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Bag-of-Features for Defect Depth Estimation and Material Identification, Applied to Carbon Fiber Reinforced Polymers

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Abstract

Thermal methods with infrared imaging systems are widely used for non-destructive evaluation of materials and structures. Infrared thermography proved to be a valuable technique due to interesting features such as: non-invasive, contact-less, real-time application, and wide area coverage. The Bag-of-features (BoF) approach has has gained increasing attention in computer vision in the past decade. Bag-of-features methods are popular for content-based image classification due to their simplicity and good performance. Pulsed thermography is an effective approach for quantitative prediction of defect depth. In this paper, we proposed a method combining the machine learning method in order to predict defects depth and material, coupled with a Pulsed thermography (PT) setup. This method is helpful to predict the thermal contrast associated with a type of defect embedded inside a CFRP material. This method was verified on a CFRP sample with Flat-bottom-hole (FBH), Pull-out (PO), and Teflon-insert (Tef) defects. The accuracy of the prediction in case of material detection was around 95.39% and the mean square error for depth estimation was 0.057 mm.

This paper presents an evaluation of different representations obtained from the bag of features approach to classify thermographic images.

1. Introduction

Infrared thermography as a non-destructive testing method has been successful in material testing and evaluation. The defect classification task is of great benefit to evaluating the safety performance of equipment and providing useful feedback information for discovering production process problems. The performance and accuracy of defect characterization methods differs for defects of various sizes and depths. Some methods for depth estimation in pulsed thermography are generally established based on the one-dimension heat conduction along the thickness of the sample. Schaefer et al. proposed to use early detection for depth prediction which could remove the effect of later thermal diffusion [1]. Maldague et al. utilized Discrete Fourier Transform (DFT) to predict defect depth [2]. Sun developed a nonlinear least-square model on the basis of the one-dimensional heat conduction from the surface along the thickness to determine the defect depth directly [3]???. Some other methods were based on the specific characteristic time (SCT). Recently, researches using neural network have been reported. Duan et al.[4] used a neural network to classify FBHs defect which water, oil, or air are trapped in them. The quantitative results indicated that the TSR data for the training set provide better results than raw data. Xu et al.[5] proposed a gated recurrent unit (GRU) based method for defect depth recognition. The comparison between a back-propagation network and proposed approach showed that the proposed method has better performance in defect recognition. Saeed et al.[6] employed a new algorithm based on a multilayer neural network post processor for anomaly detection in real-time. Later, Saeed et al.[7] the proposed a method based on a deep feed forward neural networks (DFF-NN) algorithm to estimate the defects depth. They used pre-trained networks followed by fine-tuning step. The results were relatively accurate, but it required a complex and computationally intensive training process. Marani et al.[8] used processing that approximated the temperature decay with an exponential model made of three parameters. The parameters are able to characterize the defective and non-defective regions and classify them depending on depths. Later, Marani et al.[9] enhanced defect characterization using a FIR filter to reduce the noise level and modeling the sound area and defective regions; and then the features feed a decision forest to detect the anomalies. The classification performance is increased using the proposed approach. Wang et al.[10] utilized a long-term memory recurrent neural network (LSTM-RNN) to determine the defect depth using a laser infrared thermography system.They used the TSR method for noise reduction for the models to learn the signal characteristic. Their method outperformed RNN and CNN methods. Dong et al.[11] presented a novel 3D CNN model incorporating a combination of spatial and temporal convolutional filters and batch-size independent group normalization (GN) as a unified framework to process thermal image sequences captured by lock-in thermography for simultaneous subsurface defect detection and depth estimation. They indicated that the 3D model was able to predict the defects depth accurately. Wei et al.[12] conducted a study to demonstrate that parameters such as defect size and sample thickness greatly influenced the estimation. They reported the high accurate depth estimation in their experiment. Liu et al. introduced a semi-supervised learning (SSL) framework for transient thermography detection [13]. They employed the temporal and spatial information encoded into the 3-dimensional transient thermal tensor data for defect detection.

The Bag-of-features (BoF) approach has gained increasing interest in computer vision in the past decade. BoF became popular in computer vision tasks, including image classification, video search, robot localization, object detection,image retrieval and texture recognition due to their simplicity and good performance.[14]. The three main steps that should be taken into account in the application of BoF in image classification are (i) extracting features by using a feature extraction method, (ii) clustering the features, and (iii) constructing a bag of features. The features consist of keypoints and descriptors which can be extracted by scale-invariant feature transform (SIFT) or speeded-up feature transform (SURF). Among clustering methods, Kmean is one of the traditional clustering methods. Moreover, the feature extractor and clustering method have contributed to the classification's accuracy. The important characteristics of the BoF is the robustness to occlusion and affine transformations. The robustness is improved by introducing similarity measures based on partial matching (EMD distance [15]) or histogram comparison (χ^2 distance [16]). Also, the computational efficiency makes this method more valuable [17]. Dunderdale et al. examined a deep learning and feature based approach for detecting and classifying defective photovoltaic modules using thermal infrared images [18]. Bag of Visual Words (BoVW) is used in [19, 20, 21, 22] to extract the fault features from IRT images in fault diagnosis methods. Wang et al. [21] exploited softmax regression which is the expansion of a logistic regression for multi-classification problems. Ahmed et al. employed bag of features to extract discriminating features that can be utilized to recognize different thermal breast images [23]. Another study involved Autism spectrum disorder (ASD) classification. Haputhanthri et al. in their study employed electroencephalogram (EEG) signals to diagnose ASD [24]. The classification process utilizes Naïve Bayes, random forest, logistic regression, and multi-layer perceptron algorithms and achieved an accuracy of 94% for both logistic regression and multi-layer perceptron classifiers. Hai et al. proposed an end-to-end learning algorithm based on the combined multi-level features[25]. In this research, low-level features are extracted and selected by supervised LASSO logistic regression.

2. Method and Materials

2.1 Bag-of-Features

A Bag-of-Features or Bag-of-Words approach was originally used in natural language processing and now is widely used in visual object recognition, image classification. BoF is a method that represents images as an independent collection of image features. Basically, there are four main steps in the BoF model that should be taken into account, i.e. :

- Detection and description of image features using a feature detector and extractor such as SIFT
- Clustering the descriptor with a vector quantization algorithm such as KMean
- Construction of Bag-of-Feature which estimates the number of features in each cluster
- Classification by generating the feature vector by training Bag-of-Features, and determining the category of the image.

In the first step, the independent features come from the breakdown of the image and consist of keypoints and descriptors. Keypoints contain the standout points in images that are invariant to image transformations, lighting variations, and occlusions. Descriptors are the description of the keypoints. Then, the descriptors using clustering algorithms create codebooks or a dictionary. The presence of words in the dictionary is checked through images iteratively, and as a result, the number of the particular word increases. Finally, after converting images to histogram, similar images or category prediction is estimated. The BoF framework is illustrated in Figure 1.

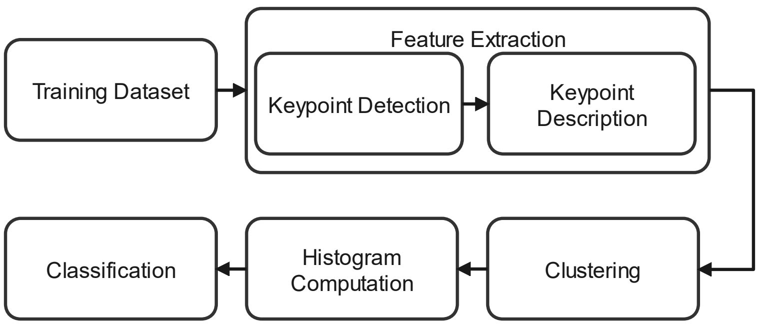

Fig. 1. *Process for Bag of Features Image Representation.*

In this work, we used a CFRP sample containing three types of defect i.e. Flat-bottom hole, Teflon inserts, and pull-outs. The acquired data from a pulsed thermography setup is employed for depth and defect-type prediction. In this method, feature vectors are clustered and then we used the logistic regression and Ridge regression for defect-type and depth estimation, respectively. Our preliminary results show 90% accuracy for defect-type estimation and the mean square error for depth predication was 0.063 mm.

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