Urban Change Detection Based on Remote Sensing Data

How are RNNs applied in the context of urban change detection?

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1. Introduction

- **Urbanisation:** drastically transformed landscapes globally, causing significant changes in land use, infrastructure, and socio-economic dynamics.
- **Urban Change Detection:** identification and analysis of transformations within urban areas over time.

Figure 1:Pre- and Post-Change Images with Corresponding Change Map [1]

2. Recurrent Neural Networks

- Neural network tailored for processing sequential data.
- Retention of information from previous inputs.
- Adept at tasks, such as time series analysis and temporal pattern recognition.

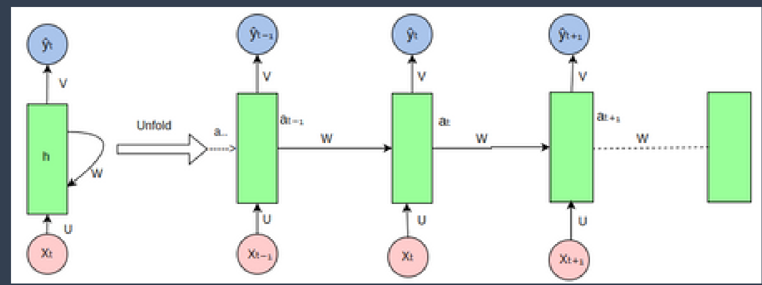

Figure 2: RNN Architecture [2]

3. Experiment

- **Experiment Goal:** Evaluate the effectiveness of RNNs for Urban Change Detection, by training and evaluating a suitable model on different datasets, each with unique properties.
- **Choosing RNN method:**
  - **LSTM:** designed to capture long-term dependencies and manage vanishing gradient problems. [5]
  - **GRUs:** computational efficiency and faster training times. [6]
  - **Attention-based RNN:** focuses on the most relevant parts of the input sequence. [4]
  - **SiamCRNN:** combination of CNN and RNN. [3]
- **Choosing datasets:**
  - **Levir-CD:** high-resolution, medium spectral range.
  - **CDD:** low-resolution, small spectral range, seasonal variations.
  - **DSIFN-CD:** low-resolution, medium spectral range, diverse urban scenarios.
  - **OSCD:** medium resolution, large spectral range, complex urban environments.

4. Results and Discussion

Evaluation Criteria	Accuracy
Recall Rate	0.5619
Precision Rate	0.4217
Overall Accuracy (OA)	0.9375
F1 Score	0.4819
Intersection over Union (IoU)	0.3174
Kappa Coefficient	0.4493

Figure 3: OSCD Results

Evaluation Criteria	Accuracy
Recall Rate	0.9827
Precision Rate	0.6218
Overall Accuracy (OA)	0.8004
F1 Score	0.7617
Intersection over Union (IoU)	0.6151
Kappa Coefficient	0.6044

Figure 4: DSIFN-CD Results

Evaluation Criteria	Accuracy
Recall Rate	0.8904
Precision Rate	0.8104
Overall Accuracy (OA)	0.9838
F1 Score	0.8485
Intersection over Union (IoU)	0.7369
Kappa Coefficient	0.8400

Figure 5: Levir-CD Results

Evaluation Criteria	Accuracy
Recall Rate	0.8866
Precision Rate	0.7318
Overall Accuracy (OA)	0.9483
F1 Score	0.8018
Intersection over Union (IoU)	0.6692
Kappa Coefficient	0.7724

Figure 6: CDD Results

- High-performance on Levir-CD suggests the model can accurately detect significant urban changes.
- High-performance on CDD suggests the model can handle seasonal changes.
- High-performance on DSIFN-CD suggests the model can handle diverse urban environments.
- Lower-performance on OSCD suggests the model has difficulties with complex urban environments and low spatial resolution.

5. Conclusion

- These findings underscore the robustness of the SiamCRNN model in detecting urban changes across various datasets.
- Challenges on datasets with higher spectral range and complex urban structures.
- Importance of spatial resolution in urban change detection tasks.

- **Future Work:**
  - Verify performance of SiamCRNN model on other datasets, especially on datasets with lower spatial resolution.
  - Explore alternative RNN methods such as LSTM, GRU, and Attention-based RNNs for Urban Change Detection.

References

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