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Progress Report:

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New Models for Radar Bias Estimation

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1 Introduction

This report summarizes the work conducted by the Robotics and Target Tracking Research Group of the Royal Military College of Canada (RMC) in response to the *Radar Bias Estimation* project. The aim of this project is to investigate the feasibility of correcting the registration problem currently evident in the North Warning System. The research group is tasked to investigate new approaches to solving the registration problem, make recommendations concerning any new algorithms that may be available, and to define the functional requirements for the execution of those algorithms.

The Bias Estimation Project was initiated in response to changes in the Canadian airspace surveillance environment. The transition from the CADIN/PINETREE to the North Warning System (NWS) brought to light limitations in the sensor fusion capabilities of the air surveillance system. These limitations present themselves as ghost tracks in areas of overlapping coverage and an overall lower level of tracking quality. These problems are directly related to the individual biases contained in each sensor, and the system deficiencies are attributed to the inability of the current algorithm to detect and correct for those individual sensor biases. Thus, the thrust of the Bias Estimation Project is to determine the source of the sensor error and determine the best method of correcting it. Contained in the Task Description, the two approaches are the hardware emphasis on a new front end processor to perform the registration, and a software emphasis on a new algorithm for detecting and defining the individual sensor biases.

The report is divided into five sections. Section 2 provides a description of the activities of the research group over the first six months of the project. Section 3 discusses the current methods of bias estimation discussed in literature and Section 4 provides a mathematical description of the problem. In the subsequent sections, we discuss non- traditional approaches to solving for sensor biases. Section 5 explores the *neural network* (NN) approach to solve the problem while Section 6 concentrates on the use of Kalman Filtering to estimate the sensor biases. Each of these methods represents improvements over the current statistical approaches to bias estimation.

2 The Project Progress

The work accomplished during the initial six month period is outlined below:

1. *January–February 1995*: This period was devoted to problem definition. This phase involved:
   - Review of the literature related to radar registration and bias estimation provided by DREO.
   - Familiarization with the `Matlab` software package. Emphasis was placed on the `control` and `neural networks` toolboxes.
   - Creating a simulation environment to evaluate registration techniques.
   - Evaluating, through analysis and simulations, existing bias estimation techniques.
2. *March– Mid April 1995*: A neural network model for range and bearing bias estimation was constructed. This involved defining network structure and how learning parameters would be updated. Finally experimentation was conducted using both noisy and no-noise measurements.
3. *Mid April– May 1995*: At the request of DREO, we investigated the integration of tracking and bias estimation functions. This required the application of a Kalman filtering approach.
4. *Mid June 1995*: In this phase, we continued to work with the Kalman Filtering approach concentrating on improving the results achieved earlier through the use of fixed and variable point smoothing. No significant results were reported.

3 Previous Work on Bias Estimation

The literature contains two basic techniques for solving the registration problem. The first technique resembles the current NWS registration procedure and is called the Real-Time Quality Control (RTQC) method. The second makes use of least squares estimation techniques to solve for registration errors and is called the Least-Squares Real-Time Quality Control (LS-RTQC) method. In this section we will describe these methods in more detail.

3.1 Real-Time Quality Control (RTQC) Algorithm

The RTQC routine concurrently analyzes radar data from many radar sites on a real-time basis to determine registration errors. For every other pair of correlated radar data returns, the RTQC program performs calculations on the data that were saved during the two-scan intervals. The output of each RTQC computation is then applied to all subsequent incoming data and a new correction is calculated.

The basic idea of RTQC is that any pair of radar returns generated from the same target should have the same position. Although the individual measurements from each radar are corrupted by measurement noise, the RTQC process averages over a set of measurements to eliminate any inaccuracy the noise term causes. The RTQC works by constructing two *independent* sets of equations: one to calculate the range bias values for the two radars and another to calculate the azimuth bias values.

Although the algorithm is computationally simple, it has many drawbacks:

1. It does not eliminate *ghost* tracks. The original tracks are just corrected by removing the calculated bias terms. The operator will see two superimposed strings of radar plots, not one integrated set of measurements.

2. The RTQC solution of the set of equations is not optimal.

3. To obtain the two sets of equation, radar measurement pairs must be derived from at least one radar track on either side of an artificial line joining the two radar sites.

4. The algorithm is based on the inversion of a 4×4 matrix, therefore the matrix should be of full rank.

5. The algorithm does not properly account for the noise normally associated with the individual radar returns.

3.2 The Least-Square Real-Time Quality Control (LS-RTQC) Routine

The LS-RTQC is an attempt to solve the basic registration error equation using an optimal least squares estimation technique.

This algorithm reformulates the matrix algebra of the RTQC approach into a minimization problem. LS-RTQC makes use of the singular value decomposition algorithm to find the solution of the matrix equations thus deriving an optimal solution.

The main advantage of the LS-RTQC over the RTQC algorithm is that it does not need data from the two sides of the artificial radar line. LS-RTQC also produces a better estimate of radar bias than RTQC given the same data.

Although the estimate is optimal, the LS-RTQC algorithm is still deficient in other areas:

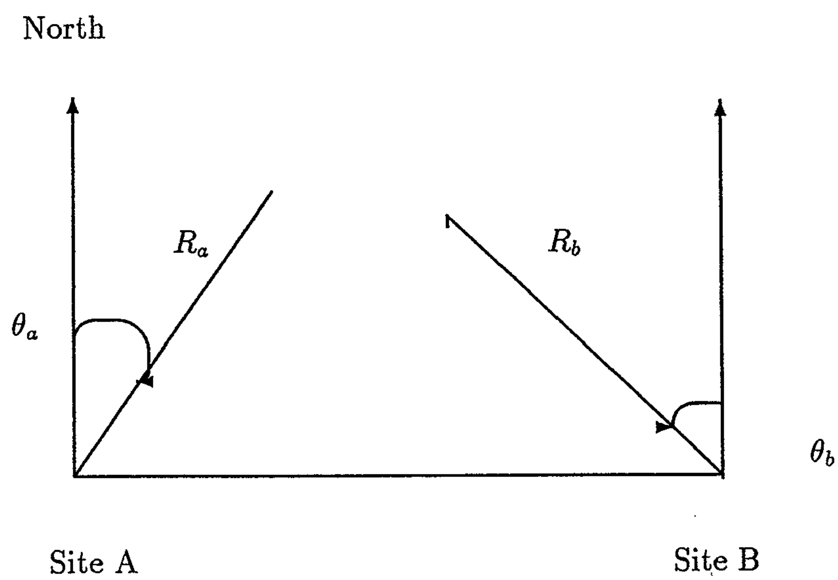
1. The LS-RTQC technique requires large quantities of intermediate storage. Given a large number of radar measurements, the computer memory required to effect the LS-RTQC algorithm may be prohibitive.

2. The LS-RTQC technique employs a single-value decomposition method for calculating the inverse of a matrix. This technique is computationally very expensive for the large matrices inherent in the formulation of LS-RTQC solutions.

3. Like its predecessor, the LS-RTQC algorithm provides poor estimates when the radar measurements are very close to the line separating the two radars.

4 Mathematical Analysis

Consider two sensors A and B which report range and azimuth on a common target. Sensor A is located at (x_{sa}, y_{sa}) while sensor B is located at (x_{sb}, y_{sb}). These locations are measured relative to a common coordinate point. This figure shows the two sensors associated with the registration error.



Let $(R_a(i), \theta_a(i))$ and $(R_b(i), \theta_b(i))$ be the radar returns from each sensor at the instant i. Also assume that the bias values associated with each sensor are: $(\delta R_a(i), \delta\theta_a(i))$ and $(\delta R_b(i), \delta\theta_b(i))$ where δR and $\delta\theta$ are the range and azimuth bias values. The measurement noise contribution is: $\left(\gamma_a^r, \gamma_a^\theta\right)$ for the return of site A and $\left(\gamma_b^r, \gamma_b^\theta\right)$ for the return of site B.

The key solution for the problem is the fact that the two sensors should return the same values, i.e.,

$$x'_a + x_{sa} = x'_b + x_{sb} \tag{1}$$

$$y'_a + y_{sa} = y'_b + y_{sb} \tag{2}$$

where, in the absence of measurement noise,

$$x'_a = (R_a - \delta R_a)\ \sin(\theta_a - \delta\theta_a) \approx R_a \sin\theta_a - x''_a \tag{3}$$

$$y'_a = (R_a - \delta R_a)\ \cos(\theta_a - \delta\theta_a) \approx R_a \cos\theta_a - y''_a \tag{4}$$

$$x'_b = (R_b - \delta R_b)\ \sin(\theta_b - \delta\theta_b) \approx R_b \sin\theta_b - x''_b \tag{5}$$

$$y'_b = (R_b - \delta R_b)\ \cos(\theta_b - \delta\theta_b) \approx R_b \cos\theta_b - y''_b \tag{6}$$

with

$$
\begin{aligned}
x_a'' &= \sin\theta_a \delta R_a + R_a \cos\theta_a \delta\theta_a && (7)\\
y_a'' &= \cos\theta_a \delta R_a - R_a \sin\theta_a \delta\theta_a && (8)\\
x_b'' &= \sin\theta_b \delta R_b + R_b \cos\theta_b \delta\theta_b && (9)\\
y_b'' &= \cos\theta_b \delta R_b - R_b \sin\theta_b \delta\theta_b && (10)
\end{aligned}
$$

The division coordinates for the returns are

$$
\begin{aligned}
x_a &= x_{sa} + R_a \sin\theta_a && (11)\\
y_a &= y_{sa} + R_a \cos\theta_a && (12)\\
x_b &= x_{sb} + R_b \sin\theta_b && (13)\\
y_b &= y_{sb} + R_b \cos\theta_b && (14)
\end{aligned}
$$

Let us define the difference in X and Y position of the two returns as P and Q

$$P = x_a - x_b = x_a'' - x_b'' = \sin\theta_a \delta R_a - \sin\theta_b \delta R_b + R_a \cos\theta_a \delta\theta_a - R_b \cos\theta_b \delta\theta_b$$

$$Q = y_a - y_b = y_a'' - y_b'' = \cos\theta_a \delta R_a - \cos\theta_b \delta R_b - R_a \sin\theta_a \delta\theta_a + R_b \sin\theta_b \delta\theta_b$$

These two equations can be solved for the four bias parameters δR_a, $\delta\theta_a$, δR_b, and $\delta\theta_b$. Both RTQC and LS-RTQC use both equations to solve for the parameters.

For the two non-traditional approaches we investigated, we start from these equations.

5 Neural Network Approach

The last two equations of Section 3, can be easily manipulated in a manner condusive to a neural network architecture. By simple trigonometric manipulation we get the following equations:

$$t_1 = P \sin\theta_a + Q\cos\theta_a$$

$$t_2 = -P\sin\theta_b - Q\cos\theta_b$$

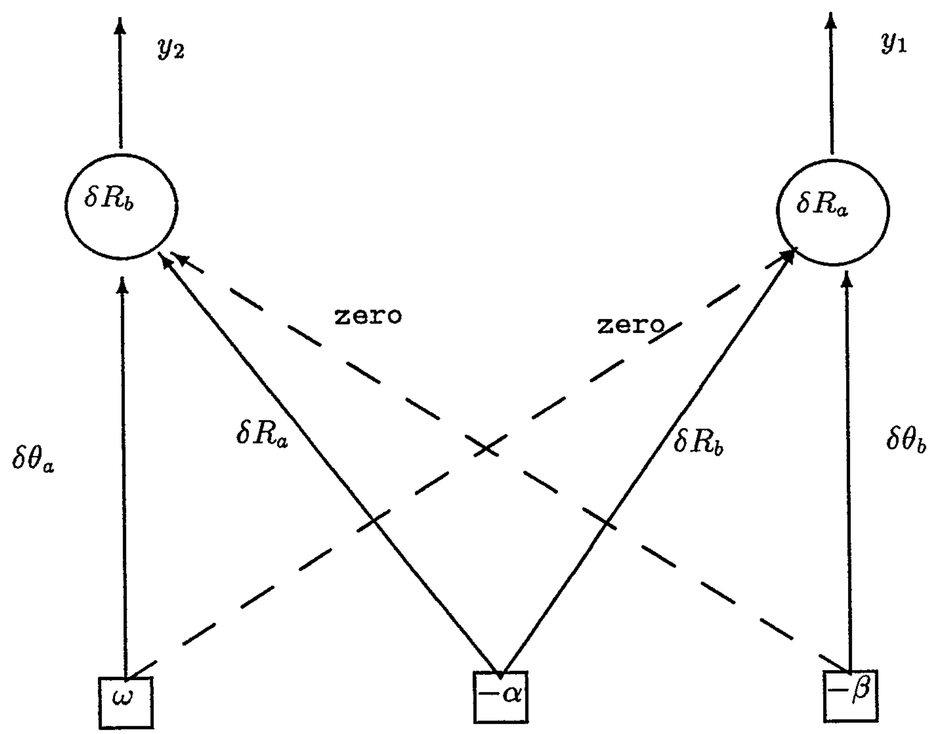
Therefore we can rearrange the terms to the form

$$t_1 = \delta R_a - \alpha\,\delta R_b - \beta\,\delta\theta_b$$

$$t_2 = -\alpha\delta R_a + \delta R_b + \omega\delta\theta_a$$

where $\alpha = \cos(\theta_a - \theta_b)$, $\beta = R_b\ \sin(\theta_a - \theta_b)$, and $\omega = R_a\ sin(\theta_a - \theta_b)$

This last pair of equations can be mapped to a *linear single–layer network* as shown.



This network functions in two modes of operation: *the learning mode and the recall mode* [4].

5.1 The Learning Mode

During the learning mode a set of inputs–target data pairs– are presented to the network. After the presentation of the ith input, $\{\alpha(i), \beta(i), \omega(i)\}$, the network output is calculated as

$$y_1(i) = \delta R_a - \alpha(i)\ \delta R_b - \beta(i)\ \delta\theta_b$$

$$y_2(i) = -\alpha(i)\delta R_a + \delta R_b + \omega(i)\delta\theta_a$$

The network then calculates the *representation error* over the whole training set. This is done via a suitable cost function, J,

$$J = \sum_{i=1}^{N}\sum_{j=1}^{2}[t_j(i) - y_j(i)]^2$$

The network parameters, $\delta R_a, \delta\theta_a, \delta R_b$, and $\delta\theta_b$, are to be changed in such a way that the cost function, J, is decreased. This requires an updating rule to modify each parameters. This rule updates the weights along the gradient descent direction of the cost function with respect to each parameter, i.e.,

$$\Omega(i+1) = \Omega(i) + \Delta\Omega(i) \tag{15}$$

where $\Omega(i)$ is value of any of the network parameters at instant i,

$$\Delta\Omega(i) = -\eta\frac{\partial J}{\partial\Omega(i)}$$

is the amount of change in Ω and η is the learning rate which controls the amount of the change in each parameter.

Using the neural network terminology, the parameters $\delta\theta_b$ and δR_b are the *weights* of the first node and δR_a represents its *bias or threshold.* Similarly, $\delta\theta_a$ and δR_a are the weights of the nodes and δR_b acts as the bias.

After each presentation of the data set, the network performance is evaluated by calculating the error J. If the error is below a prescribed value, the training is halted and the network has completed learning the task at hand. Otherwise, the data is presented once again and the parameters are updated (as mentioned above) until the error reaches the required accuracy.

A good characteristic of a neural network is that it is totally linear and therefore no possibility of the network settling on a *local* solution instead of pursuing an optimal *global* solution. This is a problem normally encountered with nonlinear optimization algorithms.

5.2 The Recall Mode

After the network is satisfactorily trained, we are ready to experiment using new data. We will present an input to the network, propagate this input through the network by calculating the activation function of the neurons, and evaluate the output to see how closely it conforms to the required solution. A network with good performance on data not used during training is said to possess good *generalization* capabilities. This characteristic is very desirable in the radar registration problem. In many instances good generalization is needed to calculate bias values using only small sets of training data and at the same time to use these values to correct the incoming data without retraining the network. This of course, requires any new data to originate from the same track.

5.3 Adjustment of The Learning Rate, η

Normally, the learning rate in the updating formula (15) is set to a small value ($\eta < 1.0$). Some algorithms set it to a scalar function of the eigenvalues of the input data [4]. With ill-conditioned data, this might result in unstable updating of the network parameters. In either case, both the input and target data are supposed to be noise–free. This is not the case with the tracks generated using the radars returns. For this particular data, if the learning rate was set to a small value, the network tries to fit both the data and the accompanying noise. This problem is exasperated when the values of some of the network parameters are much larger others (ie., the range bias is much larger than the azimuth bias). In this case the network, in its pursuit to decrease the overall error, will try to find the values of the large parameters first. By doing that, it will fit both the data and the noise as it cannot distinguish between the two. Eventually, the large parameters will receive inflated values and the small ones will receive smaller than optimal values.

To maintain optimality of the solution, the learning rate has to be adjusted in accordance with the data. In this proposed architecture, the rule used to update the learning rate for *total least-squares* parameter estimation will be adopted. Total least-squares optimization is used when the processed data is relatively noisy. The learning rate will be inversely proportional to the squared length of the gradient vector, i.e.,

$$\eta(\mathbf{x}) = \frac{1.0}{||\Delta_{\mathbf{x}} J(\mathbf{x})||^2} \tag{16}$$

where $\mathbf{x}$ represents the parameter vector. This value of η tends to weight the amount of change of any of the parameters according to the value of gradient. This will diminish the effects of noise by avoiding the network being *fooled* by the noisy data.

5.4 Simulation Results

A network is trained using two data files: one simulated data file and another with real data. The simulated data represents two tracks recorded by the NA0 and NB0 sensors. The NA0 radar has a bias in range equal to 0.2 *nm* and 0.005 *radians* bias in azimuth while the NB0 site has bias values of 0.3 *nm* and 0.0015 *radians* in range and azimuth, respectively. The returns of range and azimuth of both radars were contaminated with zero-mean Gaussian noise with variance 0.0156 for the range noise and 9.0×10^{-6} in azimuth noise. The estimated parameters resulted from the trained network are:

NA0: 0.2299 nm, 0.005 radians

NB0: 0.3167 nm, 0.00147 radians.

The corresponding values generated by LS-RTQC are:

NA0: 0.1643 nm, 0.0047 radians

NB0: 0.3694 nm, 0.00151 radians.

It is evident that the proposed neural network produced better values for the range bias while the azimuth values were very close. Using the real data file similar results were obtained.

5.5 Analysis of the Neural Network Method

There are many observations which can be drawn from the performance of the NN method:

- Computation Time. Neural Net methods are slower. NN depends on an iterative procedure to adjust the weights. The RTQC and LS-RTQC are one-shot algorithms.

- By updating the learning rate as suggested in (16), the NN could reach excessively large values when the gradient is close to zero which might destabilize a solution. A *guarding factor* is normally added to the gradient length in this case to avoid a division by zero problem.

- The noise problem can be further reduced by using different cost functions (a squashing one, for example) to eliminate the effect of the outlier samples.

- The network can be implemented on an analog structure with guaranteed convergence to the optimal values.

6 Kalman Filtering Approach

The Kalman filter is what should be considered a *classic* approach for solving the registration problem. The nature of the problem and the required outputs makes the use of a *Kalman filter* [5] very appealing.

The main objective of the Kalman filter is to estimate the state vector of a dynamic system when either/both the states or/and the measurements are contaminated with zero-mean independent Gaussian noise. This is done by minimizing a cost function which consists of a pattern representing the error in producing the measurements and another pattern representing the accuracy of the calculated state estimates. The first part of the cost function is calculated by taking the squared error between the observed measurement and the calculated ones based on the current state estimates. The second part is found by calculating the covariance matrix of the state estimates. Both parts will decrease as more data is presented to the filter. To be efficient, the model used to represent the real system has to be good enough and the statistics of the noise added to the states and the measurements have to be known *apriori*.

In the following section, the basic Kalman filter equations are presented, the model representing the bias estimation problem is derived, and finally the results of applying the proposed model to actual radar data are analysed.

6.1 Kalman Filter Equations:

Assume $\mathbf{x}$ is the system state vector (to be estimated), $\mathbf{A}$ is the state transition matrix, $\mathbf{y}$ is the observation (measurement) vector, $\mathbf{C}$ is the measurement matrix, γ_x is the state noise, and γ_y is the measurement noise. We will assume that the system is unforced, i.e., there is no external input. The discrete dynamic system equations are then:

$$\mathbf{x}(k+1) = \mathbf{A}\,\mathbf{x}(k) + \gamma_x(k) \quad (17)$$

$$\mathbf{y}(k) = \mathbf{C}\,\mathbf{x}(k) + \gamma_y(k) \quad (18)$$

The estimated state vector, $\hat{\mathbf{x}}$, is calculated in such a way that the cost function

$$J_K = E\left\{||\mathbf{y} - \mathbf{A}\,\hat{\mathbf{x}}||^2 + ||\mathbf{x} - \hat{\mathbf{x}}||^2\right\}$$

is minimized. A maximum-likelihood approach or a least-square minimization will result in the following updating equations:

$$\hat{\mathbf{x}}(k+1|k) = \mathbf{A}\,\hat{\mathbf{x}}(k|k) \quad (19)$$

$$
\begin{aligned}
\mathbf{P}(k+1|k) &= \mathbf{A}\,\mathbf{P}(k|k)\,\mathbf{A}^T + \mathbf{Q}(k) && (20)\\
\mathbf{K}(k+1) &= \mathbf{P}(k+1|k)\,\mathbf{C}^T\left[\mathbf{C}\mathbf{P}(k+1|k)\mathbf{C}^T + \mathbf{R}(k+1)\right]^{-1} && (21)\\
\hat{\mathbf{x}}(k+1|k+1) &= \hat{\mathbf{x}}(k+1|k) + \mathbf{K}(k+1)\left[\mathbf{y}(k+1) - \mathbf{C}\hat{\mathbf{x}}(k+1|k)\right] && (22)\\
\mathbf{P}(k+1|k+1) &= \left[\mathbf{I} - \mathbf{K}(k+1)C\right]\mathbf{P}(k+1|k) && (23)
\end{aligned}
$$

where $\mathbf{P}(k|k)$ is the covariance matrix of the estimation error, $\mathbf{Q}(k)$ and $\mathbf{R}(k)$ are the input and output noise covariance matrices, and $\mathbf{K}(k)$ is the Kalman gain.

6.2 Kalman Filtering for Bias Estimation

In order to solve for the bias parameters and to find the best possible track out of two unaligned tracks, a good representation model is essential.

First we define the state vector. The state vector, $\mathcal{X}(k)$, will be composed of eight components,

$$
\mathcal{X}(k) = \begin{pmatrix} x_t(k) & \dot{x}_t(k) & y_t(k) & \dot{y}_t(k) & \delta R_a(k) & \delta\theta_a(k) & \delta R_b(k) & \delta\theta_b(k) \end{pmatrix}^T
$$

where $x_t(k)$ and $y_t(k)$ represent the true x and y coordinate position at time k, $\dot{x}_t(k)$ and $\dot{y}_t(k)$ represent the corresponding speed, and the four remaining parameters are the range and azimuth bias values for radar A and B.

Since $x_t(k)$ and $y_t(k)$ represent the track points, the matrix $\mathbf{A}$ should reflect the dynamics of the track. Assuming that the sampling time is equal to the unit value, the transition matrix $\mathbf{A}$ can be expressed as

$$
\mathbf{A} = \begin{pmatrix}
1 & 1 & 0 & 0 & 0 & 0 & 0 & 0\\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0\\
0 & 0 & 1 & 1 & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0\\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0\\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1
\end{pmatrix}
$$

Here we assumed that the bias values are constant.

To find the model matrices, we rewrite the set of equations as follows:

$$
x'_a = (R_a - \delta R_a - \gamma_a^r)\,\sin\left(\theta_a - \delta\theta_a - \gamma_a^\theta\right) \qquad (24)
$$

$$y'_a = (R_a - \delta R_a - \gamma^r_a)\cos\left(\theta_a - \delta\theta_a - \gamma^\theta_a\right) \tag{25}$$
$$x'_b = (R_b - \delta R_b - \gamma^r_b)\sin\left(\theta_b - \delta\theta_b - \gamma^\theta_b\right) \tag{26}$$
$$y'_b = (R_b - \delta R_b - \gamma^r_b)\cos\left(\theta_b - \delta\theta_b - \gamma^\theta_b\right) \tag{27}$$

Then they are placed in the form:

$$R_a \sin\theta_a = x'_a + x''_a + n_{xa} \tag{28}$$
$$R_a \cos\theta_a = y'_a + y''_a + n_{ya} \tag{29}$$
$$R_b \sin\theta_b = x'_b + x''_b + n_{xb} \tag{30}$$
$$R_b \cos\theta_b = y'_b + y''_b + n_{yb} \tag{31}$$
$$\tag{32}$$

where x''_a, y''_a, x''_b, and y''_b are as previously defined and n_{xa}, n_{ya}, n_{xb}, and n_{yb} are the associated noise terms. Adding x_{sa}, y_{sa}, x_{sb}, and y_{sb} to both sides of the above four equations and using the relations

$$x_a = R_a \sin\theta_a + x_{sa}$$

$$y_a = R_a \cos\theta_a + y_{sa}$$

$$x_b = R_b \sin\theta_b + x_{sb}$$

$$y_b = R_b \cos\theta_b + y_{sb}$$

the following equations result

$$x_a = x_t + x''_a + n_{xa} \tag{33}$$
$$y_a = y_t + y''_a + n_{ya} \tag{34}$$
$$x_b = x_t + x''_b + n_{xb} \tag{35}$$
$$y_b = y_t + y''_b + n_{yb} \tag{36}$$

The following represents the measurement part of the model, i.e.,

$$\mathcal{Y} = \mathbf{C}\mathcal{X} + \mathbf{M}\mathcal{N} \tag{37}$$

where

$$\mathcal{Y} = \begin{pmatrix} x_a \\ y_a \\ x_b \\ y_b \end{pmatrix},$$

$$\mathbf{C} = \begin{pmatrix} 1 & 0 & 0 & 0 & \sin\theta_a & R_a\cos\theta_a & 0 & 0 \\ 0 & 0 & 1 & 0 & \cos\theta_a & -R_a\sin\theta_a & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & \sin\theta_b & R_b\cos\theta_b \\ 0 & 0 & 1 & 0 & 0 & 0 & \cos\theta_b & -R_b\sin\theta_b \end{pmatrix}$$

$$\begin{pmatrix} n_{xa} \\ n_{ya} \\ n_{xb} \\ n_{yb} \end{pmatrix} = \mathbf{M}\,\mathcal{N}$$

$$\mathcal{N} = \begin{pmatrix} \gamma_a^r \\ \gamma_a^\theta \\ \gamma_b^r \\ \gamma_b^\theta \end{pmatrix},$$

and

$$\mathbf{M} = \begin{pmatrix} \sin\theta_a & R_a\cos\theta_a & 0 & 0 \\ \cos\theta_a & -R_a\sin\theta_a & 0 & 0 \\ 0 & 0 & \sin\theta_b & R_b\cos\theta_b R_b \\ 0 & 0 & \cos\theta_b & -R_b\sin\theta_b \end{pmatrix}$$

For this model, we are assuming that the states are noise-free, i.e.,

$$\mathbf{Q} = \mathbf{0}$$

and

$$\mathbf{R} = \mathbf{M}\ \mathbf{V}\ \mathbf{M}^T$$

where

$$\mathbf{V} = \begin{pmatrix} \sigma_{ra}^2 & 0 & 0 & 0 \\ 0 & \sigma_{\theta a}^2 & 0 & 0 \\ 0 & 0 & \sigma_{rb}^2 & 0 \\ 0 & 0 & 0 & \sigma_{\theta b}^2 \end{pmatrix}$$

Here we assume that the four noise components are independent and normally distributed with zero-mean.

By plugging the calculated matrices for the bias model into the recursive updating equations of Kalman Filter, we can estimate the best probable track resulting from the two radar returns as well as derive an estimate of the range and azimuth bias of each radar. In the following section the implementation aspects of the model are investigated.

6.3 Implementation and Simulation:

Before starting the time and observation update process, initial conditions have to be set. This includes the true position and velocity, the bias parameters for both sites, and the covariance matrix of the estimate error.

The initial position is calculated as the average of the first two points of both tracks. Assuming that the sampling time is unity, the velocity is calculated as the difference between the two first points (in both directions). For the bias parameters, it is intuitive to start off with zero values. This is equivalent to the hypothesis that both radars are correctly aligned. Thus,

$$\mathcal{X}(\mathbf{0}) = \begin{pmatrix} x_t(0) & \dot{x}_t(0) & y_t(0) & \dot{y}_t(0) & 0 & 0 & 0 & 0 \end{pmatrix}$$

Since the matrix **P** represents the inconfidence about the accuracy of the estimate, it is conventional to start with a very large value,

$$\mathbf{P} = \epsilon\,\mathbf{I}$$

where ϵ is a large integer (we used $\epsilon = 100$ in our simulation) and **I** is the 8×8 identity matrix.

Now the recursive equations can be applied by reading one data pair for each track and then using the Kalman filter equations to update the states. By reading more data, the filter starts to approach the correct values of the states and both the error covariance matrix and the gain matrix will assume very small values. It should be noted that the **M** matrix associated with the noise is updated at each iteration as it is dependent on the values of the data pair.

Results:

When the model was applied to the same simulated data used with the neural network model, the resulted estimates were:

NA0: 0.2205 nm, 0.0046 radians

NB0: 0.3142 nm, 0.00152 radians.

The **P** matrix was very close to the zero value as was the gain matrix.

The results are very close to the correct one especially considering the noise model is not exactly Gaussian.

6.4 Problems with Kalman Filter Implementation

During the simulation of the filter updating equations, many problems were evident pertaining to Kalman filter implementation.

- First, the accuracy of the results depends on the availibilty of enough track points (data pairs). A very few data points will not allow the filter to reach a steady state estimate (unless very good initial conditions was chosen). A possible solution to this problem is to make two passes on the same track. This will require changing the velocity sign at the end of sweeping the track for the forward direction. This technique results in a better estimate of the parameters. Another option is to reformulate the problem is such a way that it solves only for the bias parameters. In this case the data can be applied recursively until a good solution is reached.

- The second problem is that the Kalman Filter involves a matrix inversion operation. A near singular matrix will result in mathematical overflow. Although the problem has not been encountered in our simulation, there is no reason it could not occur under different scenarios and track patterns. A simple remedy is to frequently add a small value to the **P** matrix, e.g., $1.0^{-6}\,\mathbf{I}$.

7 Conclusions

This report summarizes the work accomplished by RMC on the radar registration problem during the first half of 1995. Traditional approaches are reviewed and non-traditional methods were also investigated. Using Neural Networks, with a learning parameter set according to the value of the gradient generates better estimate values when compared to the conventional RTQC and LS-RTQC. The Kalman filter approach was also investigated in order to fuse into one single track the radar returns of two adjacent radars as well as calculate the estimate of the bias parameters. This algorithm proved to be very efficient. As well as providing an assessment of the methods, we also discussed implementation issues of both algorithms with suggestions on how to overcome potential difficulties. In the future, we will continue to study new techniques for radar registration as well as explore the stereographic projection system as a possible source of error.

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This report summarizes the work conducted by the Robotics and Target Tracking Research Group of the Royal Military College of Canada (RMC) on the radar registration problem. Traditional approaches are reviewed and non-traditional methods are also investigated. Using Neural Networks, with a learning parameter set according to the value of the gradient generates better estimate values when compared to the conventional RTQC and LS-RTQC. The Kalman filter is also investigated in order to fuse into one single track the radar returns of two adjacent radars as well as calculate the estimate of the bias parameters.

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