1st International Electronic Conference on Applied Sciences

Deep Anomaly Detection via Morphological Transformations

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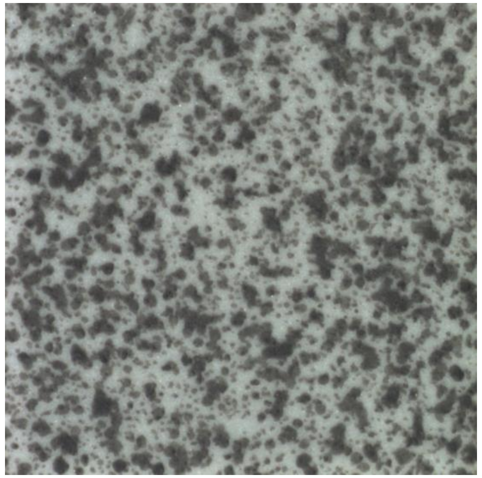
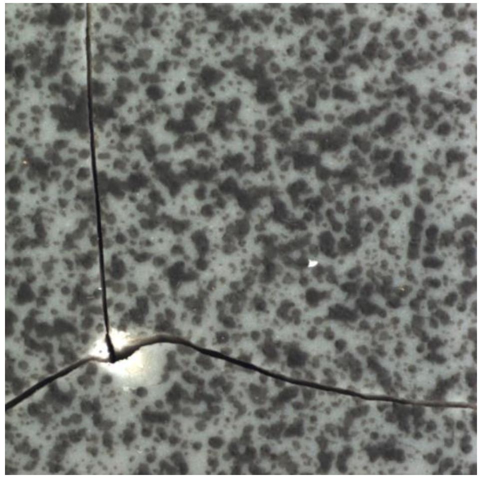
Real-world industrial anomaly detection

- The goal of deep anomaly detection is to identify abnormal data by utilizing a deep neural network trained by a normal training dataset
- Industrial visual anomaly detection problems generally **distinguish normal and abnormal data through small morphological differences**, such as crack and stain.



normal



abnormal

Semantic differences VS Morphological differenecs

- Nevertheless, most existing algorithms focused on capturing not morphological features but semantic features of normal data.

Semantic difference

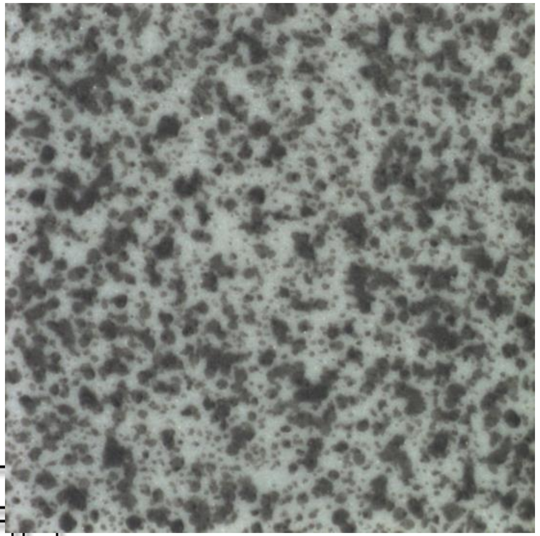
Morphological difference

Morphological transformations - Erosion

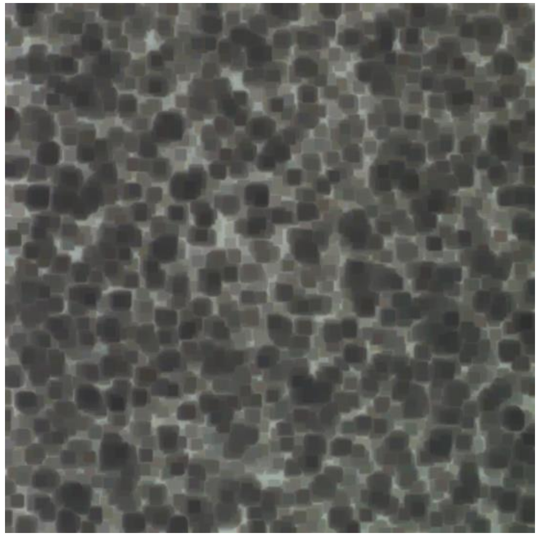
- Erosion computes the minimum pixel value of image i in every neighborhood of (x, y), coincident with kernel b, it expected that the size of bright features in i will be reduced

$$[i \ominus b](x, y) = \min_{(s,t)\in b} i(x + s, y + t)$$

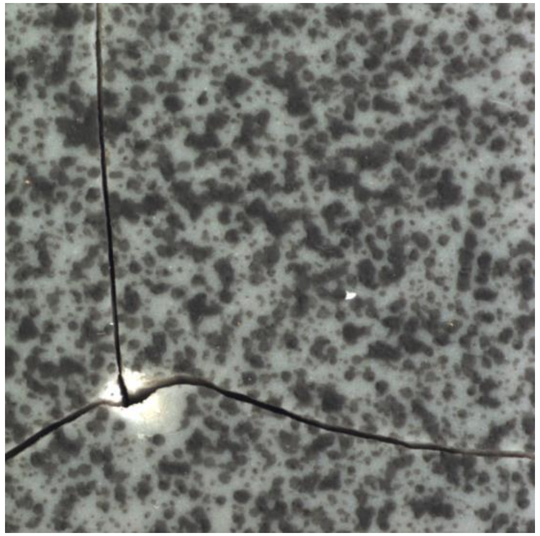
Normal



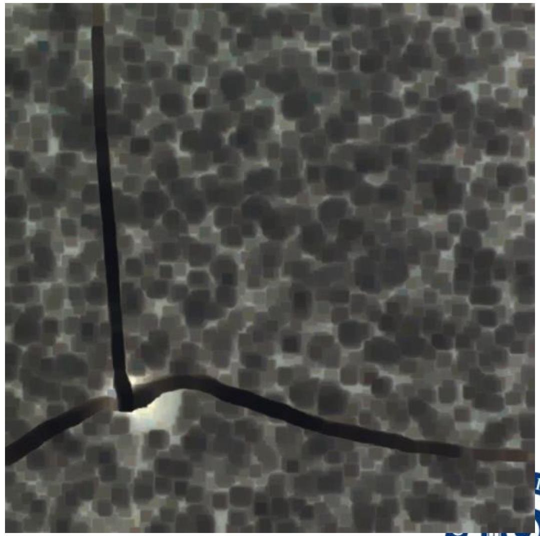
Eroded normal



Abnormal



Eroded abnormal

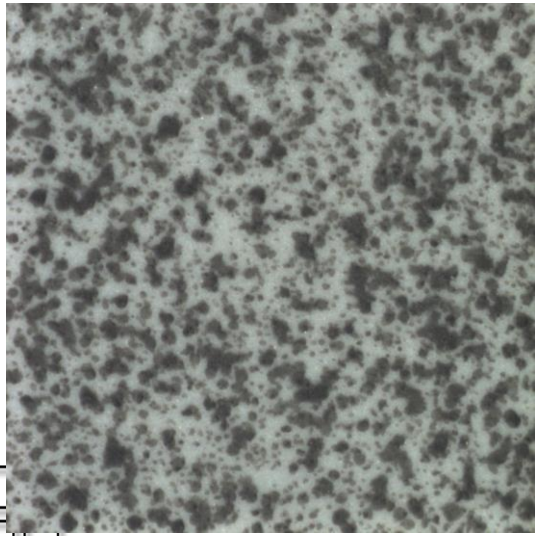


Morphological transformations - Dilation

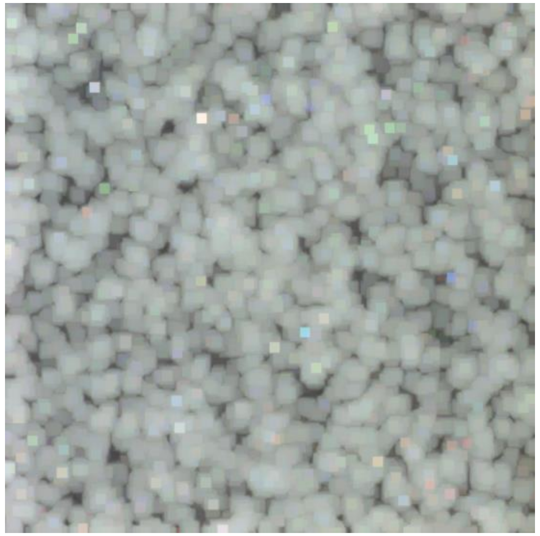
- Dilation computes the maximum pixel value of image i in every neighborhood of (x, y), coincident with kernel b, it expected that the size of darker features in i will be reduced

$$[i \ominus b](x, y) = \max_{(s,t)\in b} i(x + s, y + t)$$

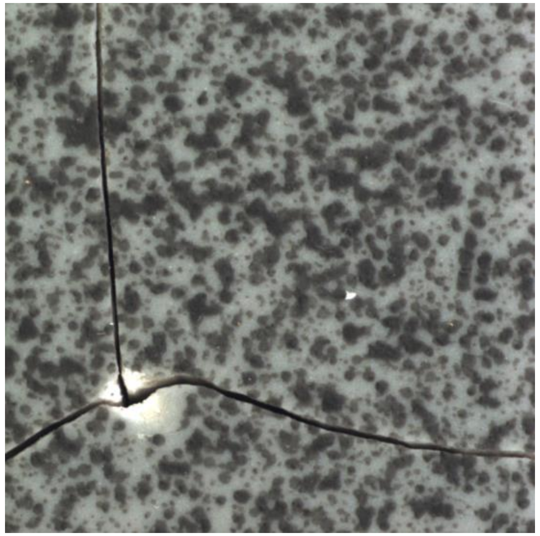
Normal



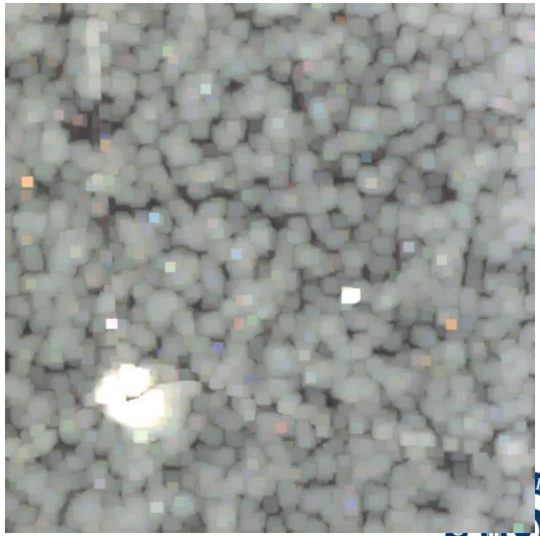
Dilated normal



Abnormal



Dilated abnormal

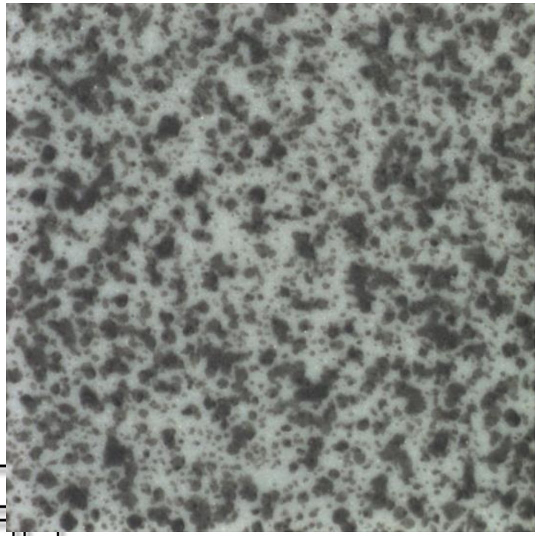


Morphological transformations – Morphological gradient

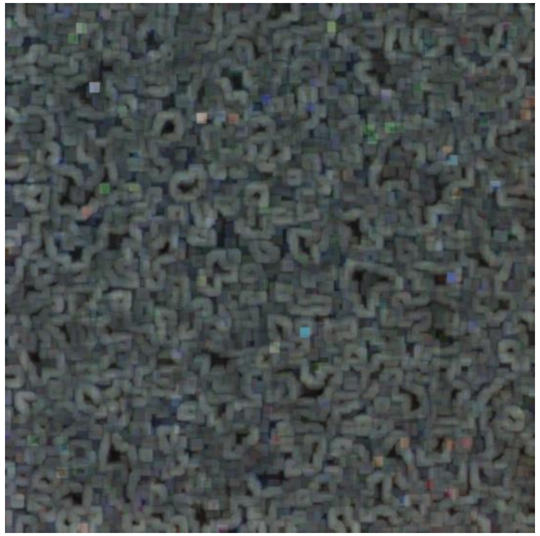
- To obtain the morphological gradient of an image, dilation and erosion can be used in combination with image subtraction.

$$i \odot b = (i \oplus b) - (i \ominus b)$$

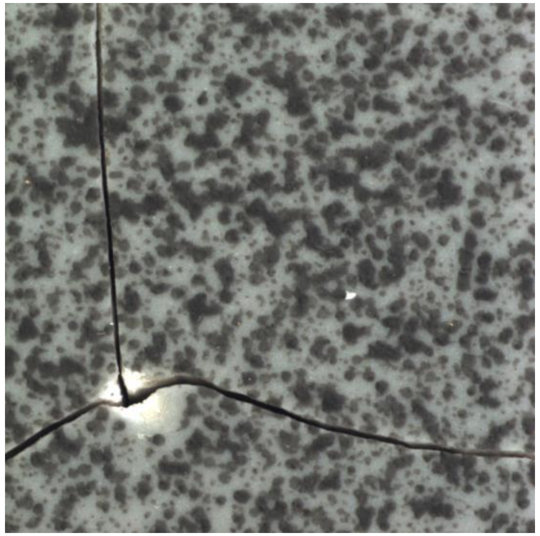
Normal



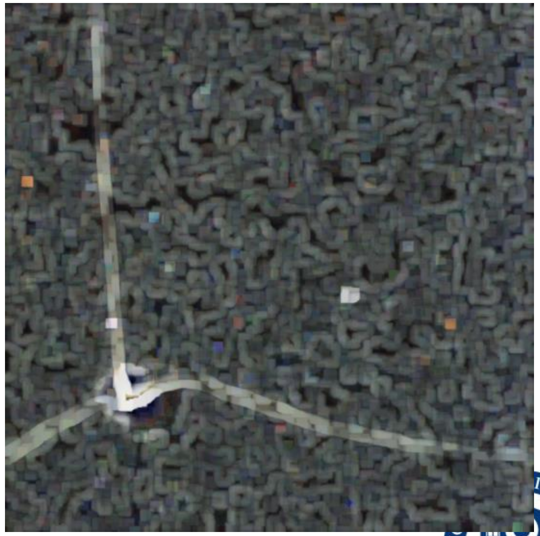
Dilated normal



Abnormal

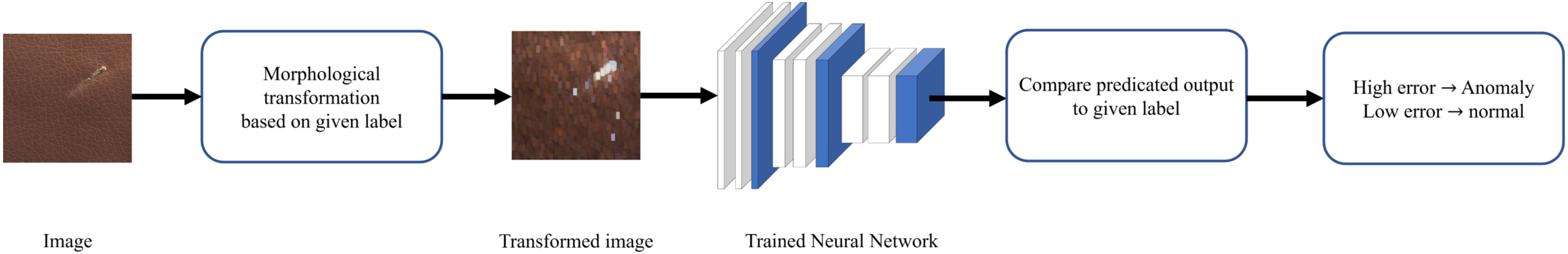


Dilated abnormal



The proposed deep anomaly detection

- The proposed deep anomaly detection aims to discriminate the abnormal data using the acquired morphological features of normal data in the training procedure.
- Therefore, if a given morphological transformed data generates a high prediction error, it can be considered abnormal.



Objective function

- The proposed algorithm aims to train deep neural network-based morphological features in a self-supervised learning manner.
- To achieve this goal, we propose to train a deep neural network F to discriminate the morphological transformation types applied to an image that is given to it as input.
- Specifically, we define a set **of $\boldsymbol{N_1}$ discrete morphological transformations**, $\boldsymbol{N_2}$ **discrete values for kernel width, and $\boldsymbol{N_3}$ discrete values for kernel height.**

Objective function

- We define a set of $N_1 N_2 N_3$ discrete morphological transformations as follows:

$$G = \{g(.|n_1, n_2, n_3)\}_{n_1=1,n_2=1,n_3=1}^{N_1,N_2,N_3},$$

  where $g(.|n_1, n_2, n_3)$ denotes that applies to image i the morphological transformation with multi-class label $\{n_1, n_2, n_3\}$ that produces the transformed image $i^{n_1,n_2,n_3} = g(i|n_1, n_2, n_3)$.

- The deep neural network F takes an input as transformed image $i^{n_1^*,n_2^*,n_3^*}$ where the label $\{n_1^*, n_2^*, n_3^*\}$ is unknown to F.

Objective function

- The deep neural network F takes an input as transformed image $i^{n_1^*,n_2^*,n_3^*}$ where the label $\{n_1^*, n_2^*, n_3^*\}$ is unknown to F.
- It produces a probability distribution of softmax response over all possible morphological transformations, which is denoted as follows:

$$F\left(i^{n_1^*,n_2^*,n_3^*} \middle| \theta\right) = \left\{F^{n_1,n_2,n_3}\left(i^{n_1^*,n_2^*,n_3^*} \middle| \theta\right)\right\}_{n_1=1,n_2=1,n_3=1}^{N_1,N_2,N_3},$$

where $F^{n_1,n_2,n_3}\left(i^{n_1^*,n_2^*,n_3^*} \middle| \theta\right)$ is the predicted probability for morphological transformation with $\{n_1^*, n_2^*, n_3^*\}$ and θ denotes the parameters of F.

Objective function

- Consequently, the proposed self-supervised objective function to capture morphological features of normal data is as follows:

$$\min_{\theta} \frac{1}{3T} \sum_{j=1}^{T} \left(-\frac{1}{N_1} \sum_{n_1=1}^{N_1} \log\left(F^{n_1}\left(i^{n_1^*,n_2^*,n_3^*} \middle| \theta\right)\right) - \frac{1}{N_2} \sum_{n_2=1}^{N_2} \log\left(F^{n_2}\left(i^{n_1^*,n_2^*,n_3^*} \middle| \theta\right)\right) - \frac{1}{N_3} \sum_{n_3=1}^{N_3} \log\left(F^{n_1}\left(i^{n_1^*,n_2^*,n_3^*} \middle| \theta\right)\right) \right)$$

  where $F^{n_1}\left(i^{n_1^*,n_2^*,n_3^*} \middle| \theta\right)$, $F^{n_2}\left(i^{n_1^*,n_2^*,n_3^*} \middle| \theta\right)$, and $F^{n_3}\left(i^{n_1^*,n_2^*,n_3^*} \middle| \theta\right)$ denote predicted probability for n_1^*, n_2^*, and n_3^*, respectively.

- Through the above formulation, we enforce the deep neural networks to learn morphological features of normal by predicting both transformation type and kernel size simultaneously.

Experimental results – implementation details

- In the experimental results, there are three types of the proposed method to **verify kernel size learning's influence;**
  - **Type 1**: $n_1 \in \{Erosion, Dilation, Gradient\}, \mathrm{n}_2 \in \{1,28,56\}, n_3 \in \{1,28,56\}$
  - **Type 2**: $n_1 \in \{Erosion, Dilation, Gradient\}, \mathrm{n}_2 \in \{8,28,56\}, n_3 \in \{8,28,56\}$
  - **Type 3**: $n_1 \in \{Erosion, Dilation, Gradient\}, \mathrm{n}_2 \in \{1,8,28,56\}, n_3 \in \{1,8,28,56\}$
- PyTorch with RTX 2080Ti 11GB GPU and Intel i7 CPU.

Experimental results

- Comparison of AUROC (area under the receiver operating characteristic, %) performance between [1] and the proposed algorithm in MVTec dataset.

Class	bottle	cable	capsule	carpet	grid	hazelnut	leather
[1]	83.10	77.81	75.31	38.12	**31.47**	67.14	64.10
Ours-type 1	87.86	76.89	**77.50**	57.22	15.62	68.71	39.67
Ours-type 2	88.41	77.55	69.92	53.97	29.91	62.29	66.58
Ours-type 3	**95.16**	**80.34**	73.08	**57.91**	29.99	**68.04**	**82.88**
Class	pill	screw	tile	toothbrush	transistor	wood	average
[1]	62.17	27.73	52.13	82.73	**88.25**	84.30	64.18
Ours-type 1	50.60	28.06	84.70	**93.33**	77.92	85.44	63.17
Ours-type 2	51.72	46.96	92.71	70.22	84.04	**90.96**	66.19
Ours-type 3	**57.23**	**61.86**	**93.58**	91.67	83.29	87.37	**72.92**

[1] Golan, Izhak, and Ran El-Yaniv. "Deep anomaly detection using geometric transformations." *Advances in Neural Information Processing Systems*. 2018.

Conclusion

- The proposed method achieves superior performance in deep anomaly detection on industrial inspection by training the deep neural network to capture salient morphological features of normal data.
- The proposed algorithm can flexibly adapt to various real-world deep anomaly detection problem by choosing the adequate morphological transformation in image processing technology.
- Because the proposed methodology utilizes self-supervised learning, it has low computational complexity than other deep anomaly detection methods such as reconstruction-based algorithm.

Thank You!

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