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Cause and Severity Evaluation of Defects in Cu interconnects by Machine Learning of S-parameter Patterns

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1. Introduction

It is fundamentally important to forecast the failure of interconnects to achieve high reliability of the system. Researchers, so far, have focused on means to assess the extent of deviation or degradation from expected normal operating to do the task above [1]. However, it is also important to find out the root cause of the defect to reduce the life cycle cost of equipment by decreasing inspection costs, downtime, inventory and logistical support of fielded and future systems. Failures of the electronic systems are initiated by ones in interconnects in general. In order for reliability monitoring of electronic interconnects, the industry and academy has been using either event detectors or data loggers that basically monitor DC resistance [2-4]. Furthermore, previous research work has developed the nondestructive health monitoring technique using RF impedance [5-10]. Compared to the DC resistance method, the RF impedance method can detect defects initiated from the surface and interfaces because of the skin effect.

Here, we paid attention to the certain s-parameter patterns of each defective interconnect to provide information about both the severity of defects and the causes. S-parameters describe the electrical behavior of electrical networks when undergoing various steady state stimuli by electrical signals. Many electrical properties of networks of components (inductors, capacitors, resistors) may be expressed using S-parameters. Also, the S-parameter measurements using network analyzers are the most basic work of RF engineering. Thus, it would be highly convenient if the defects could be detected and analyzed by the s-parameter measurement itself. As well as convenience of using it, the s-parameter patterns give us 2D pattern information such as magnitudes to frequencies rather than just one value at a time. This is where the machine learning technique comes into effect. If certain causes and severities of defects have certain s-parameter patterns, one can develop a machine learning algorithm to detect defects in interconnects with the information of their causes and severities at once.

In this study, the results of experiments with Cu interconnect specimens show that the s-parameter patterns differ from the root cause and severity of the defects. Furthermore, we modified the ranking-CNN machine learning algorithm that is originally a facial age recognition program and applied it for detection and the root cause analysis of the defects in interconnects.

2. Experiments

the s-parameter patterns of Cu electrodes with cracks and oxidated ones were obtained and compared to the patterns of the pristine electrodes. Interestingly, it is found out that defective interconnects showed certain and unique s-parameter patterns. If the cause of the defect is fixed, severity of the defects changes the level of the pattern without affecting its shape. In addition, DC resistances of defective specimens had not been changed while different s-parameter patterns were obtained compared to the normal interconnects. It is speculated that the small defects initiated from the surface affect the signal propagation within the skin depth of the signal line. Also, parasitic effects are exaggerated with increasing working frequencies in RF electronics. This means that the s-parameter measurement method can achieve earlier detection of defects in interconnects than the conventional DC resistance method does.

3. Machine learning algorithm

In the literature of machine learning research, the ranking-CNN algorithm is the first work that uses a series of binary CNN models trained by all the labeled age data for facial age estimation [12]. This research work shows that ranking method is better than the softmax method for the facial age estimation which requires a solution to recognize both faces and ages. We modified this algorithm to decide both causes (faces) and severities (ages) of defects in interconnects from the s-parameter patterns. Each basic CNN in ranking-CNN can be trained using all the labeled data. In result, we were able to distinguish the cause and severity of the defect in the interconnect specimen at once with a tight error bound and fast process time.

The estimation model for the early detection and instantaneous cause analysis was composed of a series of ranking-CNN models. Each ranking-CNN of the estimation model classified the defect level of the specific cause. In this study, we classified the defects into 4 levels: the normal state, the first defective state (however still usable), the second defective state (highly recommended for replacement), and the third defective state (out of order). The entire estimation model consists of ranking-CNNs and the number of them was related with the number of the defect levels that the network is handling. The s-parameter input goes to all the ranking-CNNs and we can obtain the severity of the defect. After every ranking-CNN has decided the defect level with the deep classifier, a predictor of the machine learning algorithm finally provides the information about the cause and the level of the defect in the interconnect. A ranking-CNN model which is a subcomponent of the estimation network takes the 1-Dimentional (1-D) S-parameter pattern as an input and outputs the defect level. Because the input of 1-D S-parameter pattern has spatial features like peak, fall-down, rising-up and certain shapes, 1-D convolutions are recommended for extracting the feature map rather than the dense layers. Our ranking network has three 1-D convolutional layers followed by ReLU and Max pooling layers and the last connected layer has two output nodes (figure 2).

In figure 2, the C1 layer has 96 filters with a 7×1 convolutional function and is followed by a 3×1 max pooling layer and ReLU. The C2 layer has 256 filters with a 5×1 convolutional function and is followed by 3×1 max pooling layers and ReLU. The C3 layer has 384 filters with 3×1 convolutional functions and is followed by 3×1 max pooling layers and ReLU. Then flattened features of the convolutional network is connected to the F4 layer with 256 nodes. The F5 layer with 256 nodes and the F6 with 2 nodes follow the upper nodes.

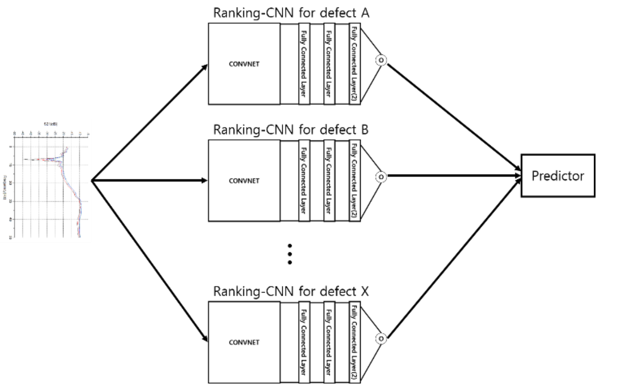

Fig.1 The structure of the estimation for deciding severities and causes of the defects

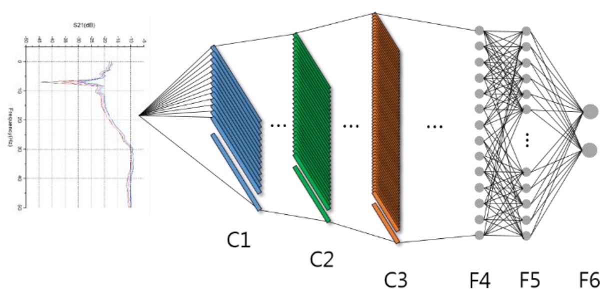

Fig.2 Architecture of a ranking-CNN

4. Results

In this section, the performance of the estimation model is demonstrated. The estimation model takes the s-parameter pattern as an input, and returns the defect cause and its corresponding severity level. We used 360 training s-parameter patterns obtained by the experiments and 45 random test s-parameter datasets. The simulation result showed that the estimation system can examine the cause and severity of defects in interconnects efficiently. The estimation system decided the defect cause with 95.56% accuracy and the severity level with 91.11%. Regarding incorrect inference, an error bound was 1 severity level difference compared to the correct answer.

5. Conclusion

This study has experimentally shown that defective interconnects showed certain and unique s-parameter patterns. If the cause of the defect is fixed, severity of the defects changes the level of the pattern without affecting its shape. Also, the s-parameter measurement method can achieve earlier detection of defects in interconnects than the conventional DC resistance method does. We modified the ranking-CNN machine learning algorithm, which was originally developed to estimate the facial age, to distinguish defective interconnects with information of the cause and severity of the defect. Utilizing the training datasets of s-parameter patterns obtained from pristine, cracked and photodegraded ITO specimens, our algorithm returns the defect cause with 95.56% accuracy and the severity level with 91.11%.

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