A Combined Twin and Single Network for Fast and Robust Inspection of IC Substrates

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01. Intro

Change Detection

Change Detection

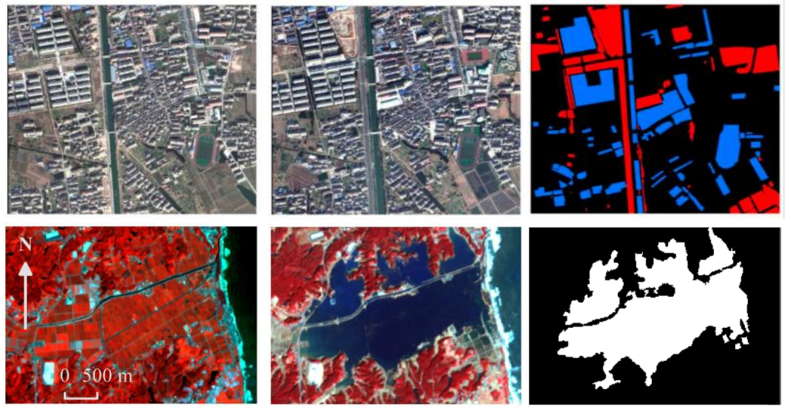
- Task of identifying changed areas in two images.
- Changes are defined differently for each task.

Application Examples

1. Remote Sensing
- Urban environment change detection
- Post-disaster damage mapping
- Deforestation monitoring

2. Inspection
- Inspection of PCBs
- Inspection of IC substrates

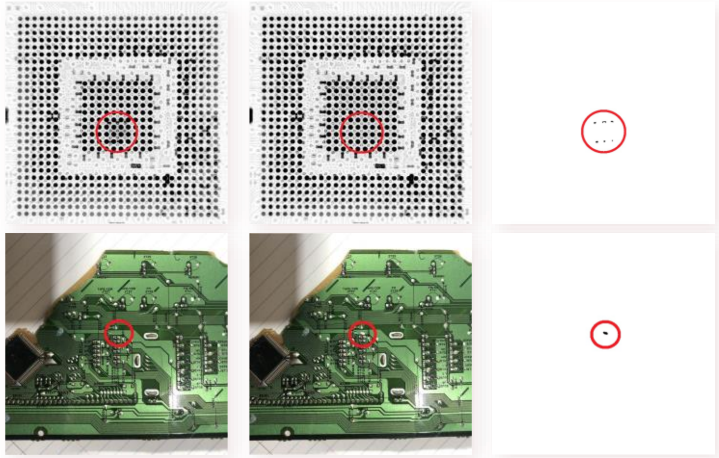
3. Medical Imaging
- Disease diagnosis
- Landmark tracking
- Searching in database



(a)*
(b)**

pre-change post-change change mask

Figure 1. Examples of change detection application
(a) Urban area buildings (b) Tsunami damaged area



reference PCB test PCB ground truth

Figure 2. Example of PCB inspection***

[*] Ma, Lei, et al. "Object-Based Change Detection in Urban Areas: The Effects of Segmentation Strategy, Scale, and Feature Space on Unsupervised Methods." Remote Sensing, vol. 8, no. 9, Sept. 2016
[**] Sublime, Jérémie, and Ekaterina Kalinicheva. "Automatic post-disaster damage mapping using deep-learning techniques for change detection: Case study of the Tohoku tsunami." Remote Sensing 11.9 (2019).
[***] Fridman, Yehonatan, Matan Rusanovsky, and Gal Oren. "ChangeChip: A reference-based unsupervised change detection for PCB defect detection." 2021 IEEE Physical Assurance and Inspection of Electronics (PAINE). IEEE, 2021.

01. Intro

Inspection using CD

- Manual inspection has several limitations, including a lack of precision, slow speed, and inconsistent criteria among different inspectors.
- Automatic detection of defects in manufacturing fields, such as printed circuit board (PCB) or integrated circuit (IC) substrate, is necessary during the manufacturing process.
- IC chips consist of repetitive patterns, allowing for effective inspection through change detection by comparing reference and test images.
- However, registration errors and characteristic differences can cause poor performance since detecting micro differences is essential for accurately inspecting IC substrates.

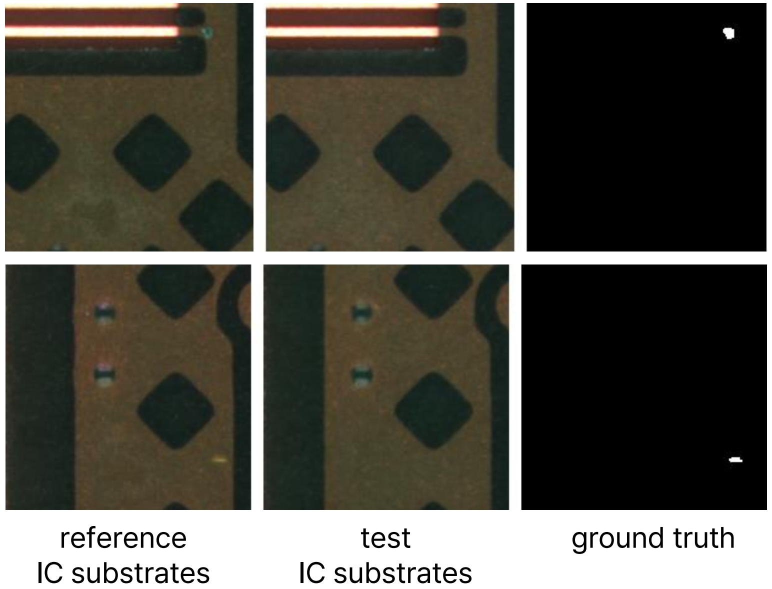


Figure 3. Example of change detection dataset for defect detection in IC substrates

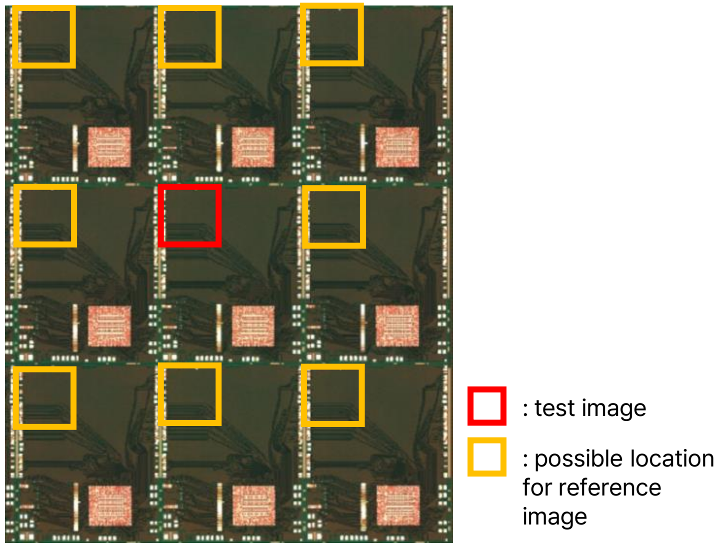


Figure 4. Example of IC substrates

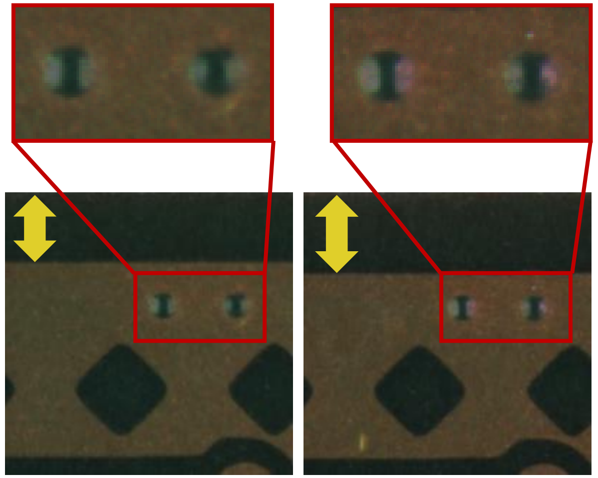


Figure 5. Example of IC substrate dataset including registration error and characteristic difference

02. Related works

Fully Convolutional Siamese Network

Fully Convolutional – Early Fusion*

- Based on auto-encoder structure
- Combine the two images which are wanted to compared in the channel direction and use them as input
- Limitation : focused on segmentation, not directly consider changes among two inputs.

Fully Convolutional Siamese - Difference *

- Based on twin network, which includes two encoders sharing weight
- Consider absolute difference between feature maps for change detection
- Limitation : vulnerable to pseudo-changes due to absolute difference operations

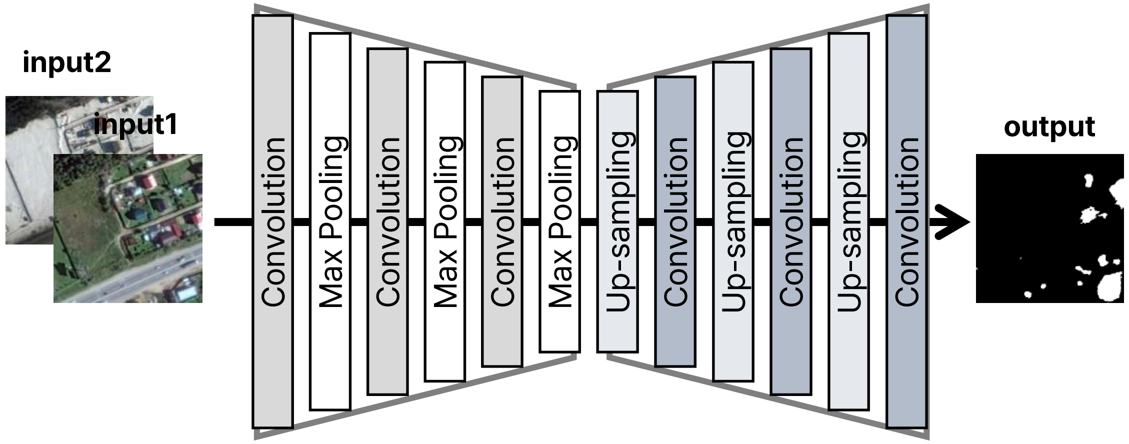


Figure 6. FC-EF (Fully Convolutional – Early Fusion)

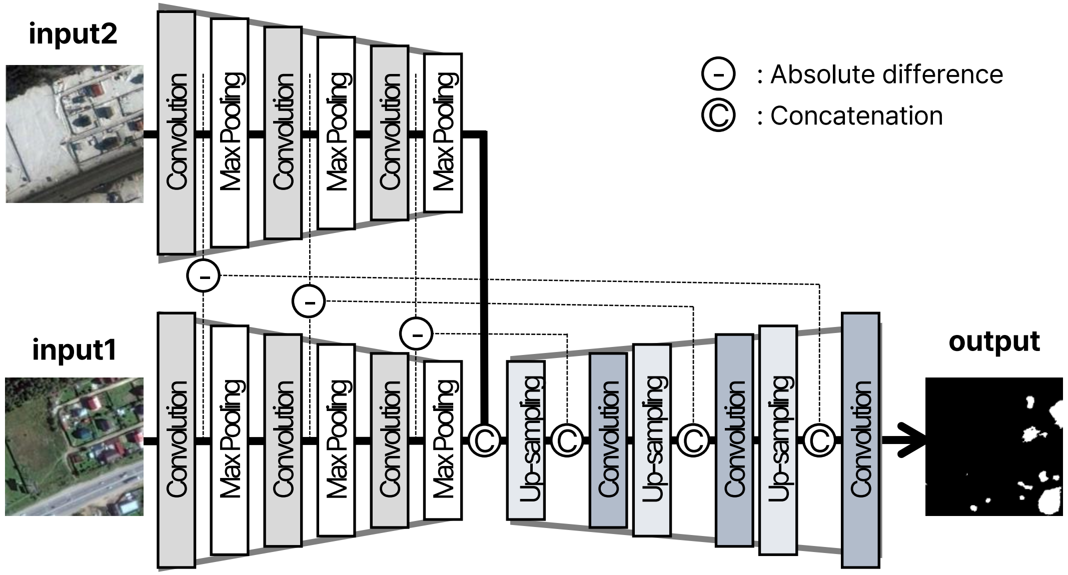


Figure 7. FC-Siam-diff (Fully Convolutional Siamese - Difference)

[*] Daudt, Rodrigo Caye, Bertr Le Saux, and Alexandre Boulch. "Fully convolutional siamese networks for change detection." 2018 25th IEEE International Conference on Image Processing (ICIP). IEEE, 2018.

02. Related works

DASNet *

- DASNet is a self-attention-based change detection method designed to overcome pseudo change problems.
- Utilizes self-attention-based dual attention modules to capture global context information within a single image.
- Limitation : considers feature dependencies only within a single image; it needs to consider feature dependencies between two input images to improve robustness to registration errors or color variants.

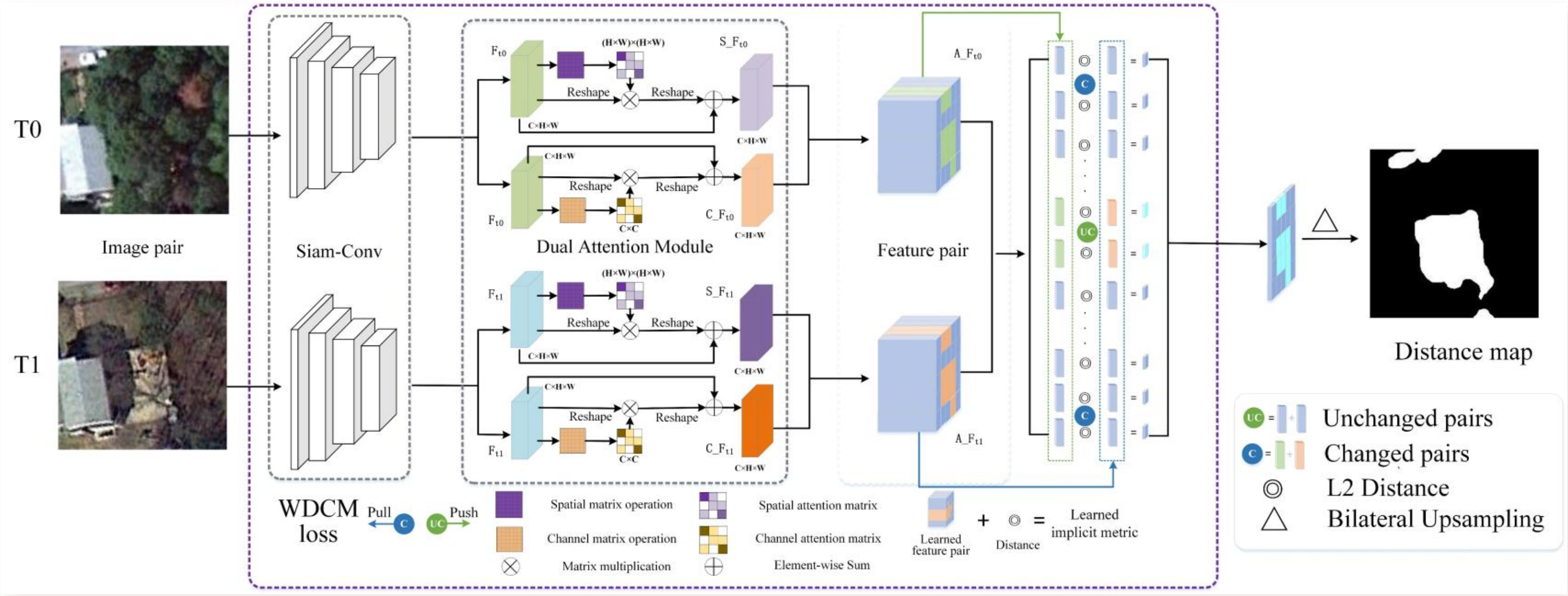


Figure 8. Overview of DASNet [*]

[*] Chen, Jie, et al. "DASNet: Dual attentive fully convolutional Siamese networks for change detection in high-resolution satellite images." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 14 (2020)

02. Related works

PCB inspection with twin network

- A few investigations have explored on twin network-based inspection methods.
- Ling et al. proposed method for detecting welding defects on PCBs using a twin network with skip connections. [*]
- Introduce correlation module that assigns small weights to local patches with high similarity to template patches
- To avoid errors caused by mis-registration, a global pooling operation is applied to features before they enter the correlation module.
- Limitation : this pooling operation may potentially compromise spatial information.

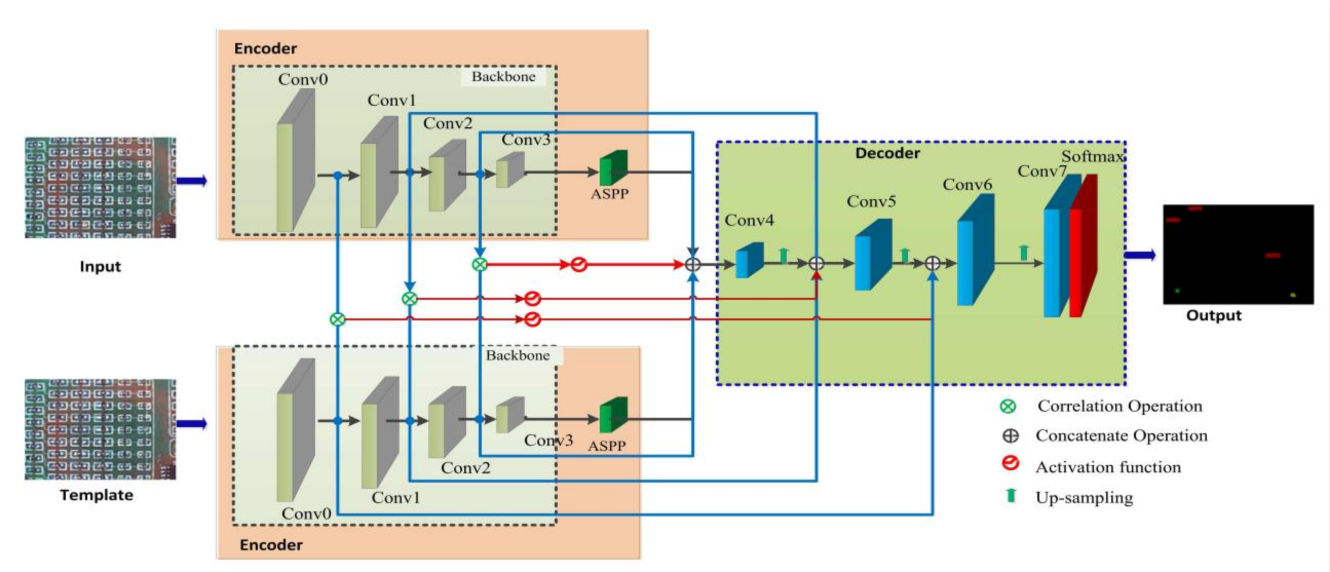


Figure 9. Overview of twin network for PCB welding defect detection [*]

[*] Ling, Zhigang, et al. "Deep Siamese semantic segmentation network for PCB welding defect detection." IEEE Transactions on Instrumentation and Measurement 71 (2022): 1-11.

02. Related works

Sp-Ch-wise Co-Attention-based Twin Network System *

- Improving robustness to both mis-registration and characteristic differences.
- Modifies given feature maps using the correlation between test and reference feature maps along both channel and spatial dimensions.
- Limitation : the increased computational demand of this approach may limit its practicality in real-time manufacturing environments

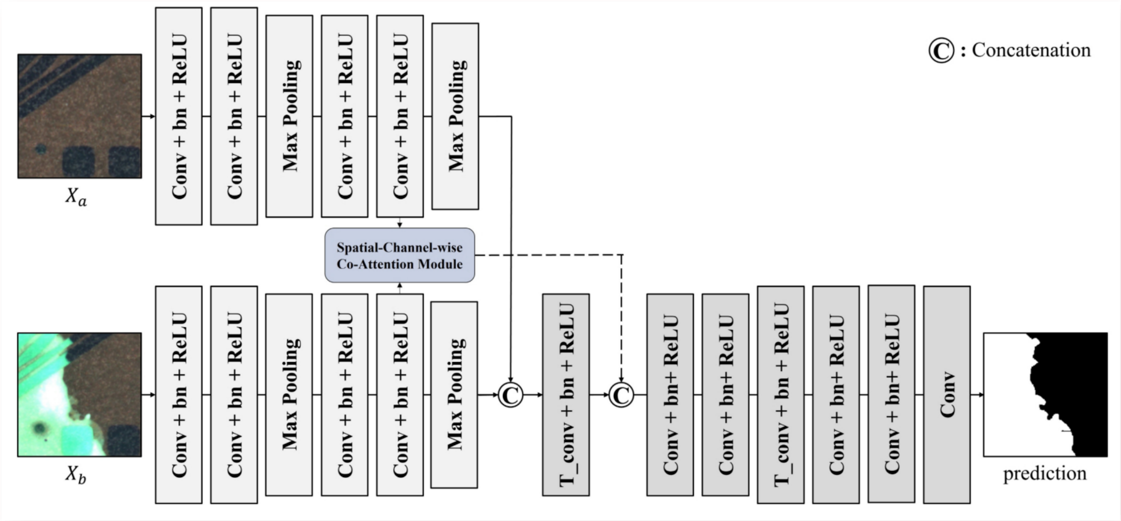


Figure 10. Overview of Twin-Comb-Co-Att network [*]

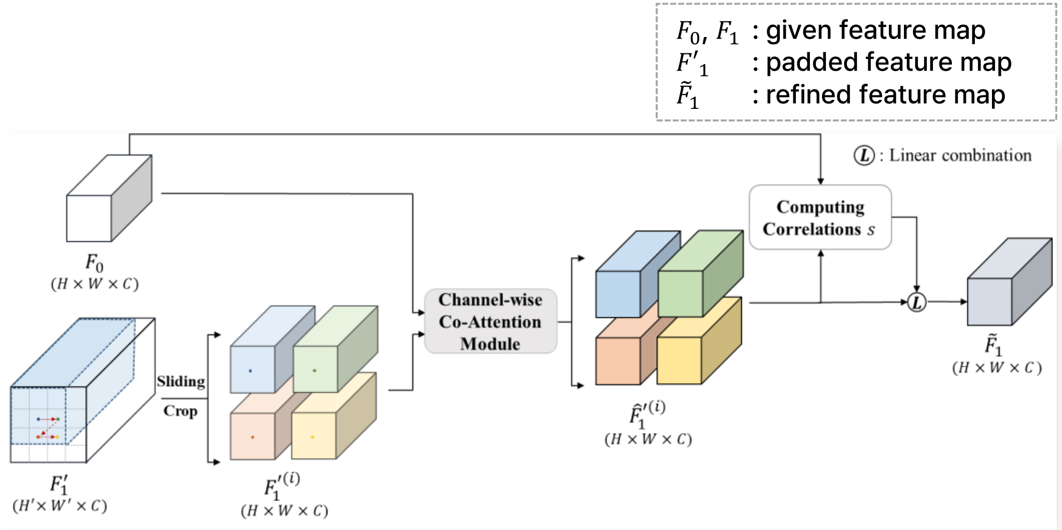


Figure 11. Overview of spatial-channel-wise co-attention module [*]

[*] Choi, Eunjeong, and Jeongtae Kim. "Spatial and Channel-wise Co-Attention-based Twin Network System for Inspecting Integrated Circuit Substrate." IEEE Transactions on Semiconductor Manufacturing (2023).

03. Proposed methods

Proposed network architecture – C-TSNet (1)

- A combined twin and single network for fast and robust inspection of IC substrates
  - Designed to reduce errors caused by mis-registration without attention modules.
  - Maintains relatively small computational latency.

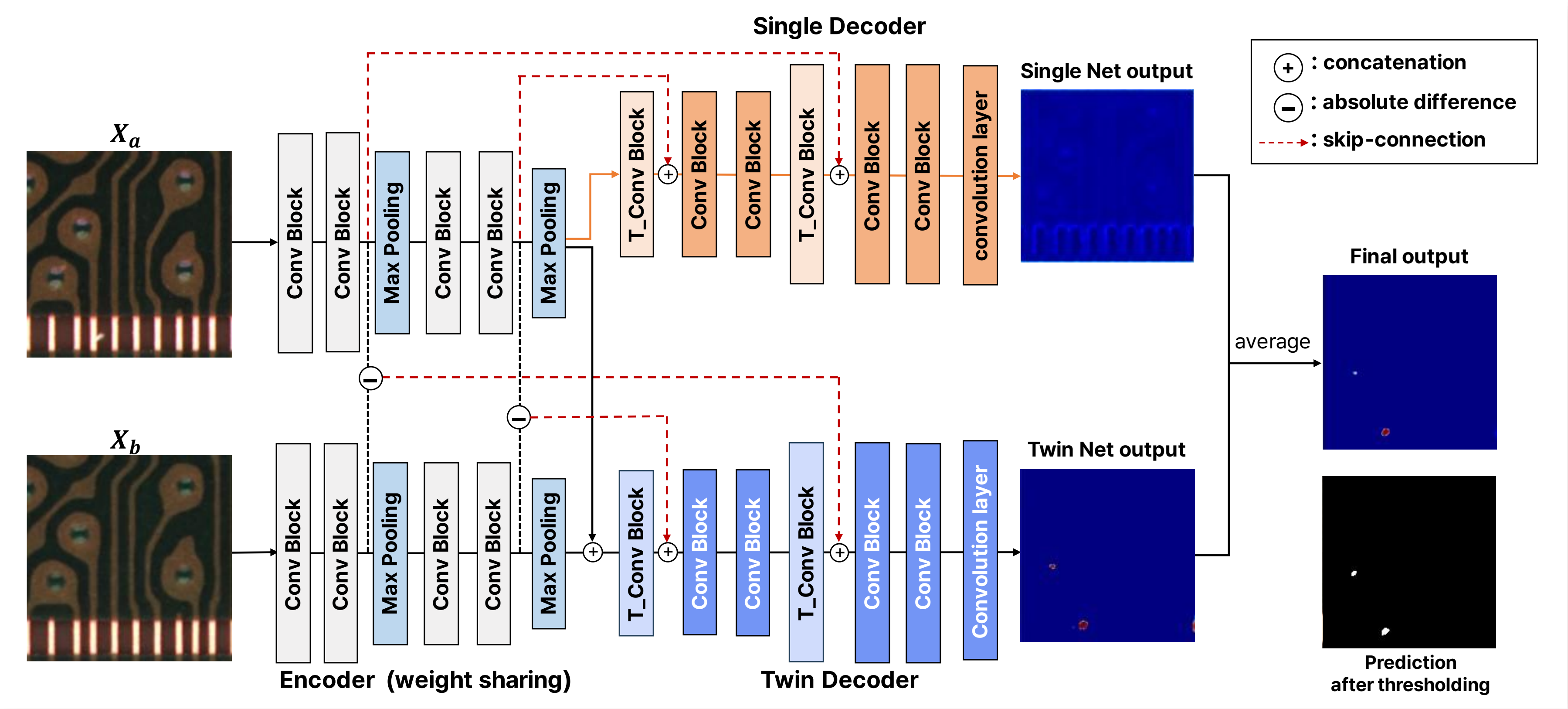


Figure 12. Architecture of C-TSNet for experiments

03. Proposed methods

Proposed network architecture – C-TSNet (2)

- Twin network directly compares two input images by subtracting features from each encoder.
- This makes the network vulnerable to mis-registration, which can cause poor performance for inspecting semiconductor products.

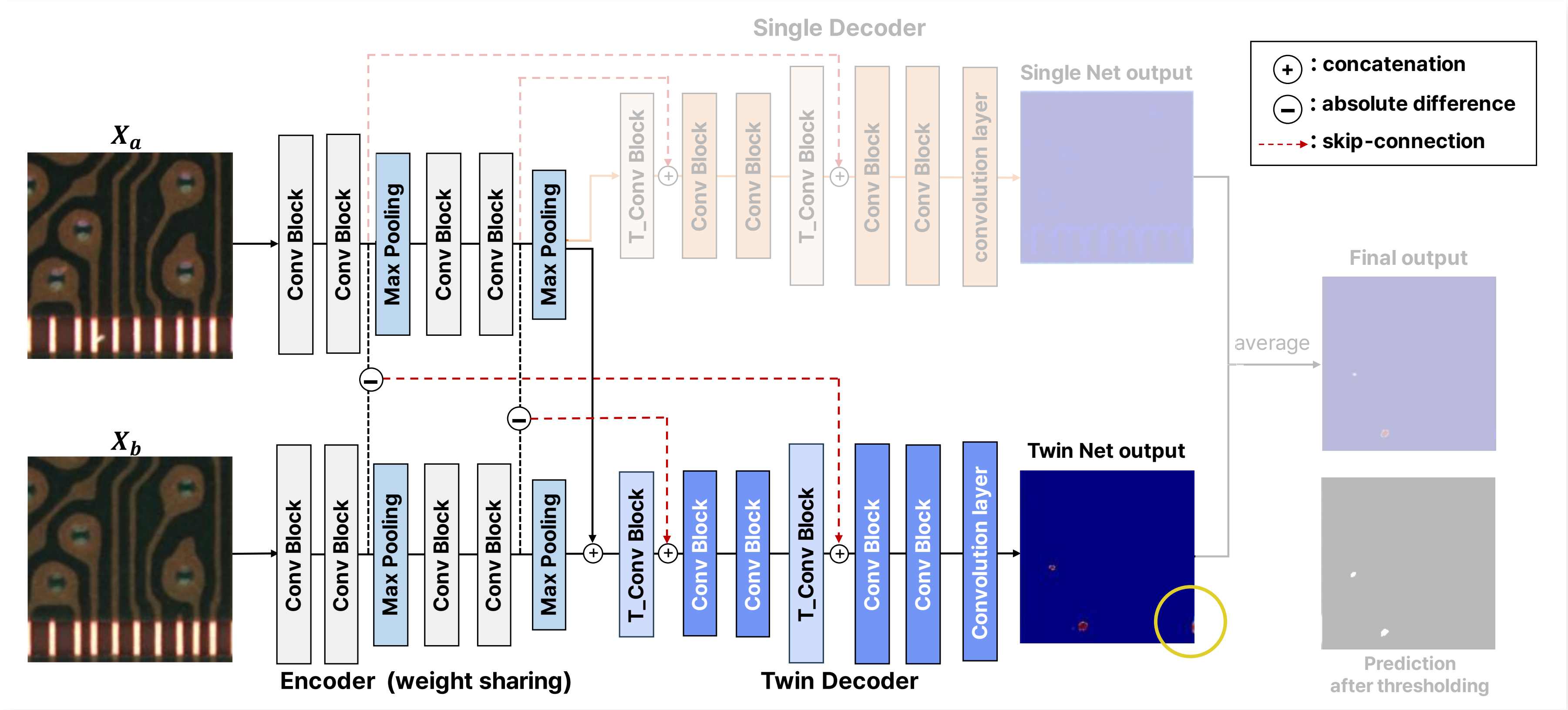


Figure 13. Architecture of C-TSNet for experiments – twin network part

03. Proposed methods

Proposed network architecture – C-TSNet (3)

- A single-network structure is sensitive to distinguishing between defects and complex patterns.
- However, it is free from pseudo-change issues or registration error.

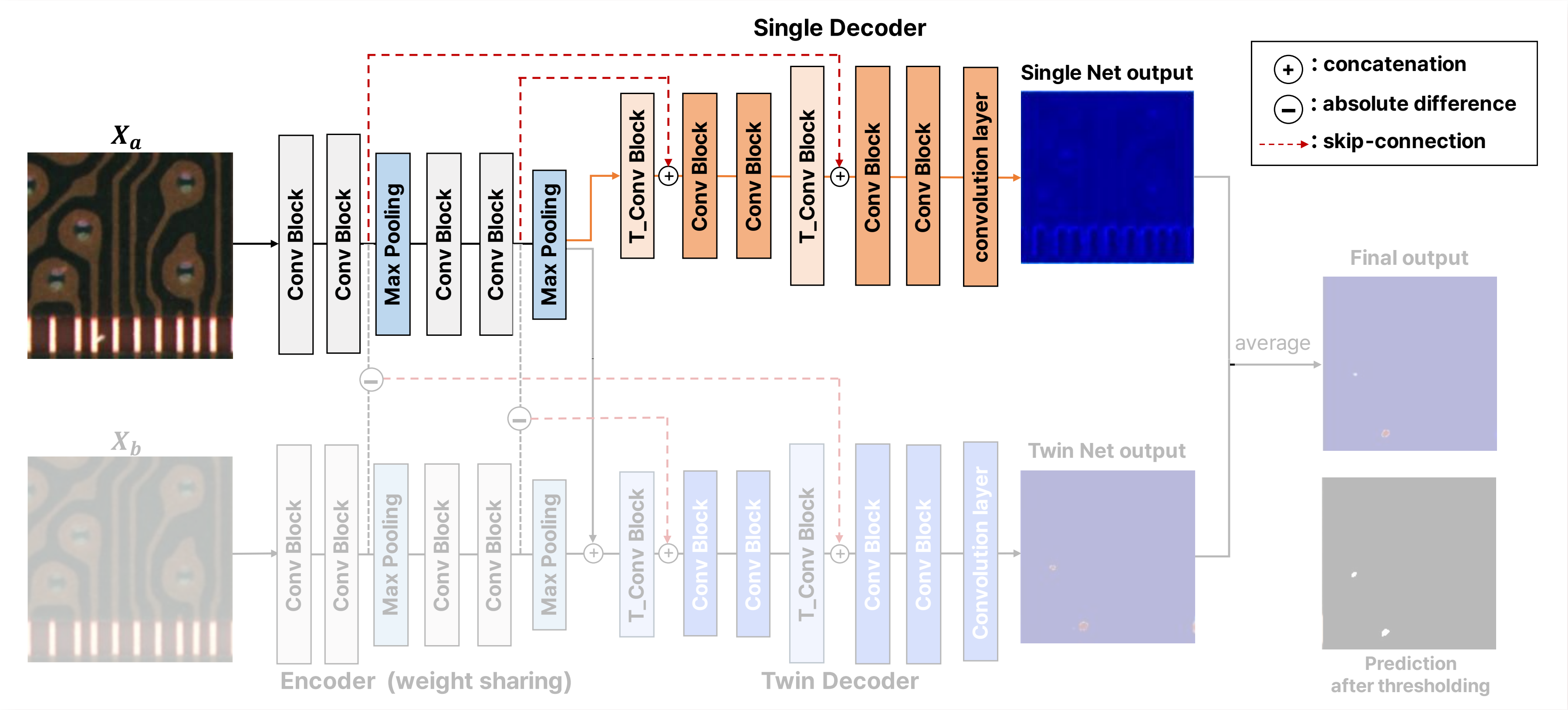


Figure 14. Architecture of C-TSNet for experiments – single network part

03. Proposed methods

Proposed network architecture – C-TSNet (4)

- By combining twin network with single auto-encoder structure, the network can be robust to registration errors and pseudo-changes.

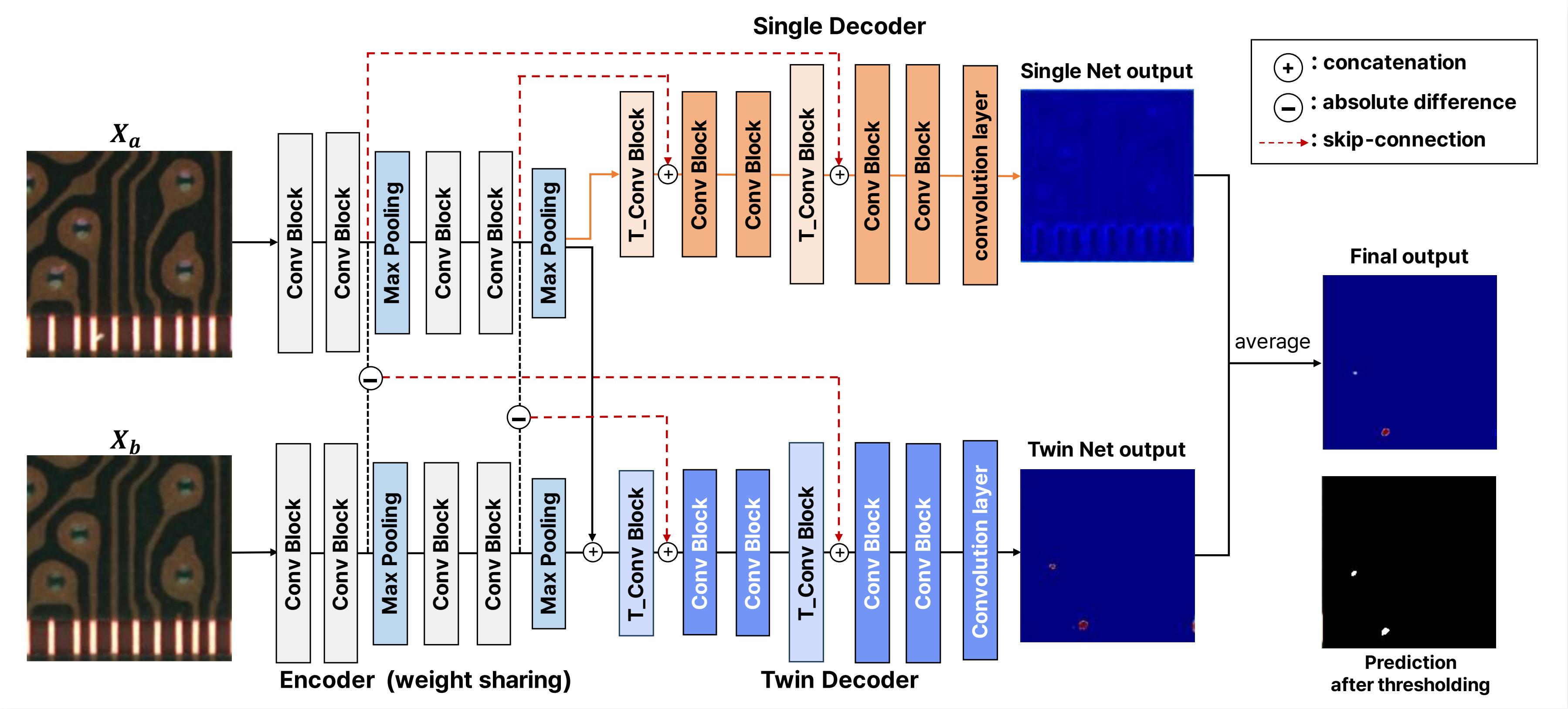


Figure 15. Architecture of C-TSNet for experiments

03. Proposed methods

Proposed network architecture – CC-TSNet

- Integrating two structures focused on reducing false positives caused by mis-registration.
- Utilizes a channel-wise co-attention module[*] to make the model more robust to color variations.
- After applying the channel-wise co-attention module, the feature maps from the encoder are transferred to the twin decoder via skip-connections.
- This module can help alleviate pseudo-changes, such as color variations, by identifying similar feature maps in the other image and generating refined feature maps.

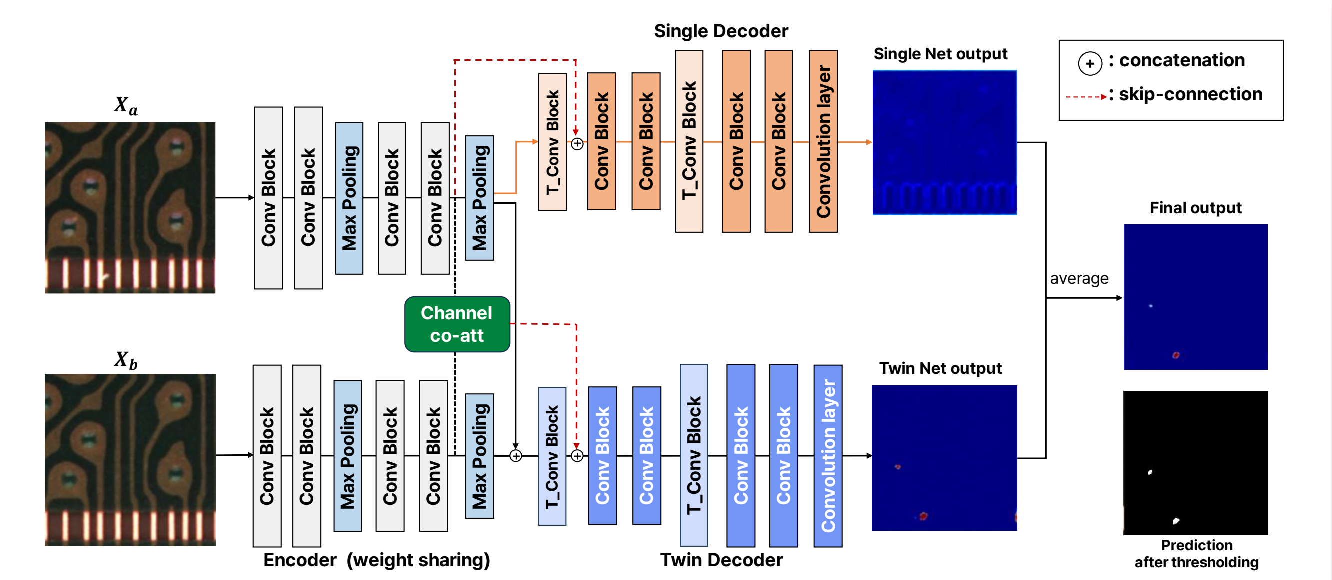


Figure 16. Architecture of CC-TSNet for experiments

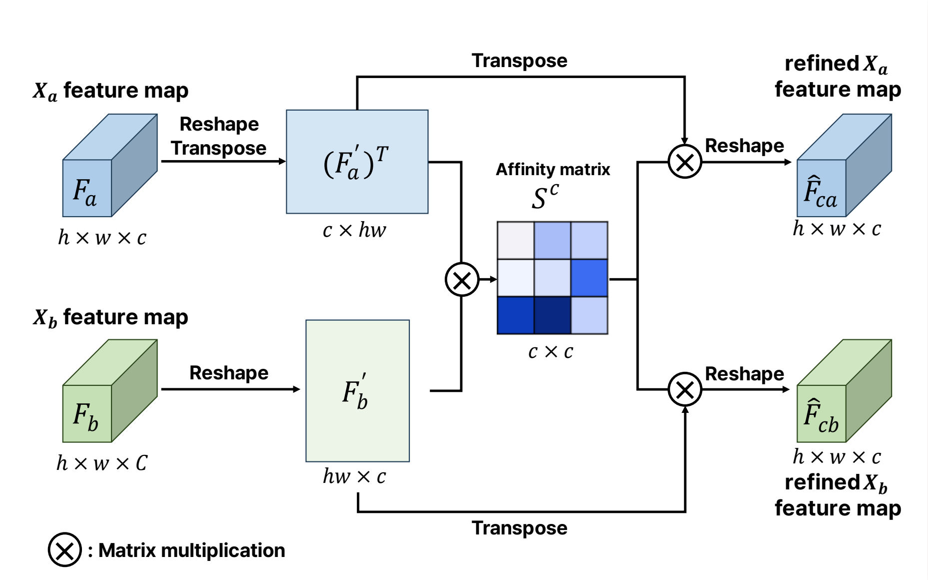


Figure 17. Channel-co-att module [*]

[*] Choi, Eunjeong, and Jeongtae Kim. "Robust change detection using channel-wise co-attention-based Siamese network with contrastive loss function." IEEE Access 10 (2022): 45365-45374.

04. Experiment

IC substrate Dataset

- Generating real-world IC substrate pair-set dataset
- Dataset size : 200 × 200 pixels per image
- Training set : total 22,432 image pairs (7,264 defective image pairs and 15,168 defect-free image pairs)
  - Horizontal and vertical flip augmentation is applied
- Test set : 6,352 image pairs (823 defective image pairs and 5,529 defect-free image pairs)
  - Contains 838 defect segments

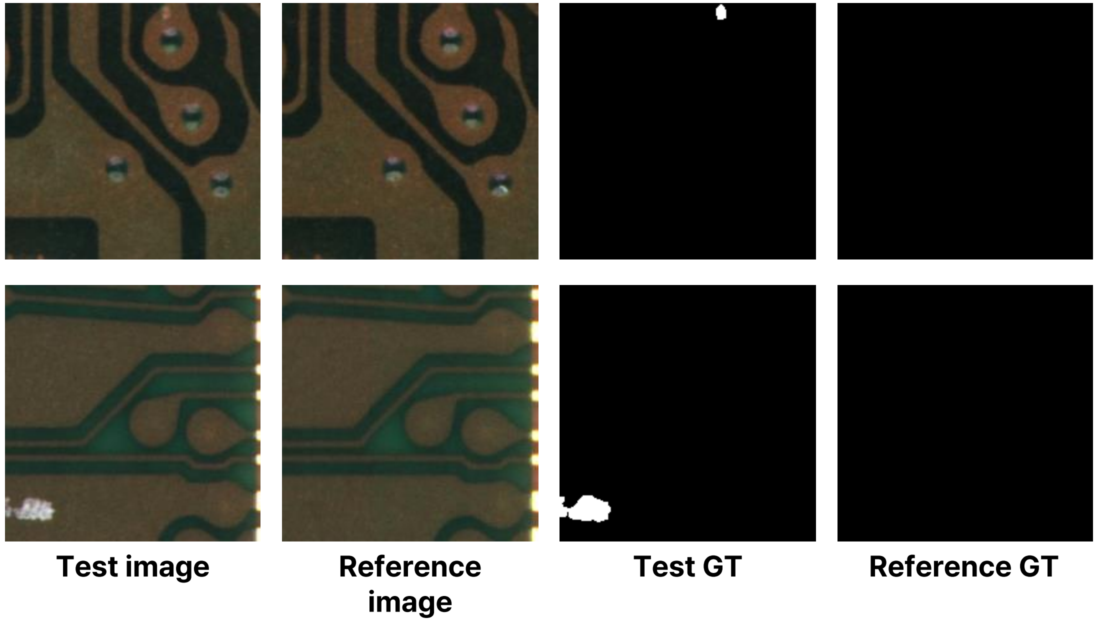


Figure 18. Examples of IC substrate dataset

04. Experiment

Performance metrics

- TP : the number of true positives
- FP : the number of false positives
- FN : the number of false negatives

- Precision (%)
  - $P = \frac{TP}{TP+FP}$
- Recall (%)
  - $R = \frac{TP}{TP+FN}$
- F1-score (%)
  - $F = \frac{2PR}{P+R}$

04. Experiment

Inference Time

- The inference time for one 200 × 200 image pair was measured using RTX 3090 graphics card
- The Twin-Comb-Co-Attention network took the longest time to process results due to extensive computations of correlations and the refining process.
- The proposed networks were approximately three times faster than the Twin-Comb-Co-Att network but 1.16 times slower than the Base-Twin network.
- The CC-TSNet took slightly more time when utilizing the ch-co-att module.

Table 1. inference time for one 200X200 image on NVIDIA GeForce RTX 3090

	Twin-Comb-Co-Att	**Base-Twin**	**U-Net**	**C-TSNet (proposed)**	**CC-TSNet (proposed)**
# of parameters	118,722	116,610	91,010	190,580	190,388
Inference time	4.557ms	1.253ms	0.716ms	1.459ms	1.542ms
Ratio	1	0.275	0.157	0.320	0.338

04. Experiment

Experimental Results

- For a fair comparison, the recall values of all methods were fixed.
- The performance of all methods was averaged after repeating the experiments three times with the same hyper-parameters.
- The proposed methods achieved an F1-score that was 2.83 to 3.03 percentage points higher compared to the Base-Twin network, but 0.23 to 0.43 percentage points lower than the Twin-Comb-Co-Att method.
- By utilizing the channel-wise co-attention module, the performance of the CC-TSNet slightly increased, demonstrating that some false positives caused by color variations were corrected.

Table 2. Experimental results for IC substrate dataset

Method	Recall (%)	Precision (%)	F1-score (%)
U-Net	93.68	84.59	88.90
Base-Twin	93.68	88.21	90.85
Twin-Comb-Co-Att	93.68	94.54	**94.11**
C-TSNet (proposed)	93.68	93.68	93.68
CC-TSNet (proposed)	93.68	94.09	**93.88**

04. Experiment

Qualitative performance evaluation (1)

- U-Net, a non-referential method, has difficulty identifying defect-free areas that look similar to defects.
- Other methods which are referential methods have better performance with distinguishing defects and pattern.

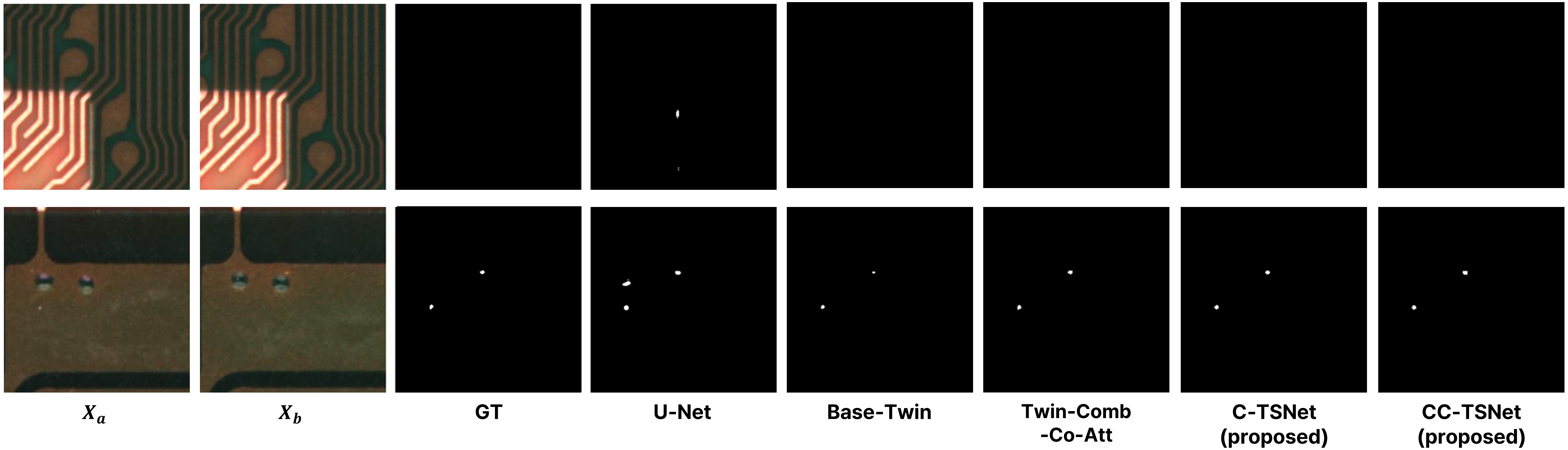


Figure 19. Prediction results of each method

04. Experiment

Qualitative performance evaluation (2)

- Prediction results of each method when inspecting image pairs with registration errors
- It shows that the Base-Twin network is vulnerable to mis-registration between the test and reference images.
- In contrast, the proposed methods are robust to registration errors, performing similarly to the Twin-Comb-Co-Att network.

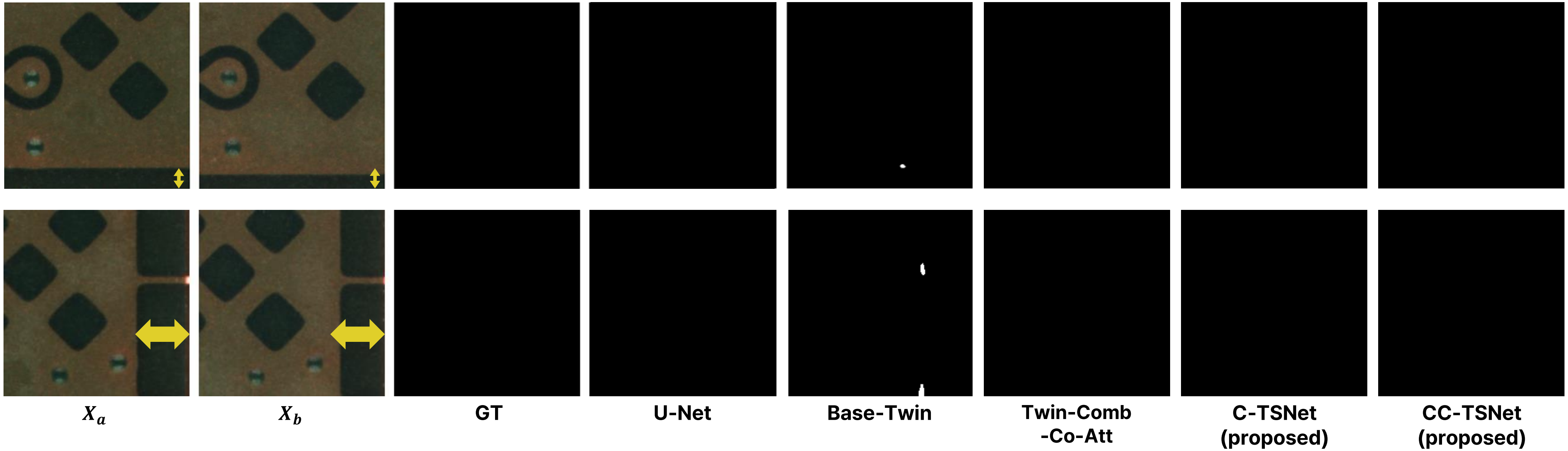


Figure 20. Prediction results of each method

04. Experiment

Qualitative performance evaluation (3)

- Prediction results of each method when inspecting image pairs with characteristic differences.
- It indicates that the Base-Twin network is also vulnerable to these differences.
- In contrast, the proposed methods demonstrate greater robustness to color changes.
- The single decoder part of the C-TSNet may have an effective influence on correcting false positives caused not only by registration errors but also by characteristic differences.

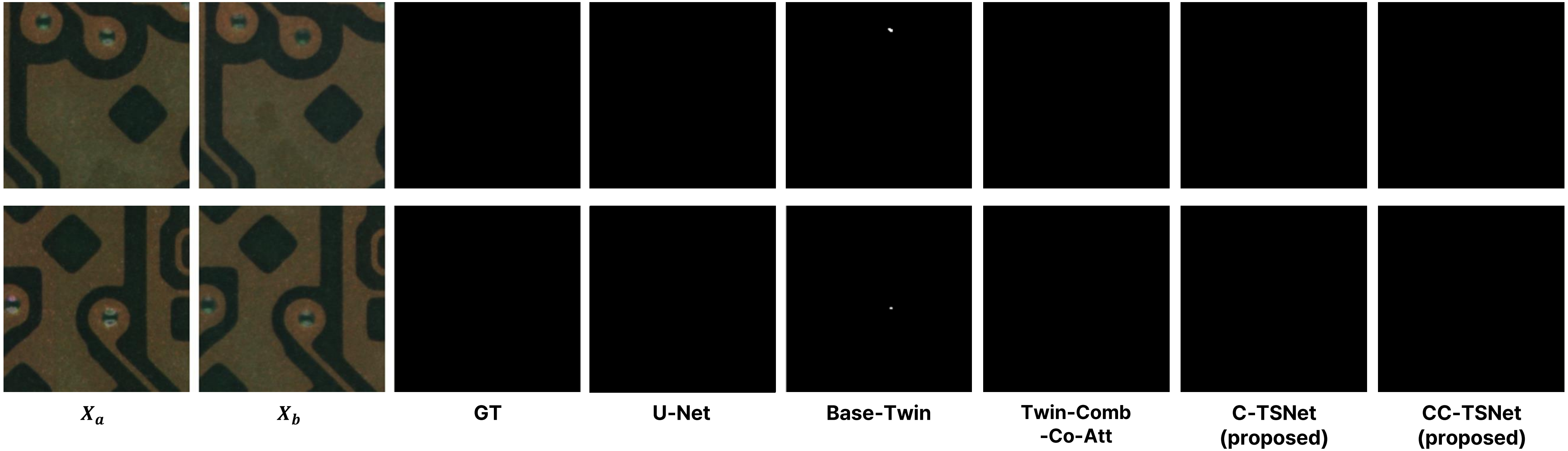


Figure 21. Prediction results of each method

04. Experiment

Qualitative performance evaluation (4)

- Even though some characteristic differences are corrected, the C-TSNet still has some errors caused by characteristic differences.
- Some errors due to color variations are corrected with the CC-TSNet, similar to the Twin-Comb-Co-Att network.

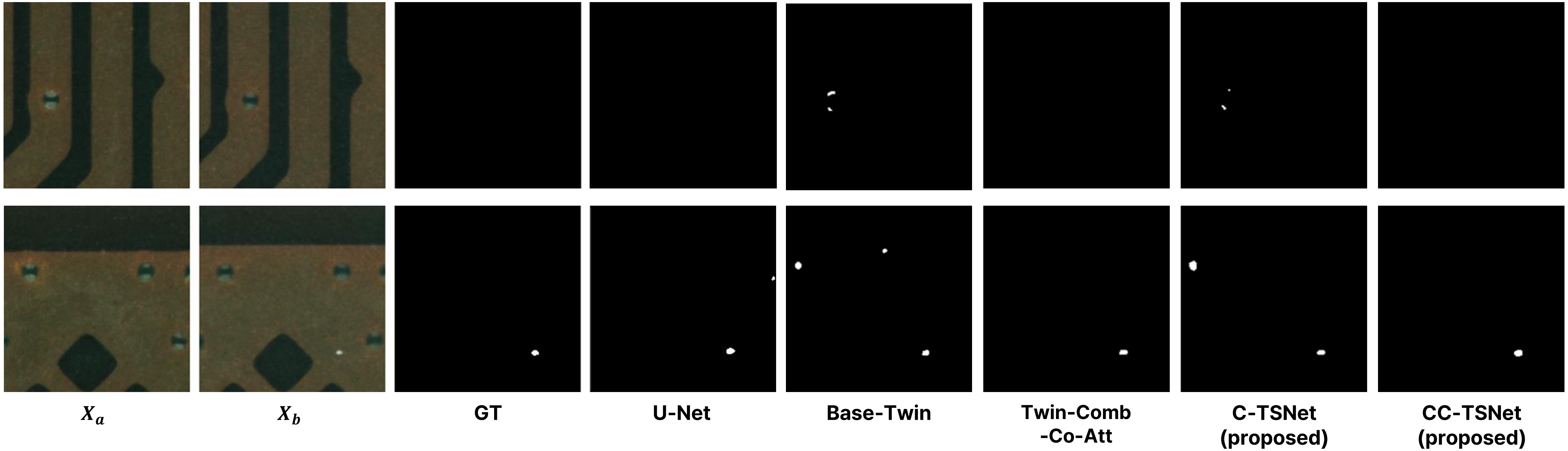
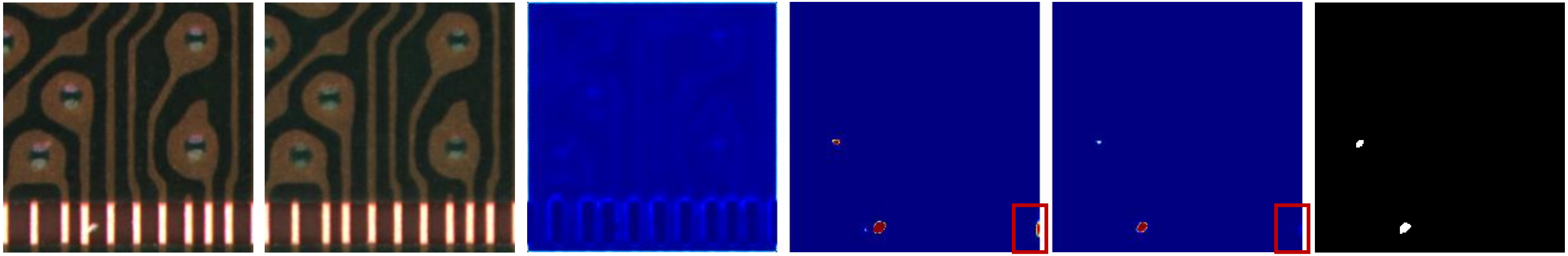


Figure 22. Prediction results of each method

04. Experiment

Qualitative performance evaluation (5)

- The output from the single decoder shows that both patterns and defects are activated.
- The output from the twin decoder, however, includes errors due to registration errors within X_a and X_b.
- By merging the logits from the single decoder and the twin network decoder, errors caused by registration discrepancies are reduced.



X_a | X_b | Single decoder logit | Twin decoder logit | C-TSNet final logit | GT

Figure 23. Illustrations of logits from C-TSNet

04. Experiment

Qualitative performance evaluation (6)

- X_a and X_b contains characteristic difference caused by illumination changes.
- The C-TSNet did not correct these differences with the single decoder, but with the ch-co-att module, it showed that these errors were corrected.

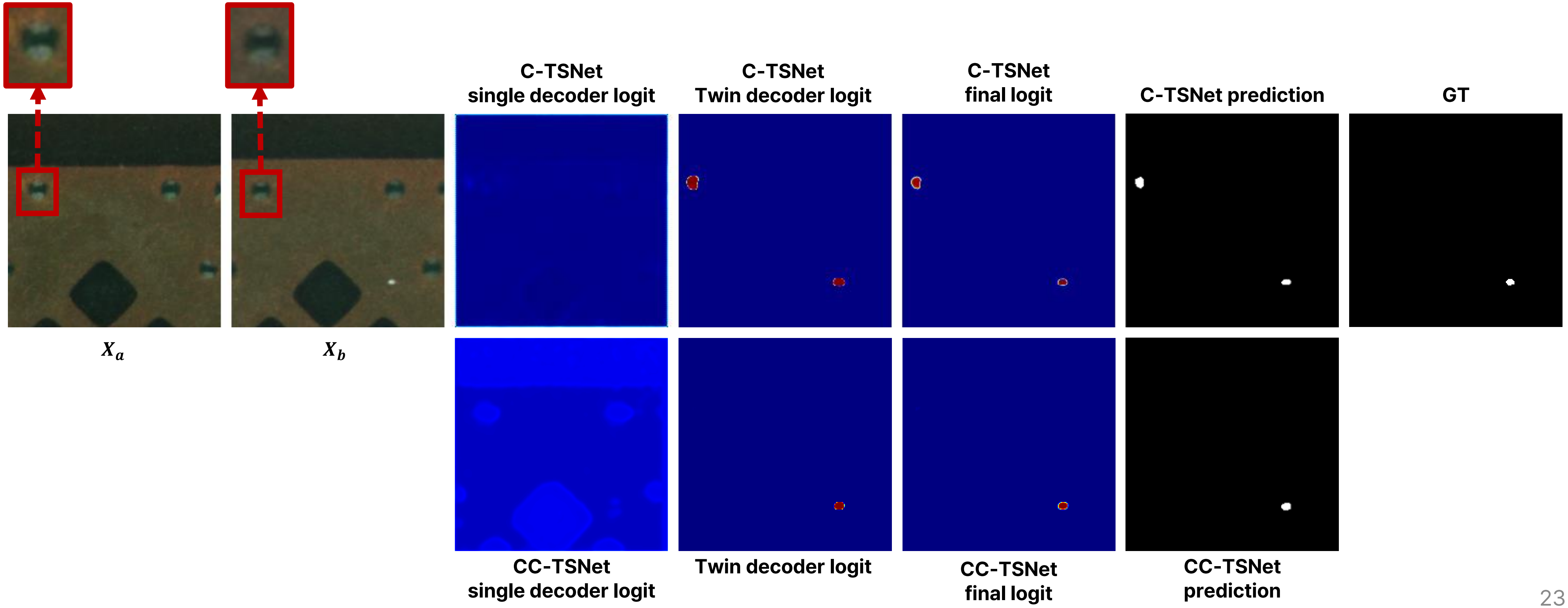


Figure 24. Illustrations of logits from the proposed methods

Conclusion

- This study proposes the C-TSNet and CC-TSNet for integrated circuit substrate inspection, combining twin and single network architectures.
- The proposed methods demonstrate increased robustness to both registration errors and characteristic differences while maintaining low latency.
- C-TSNet with channel co-attention (i.e. CC-TSNet) showed improved robustness to color changes.
- CC-TSNet achieved an F1-score only 0.23 percentage points lower than the Twin-Comb-Co-Att network, but with just one-third of the computational latency. This may be more practical for using in the manufacturing process.

Thank you