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AI BASED SURFACE DEFECT ANALYSIS AND DETECTION - A SURVEY

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Abstract

Automated computer-vision-based defect detection has received much attention with the increasing surface quality assurance demands for the industrial manufacturing It can be divided into colour analysis, dimension verification, and surface defect detection, which is the main purpose of our work. Defects detection is still based on the judgment of human operators while most of the other manufacturing activities are automated so, our work is a quality control enhancement by integrating a visual control stage using image processing and morphological operation techniques before the packing operation to improve the homogeneity of batches received by final users. An automated defect detection and classification technique that can ensured the better quality of tiles in manufacturing process as well as production rate.
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Keywords*:* Control, Defects Detection, Morphological, Quality, Segmentation

1. Introduction

Detecting defects may be a critical capability in manufacturing applications. Ensuring that a producing process is in check and dealing needless to say requires defect detection. supported the character and extent of the detects, appropriate corrective actions are often performed to make sure that process performance remains satisfactory. These actions range from replacing a tool on the machine to performing maintenance on other parts of the machine. Defect detection are often viewed as a precursor to the diagnostics phase of machine maintenance. Defect detection is additionally a critical a neighborhood of the inspection process to simply accept or reject a part produced by a process or delivered by a supplier. Moreover, it also can enable part rework and repair, hence reduce material wastage. Some manufacturing processes have a feedback system which will be wont to prevent the defect formation if defects are often detected early. Defect detection is additionally critical for building process models which will be used for process optimization.

2. Defect Detection

Multi-scale pyramidal pooling network for the classification of steel defects, which may adapt to the input images of various sizes. Natarajan et al. [1] proposed a versatile multi-layered deep feature extraction framework supported CNN via transfer learning to detect anomalies in anomaly datasets. A majority voting mechanism is additionally designed to beat the issues of over fitting by combining deep features with linear support vector machine (SVM) classifiers. The deep network structures designed by the above two methods are primarily aimed toward the classification task of the defect image, and therefore the position of the defect isn't localized. Wang et al. [2] proposed a quick and robust automated quality visual inspection method that utilized traditional CNN with a window to localize the merchandise damage. Cha et al. [3] developed a structural damage detection method supported Faster R-CNN to detect five sorts of surface damages: concrete cracks, steel corrosion (medium and high levels), bolt corrosion, and steel delamination. Lin et al. [4] built a convolutional neural network (CNN) for light emitting diode (LED) chip defect inspection. The defect regions are localized by employing a class activation mapping technique without region-level human annotations. Liu et al. [5] proposed a detection system that has three deep convolutional neural network (DCNN) based detection [6] stages, including two detectors to localize key components and a classifier to diagnose their status. Those above-mentioned methods convert the surface defect detection task into an object detection problem in computer vision. The localization [7] of defects is usually within a bounding box that doesn't actually representing a defect's borders and can't describe its shape. In , Ren et al.[8] proposed a deep learning-based approach that used a pre-trained deep learning network to classify defect image patches. The pixel-wise prediction of defect is obtained by Felzenswalb's[9] segmentation method supported the heatmap. This pixel-wise prediction method may be a graph-based method that's vulnerable to various thresholds and doesn't obtain the defect.

3. Various Methodologies

3.1 Thresholding

Thresholding methods [10] are usually wont to separate the defective regions on flat steel surfaces, which are widely applied in online AVI systems. The normal thresholding methods identify defects by comparing the worth of image pixels to a fix number and switch the test image into an easy binary frame, which is sensitive to random noises and non-uniform illuminations.

3.2 Edge Basesd Method

The purpose of edge detection [11] is to spot points with obvious brightness changes in digital images. Researchers often use local image differentiation technique to get edge detection operator, the commonly used edge detection templates for flat steel surface are Kirsch, Sobel and Canny operator. it's investigated that Sobel is specialized in weighing the influence of pixel position to scale back the anomaly of edge, but it's sensitive to uneven illumination on flat steel surface, which easily results in false edge detection.

3.3 Morphological Method

Dilation is same as convolution, where the structuring element is moved altogether four directions. Dilation and erosion that's performed on binary images is that the same as that of convolution of Boolean functions, that are explained within pixels of respective areas in both the pictures of same cross section. Opening and shutting are higher end procedures and extended versions of dilation and erosion. Since erosion and dilation have an association with Boolean operations, it enables to change the black pixels white also because the white pixels black when the specified circumstances are satisfied.

Figure 1: morphological method of analysis

3.4 Histogram of Oriented Gradients

Gray Level Co-Occurrence Matrix an efficient technique for statistical analysis of the image. to work out a GLCM, a comparison of the intensity values of neighbouring pixels is administered and intensity pairs are saved during a matrix . Within the proposed work, it utilizes the GLCM matrix inputs and therefore the derived parameters like contrast, correlation, homogeneity and energy as feature vector. the ultimate feature vectors might be utilized to coach several classifiers.

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3.5 Clustering

Based on the similarity among image[11] pixels, clustering method is specialized in mining information implicitly existing in texture images, then defect detection are often achieved by the multiple-class defect classification. Rea-time and anti-noise capabilities are always the essential requirements of commercial defect detection.

3.6 Hough transform

Hough transform (HT) is taken into account as a strong tool in well-defined line-feature detection. Its applications are often found [12] in fingerprint identification and vehicle car place recognition. HT to detect defects of holes, scratches, coil breaks and rusts on cold-rolled steel strips.

3.7 Local Bottleneck

In Local binary patterning algorithm, the commonly used methods for feature extraction is pattern definition . The amount of attributes extorted within the algorithm is independent of the window size. thanks to this reason. Then the primary pixel in the picture [6]center point of the required window are going to be placed inside the window , the balance neighboring pixels that are greater than the middle pixel are pixilated as 1 for the equal ones and" 0 "for the remainder . a worth for that center pixel is acquired. Then the window is moved over the complete image and the above mentioned steps are repeated for all pixels. The value for every pixel supported the dimensions of the window chosen, from 0 to n is obtained. As a result , the worth of each ndimensional attribute vector machine to be utilized for training in learning methods is decided and therefore the algorithm is terminated.

3.8 Gray Level Materials Of Creation

The gray level co-occurrence matrix is one among the most commonly utilized statistical methods for the aim of analyzing. this is often a two-step procedure, within the first major step the pixel values within the image are represented as 0 °, 45 °, 90° and 135 °, within the second step the (CM) matrix is made .This CM matrix may be a square matrixes generated[15] depending upon the gray level of the image and a private matrix for every direction is computed. When the matrix is generated, n * n (n indicates gray level), if all elements are 0 a matrix is made .The CM matrix is computed and therefore the first main stage is completed. Within the second main phase with the assistance of generated CM matrices we compute the image contrast, addiction and energy values and thereby terminate the algorithm.

3.9 Template Matching

One of the only and earliest approaches[14] to pattern recognition is predicated on template matching. Matching may be a generic operation in pattern recognition which is employed to work out the similarity between two entities of an equivalent type. In template matching, a template of the pattern to be recognized is out there. The pattern to be recognized is matched against the stored template while taking under consideration all allowable pose and scale changes. The similarity measure, often a correlation, could also be optimized supported the available training set. Often, the template itself is learned from the training set. Template matching is computationally demanding, but the supply of faster processors has now made this approach more feasible. The rigid template matching mentioned above, while effective in some application domains, features a number of disadvantages.

3.10 Statistical Approach

In the statistical approach, each pattern[13] is represented in terms of d features or measurements and is viewed as some extent during a d dimensional space. The goal is to settle on those features that allow pattern vectors belonging to different categories to occupy compact and disjoint regions during a d-dimensional feature space. The effectiveness of the representation space (feature set) is decided by how well patterns from different classes are often separated. Given a group of coaching patterns from each class, the target is to determine decision boundaries within the feature space which separate patterns belonging to different classes. Within the statistical decision theoretic approach, the choice boundaries are determined by the probability distributions of the patterns belonging to every class, which must either be specified or learned. Below table 1 shows [15] comparison of various methods of defect detection

Table 1: Various Methods of Defect Detection

Methods	Applications	Problems	Database	Performance
Markov random field model	Sheet-metal	Noise and uneven illumination	PUB	TPR = 0.84
Hidden Markov tree	Steel strips	Complex texture characteristics	PRI	TPR = 0.84
Weibull distribution	Steel surface	Arbitrary deviations of the reference texture	PRI	TPR = 0.74
Active contour model	Silicon Steel Strip	Low contrast and Pseudo-noise interference	PRI	TPR = 0.762

4. Classification

4.1 Artificial Neural Networks

Artificial Neural Networks resembles [17] the human nervous system which involves a supervised machine to learn . The most frequently utilized artificial neural network model is layered sensor neural network model; input layer, hidden layer and output layer come to picture. The input layer reads the data layers. Since every neuron denotes a feature, it consists of many neurons as the number. The output layer is the class the specified layer.

4.2 Supervised Learning

Supervised learning is to model a conditional distribution between input vectors (surface images) and target vectors. Support vector machine (SVM), decision trees and neural network are classical examples in this category. As a generalized linear [18] classifier for binary classification of data, SVM is frequently utilized to identify defective and defect-free regions. The performance of classifiers in defect detection depends on the feature and classifier combination. The authors fused the classifiers with different feature sets to divide the test images into defective and normal ones, finding that the performance of one-level Haar features ranks first among all the feature-classifier combinations. The neural network can learn the pattern from the training dataset, and determine the category of the new data according to the previous knowledge. Two-layer feed-forward neural network to classify the pixel of test images into defect and defect-free regions on the basic idea that the defect detection task is actually a binary classification problem. Convolution and subsampling in convolution neural network (CNN) effectively reduce the model size by tailoring the model parameters. Thus, CNN-based architectures are widely applied on automatic feature extraction as well as on image defect detection in industrial inspection.

4.3 Support Vector Machine

Support Vector Machine [18], calculates the best isolating hyper plane between two sample sets. Random Forests (RF) , a continuation of the decision tree algorithm in which a complete decision tree is divided into a cluster of small decision trees with incidentally picked nodes. This technique greatly enhances durability while reducing the chances for over fitting. Random forests are classifiers that can be easily trained, thereby depicting a challenging achievement in difficult tasks

4.4 Unsupervised Learning

Automated defect detection has always been a challenging task especially in actual industrial application. It is not always easy to gather a large number of labeled image samples. Below table 2, shows performance measure results [12].

Table -2 Performance Measure Result

Method	Intersection-Over-Union
FCN	81.58%
Single AE without convolution	83.40%
Single AE	84.68%
CASAE without convolution	87.30%
CASAE	89.60%

5. Conclusion

Deep learning is gaining popularity in the defect detection community. This paper presents three different perspectives for examining the existing literature. The first perspective is based on identifying the scope of different detection problems based on application contexts and requirements. This perspective helps us define and understand different types of defect detection problems. The second perspective examines the literature from a machine and deep learning perspective and explains why certain learning approaches are useful for certain kinds of problems.

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