} + \Delta u_i) =$$

$$= K_i \cdot \phi_i + K_i \cdot \Delta \phi_i + (1 - K_i) \cdot \phi_{i-1} + (1 - K_i) \cdot \Delta \phi_{i-1} + (1 - K_i) \cdot \Delta u_i =$$

$$= \phi_i + K_i \cdot \Delta \phi_i + (1 - K_i) \cdot \Delta \phi_{i-1} + (1 - K_i) \cdot \Delta u_i$$

$K_i$ – Kalman Gain, $\hat{\phi}_{i-1} = \hat{\phi}_{i-1} + \hat{u}_i$ – prediction of bearing on the beacon, $\hat{u}_i = \phi_i - \phi_{i-1} + \Delta u_i$ – control action, $\phi_i$ – the true value of bearing, $\Delta u_i$ – prediction error.

Bearing estimation error is equal to:

$$\Delta \phi_i = \hat{\phi}_i - \phi_i = \phi_i + K_i \cdot \Delta \phi_i + (1 - K_i) \cdot \Delta \phi_{i-1} + (1 - K_i) \cdot \Delta u_i - \phi_i =$$

$$= K_i \cdot \Delta \phi_i + (1 - K_i) \cdot \Delta \phi_{i-1} + (1 - K_i) \cdot \Delta u_i = K_i \cdot \Delta \phi_i + (1 - K_i) \cdot \Delta \phi_{i-1} +$$

$$+ ... + (1 - K_i) \cdot \Delta \phi_i + (1 - K_i) \cdot \Delta \phi_{i-1} + ... + (1 - K_i) \cdot \Delta u_i + ... + (1 - K_i) \cdot \Delta \phi_i +$$

$$+ (1 - K_i) \cdot \Delta u_i + (1 - K_i) \cdot \Delta \phi_{i-1} + ... + (1 - K_i) \cdot \Delta u_{i-1} + ... + (1 - K_i) \cdot \Delta u_0$$

If the variance of the noise after filtering is zero (Q), than Kalman Gain is equal to

$$K_i = \frac{1}{i + 1},$$

and the expression for the bearing estimation error takes the following form:

$$\Delta \phi_i = \sum_{k=0}^{i} \frac{\Delta \phi_k}{i + 1} + \sum_{k=i+1}^{\infty} \frac{\Delta \phi_k}{i + 1} \cdot \Delta u_k + \Delta u_i$$

Control action $u_i$ on step i is equal:

$$u_i = \frac{V \cdot dt \cdot \sin(\Psi - \phi_{i-1}) - \sqrt{(\Delta x_i)^2 + (\Delta y_i)^2} \cdot \sin\left(\arg\left(\frac{\Delta x_i}{\Delta y_i}\right) - \phi_{i-1}\right)}{D_i} = \frac{A_i}{D_i}$$

$$D_i = D_{i-1} + V \cdot dt \cdot \cos(\Psi - \phi_{i-1}) - \sqrt{(\Delta x_i)^2 + (\Delta y_i)^2} \cdot \cos\left(\arg\left(\frac{\Delta x_i}{\Delta y_i}\right) - \phi_{i-1}\right) - \text{the value of the current range to the beacon, } D_0 - \text{the initial range to the target.}$$

The estimated control action (in case of errors) for the hypothesis with indices abc, provided $\cos \hat{\phi}_i \approx \cos \phi_i$ and $\sin \hat{\phi}_i \approx \sin \phi_i$, is equal:
The expectation and the variance of the bearing estimation error for accurate prediction are:

\[ V^b \cdot dt \cdot \sin(\Psi^c - \tilde{\phi}^{abc}_{t-1}) - \sqrt{(\Delta x_i)^2 + (\Delta y_i)^2} \cdot \sin \left( \arg \left( \frac{\Delta x_i}{\Delta y_i} \right) - \tilde{\phi}^{abc}_{t-1} \right) = \hat{D}^{abc}_i \]

\[ V^b \cdot dt \cdot \sin(\Psi^c - \phi_{t-1}) - \sqrt{(\Delta x_i)^2 + (\Delta y_i)^2} \cdot \sin \left( \arg \left( \frac{\Delta x_i}{\Delta y_i} \right) - \phi_{t-1} \right) = \hat{A}^{abc}_i \]

The error of the control action is equal to:

\[ \Delta u_i = \frac{\hat{A}^{abc}_i}{\hat{D}^{abc}_i} - \frac{A_i}{D_i} \]

Next character \( \Delta \tilde{\phi}_i \) we will denote the error of bearing estimation in case of accurate prediction, i.e. \( U_i = 0 \).

The bearing measurement error has a normal distribution with zero mean and variance \( \sigma^2_\phi \) (\( M[\Delta \tilde{\phi}_j] = 0, D[\Delta \tilde{\phi}_j] = \sigma^2_\phi \)). The bearing measurement are considered to be uncorrelated.

### 4. The sum of squares of residuals without error prediction

The expectation and the variance of the bearing estimation error for accurate prediction are:

\[ M[\Delta \phi] = M \left[ \frac{1}{i+1} \cdot \Delta \phi_i + \ldots + \frac{1}{i+1} \cdot \Delta \phi_0 \right] = M \left[ \frac{1}{i+1} \cdot \Delta \phi_i \right] + \ldots + M \left[ \frac{1}{i+1} \cdot \Delta \phi_0 \right] = 0 \]

\[ D[\Delta \phi] = M \left[ \left( \frac{1}{i+1} \cdot \Delta \phi_i + \ldots + \frac{1}{i+1} \cdot \Delta \phi_0 \right)^2 \right] - M^2[\Delta \phi_i] = \frac{\sigma^2_\phi}{i+1} \]

The sum of squares of residuals for accurate forecasting (\( U_i = 0 \)) is equal:

\[ S^0_i = \sum_{j=1}^{i} (\Delta \tilde{\phi}_j - \Delta \phi_j)^2 \]

We define the mean of the sum of squares of residuals:

\[ M[S^0_i] = M \left[ \sum_{j=1}^{i} (\Delta \tilde{\phi}_j - \Delta \phi_j)^2 \right] = M \left[ \sum_{j=1}^{i} (\Delta \tilde{\phi}_j - \Delta \phi_j)^2 \right] + \ldots + M \left[ \sum_{j=1}^{i} (\Delta \tilde{\phi}_j - \Delta \phi_i)^2 \right] = \sigma^2_\phi \cdot \left( \sum_{j=1}^{i} \frac{j}{j+1} \right) \]

Determine the variance of the sum of squares of residuals:

\[ D[S^0_i] = M \left[ \left( \sum_{k=1}^{i} (\Delta \tilde{\phi}_k - \Delta \phi_k)^2 \right)^2 \right] - M \left[ S^0_i \right]^2 = M \left[ \sum_{k=1}^{i} (\Delta \tilde{\phi}_k - \Delta \phi_k)^4 \right] + \]

\[ + 2 \cdot \sum_{k=1}^{i} \sum_{j=1}^{k-1} (\Delta \tilde{\phi}_j - \Delta \phi_j)^2 \cdot (\Delta \phi_k - \Delta \phi_k)^2 - M \left[ S^0_i \right]^2 = \]

\[ = \sigma^4_\phi \cdot \left( \sum_{k=1}^{i} \frac{4 \cdot k^2 - 2 \cdot k}{(k+1)^3} - 4 \cdot \sum_{k=2}^{i} \sum_{j=1}^{k-1} \frac{j}{(k+1)^2 \cdot (j+1)} \right) \]
To simplify the calculation of the variance, we approximate it as follows:
\[ D[S_i^0] = \sigma^4 \cdot \log_{1.645}(i) \]

5. Sum of squares of residuals with prediction errors
The sum of squares of residuals with prediction error:
\[ S_i^1 = \sum_{j=1}^{i} (\tilde{\phi}_j - \hat{\phi}_j - U_j)^2 = \sum_{j=1}^{i} (\phi_j + \Delta \tilde{\phi}_j - \phi_j - \Delta \hat{\phi}_j - U_j)^2 = \sum_{j=1}^{i} (\Delta \tilde{\phi}_j - \Delta \hat{\phi}_j - U_j)^2 \]

We define the expectation of the sum of the squares of the residuals when predicting with an error:
\[ M[S_i^1] = M\left[ \sum_{j=1}^{i} (\Delta \tilde{\phi}_j - \Delta \hat{\phi}_j - U_j)^2 \right] = \sigma^2 \cdot \sum_{j=1}^{i} \frac{j}{j+1} + \sum_{j=1}^{i} M[U_j^2] \]

Since the prediction error does not include measurement errors, the expectation of the prediction error is equal to:
\[ M[U_j^2] = U_j^2 \]
\[ M[S_i^1] = \sigma^2 \cdot \sum_{j=1}^{i} \frac{j}{j+1} + \sum_{j=1}^{i} U_j^2 \]

Therefore
\[ D[S_i^1] = M\left[ \left( \sum_{j=1}^{i} (\Delta \tilde{\phi}_j - \Delta \hat{\phi}_j - U_j)^2 \right)^2 \right] - \left( M[S_i^1] \right)^2 = \sigma^4 \cdot \sum_{j=1}^{i} \left( \frac{j}{j+1} \right)^2 + \frac{2 \cdot \sum_{k=1}^{i} \sum_{j=1}^{k} \sum_{j}^{i} \left( \Delta \tilde{\phi}_j - \Delta \hat{\phi}_j - U_j \right)^2 \cdot \left( \Delta \tilde{\phi}_j - \Delta \hat{\phi}_j - U_j \right)^2}{\left( \sum_{j=1}^{i} \left( \Delta \tilde{\phi}_j - \Delta \hat{\phi}_j - U_j \right)^2 \right)} - \left( M[S_i^1] \right)^2 = \sigma^4 \cdot \log_{1.645}(i)^2 + \frac{2 \cdot \sigma^2 \cdot \left( \frac{3 \cdot \sum_{k=1}^{i} U_k^2 \cdot k}{k+1} + \frac{\sum_{k=2}^{i} \sum_{j=1}^{k} \left( \frac{k \cdot U_k^2}{k+1} + \frac{j \cdot U_j^2}{j+1} - \frac{4 \cdot U_k \cdot U_j}{(k+1) \cdot (j+1)} \right) \cdot \sum_{j=1}^{i} \frac{k}{k+1} \cdot \sum_{j=1}^{i} U_j^2} \right)}{\left( \sum_{j=1}^{i} \left( \Delta \tilde{\phi}_j - \Delta \hat{\phi}_j - U_j \right)^2 \right)} \]

6. Calculating the probability of the correct choice of hypothesis
The hypothesis with the minimum sum of squares of residuals is considered without prediction errors, its mathematical expectation and standard deviation are respectively equal to:
\[ M[S_i^0] = \sigma^2 \cdot \sum_{j=1}^{i} \frac{j}{j+1} \]
\[ \sigma_{S_i^0} = \sigma^2 \cdot \log_{1.645}(i) \]

Mathematical expectation and RMS of the hypothesis with the prediction error are respectively equal to:
\[ M[S_i^1] = \sigma^2 \cdot \sum_{j=1}^{i} \frac{j}{j+1} + \sum_{j=1}^{i} U_j^2 \]
\[
\sigma_{s_{ij}} = \left( \sigma^2 \cdot \left( \log^{0.147}(i) \right) \right)^2 + \\
+ 2 \cdot \sigma^2 \cdot \left( 3 \cdot \frac{\sum_{k=1}^{i} U_k \cdot k}{k + 1} + \frac{\sum_{k=2}^{i} \sum_{j=1}^{k} \left( \frac{k \cdot U_k^2}{j + 1} - \frac{4 \cdot U_k \cdot U_j}{(k + 1) \cdot (j + 1)} \right)}{\frac{1}{k + 1} \cdot \sum_{k=1}^{i} U_k^2} \right)^{0.5}
\]

To obtain the sum of squares of residuals without prediction errors to the standard normal value, we subtract the value from both sums \(M[S_{ij}^0]\) and then divide by \(\sigma_{s_{ij}}^2\). As a result, we get:

\[
M[S_{ij}^0] = 0 \\
\sigma_{s_{ij}} = 1 \\
M[S_{ij}^0] = \frac{1}{\log^{0.147}(i)} \cdot \frac{\sum_{j=1}^{i} U_j^2}{1 + \frac{2 \cdot \sigma^2 \cdot \left( 3 \cdot \frac{\sum_{k=1}^{i} U_k \cdot k}{k + 1} + \frac{\sum_{k=2}^{i} \sum_{j=1}^{k} \left( \frac{k \cdot U_k^2}{j + 1} - \frac{4 \cdot U_k \cdot U_j}{(k + 1) \cdot (j + 1)} \right)}{\frac{1}{k + 1} \cdot \sum_{k=1}^{i} U_k^2} \right)^{0.5}}{\left( \log^{0.147}(i) \right)^2}
\]

Thus, the expression for calculating the probability of choosing a hypothesis without prediction errors can be rewritten as follows:

\[
p(S_{ij}^0 < S_{ij}) = \frac{1}{2} \cdot \int_{-\infty}^{\infty} \left( 1 + \frac{\exp(-\left( \frac{h - M[S_{ij}^0]}{2 \cdot \sigma_{s_{ij}}^2} \right)^2}{\sigma_{s_{ij}} \cdot \sqrt{2 \cdot \pi}} \right) \cdot dh
\]

7. Conclusions

To check the efficiency of the proposed method of calculating the probability of correctly determining the range calculated by the formula (1), 20 realizations for each set of parameters were simulated. For each implementation, the following parameters were set for the movement of targets and their relative location: the speed of movement of the direction finder 14 m/s, the initial course of movement of the direction finder 0°, the changed course – 180°, the time of change of course 600 seconds, the initial bearing on the beacon 90°, the initial range to the beacon 150, 200 and 250 km, the speed of movement of the beacon 10 m/s, the course 0°, the bearing 0.2° and 0.3°. The number of hypotheses about the initial range is 40, the minimum range is 40 km, the step of hypotheses is 10 km, the number of hypotheses of the beacon speed is 21, the initial speed is 0 m/s, the step of hypotheses is 1 m/s, the number of hypotheses about the course of the beacon is 72, the initial value of the course is 0°, the step between hypotheses is 5°.

Simulation results are shown (see figures 2-4), where the graph "frequency" shows what part of the solutions at a time t has an estimate of the range with an error not exceeding \(\delta D = 10\%\) from the true range. As can be seen from the graphs, before the change of course of the direction finder, the probability of determining the range with a given accuracy to the beacon is low, and after the change of course, as data accumulate, the probability of determining the range with a given accuracy approaches one.

The probability graph is calculated by the formula (1) from one realization of a data set. Since there is no a priori information about the range to the target at each step of the algorithm, the true value of the range
is taken as the current range to the Kalman filter beacon having the smallest sum of squares of residuals, respectively, the probability of the correct choice of this hypothesis at this step of the algorithm will be at least 0.5.

Despite the fact that the graphs are different at the beginning (before the time of the change of the direction finder's course), they are similar in speed approaching the probability value 1.

**Figure 2.** Comparison of probabilities (range to the beacon 150 km, the standard deviation of bearing 0.2)

**Figure 3.** Comparison of probabilities (the distance to the beacon 200 km, the standard deviation of bearing 0.2)
Summary

As can be seen from the results, the analytically obtained probability of determining the range with a given accuracy reaches a probability of 0.9..0.95 in the same time interval as the probability of determining the range obtained from many implementations. Accordingly, using the proposed technique can be considered for determining the location of the beacon with a given probability, in contrast to the methods with a fixed time required to perform the maneuver.

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