Introduction

Precise navigation data is necessary for autonomous vehicles.

- In normal circumstances: GPS is typically used

**PROBLEM:**

- GPS may not always be available
  - We use synthetic aperture radar (SAR) images to estimate the navigation data.
  - The Back-projection Algorithm (BPA) is used to create SAR images [1].
  - Any error in position, velocity, or attitude results in distorted SAR images [2].
  - Different navigation error combinations create subtly different image distortions.

**SOLUTION:**

- We use convolutional neural networks (CNN) to estimate initial navigation errors from distorted SAR images.
  
- True flight trajectory is recovered from the initial navigational errors [3].
  
- We compare distorted images to previously-obtained reference images.

The SAR Data

Three different sets of SAR image data:

- Simulated data: 5 second aperture length (MATLAB)
- Real datasets: 2 and a 10 second aperture lengths (Space Dynamics Laboratory)

For each of the datasets, six different scenarios were studied.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Simulated (5-sec)</th>
<th>Simulated (10-sec)</th>
<th>Real-2-sec</th>
<th>Real-10-sec</th>
</tr>
</thead>
<tbody>
<tr>
<td>Position</td>
<td>AT</td>
<td>AT</td>
<td>CT</td>
<td>CT</td>
</tr>
<tr>
<td>Velocity</td>
<td>None</td>
<td>AT</td>
<td>None</td>
<td>None</td>
</tr>
<tr>
<td>Attitude</td>
<td>None</td>
<td>Small AT</td>
<td>None</td>
<td>None</td>
</tr>
<tr>
<td>MSE (Real-2-sec)</td>
<td>0.2458</td>
<td>0.2458</td>
<td>0.2458</td>
<td>0.2458</td>
</tr>
<tr>
<td>MSE (Real-10-sec)</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
</tbody>
</table>

Table 1: Effect of navigation errors on BPA-SAR images (AT = Along Track, CT = Cross Track, D = Down). For each target, we generated 100 distorted images of size 60 x 80 pixels, paired with the corresponding navigation errors.

Nautical errors are standardized to ensure equal consideration during training.

Neural Network Architecture

We used transfer learning with the pretrained Wide ResNet 50_2 architecture forming the base of our model [3].

Our model:

- Input: the distorted image, reference image, and the difference image.
  - Input is fed into a randomly initialized convolutional layer followed by the ResNet architecture.
  - ResNet final layer replaced with a fully connected layer with same output number as error states.

L2 regularization and the average mean squared error (MSE) loss function was used across all considered initial errors for training and testing:

$$\text{MSE} = \frac{1}{m} \sum_{i=1}^{m} (\hat{x}_i - x_i)^2,$$

where $x_i$ is the true label, $\hat{x}_i$ is the predicted label, and $m$ is the number of samples.

MSE is less than one indicates that the neural network is learning relevant information for this task.

Experimental Results

Fig. 2: Distribution of error states before (blue line) and after (histogram) estimation for real-2-sec dataset for scenarios 1 and 4.

Discussion

- Network performs well in the absence of ambiguous error sources, reducing the MSE of the active navigation errors.
- Network successfully distinguished between CT shifts caused by CT and D pos errors in real data.
- Increasing aperture length improves performance with blur-related errors.
  - Some degree of learning occurs in most scenarios

Future work: different aperture lengths, including vehicle/target geometry, more training data.

References


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