Application of Contrastive Representation Learning to Unsupervised Defect Classification in Semiconductor Manufacturing

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Contrastive representation learning (CRL) has recently received much attention due to its great successes in unsupervised visual learning. In this work, we applied CRL to unsupervised defect classification and found that CRL has a strong ability to learn representations, achieving more than three times better accuracy than a conventional method in the classification of artificial defect images.

Semiconductor devices are manufactured by hundreds of processes involving tools, materials, and recipes that are carefully selected to realize the required level of performance. In the process development phase, electrical testing is only partially available and defect inspection is an excellent means of process evaluation (Fig. 1).

Defect inspections detect inadequate shapes or unexpected residues following process completion. In the early stage of process development, there are various defects due to process immaturity. Engineers examine the defects one by one, identifying defect types based on their knowledge, and analyze the cause to improve the process.

Supervised defect classification is widely used for defect analysis. However, supervised methods require the preparation of a large amount of labeled data, which takes considerable time and effort. In addition, new kinds of defects appear one after another during the course of process improvement, which make it infeasible to keep up with data labeling (Fig. 2).

Hence, unsupervised methods are preferable. Unfortunately, conventional methods are not sufficiently accurate in defect classification because they tend to make groups (i.e., clusters) based on representations not of the defect but of the background occupying most of image pixels (Fig. 3).

To tackle these problems, we utilized CRL [1]. In recent years, CRL has achieved the most success among unsupervised visual learning approaches, which do not require true labels. By comparing similar inputs and dissimilar inputs, CRL learns useful representations for various downstream tasks. Among several CRL methods with different similarity criteria, we selected instance discrimination and feature decorrelation (IDFD) [2] for defect image clustering because it achieves high accuracy by a simple clustering method. Fig. 4 shows a schematic overview of IDFD. IDFD extracts representations (i.e., feature vectors) from input images for clustering.

To assess the effectiveness of IDFD, we performed an experiment on an artificial image dataset. As shown in Fig. 5, we generated 15,000 images in 15 classes by overlaying a defect on a background, aiming to reproduce difficulties encountered in real-world data. Fig. 6 shows the experimental flow, which consists of two parts: unsupervised representation learning and image clustering. Feature vectors were converted to 2-dimensional vectors and mapped for visualizing the qualitative properties of representation learning. In a quantitative evaluation, we compared the prediction labels obtained by clustering with true labels. We also evaluated autoencoder (AE) as a baseline learning method for comparison.

Fig. 7 (a) shows 2-dimensional feature vectors of the artificial images in a qualitative comparison of AE and IDFD. Both AE and IDFD could identify differences in backgrounds. For defects, however, AE features partially overlapped, indicating that it failed to extract defect representations. By contrast, IDFD grouped different defects separately, showing that it could learn defect representations in spite of variation in backgrounds. Confusion matrices in Fig 7 (b) compare the two methods quantitatively. The accuracy was 30.7% for AE and 99.9% for IDFD.

We also conducted a verification experiment on a real defect image dataset with various defects and backgrounds. The accuracy results were 43.6% for AE and 74.8% for IDFD. With this practical accuracy of IDFD, engineers will no longer have to take pains to check defects individually. These results strongly indicate that CRL will enable precise defect analysis, thereby contributing to rapid process development.

References:
[1] P. H. Le-Khac, G. Healy, and A. F. Smeaton. Contrastive Representation Learning: A Framework and Review. In *IEEE Access*, vol. 8, pp. 193907-193934, 2020.
[2] Y. Tao, K. Takagi, and K. Nakata. Clustering-friendly representation learning via instance discrimination and feature decorrelation. In *ICLR*, 2021.

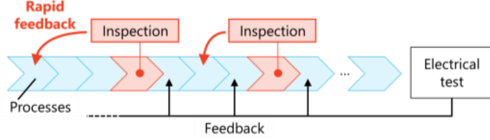


Fig. 1. Semiconductor manufacturing process with feedback from inspections and electrical tests.

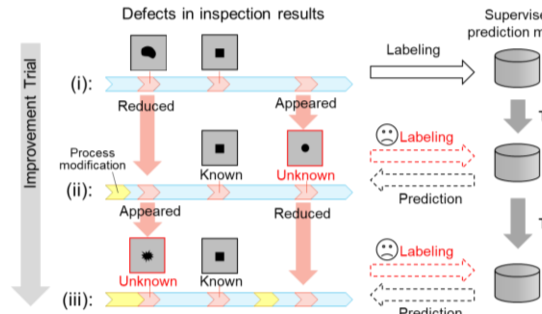


Fig. 2. Various defects are observed in the early stage of process development. Therefore, it is infeasible to prepare true labels for each one.

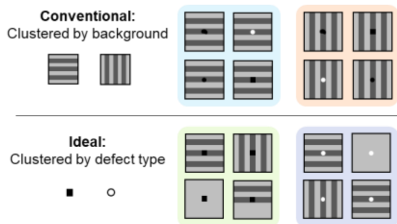


Fig. 3. Conventional unsupervised methods tend to have clusters dominated by backgrounds.

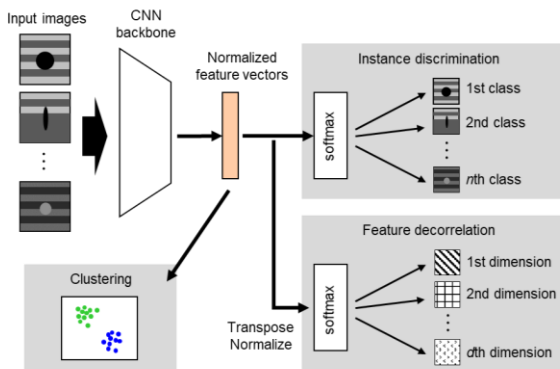


Fig. 4. Schematic overview of IDFD [2]. Once learning is complete, feature vectors are extracted from input images and used for clustering.

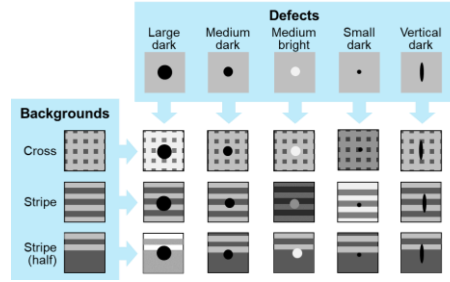


Fig. 5. Artificial images are composed of various defects and backgrounds. (Note that these images are simply drawn for illustration purposes and more realistic images were used for experiments.)

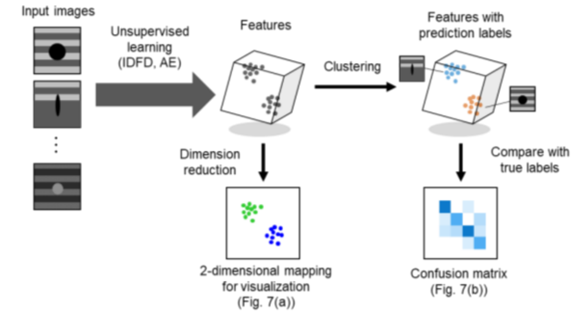
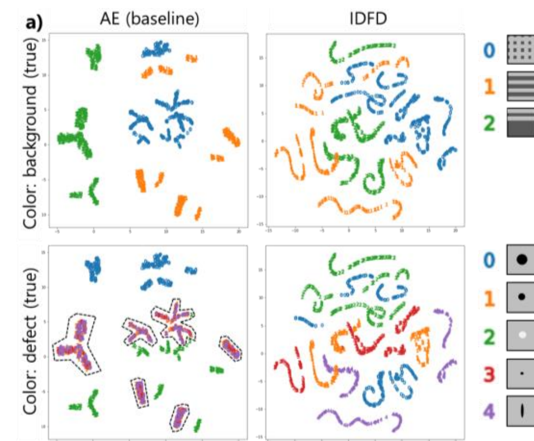


Fig. 6. Experimental flow. Feature vectors are extracted for clustering and accuracy evaluation. Two-dimensional feature vectors are shown for discussion and visualization.



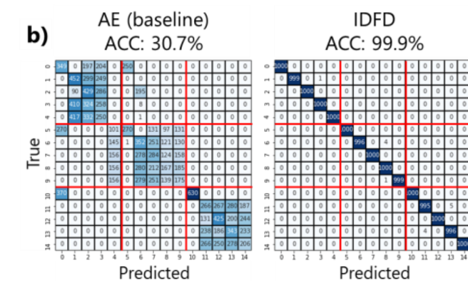


Fig. 7. Comparison of AE and IDFD using artificial images. (a) Two-dimensional feature vectors colored by true background/defect type. (b) Confusion matrices. Red lines divide different background conditions.