Counterfeit IC Detection By Image Texture Analysis

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Abstract—The widespread penetration of counterfeit integrated circuits (ICs) is not only a major threat to the electronic goods supply chain, but also constitute a great threat to national security. Image processing based counterfeit IC design techniques are promising, but currently often suffer from high computational complexity and requirement of expensive image acquisition infrastructure. We describe two techniques based on image texture analysis to automate the process of counterfeit IC detection. The first method employs local textural feature identification to detect counterfeit ICs. The second method includes identification of counterfeit ICs by segmenting the image into regions of different textural features using texture filters. The first method is of lower computational complexity compared to the segmentation method, but the second method is capable of blind identification in the sense that it does not require knowledge of the textural features of a golden IC sample. Our experimental results show that these methods have high detection accuracy, even for images acquired using ordinary digital cameras and low-end digital microscopes.

Keywords—Counterfeit IC detection, image processing, texture analysis.

I. INTRODUCTION

Counterfeit Integrated Circuits (ICs) is a major threat to the current electronic supply chain and the customer of electronic products [1]. Not only the supply chain, but the use of such ICs can jeopardize the national security system in many ways. The trend of counterfeit IC proliferation is on the rise, and it is estimated that about 1% of the semiconductor sales every year consists of counterfeit ICs [1]. They can cause premature failure of the system, and may contain hard-to-detect malicious modifications in the circuitry (“Hardware Trojan Horse”). Hence, it is a serious reliability and security As a matter of fact, over the years the counterfeiters have increased their level of sophistication, to the extent of duplicating entire companies [1]!

Some of the external properties of an IC that help in physical inspection based counterfeit IC detection include [2]:

- **Country of origin stamping mismatch**: for two ICs with the same part number and belonging to the same lot, as shown in Fig. 1(a).

- **Marking imperfections**: Fig. 1(b) shows one such marking imperfection on a possibly counterfeit IC.

- **Indent mismatch**: Fig. 1(c) shows two ICs of same part number and lot code having different number of indents (one with two and one with three), with differing shapes and placements.

- **Texture mismatch**: counterfeiters usually try to achieve similar and uniform texture over the entire package surface to hide previous markings. This texture difference is not visible to the naked eye, but with the help of a microscope one can get many signs that may help to identify the fake surface, as shown in Fig. 1(d).

One of the earliest works which explored image processing for counterfeit IC detection was [3], in which the authors used advanced image acquisition techniques such as Scanning Electron Microscope (SEM), X-Ray microscopy and Energy Dispersive Spectroscopy (EDS). In order to avoid the need for SME to analyze the SEM-acquired images to reach a conclusion, 3-D reconstruction of the SEM images was performed using stereo-photogrammetry. The advantage of this scheme is that it allows a combined analysis of the package composition, internal structure of the IC, and texture of the package surface. However, the methodology necessitates expensive equipment and software which might not be readily available, and the statistical metric-based texture analysis methodology does not achieve satisfactory accuracy. A relatively recent work [4] applies machine learning techniques such as Artificial Neural Networks (ANN) as with image processing to automate the process of detecting counterfeit ICs, based on scratch defects present on its surface, using images from [5]. The technique is useful, but since it requires several pre-processing steps such as image filtering (threshold-based), edge detection and normalization of the image, and along with that it required training of the ANN model, it is unsuitable for high throughput applications.

In this paper, we propose an image texture analysis based counterfeit IC detection technique. The main advantage of the proposed technique lies in its relatively low computational complexity, ease of automation (since no sample preparation is required), and its ability to achieve high classification accuracy by employing relatively low-end equipment (e.g. optical microscope) and widely available software. We demonstrate two variations of the technique: (a) local texture feature identification using Local Binary Patterns and Law’s Texture Identification [6], and, (b) segmentation of the image in different segments based on texture filters [6], [7]. These two techniques trade-off between higher computational complexity (second technique) and availability of golden IC texture image (first technique). Our experimental results demonstrate higher accuracy of the proposed technique compared to similar techniques such as [3].

II. BACKGROUND: TEXTURE RECOGNITION AND ANALYSIS

An exact objective definition of “Texture” is difficult, but subjectively texture is a property that gives us information
about the spatial arrangement of the color or intensities in an image [7] [6]. Fig. 2 shows examples of three different textures of IC package surface images, one of which is known to be Golden (i.e. non-counterfeit). Texture analysis is broadly divided into three categories: (a) Structural analysis; (b) Spectral analysis, and (c) Statistical analysis. We have used statistical analysis based texture detection and classification in this work, for its effectiveness and computational efficiency. Next we describe this technique in more detail.

A. Statistical Analysis for Texture Detection

Several methods have been proposed over the years. We discuss some of these techniques which are relevant in our context, i.e. either employed by previous works on image processing used counterfeit detection, or used by us in this work.

1) Statistical Metric based Texture Analysis: One of the simplest approaches to describe texture is to calculate simple parameters or statistical metrics such as histogram maxima; histogram minima; (normalized) statistical moments of the intensity histograms of an image or a region, e.g. arithmetic mean, variance, skewness (the 3rd moment about mean) and kurtosis (the 4th mean about mean). Another metric used is the entropy of the pixel value distribution [7]. Some of these metrics were used in [3] for texture analysis of IC package surface images. The shortcoming of this approach is that the calculated metrics do not provide any information about the relative spatial positions of the pixels with respect to each other, which is important for texture recognition. To overcome this, higher resolution texture detection techniques that are more capable of extracting local textural features are employed, as described next.

2) Texture Features: A popular technique of this type is the Laws’ Texture Energy Measures technique [6], [8]. This “texture-energy” approach measures the amount of variation within a fixed-size window (a typical window size is $15 \times 15$). In this method, four vectors are used to form nine 5 convolution masks. Each of the vectors are chosen to detect particular features, as follows:

\[
\begin{align*}
L5 \quad \text{(Level)} & = [1 \ 4 \ 6 \ 4 \ 1] \\
E5 \quad \text{(Edge)} & = [-1 \ -2 \ 0 \ 2 \ 1] \\
S5 \quad \text{(Spot)} & = [-1 \ 0 \ 2 \ 0 \ -1] \\
R5 \quad \text{(Ripple)} & = [1 \ -4 \ 6 \ -4 \ 1]
\end{align*}
\]

The typical steps performed in Laws’ method are as follows:

1) Removal of illumination effects by applying a small window around the image, and subtracting the local average from each pixel to produce a pre-processed image where the average intensity of each neighborhood is close to zero. Note that the computational complexity of this pre-processing step is much lower than that employed by [3].

2) Each of the sixteen $5 \times 5$ masks are applied on the image, obtaining sixteen filtered images $F_k[x, y]$, for the $k$-th filter.

3) The texture energy map $E_k$ for the $k$-th filter is obtained as:

\[
E_k[r, c] = \sum_{y=c-7}^{c+7} \sum_{x=r-7}^{r+7} |F_k[x, y]|
\]

Note that $E_k[r, c]$ is itself a full image.

4) Certain symmetric pairs are combined to produce the following nine $5 \times 5$ convolution masks: \(L5E5/E5L5, L5S5/S5L5, L5R5/R5L5, E5E5, E5S5/S5E5, E5R5/R5E5, S5S5, S5R5/R5S5\) and \(R5R5\) (each pair is represented by its average).

5) These nine energy map images are combined to produce a 9-dimensional feature vector at each pixel position.

6) Finally, these texture features are used to cluster an image into regions of uniform texture, using a segmentation algorithm.

Local Binary Patterns (LBP) [6], [9] is another simple but extremely powerful approach for statistical analysis of texture. In this method, the following steps are performed:
sizes with respect to the total sample size. These probabilities can be calculated by normalizing the bin distributions so-called Kullback-Leibler Divergence Measure (KL-Divergence or KL-Distance) [10]. KL divergence is a measure of the non-symmetric difference between two discrete distributions \( p_i \) and \( q_i \), defined as:

\[
D_{KL} = \sum_{i=1}^{n} p_i \log_2 \left( \frac{p_i}{q_i} \right)
\]

where \( n \) is the total number of points in the two distributions. These probabilities can be calculated by normalizing the bin sizes with respect to the total sample size. We expect that for similar textures, i.e., when a non-counterfeit IC texture is compared with the golden IC texture, this difference should be very small, while the comparison between a counterfeit and a non-counterfeit IC leads to relatively large KL-Distance.

3) Texture Segmentation: Segmentation is a process in which an image can be divided into different segments or clusters of similar textures [7]. This is the step usually performed after texture features have been generated using a technique described above. Segmentation is mainly of two types: i) region-based, and ii) boundary-based. In this technique, first the texture image of the original image is computed, where the texture image refers to the image obtained after feature extraction, in this case using image entropy as filter, where each output pixel contains the entropy value of the 9-by-9 neighborhood around the corresponding pixel in the input image. Then, a rough mask of one segment is created. This rough mask is then used to segment the other texture. Thus, the final segmented image is obtained. A detailed example is provided in the next section.

In our work, to reach a balance between accuracy and computational overhead, we adopted simplified versions of Law’s Texture Energy Measure approach and LBP, whereby the last segmentation step was not used. Rather, the generated feature vectors at each pixel was used for clustering using a simple scheme. Similarly, we used region-based segmentation technique [11] based on the Entropy metric, which can be calculated at relatively low computational overhead. Details are provided in the next section.

### III. Methodology

Fig. 3 shows the steps of the overall methodology, which allows identification of counterfeit ICs both in the presence or absence of golden IC package surface images. The first step is to pre-process all images (both test images as well as golden sample images, if available), to remove illumination effects, as described in Section II-A2. After pre-processing, two different texture feature extraction algorithms, namely: (a) Laws’ Texture Energy Measures and (b) LBP, are applied in presence of the golden IC sample image. We consider the details of the detection technique based on these two feature sets separately. In absence of the golden IC, one of the statistical data, like entropy, is used for segmentation.

#### A. Experimental Setup

For experimental purpose we have used microscopic images of three 74LS00 (quad 2-input NAND TTL) ICs, acquired at 50X magnification, using a Carl Zeiss optical microscope capable of providing a maximum magnification of 100X. Fig. 2 shows the IC package surface texture images used in our experiment. “Golden IC” is the texture image corresponding to a known non-counterfeit IC, while Testcase-1 and Testcase-2 are for two ICs whose authenticity is to be established. All the image processing code were written in Matlab (v. 2016B).

#### B. Detection in Presence of Golden IC Sample Image

Table I shows Laws’ Texture Energy Measure features values for the three images. It is observed that Testcase-1 features are closer to the golden IC feature values, compared to the Testcase-2 features, suggesting Testcase-2 to be the counterfeit IC. We observe that the metrics are close in value for Golden IC and Testcase-1. Table II shows the distance

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Fig. 3: Flowchart of counterfeit IC detection methodology.
measure (KL-divergence and Euclidean Distance) between the LBP-generated histograms. From the values, we observe that the KL-divergence between the Golden IC and the Testcase-2 images is much more than the original and the Testcase-1 image. So, again it seems that Testcase-2 is the probable counterfeit IC. The values obtained for the Euclidean distance measure also lead to the same inference.

For the sake of comparison, we also calculated the values of different statistical metrics for each of the texture images as used in [3], the primary procedural difference being that we perform no 3-D reconstruction, as was done in [3]. The results are shown in Table III. We notice that these metric values are almost the same for the three samples (except Average Roughness), which makes it slightly difficult to apply these metrics for counterfeit detection.

### C. Detection in Absence of Golden IC Sample Image

In the absence of known golden IC samples, the feature extraction and comparison techniques described above are not always useful. Counterfeit IC images often have regions with differing textures, which can be used to identify them. The Golden IC image and Testcase-1 image did not lead to multiple textured regions, while Testcase-2 leads to clearly segmented regions, as shown in Fig. 4(a) (before segmentation) and Fig. 4(b) (after segmentation).

From the experimental results presented, we conclude that Testcase-2 is a counterfeit IC, while Testcase-1 is an authentic IC.

### V. Conclusions

We have investigated the effectiveness of two types of counterfeit IC detection methods based on textural features of IC package surface images acquired with optical microscopes. With these techniques one can identify counterfeit ICs both in the presence and absence of the golden IC textural information. Moreover, these methods do not require expensive equipment or computationally expensive operations like 3-D reconstruction or machine learning model building. Also we demonstrate that the simple statistical metric based texture analysis used in [3] does not provide enough texture difference information when applied on optical microscopic images. Our future research will be directed towards applying the proposed techniques to detect counterfeit ICs based on other surface imperfections such as scratches, defects in the pin, etc.

### REFERENCES


