Experimental Comparison of Complex Event Processing Systems in the Maritime Domain

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1 Complex Event Processing and Maritime Analytics
   ▶ Anomaly Detection Service
   ▶ Run-time Event Calculus

2 Dataset

3 Experimental Comparison
   ▶ Setup
   ▶ Results
   ▶ Case Study

4 Conclusions and Future Work
Complex Event Processing (CEP) is responsible for detecting patterns upon sequences of input events.

In this study we present and compare two separate CEP systems:
- An anomaly detection service, based on machine learning techniques.
- RTEC, a rule-based implementation.

Using a real dataset, we detect patterns regarding the navigation of vessels into challenging areas (*Tugging* and *Piloting*) and cargo or fuel *Transfers* using both systems and compare the results to a given ground truth.
Anomaly Detection Service

- A distributed system that detects complex events on vessel movements

- ‘Patterns of Life’ are extracted using machine learning algorithms and multiple types of simple events (i.e., anomalies) are detected in real-time.

- A machine-learning extension allows for the system to perform classification and detect vessels’ activities (i.e., tugging, piloting, bunkering, ship-to-ship transfers, etc.) using Random Forest.

- Training is performed offline and prediction is performed in streaming data.
Run-time Event Calculus (RTEC) is an efficient dialect of Event Calculus, implemented using the Prolog language.

The system detects the occurrence of patterns based on static conditions upon the vessel’s movement and characteristics.

Besides the positional messages of the dataset, a preprocessing step creates additional critical and spatial points regarding the vessels’ movement.
In order to compare the two systems’ efficiency we used a global dataset with real cases.

This dataset includes approx. 128K AIS messages of 1149 different vessels, over a period of 6 months.

After the preprocessing step the RTEC system receives a stream of 475K events.

Vessel trajectories used near the island of Cyprus.
Experimental Comparison - Setup

- All RTEC patterns are based on proximity events between two vessels, produced during the preprocessing step.

- In order to achieve the best accuracy possible, we tested three versions of the RTEC patterns. The conditions of each version include the vessels’:
  1. speed and distance from the coastline and port areas
  2. speed and distance from the coastline and port areas and types
  3. speed and distance from port areas

- For the Anomaly Detection Service a 5-fold cross validation has been applied and the average scores are presented.
Experimental Comparison - Results

Efficiency regarding complex events:

<table>
<thead>
<tr>
<th>CEP System</th>
<th>Precision</th>
<th>Recall</th>
<th>F₁-score</th>
<th>Positions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anomaly Detection</td>
<td>0.817</td>
<td>0.832</td>
<td>0.821</td>
<td>83.33 %</td>
</tr>
<tr>
<td>RTEC (1)</td>
<td>0.556</td>
<td>0.361</td>
<td>0.438</td>
<td>32.6 %</td>
</tr>
<tr>
<td>RTEC (2)</td>
<td>0.556</td>
<td>0.448</td>
<td>0.496</td>
<td>44.8 %</td>
</tr>
<tr>
<td>RTEC (3)</td>
<td>0.439</td>
<td>0.529</td>
<td>0.48</td>
<td>52.9 %</td>
</tr>
<tr>
<td>proximity events</td>
<td>0.934</td>
<td>0.922</td>
<td>0.928</td>
<td>92.2 %</td>
</tr>
</tbody>
</table>

The results show that the anomaly detection system captures most of the event occurrences, while the static conditions imposed in the RTEC evaluation excludes a large portion of them.
Piloting event near the Milford Haven Port, recognized by the anomaly detection service, but not by RTEC, because of high speeds recorded.
Conclusions and Future Work

Conclusions:

- We presented two CEP systems, used in the Maritime domain to model vessel activity between multiple vessels.
- We compared them by using a labeled dataset of approx. 128K AIS messages.
- Results show that static conditions regarding such activities are not sufficient enough and should be fine-tuned in each case separately, while a machine learning approach better captures the truth.

Future work:

- We intend to expand our study by examining the performance of other popular CEP systems (i.e. FlinkCEP and Siddhi) and by including their runtime execution aspects.
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