Material Identification Via Multi-Spectral Imaging and Its Application to Circuit Boards

Shoji Tominaga Department of Engineering Informatics Osaka Electro-Communication University Neyagawa, Osaka 572-8530, Japan

Abstract

This paper describes a method for identifying object materials on a raw circuit board by means of multi-spectral imaging. First, we develop a spectral camera system for observing tiny objects. Second, an algorithm is proposed for estimating the spectral reflectance functions of object surfaces. We do not use the finite-dimensional linear model, but present a direct method under the narrow band assumption. We distinguish metals and dielectrics based on the difference of reflectance in changing illumination geometries. Third, an algorithm is presented for classifying the objects into several circuit elements by using the estimated spectral-reflectances. Finally, region segmentation results are demonstrated in an experiment using a real circuit board.

Introduction

Spectral-spectral reflectance of an object is based on the material composition of its object surface. This property can be helpful to recognize objects and segment regions in the illumination invariant way. The reflectance is usually divided into two parts: interface (or specular) reflectance and body (or diffuse) reflectance. Reflection from homogeneous materials like metals is based mostly on the interface reflection. For inhomogeneous materials like plastics and paints, the body reflectance component is meaningful. Therefore the surface-spectral reflectance varies with the material compositions and the illumination In principle, metals and plastics can be geometries. distinguished using the above reflection components. So far several methods were proposed for estimating object surface reflectances [1][2]. However there is no practical imaging system and algorithms for identifying object materials in a natural scene.

An integrated circuit board used in a variety of industries is one of the most complicated objects to understand from the observed color image. The surface layer of a raw circuit board includes various elements, which are a mixture of different materials such as substrate, metal plate, metal wire, solder, and paint. Moreover, the area of each element is as small as metal wire is less than 100 micron in width. These features make the machine inspection problem difficult in using a color image of a circuit board.

The present paper describes a method for identifying objects of different materials on a raw circuit board by means of multi-spectral imaging. First, we develop a spectral camera system for observing tiny objects under a uniform illumination. The system consists of a LCT (liquid crystal tunable) filter, a monochrome CCD camera, a macro lens, and a personal computer.

Second, an algorithm is proposed for estimating the spectral reflectance functions of object surfaces. We do not rely on the finite-dimensional linear model that is often used for reducing the dimensionality of surface-spectral reflectances (see [3]-[5]). A direct method is presented for reflectance recovery under the narrow band assumption of filtration transmittance. We distinguish metals and dielectrics based on the difference of reflectance in changing illumination geometries.

Third, an algorithm is presented for classifying the objects into several circuit elements by using the estimated spectral-reflectance functions pixel-by-pixel. From a computational speed and time viewpoint, this algorithm is much more effective than the usual clustering algorithms such as the k-Means algorithm.

Finally, region segmentation results are demonstrated and the reliability of the method is confirmed in an experiment using a real raw circuit board.

Spectral Imaging System

Figure 1 shows a camera system for spectral imaging that we realized in this study using a LCT filter. The LCT filter is convenient for spectral imaging because the wavelength band can be changed easily and electronically [6]. That is, the center wavelength of filtration is electronically tunable with no moving parts. This filter is regarded as a type of polarization interference filter based on the design of the Lyot filter type [7]. The filter is the CRI-model VISI, which operates over the range [450 - 650 nm]. We use a monochrome CCD camera (SONY XC-75) and place this filter in front of the macro lens (SONY 50MM) of a C mount. Moreover we created a mechanism

for rotating the filter as shown in Figure 1, so that the polarization effect can be detected in the acquired images. Figure 2 depicts a set of relative functions for representing the whole spectral sensitivities. The bandwidth of the spectral sensitivity functions is about 50 nm.



Figure 1 Spectral camera system.



Figure 2 Set of spectral sensitivity functions.

Features of Circuit Boards

Figure 3 shows the observed image of a small part on a raw circuit board under the light source of an incandescent lamp. The main elements on the board surface are (1) a substrate, (2) gray metallic footprints, (3) resist-coated metals, (4) coated via-hole metals, (5) coated metallic wires, and (6) silk-screen prints. Figure 4 shows a partial cross section of the board. The via-hole metals and the metallic wires have the same material composition. Therefore the materials on the board surface are classified into five element materials of (1) a substrate, (2) footprints, (3) resist-coated metals, (4) non-resist metals, and (5) silk-screen prints.



Figure 3 Image of a raw circuit board.



Figure 4 Cross section of the board.

Spectral Reflectance Estimation

Most algorithms for recovering surface reflectance from image data used the constraint that the spectral reflectance functions of object surfaces in a natural scene are approximated with the finite-dimensional linear model. Although this model is useful for reducing the number of unknown parameters of spectral reflectance, it is difficult to determine an appropriate model dimension and the algorithm is somethimes unstable in solving an inverse estimation problem. Here we propose a straightforward way of obtaining a reliable estimate of the reflectance function from the camera outputs of narrow band filtration.

Let the wavelength bands of the filter be f bands of λ_1 , λ_2 , ..., λ_f . If each band is narrow, then the sensor outputs $\rho_k(x)$ at spatial location x can be represented by the equation

$$\rho_{k}(x) = \int S(\lambda, x) E(\lambda) R_{k}(\lambda) d\lambda$$

= $S(\lambda_{k}, x) \int E(\lambda) R_{k}(\lambda) d\lambda$, (1)
 $(k = 1, 2, ..., f)$,

where $S(\lambda, x)$ is the surface-spectral reflectance, $E(\lambda)$ is the illuminant spectral power distribution of a light source,

and $R_k(\lambda)$ is the k-th sensor spectral sensitivity function in Figure 2, and the integration is done in the visible range [400-700nm].

The spectrum distribution illuminating an object surface is measured directly using a spectro-radiometer and a reference white standard. Therefore the spectral reflectance is estimated in the form

$$S(\lambda_{k}, x) = \rho_{k}(x) / \int E(\lambda) R_{k}(\lambda) d\lambda.$$
⁽²⁾

Thus, the spectral reflectance is recovered by eliminating the lighting and sensing effects from the senor outputs.

Detection of Specular Metal

We should note that the observed surface reflectances depend not only on the material composition, but also on the surface geometry of roughness. The footprint is a metal composed of uncoated solder. This object surface is rough, and strong specular highlights appear on the surface at some angles of viewing and lighting. This leads to large fluctuation of pixel values between highlight area and matte area. Here we solve the material detection problem by controlling the illumination direction of a light source, because the metal surface reflectance depends greatly on the illumination direction. Figure 5 shows the measuring system with two light sources. The viewing direction of a camera is always perpendicular to the board surface. The light sources illuminate the same surface alternatively from one of two directions (from left or right) that are mirrored about the viewing direction.

All objects except for footprints exhibit the dielectric reflection property and the surfaces are smooth. Therefore the observed body reflectances should be coincident at two illumination directions when a calibrated uniform light beam is used. On the other hand, if the two reflectances are different as one is specular highlight and another is matte, the surface is a rough surface of the footprint. Then we discard the specular reflectance and select the matte reflectance as the estimate. It is possible for the footprint that the both observations are matte.

Moreover, the measuring system in Figure 5 is effective for eliminating shadows appearing in an image at hollows of the board and at sharp edges of the element.



Figure 5 Measuring system with two illumination directions.

Detection of Holes

There are many holes through a circuit board. The holes are classified into two types of the via-hole and through-hole as shown in Figure 4. Transmitted light is more effective than reflected light for detecting these holes. Figure 6 shows a measuring system with back illumination. We sense the light passing through the board. Then the holes are detected as highlight disks in the backilluminated image.



Figure 6 Measuring system with back illumination.

Material Classification Algorithm

We use 21 sensor outputs in the range [450 - 650 nm] at 10 nm increments to classify each pixel point into the element materials on the board. This classification could be performed using a multi-dimensional clustering algorithm such as k-Means algorithm [8]. However, the algorithm does not often work well because of high dimensionality of the reflectance data. Figure 7 shows the typical spectral curves of the estimated reflectances for different materials. Therefore an effective classification algorithm is proposed using the shape features of spectral reflectance.

The basic process is summarized as follows:

- Two sets of spectral reflectance data are obtained at two illumination directions. The two dimensional array of reflectance data is called the reflectance image. The two reflectance images are then scaled so that the left and right data sets have the same average reflectance.
- 2. Let $\overline{S}_1, \overline{S}_2, ..., \overline{S}_{21}$ be the averaged spectral reflectance over the whole image. High reflectance satisfying the condition $S_1(x) > \overline{S}_1, S_2(x) > \overline{S}_2, ..., S_{21}(x) > \overline{S}_{21}$ corresponds to white of the screen print or highlight of the footprint and metal. If this condition holds for both images, the pixel point is classified into the print area. Otherwise, it is into the footprint.
- Two reflectance images are combined into a single reflectance image. The average reflectance of the corresponding two pixels is used for the screen print,

and the lower reflectance is selected for the footprint. The higher reflectance is for the remaining pixels.

- 4. If the spectral peak is located in [560-620nm] and the condition $S_{12}(x) > \overline{S}_{12}, S_{13}(x) > \overline{S}_{13}, ..., S_{18}(x) > \overline{S}_{18}$ holds, then the pixel is classified into the bright non-resist metal.
- 5. The remaining pixels except for the print and non-resist metal are examined. If the spectral peak is in [500-570nm] and $S_6(x) > \overline{S}_6, S_7(x) > \overline{S}_7, ..., S_{13}(x) > \overline{S}_{13}$ holds, then the pixel point is classified into the resist-coated metal
- 6. If the spectral curves at the remaining pixels have large peaks, then the pixel points can be dark non-resist metal or dark resist-coated metal. Otherwise those belong to the regions of footprint or substrate. In the first case, if $S_1(x) \ge S_{21}(x)$, it is classified into the resist-coated metal, and if $S_1(x) < S_{21}(x)$, it is classified into the non-resist metal.
- 7. If the spectral peak is in the range [460-520nm] and the condition $S_2(x) > \overline{S}_2, S_3(x) > \overline{S}_3, ..., S_8(x) > \overline{S}_8$ holds, then it is classified into the substrate.
- 8. The average reflectance $y(x) = \sum S_k(x)$ is computed over wavelength at each pixel. *k* Moreover the fixed average \overline{y} is calculated over the remaining whole pixels. If the condition $y(x) > \overline{y}$ holds, the pixel is classified into the footprint. Otherwise it is into the substrate.



Figure 7 Typical spectral curves of the estimated reflectances for the different materials.

Experimental Results

Figure 8 shows the scenes of the raw circuit board, which was illuminated from two different directions with incandescent lamps. The incident angles were 60degrees to the surface normal of the board. The spectral image of each scene was captured with an image size of 486x688. Two reflectance images were then obtained by eliminating illumination effects from the observed spectral images.

Next, the proposed material classification algorithm was applied to the reflectance images. In the classification process, the two reflectance images were combined into a reflectance image, based on comparison between two reflectances at the same pixel point. The element label was then assigned to each pixel as (1) substrate, (2) footprints, (3) resist-coated metals, (4) non-resist metals, and (5) silkscreen prints. Figure 9 shows the material classification results. The original board region is segmented into the five element regions with different materials.



(a) Illuminated from the left.



(b) Illuminated from the right.

Figure 8 Scenes of the raw circuit board illuminated from two different directions.



Figure 9 Material classification results by the proposed method.

Because of various noise effects, the pixel-by-pixel identification includes some errors that are inevitable. Most of the errors occur at random dots or around material edges. So we executed an image processing for correcting the errors with miss labels so that the given part of the board was segmented into a set of uniform element regions. This processing is a type of region merging. If the area of a region is less than a certain threshold, then the element label of the objective region is replaced with the neighbor's element label. Next, another smoothing operation was done for the material edges. Finally, the holes detected in a separate way were superimposed on the segmented region. Figure 10 shows the final region segmentation results after the above region processing.

Thus, the raw circuit board was well segmented into six regions with different materials including holes. Especially note that the footprints are correctly identified as the rough metallic surface. In comparison with a traditional approach, we applied the k-Means algorithm [8] to the reflectance image. Figure 11 shows the results by the k-Means clustering algorithm. The initial values of the cluster centers were given from the known regions. There are errors at some regions including metallic surfaces. The k-Means algorithm has disadvantages of (1) initial clustering centers affecting the classification performance and (2) expensive computational cost.



Figure 10 Final region segmentation results.



Figure 11 Classification results by the k-Means algorithm.

Conclusion

The present paper has described a method for identifying objects of different materials on a raw circuit board by means of multi-spectral imaging. First, we introduced a spectral camera system for observing tiny objects under a uniform illumination. The system consists of a LCT filter, a monochrome CCD camera, a macro lens, and a computer. Second, an algorithm was proposed for estimating the spectral reflectance functions of object surfaces. We did not use the linear model, but a direct method under the narrow band assumption of filtration transmittance. We distinguished metals and dielectrics by changing illumination geometries. Third, an algorithm was presented for classifying the objects into several circuit elements by using the estimated spectral-reflectances pixel-Finally, region segmentation results were by-pixel. demonstrated in an experiment using a real raw circuit board.

The proposed method can be applied to material identification of any objects in a natural scene.

References

- G. Healey: Using color for geometry-insensitive segmentation, JOSA A, Vol.6, No.6, pp.920-937, 1989.
- S. Tominaga: Surface identification using the dichromatic reflection model, IEEE Trans. PAMI, Vol.13, No.7, pp.658-670, 1991.
- Y. Miyake et al.: Development of multiband color imaging systems for recording of art paintings, Proc. of SPIE, Vol.3648, pp.218-225, 1999.
- 4. S. Tominaga: Spectral imaging by a multi-channel camera, J. of Electronic Imaging, Vol. 8, No. 4, pp. 332-341, 1999
- J.M. DiCarlo, F. Xiao, and B.A. Wandell: Illuminating illumination, Proc. The Ninth Color Imaging Conf., pp.27-34, 2001.
- F.H. Imai, M.R. Rosen, and R.S. Berns: Comparison of spectrally narrow-band capture versus wide-band with a priori sample analysis for spectral reflectance estimation, Proc. The Eighth Color Imaging Conf., pp.234-241, 2000.

- 7. P.J. Miller and C.C. Hoyt: Multispectral imaging with a liquid crystal tunable filter, Proc. of SPIE, Vol.2345, pp.354-365, 1995.
- R.O. Duda, P.E. Hart, and D.G. Stork: Pattern Classification, John Wiley&Sons, New York, 2001.

Biography

Shoji Tominaga received the B.E., M.S., and Ph.D. degrees in electrical engineering from Osaka University, Japan, in 1970, 1972, and 1975, respectively. Since April 1976, he has been with Osaka Electro-Communication University, Neyagawa, Osaka, where he is currently a Professor in the Department of Engineering Informatics. His research interests include computational color vision, color image analysis, and computer graphics. He is a senor member of IEEE, and a member of OSA, IS&T, and SPIE.