Automated Detection of Counterfeit IC Defects Using Image Processing

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***Abstract*—In recent years, the counterfeit IC chips industry has grown exponentially, but the number of qualified experts who can identify these potentially dangerous parts remains inadequate. With the growing reliance on IC chips in important national security operations, the identification of counterfeit parts is now increasingly important. A possible solution to this problem is the use of image processing to help reduce the manpower needed for counterfeit identification. In this paper, we lay the groundwork to perform automated detection of physical defects that can indicate a counterfeit chip, thereby reducing the need for personal examination by an expert. We focus on simpler physical defects (such as mark displacement and texture discrepancies) and provide some direction for possible improvements at the end of the paper.**

Keywords*—defect; image registration; texture analysis; mark displacement; counterfeit

I. Introduction

The rapidly growing problem of counterfeit electronics can be described by noting the estimated value of the industry. In 1990, the value was estimated at $100 billion, which increased to $250 billion five years later [1]. By 2001, it became $350 billion, increasing to $650 billion in 2008 and finally a staggering $1.8 trillion in 2015 [2, 3]. The exponential rise of the counterfeit industry certainly cuts deeply into commercial pockets, but its effect on national security is an even larger issue. The government is one of the largest purchasers of integrated circuit (IC) chips but has no easy and efficient way of verifying the validity of the chips it purchases. A recent example of the effect of this deficiency is the discovery in 2014 that the Navy's nuclear submarines had counterfeit electronic parts installed [4]. Also, in 2011, the Navy discovered that the newly commissioned Poseidon aircraft had counterfeit electronic parts in the ice detection modules [5]. In addition to the fact that the counterfeit electronics could have been programmed to allow backdoor access, their performance could have been suboptimal and endangered thousands of people.

The current procedure to check for counterfeit parts involves hiring or training a subject matter expert (SME) to identify the nature of the parts in question. One approach to the problem would be to take a test sample out of the batch of products and run destructive electronic tests to verify the performance of the parts. Since these tests end up destroying the parts in question, the other approach is a physical inspection conducted personally by the SME. The expert must look at each part closely, and identify any anomalies in the packaging, pins, labeling, or other physical markers on the chip. However, the number of electronic parts that need to be checked continues to grow rapidly and the number of experts available remains woefully inadequate.

In this paper, we propose a system using image processing techniques to detect some simple physical defects present on the surface of IC chips. This will allow for some automation in the counterfeit detection process, which will go a long way in alleviating the burden on the current systems. The rest of the paper shall discuss the following: (II) A quick overview of the process undertaken to create this preliminary automated detection system; (III) A discussion of the implementation of said system and the methods used; (IV) A summary of the results and description of the test environment; and lastly (V) A conclusion and discussion about the future direction for these ideas.

II. Overview Of Proposed Approach

This section is primarily concerned with discussing our general approach to the problem of automated defect detection. From the many possibilities of defects, we chose to address the simpler, surface related defects that were well-suited for detection through image processing. Once we chose the defects we were targeting, the problem was broken down into four stages: one for image registration, and the other three for the defects chosen. The general overview is shown in Figure 1.

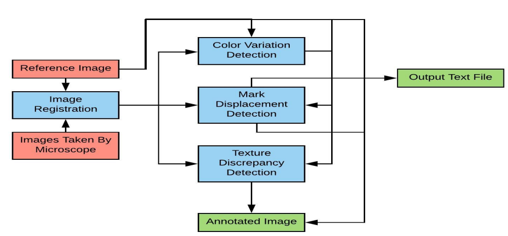


Fig. 1. Block Diagram of Proposed Approach

A. *Selecting Target Defects*

Defects can be broadly categorized into two categories: mechanical and environmental [6]. Many of these defects are related to the physical appearance of the IC chip, due to the external casing often being altered due to the procedures involved in the counterfeiting process. Currently, an SME must personally examine each of these chips to identify the physical surface defects present. Some examples of these mechanical defects are: (1) any sort of damage or alteration to the leads of the chips; (2) missing or misaligned balls/columns if the chip uses ball leads; (3) sanding or grinding marks; (4) color variations; (5) identification marking displacement; and (6) resurfacing or blacktopping. Aside from these physical defects, other possible signs of a counterfeit chip can be found by analyzing the electrical behavior of the part in question. These defects are related to the wiring inside the chip, and can usually only be found through time-consuming electrical test setups.

Many defects can only be found through destructive or painstaking examination of each IC chip. Some of the simpler defects are present on the surface of the chip, and can be represented easily by capturing an image of the surface. Of the defects specifically mentioned earlier, the defects we chose to focus on were signs of surface remarking like (1) sanding or grinding marks and resurfacing or blacktopping and (2) identification marking displacement. We also looked at the detection of color variations as a sign of the counterfeit nature of the IC chip. However, before designing the automated detection system, we had to ensure that the captured images were all spatially identical.

B. *Image Registration*

Image registration is the process of aligning two or more images, which is mathematically defined as transforming the different sets of data into a single coordinate system. By performing this step, we can easily identify correlations between images of the test chips and the images of known valid IC chips. Due to the nature of the defects we are seeking to identify, image registration is a convenient process that reduces the complexity of the problem.

C. *Identifying Target Defects*

The first defect we focused on was the displacement of identification markings. Every IC chip has some identification marking printed on its surface, so both the user and manufacturer can track the chip back to its manufacturing batch and group. A common practice among electronic counterfeiters is to sell an older, cheaper IC chip in place of a newer, more expensive one. This can only be achieved by changing the identification markings present on the surface of the chip. However, it becomes nearly impossible to place the markings in the exact location an automated manufacturing process places them in. This small variation can be identified and recorded when judging validity of a chip.

The second defect was surface texture discrepancies. Part of the process of remarking or relabeling a chip is to remove the previous markings. The most common method of removal is sanding and then blacktopping. Sanding is the process of removing the protective coating over the package of an IC chip, and blacktopping is the process of reapplying the protective coating. The new markings mentioned previously are then applied over the newly blacktopped surface. These processes often leave signs on the surface, usually a discrepancy in surface texture, and these signs can be detected from a simple picture of the surface.

Lastly, we looked at the detection of color variations on the surface of the chip. These color variations usually occur due to improper packaging, and that is a clear sign of counterfeiting.

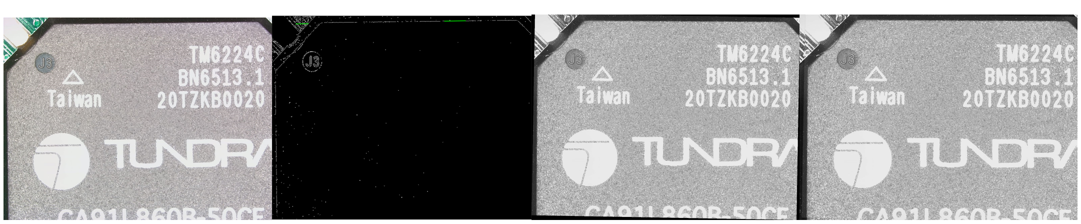
III. IMPLEMENTATION

Once the overall procedure was laid out, we began the implementation process. This section details the actual implementation of each of the stages mentioned in the previous section. There will be some discussion of other implementations, along with some additional explanations regarding the theory being applied to facilitate the implementation.

A. *Image Registration*

As discussed earlier, image registration is the process of aligning two or more images. The general algorithm involves comparing each image that needs to be aligned to a standard image chosen as the reference by the user. The program then aligns the test image with the chosen reference by comparing features common between the two images. The inbuilt MATLAB image registration function *imregister* uses a technique called *pyramiding* to compare features between the images on different levels of complexity when performing registration. However, when this technique was employed on 100 test images of IC chips, 11 of the images failed to be registered adequately. Thus, a custom image registration function was required.

The test images obtained are focused on either the top left or bottom right corners of the IC chip in question. This feature was used positively during the design of the custom image registration function. The key idea during this development was that the edges of the chip were not altered and could be used as guidelines for the alignment process. The first step of the custom image registration algorithm developed involved binarizing the image and performing an edge detection to highlight the edges of the chip. Then, using a Hough transform and line detection, the main edges of the chip in the image were identified.



a) b) c) d)

Figure 2. Stages of Registration: a) Original, b) Edges Identified (shown in green), c) Transformed, d) Final

Once the edges were identified, their orientation and position relative to the axes of the image could be calculated. These values are compared to the corresponding values in the image chosen as the reference by the user. By calculating the difference in x and y positions, and the difference in orientation, of the edges, a 2D transform matrix can be generated to align the edges present in the two images. For the purposes of keeping the images as similar as possible, the resulting black spaces (present where there is no data due to the transformation) are filled in with information from the reference chip image. The main stages of this process are shown in Figure 2.

Using this process, of the 100 test images, only 2 failed to be registered satisfactorily. By using the calculation of orientation employed by the custom algorithm, we layered the inbuilt registration function and our custom algorithm to generate the best result for every chip image i.e. the custom algorithm is applied, the result is checked, and if it is not satisfactory, *imregister* is applied to generate a different result. Using this slightly more complex process, all 100 test images were successfully registered

B. *Identification Marking Displacement*

Once the chip images are registered, the user is prompted to examine the reference images once again. At this stage, however, there is a prompt to select the pertinent identification markings present on the surface of the reference chip. Each of these selected smaller images is then compared to each test image using a normalized cross-correlation function. Cross-correlation is a process that moves the smaller image over the larger test image and calculates the correlation between the smaller label image and the area on the test image it is moved over. Higher values of correlation indicate higher similarity between the image of the label and a location on the test image. Thus, this process generates a 3D surface with peaks corresponding to possible locations of the corresponding label. A simple function to find the location of the highest peak is used to find the location of each label. In Figure 3, the surface is shown, and the highest peak is tinged in red.

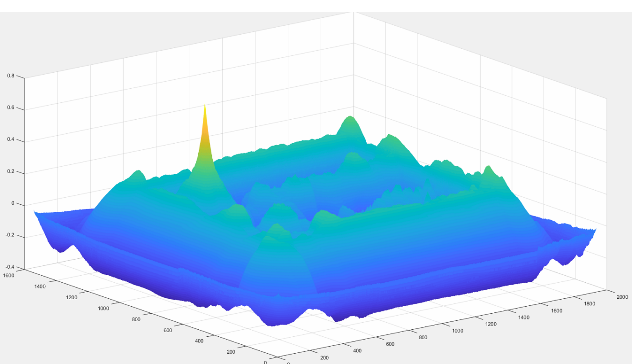


Figure 3. 3D Surface Generated by Mark Displacement Algorithm

The same process is performed on the reference images to determine the desired location of each of the indicated labels. The difference in calculated location on the test images and identified location in the reference images is used to determine the identification marking displacement for each of the test chips. Since the displacement is calculated in relation to the images, the values must be converted from number of pixels to a physical measurement using a scaling factor determined by the test environment. These displacements were marked on output images for the user to peruse, and also recorded in output text files.

C. *Texture Discrepancy Detector*

The main concept employed in this stage is *local binary patterns* (LBP), which is a technique that uses the distribution of pixel values to determine the texture represented by the section of an image being considered [7]. The LBP algorithm works by generating a *binary pattern* for each pixel in a sub-image. The pattern consists of 1s and 0s indicating whether the neighboring pixels are higher or lower in intensity value. Each of these patterns is then collated into a single distribution for the sub-image, and a decision regarding the represented texture can be made. There are two primary steps involved in this stage: (1) Creating texture categories; and (2) Generation of reference images for each category. The four categories specifically identified on these chips are: (1) noise; (2) edges; (3) labels; and (4) regular surface. Clearly, if the distribution of pixel values for any of these categories was compared to that of a bright surface, there would not be a discernable difference. However, when comparing between the four categories, there is sufficient difference due to the nature of the test images.

To capture a representative amount of reference images for each category, we manually analyzed ten different reference IC chips. Each image was split into 100 sub-images, and each sub-image was categorized into one of the four categories. This resulted in approximately 200 edge images, 500 regular surface images, 200 labels images, and 100 images of noise. Noise images were defined as sub-images dominated by the lighting, creating a possibility of a misclassification. For each category, an average LBP distribution was calculated using all the associated reference images.

Then, each test image was split into 100 sub-images, and each sub-image was classified into a category by comparing its LBP distribution to the average distribution calculated earlier. This comparison is made using Kullback-Leibler divergence, which is a statistical measure of how much one distribution diverges from a second, expected distribution (the calculated average distribution). Due to the previously performed image registration, each sub-image was assigned an expected category. If this category differed from the calculated category, the sub-image was marked as an anomaly and indicated on the output image. Using this process, texture discrepancies were identified and marked for the user to see, as shown in Figure 4.

a) b)

Figure 4. a) Heavily Binarized Image to Show Texture Discrepancy in Top Right, b) Annotated Image from Algorithm Indicating Texture Discrepancy

TABLE I. SUMMARY OF RESULTS

Algorithm	Results
Registration	100 out of 100 images satisfactorily registered
Mark Displacement	All displacements correctly identified
Texture Discrepancy	4% true positives, 3% false negatives, 4% false positives, 89% true negatives
Color Variation	4 out of 5 examples correctly identified (limited sample size)

D. Color Variation Detection

By analyzing the color histogram of the original chip images, we created a simple color variation detection algorithm. The divergence of the histogram of each color channel of the test image from the reference image can be measured using Kullback-Leibler divergence. Whichever channel has the noticeable divergence can be subtracted from the corresponding reference image channel to generate a color difference map. Then, the location of the highest amount of color difference becomes the location of the color variation.

IV. RESULTS AND DISCUSSIONS

To completely test the developed algorithms, a Leica DVM-6 microscope was used to quickly generate images of 234 Tundra chips and 273 ICS chips. Each chip has two images, one focused on the top left corner, and one on the bottom right corner. This allowed for more surface detail to be captured. Each image is sized at 1600x1200, meaning each sub-image has dimensions 160x120.

As mentioned earlier, the layered registration algorithm successfully registered all the chip images it was tested on. The marking displacement algorithm was able to successfully identify every displacement, and this was easily verified by viewing the test image overlaid on the reference image. The texture discrepancy algorithm had some deficiencies. About 7% of all the sub-images contained texture discrepancies, and the algorithm designated about 8% of the sub-images as containing texture discrepancies. Of the 8%, about 50% were correctly identified and 50% were false positives. This means the algorithm had a performance of 4% correctly identified, 3% false negatives, and 4% false positives. The remaining 89% of the sub-images were correctly identified as not having any texture discrepancies.

The color variation algorithm performed well on a limited sample size. Of the five examples, it was able to correctly identify four. However, these examples were extremely obvious and this performance cannot be taken as representative of the performance of the actual algorithm. These results are summarized in Table 1. A final annotated image is shown in Figure 5.

Figure 5. Final Annotated Image

V. CONCLUSION AND FUTURE WORK

Some of the obvious areas of improvement lie in the color variation algorithm. Generation of more realistic test examples is a priority. Additionally, the current algorithm is heavily dependent on consistent lighting and text environment. It is a necessary goal to increase the independence of the algorithm to reduce the possibility for false success. Other areas of improvement involve the texture discrepancy detector, which can be improved to reduce the number of false positives and negatives. Currently, a sufficient number of texture discrepancies are identified, but any counterfeit detection process needs to be able to collect all the relevant information. The registration and mark displacement algorithms work extremely well. The only drawback is the dependency on the test data i.e. the registration algorithm is heavily dependent on the way the images were captured. While this is not a huge issue, it remains an area of possible improvement.

Future goals for this research would involve expanding the defect detection to other defects such as improper or tampered leads and scratches present on the surface. An additional goal is to involve neural networks in the process to make it a truly intelligent and automated process. Steps in this direction will go a long way in making the entire counterfeit detection process easier and will improve the security of our nation.

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