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Micro-cracks Detection of Polycrystalline Solar Cells with Transfer Learning

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Abstract. As the photovoltaic (PV) systems are universally utilized in power systems, the defect of solar cells, the core components of PV system requires to be detected in a low-cost and high-efficiency method, because of its wide application and direct influence on power generation efficiency and system stability. The principal aim of this study is to apply transfer learning in defect detection of polycrystalline cells with image-level labelled mono images and unlabelled poly images. The experiment was conducted with DAN models based on a MK-MMD to represent the distance between source domain and target domain and Resnet-50 backbone to learn transferable features. Three contrast methods were designed to make comparison with DAN. It has been proved that DAN model based on MK-MMD and Resnet-50 shows a promising performance on transferring from monocrystalline tasks to polycrystalline tasks.

1. Introduction

Nowadays, power systems are being changed by substituting traditional generation with alternatives such as photovoltaic (PV) systems[1]. Solar cells installed on the solar panels play an important role in photovoltaic system, which can affect the power generation efficiency and stability directly[2]. Unfortunately, it is easy for solar cells to be damaged during production and transportation[3], hence, it is necessary to develop a method of object detection[4,5] for evaluating the damage in industrial scene.

Actually, electroluminescence (EL) is one of the universal methods to make these defects visible, based on which current studies propose various approaches to detect defect on solar cells[6-9]. A method using two dimensional matched filters was developed to recognize severe types of micro-cracks, which are larger than 3 cm in length[6]. More promising results were reported by the vesselness algorithm for automatic processing of EI images[7]. Recent studies demonstrate that Convolutional Neural Networks-based methods shows favourable results for given tasks[8,9], however, these require labels whatever image-level annotations or pixel- level annotations. To be specific, solar panels can be divided into monocrystalline cells and polycrystalline cells. In polycrystalline cells, because normal crystallographic defects may be misclassified as cracks by the segmentation algorithm, micro-cracks detection is much more difficult than in monocrystalline cells[6]. Moreover, manual labeling of sufficient training data requires expensive labor and effort.

To address this issue, we propose to utilize domain adaptation to construct the transference from relevant source domain to target domain[10]. Recent researches reveal that deep neural networks can learn more transferable features for domain adaptation[11]. Volume work has been done to explore the relationship between the transferability of features and the layers of deep convolutional neural network[12]. DDC and DAN models are proposed to adapt different layers in deep-CNN, which can be utilized in transferring from monocrystalline task to polycrystalline task. To sum up, the dominant contribution of this paper is advocating a transfer learning approach based on improved-DAN to detect defect on polycrystalline cells, which only requires image-level labeled mono images rather than labeled poly images.

2. Related work

In the area of transfer learning based on deep neural network, the researches on transferability of features demonstrate that the deeper the layers of the network, the more specific the features learned are to the specific tasks, while the features learned by the first few layers are more general to many dataset and tasks. In addition, it provides the evidence that the increase of distance between the source task and the target task leads to the decrease of feature transferability, but the transferable features extracted from the distant tasks perform a better effect than the random features[12]. DDC model, which is a variant of deep CNN with an adaptation layer and a dataset shift loss is proposed to learn a domain-invariant representation[13]. Subsequently, DAN model is proposed to adapt all the layers relevant to task-specific features in a layerwise manner. Furthermore, multiple kernels for adapting deep representations is used in DAN model to calculate maximum mean discrepancy, which is a distance between embeddings of the probability distributions in a reproducing kernel Hilbert space. Hence, DAN improves adaptive effectiveness compared with single-kernel MMD-based methods[14].

3. Method

The source domain D_s is formulated as $D_s = \{(x_i^s, y_i^s)\}_{i=1}^{n_s}$, where n_s is the number of labelled examples, and the target domain D_t is formulated as $D_s = \{(x_i^t)\}_{i=1}^{n_t}$, where n_t is the number of unlabeled examples. Denote by p and q be the probability distributions of source domains and target domains. The goal is to build a classifier to predict y^t.

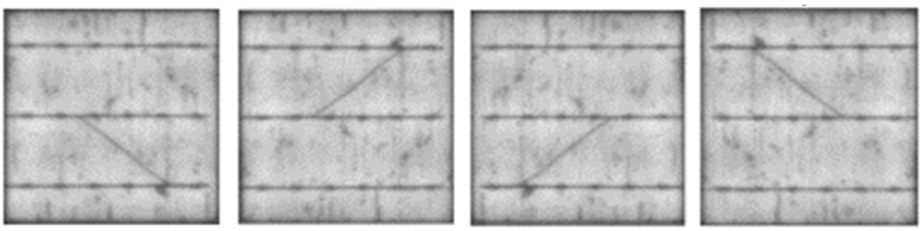
3.1. Data augmentation

The dataset for this experiment is a benchmark for visual identification of defective solar cells in electroluminescence imagery[15-17]. In the dataset, every image is annotated with a defect probability and the type of the solar module that the solar cell image was originally extracted from. The defect probability is a floating point value between 0 and 1. The type of the solar module includes "monocrystalline" and "polycrystalline".

According to the defect probability, the monocrystalline samples and polycrystalline samples are divided into two classes, C_0 and C_1, respectively. In C_0 there are non-crack images, conversely, in C_1 are images cracks.Specifically, samples can be classes with the following formulation:

$$l_i^s = \begin{cases} C_0, & p_i^s < 0.5 \\ C_1, & 0.5 \le p_i^s \le 1 \end{cases} \tag{1}$$

where l_i^s is the label and the p_i^s is the defect probability of image i in source domain. Images in target domains are prepared by the same method.



(a) (b) (c) (d)

Figure 1. An example of data augmentation. (a)(b)(c)(d) are original, vertically inverse, horizontally inverse, and both inverse images in order.

Then, it can be observed that the number of images in C_0 is twice as large as C_1 both in source domain and target domain. Therefore, we utilize the three common approaches to augment dataset, including flipping vertically, horizontally and both all. Figure 1 shows an example of data augmentation.

3.2. *Deep Adaptation Network*

Deep adaptation network (DAN) aims to reduce the discrepancy between source domain and target domain by the multiple kernel variant of MMD, hence enhancing the feature transferability in the layers corresponding to specific task of the deep neural network[14].

3.2.1. MK-MMD. Multiple kernel variant of MMD (MK-MMD) is developed based on single-kernel MMD, which maps source domain and target domain to a reproducing kernel Hilbert space (RKHS) endowed with a characteristic kernel and computes the maximum mean discrepancies (MMD)[18]. Basing on above theory, multi-kernel to compute MMD is designed to for optimal kernel selection[19].

Denote by H_k be the reproducing kernel Hilbert space (RKHS) endowed with a characteristic kernel k. The MK-MMD $d_k(p,q)$) between probability distributions p and q is characterized by the RKHS distance between the mean embeddings of p and q. The function of MK-MMD can be formalized as:

$$d_k^2(p,q) \triangleq \left\| E_p[\phi(x^s)] - E_q[\phi(x^t)] \right\|_{H_k}^2 \tag{2}$$

The characteristic kernel associated with the feature map ϕ, $\mathrm{k}(x^s, x^t) = \langle \phi(x^s), \phi(x^t) \rangle$, is defined as the convex combination of m PSD kernels $\{k_u\}$,

$$\mathrm{K} \underline{\underline{\Delta}} \{\mathrm{k} = \sum_{u=1}^{\mathrm{m}} \beta_u k_u : \sum_{u=1}^{m} \beta_u = 1, \beta_u \ge 0, \forall u\} \tag{3}$$

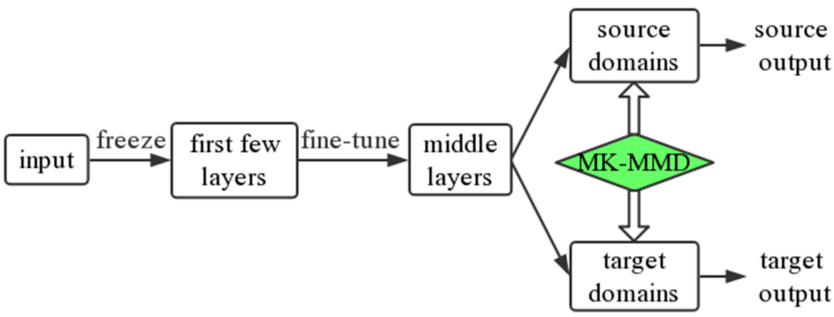


Figure 2. The architecture of DAN model.

3.2.2. DAN. Because of the lack of labelled information in target domains, over-fitting often occurs when directly adapting CNN to the target domain with fine-tuning. Therefore, DAN is proposed to utilize both source-labeled data and target-unlabeled data with MK-MMD[14]. Figure 2 demonstrate the architecture of DAN model. In this experiment, we adapt DAN based on Resnet50, which is comprised of five convolutional layers (conv1-conv5_x) and a fully connected layer (f_c). The convolutional layers can learn general features which can be transferred to the first few layers and are slightly domain-biased in middle layers[12]. Hence, when adapting the pre-trained Resnet50 to target, we freeze the first few layers and fine-tune the middle layers to maintain the effectiveness of fragile co-adaptation. The empirical risk of Resnet50 is:

$$\min_{\Phi} J(\theta(x_i^a), y_i^a) \tag{4}$$

where Φ are the weights and bias of all layers, J is the cross-entropy loss function, and $\theta(x_i^a)$ is the conditional probability that the Resnet50 assigns x_i^a to label y_i^a.

For fully connected layer f_c, it learns deep features and is designed for the specific task, which leads to the poor performance on the target task. For this reason, fully connected layer need to be retrained on the similar distributions of the source and target, which can be achieved by adding an MK-MMD-based multi-layer adaptation. Then the loss function becomes to:

$$\min_{\Phi} J(\theta(x_i^a), y_i^a) + \lambda \sum_{l=l_1}^{l_2} d_k^2(D_s^l, D_s^l) \tag{5}$$

where $\lambda > 0$ is a penalty parameter, l_1 and l_2 are fully connected layers which need to be retrained.

4. Experiment

4.1. Dataset

The dataset are captured from 44 different solar modules with varying degrees of degradation of the functional and defective solar cells. All images are normalized with respect to size and perspective. And any distortion produced during capturing the EL images was eliminated before the solar cell extraction. After data augmentation, the dataset contains 2886 mono samples and 2154 poly samples of 300x300 pixels 8-bit grayscale images. The specific numbers of non-crack images and crack images in mono and poly dataset are shown in Table 1. The experiment was conducted to perform the transfer task, mono dataset → poly dataset.

Table 1. A slightly more complex table with a narrow caption.

	Non-crack C_0	Crack C_1	Sum
Mono-	1410	1476	2886
Poly-	1098	1056	2154

4.2. Experiment Setup

We compare DAN with three methods: DaNN[19], MRAN[20] and DDC[13]. DDC is a domain adaptation variant of CNN in which the last fully connected layer is retrained by single-kernel MMD[13]. In both four methods, the all source examples with labels and all target examples without labels are utilized for unsupervised adaptation. Because it is difficult to train a deep CNN for its lack of numerous labeled data in domain adaptation, the experiment begin with a pre-trained Resnet50 model. For single-kernel based method DDC, we apply a Gaussian kernel and the MMD penalty parameter λ is constant[21]. For DAN method, we use multi-kernel MK-MMD with a series of Gaussian kernel. According to the test errors of the source classifier and classifying the source from the target, the MMD penalty parameter λ is automatically selected on a validation set, which contains source-labeled examples and target-unlabeled examples. We fine-tune the convolutional layers that are shared from the pre-trained model and train the classifier layer both with back propagation. Stochastic gradient descent (SGD) with 0.9 momentum and the learning rate annealing strategy are utilized in learning phrase.

4.3. Results and Discussion

The loss and accuracy on source domain and target domain during learning phrase are shown in Figure 3 and Figure 4. It can be observed from the figures that the loss on target domain fluctuate sharply at the beginning, and then descend in a fluctuation to the level at around 1. The polyline of accuracy is opposite to the loss and climb to around 77%. The polyline on source domain is rather perfect, which reveals that the network can extract features from source domain flawlessly.

In order to make comparison with other methods and avoid contingency, we repeat experiment with every method for five times and compute the average accuracy respectively. The results of experiment are shown in Table 2. The average accuracy of DAN is 76.2%, which is much higher than other three methods. The results provide the evidence that the multi-kernel MMD can reduce the domain discrepancy more effectively than single-kernel MMD. It confirms that learning transferable features with domain-adaptive deep models can be applied in detection of polycrystalline cracks.

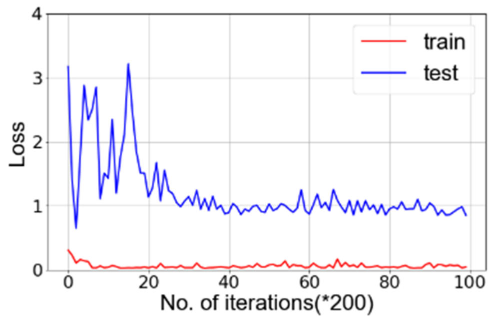


Figure 3. Train loss and test loss with DAN

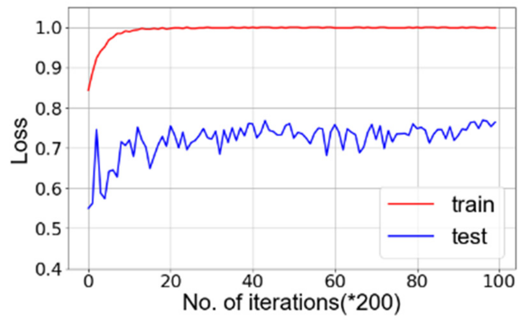


Figure 4. Train and test accuracy with DAN

Table 2. Accuracy of repeated DDC and DAN experiment

	1st time	2nd time	3rd time	4th time	5th time	Average
DaNN	51%	50%	49%	51%	51%	50.4%
MRAN	67%	67%	68%	67%	65%	66.8%
DDC	71%	72%	72%	71%	72%	71.6%
DAN	**77%**	**75%**	**77%**	**75%**	**77%**	**76.2%**

Although DAN performs a positive effect in the transfer learning from monocrystalline to polycrystalline solar cells, much work need to be done to improve the accuracy for further. We once attempted to preprocess the dataset to highlight the features extracted from different categories of samples, but unfortunately, we failed to find a suitable preprocessing method. Additionally, the original dataset may contain some defective data, including the wrong classification of images and some images with very little brightness.

5. Conclusion

The present study was designed to explore an appropriate method to detect micro-cracks on polycrystalline solar cells without labeled poly images. We have shown that the domain adaptation can be used to reduce the domain discrepancy between monocrystalline images and polycrystalline images and achieve the transference from source tasks to target tasks. The backbone of DAN was changed by replacing Alexnet with Resnet-50 to reach a superior accuracy. Experimental results observed by comparison with other methods have shown that DAN model with MK-MMD is preferable for micro-cracks detection. Clearly, it also raises further questions for future investigations on this topic. We hope to find a suitable method to preprocess the data set to improve the detection accuracy.

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