A machine learning approach to improve UHF RFID gate operation

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5th International Conference on Smart and Sustainable Technologies, September 2020, Bol, Croatia
Machine learning in RFID

- **Smart processing of raw data:** discriminate tags by position or direction, characterize physical signature privacy.

- **Enhanced services:** position estimation enhancement or data stream enhancement.

- **RFID network planning.**

- **Smart gate control.**
Machine learning for smart gate control

- Self-configuration of channel, power, etc.
- If conditions change dynamically, the parameters have to be adaptively tuned.
- Machine learning approaches to adapt to previously unseen situations.
Portal has two bistatic dislocated antenna pairs, which can be configured with 3 different policies: $\alpha, \beta, \gamma$. 
Scenario setup (II)

Random variations (box placement, size, tag distribution, number of tags, materials) occur for each box.
Goal is **select the best interrogation policy** for each box, i.e., the one maximizing the batch identification chances.
Predictive system

- The input features act as a signature for the batch reading process.
- The **policy** is also an input data.
- The output indicates **whether the batch will be totally identified**.
Provide a good and homogeneous representation for each batch’s interrogation characteristics.

The first $R$ frames have always the same configuration and the following statistics are obtained:

- The number of tags read in the frame.
- The average received signal strength (RSS) in slots with successful tag identification.
- The average RSS in slots with collision.
Predictive system (III). Output usage

- For each policy the predictive system outputs the **probability of batch identification** (BIP).
- The smart gate uses the predictive system for each possible policy and selects the one with the **highest predicted BIP**, or triggers and alarm reporting a batch-reading problem if BIP is too low.
Dataset has been obtained using a simulator whose main characteristics are:

- DFSA anti-collision protocol
- Detailed link budget considering distance, antenna aiming, multi-path propagation, and shadowing effects.
- Detailed physical level operation: outage, capture-effect, etc.
Predictive system (V). Training dataset

Dataset contains **120000 records** where the policy as well as the box characteristics are randomly selected.
Predictive structure

- Predictions are created with a 2-layer artificial-neural-network.
- Inputs are normalized and passed to a 20-nodes hidden layer with $tanh$ activation.
- Policy is provided as input with one hot encoding.
- Output layer activation is sigmoid and the ann loss function is the binary cross-entropy.
Network has been implemented in Keras/TF

- 20% of the training records are left out as validation
- Training used back-propagation with Adam optimizer, using 32 as batch size.
- Network training ends using early stopping mechanism using 100 epochs patience. About 600 training epochs are used.
Predictive structure (III). Results

<table>
<thead>
<tr>
<th>Configuration</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>Fall-out</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R = 1$</td>
<td>89.74%</td>
<td>89.98%</td>
<td>89.27%</td>
<td>9.80%</td>
</tr>
<tr>
<td>$R = 2$</td>
<td>94.55%</td>
<td>94.30%</td>
<td>94.61%</td>
<td>5.50%</td>
</tr>
<tr>
<td>$R = 3$</td>
<td>94.86%</td>
<td>94.75%</td>
<td>94.81%</td>
<td>5.10%</td>
</tr>
</tbody>
</table>

- $R=3$ achieves the best results (very close with $R=2$)
- Accuracy is high (95%) with low fall-out (5%)
Predictive structure (IV). Results

<table>
<thead>
<tr>
<th>Policy</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>Fall-out</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\alpha)</td>
<td>94.59%</td>
<td>92.92%</td>
<td>94.03%</td>
<td>5.02%</td>
</tr>
<tr>
<td>(\beta)</td>
<td>94.73%</td>
<td>92.44%</td>
<td>94.92%</td>
<td>5.40%</td>
</tr>
<tr>
<td>(\gamma)</td>
<td>95.26%</td>
<td>97.51%</td>
<td>95.24%</td>
<td>4.70%</td>
</tr>
</tbody>
</table>

- Slightly better reliability of the \(\gamma\) policy predictions
- Very close to the operation reliability of the other policies.
Smart versus normal gate comparison

- The operation of the smart gate has been compared against a normal one.
- Normal gate uses always a predefined policy.
- The simulator measures the cumulative time required for boxes interrogation.
- Batch interrogation time has been determined using an auxiliary ANN.
- Unreadable batches are relocated, a process performed by a human operator which takes a random time between 10 and 30 s.
- After relocation it is assumed that the batch can always be read.
The performance of the best policy, which is adaptive, outperforms the best static one by 30%.
The ratio of batches which don’t require relocation to complete the interrogation is 80.2% with the adaptive policy, but it drops to 64% with the best static policy.
Conclusions

- New predictive capability for RFID gates proposed.
- Based on the signature from initial reading frames, the batch identification probability is predicted.
- Results indicate a good predictive performance, suitable for online gate operations.
- This method is able to save operation time.
- Dataset and code available at https://github.com/javiervales/smartgate