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Unsupervised Material Classification of Printed Circuit Boards Using Dimension-Reduced Spectral Information

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Abstract

This paper proposes an unsupervised method for material classification of raw printed circuit boards (PCBs) based on the dimension-reduced spectral information. First, a spectral imaging system is constructed for acquiring precise spectral reflectance images. Only 3-dimensional spectral features are then extracted from the original 31-dimensional spectral image data by PCA for segmentation proposes. Next we apply the normalized cut and k-means clustering algorithms to the material classification using the reduced spectral reflectance data. Experimental results show the feasibility of the proposed method in comparison with the relevant 3-dimensional RGB imaging system. It is shown that the proposed method achieves very high quality in the material classification.

1. Introduction

A printed circuit board is one of the most complicated objects to understand from the observed image in a variety of industries. A raw PCB surface layer is composed of various elements, which are a mixture of different materials such as paint, metal, resist, and substrate. The area of each element is very small. These features make the machine inspection difficult by using general color imaging systems based on only three spectral bands RGB [1].

Recently, spectral imaging has drawn great attention due to its potential applications such as object recognition in many fields. A spectral image comprising monochrome images at more than four different wavelengths has a large amount of spectral information which improves the ability to detect object materials or distinguish different areas. Tominaga et al. [2], [3] proposed material classification algorithms for raw PCBs based on surface-spectral reflectance. However, those algorithms had limitations due to spectral imaging system. Moreover, they required huge data storage and computational complexity for dealing with the high-dimensional spectral components to obtain enough accuracy in classifying PCB elements.

The present paper proposes a method for unsupervised material classification for raw PCBs based on the dimension-reduced spectral information. We construct a new spectral imaging system for acquiring precise spectral reflectance images. For solving the problem of the huge volume on the spectral reflectance data for PCBs, we consider extraction of low-dimensional spectral features to be used in the process of material classification. A variety of methods for dimensionality reduction have been proposed [4]. In this paper, PCA is invested for the present problem. As well known, the PCA is a classical technique which reduces dimensionality by forming linear combinations of some statistical features. This analysis leads to effective material classification and image segmentation under the reduced degrees of freedom, space and time complexities.

The well-known normalized cut [5] and k-means clustering [4] algorithms are used for the material classification based on the reduced spectral reflectance data. The performance of the proposed method is examined on experiments using real PCBs. We compare the classification results to the relevant RGB imaging system. The most effective imaging system and algorithm are determined for improving the accuracy of PCBs material classification.

2. Spectral Imaging System

We have constructed a spectral imaging system for PCBs observation as shown in Fig. 1. The camera system consists of a monochromatic CCD camera (Retiga 1300) with 12-bit dynamic range and Peltier cooling, a macro lens of C-mount connected directly to the camera, VariSpec™ Liquid Crystal Tunable Filter (LCTF), and a personal computer. The LCTF has the spectral properties of bandwidth 10nm and wavelength range [400-720nm].

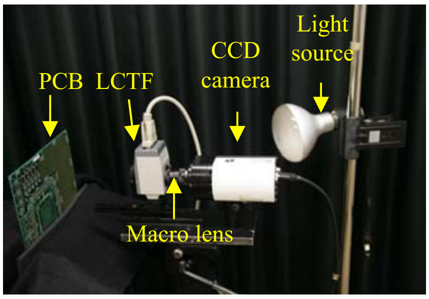


Figure 1. Spectral imaging system.

The image resolution is 1280x1024 pixels for the area of 35mm x 30mm. The system in Ref. [3] had the limited spectral resolution and range of 40nm and [450-650nm]. Thus the image resolution and sensitivity are much improved in the present system. The PCB can easily move in XY directions to capture the required part of circuit board.

Figure 2 shows the measuring geometry with two light sources for effective surface illumination. In order to avoid large fluctuation of pixel values between highlight area and matte area, we control the illumination direction of a light source. In our system, the two incandescent light sources of 300W illuminate the same surface alternatively from one of two directions (from left or right) that are mirrored about the viewing direction. The viewing direction of the camera is always perpendicular to the board surface. We investigated a proper illumination angle for observing PCB materials. We found that the minimum illumination angle is 20° this is because of the camera shadow on the board. Then the incidence angel 25° was chosen in our imaging system. Decreasing the incident angle to less than 25° makes strong specular highlight on the board especially on metal parts, and increasing this angle to more than 25° makes metal parts more noisy and difficult to classify.

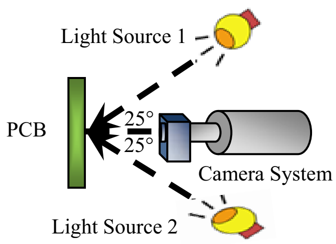


Figure 2. Measuring geometry for PCBs.

3. Material-based Reflectance Estimation

We describe an algorithm for estimating surface-spectral reflectance from multiple spectral images based on the material features of raw PCBs.

3.1 PCB Material Features

The PCBs used in this paper are composed of four materials metal, resist-coated metal, silk-screen print, and substrate as shown in Fig. 3. The observed surface reflectance properties depend not only on the material composition, but also on the surface geometry and roughness. The PCB materials can be divided into metal parts and dielectric parts on the basis of reflection.

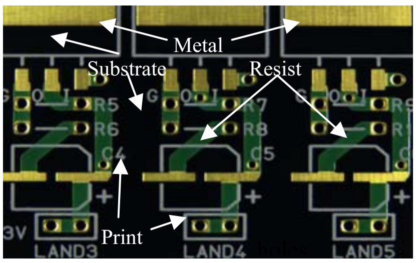


Figure 3. Part of a raw PCB.

In the case of metal, incident light is specularly reflected. Sharp edges of metal flakes and holes produce specular highlights and shadowing effects on the other side [6]. Metal surface at some angles of viewing and lighting, strong specular highlights appear on the surface. The surface reflectance observed from metal depends on the illumination direction, so changing the illumination angle has a great effect on the spectral reflectance estimation. Thus specular reflection and shadowing effects can be controlled by changing direction of light.

For dielectric parts, materials surfaces are smooth, and strong specular highlights cannot occur at some illumination directions. According to the dichromatic reflection model [7], the diffuse reflection component of each surface provides a constant spectral reflectance inherent to the surface material. Thus, changing the illumination angle will not have a great effect on the spectral reflectance estimation for such type of materials. The elements of substrate, print, and resist are classified into this type.

3.2 Spectral Reflectance Estimation

We use a straightforward way of obtaining a reliable estimation of the surface-spectral reflectance function from the camera outputs under narrow band filtration. Let the wavelength bands of the filter be 31 bands of $\lambda_1, \lambda_2, ..., \lambda_{31}$ corresponding to 400, 410,…,700nm. Also let $S(\lambda_k; x, y)$ be the surface-spectral reflectance at wavelength λ_k $(k = 1, 2, ..., 31)$ at location (x, y). Then the reflectance can be recovered by eliminating the illumination effect from the sensor outputs as follows:

$$S(\lambda_k; x, y) = \frac{\rho_k(x, y)}{\int_{400}^{700} E(\lambda) R_k(\lambda) d\lambda}, \quad (1)$$

where $E(\lambda)$ is the illuminant spectral power distribution of the light source, and $R_k(\lambda)$ is the *k*-th sensor spectral sensitivity function. This process is repeated from both lightning directions of left and right.

3.3 Spectral Reflectance Unification

The light sources illuminate the same surface alternatively from one of two directions to produce two spectral reflectance images. We then unify the spectral reflectance data to produce only one spectral reflectance image from captured images. Because the shape of spectral reflectance characterizes the material properties of each pixel point on the PCB, some features of the spectral curves are used in the unification operation. The combination process, in this paper, is composed of the following steps,

1. Let $\overline{S}_k = \overline{S(\lambda_k; x, y)}$ be the average of the observed reflectance at a particular wavelength k over the entire image region. Then the average spectral reflectance $(\overline{S}_1, \overline{S}_2, ..., \overline{S}_{31})$ from both images is calculated.
2. If both pixel values from left and right images are high and the both reflectances achieve the condition $S(\lambda_k; x, y) > \overline{S}_k$ $(k = 1, 2, ..., 31)$, this pixel is classified into the silk-screen print area, and the higher reflectance is chosen.
3. If one pixel value from both images is very high and the other is extremely low, this pixel includes specular highlight of metal. The higher reflectance is chosen for a metal surface.
4. If both pixel values do not have big difference in reflectance, this pixel is classified into dielectric. The average reflectance is calculated.
5. For the remaining pixels except for the material areas extracted in the above, the higher reflectance from both sides is chosen.

The typical surface-spectral reflectances obtained for the PCB in Fig. 3 are shown in Fig. 4.

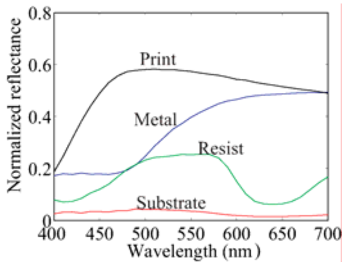


Figure 4. Typical surface-spectral reflectance curves for PCB material elements shown in Fig. 3.

4. Dimensionality Reduction for Spectra

We use the PCA for reducing the dimension of the estimated spectral reflectance data. The unified spectral reflectance image is converted to a set of input vectors $\mathbf{X}=\{\mathbf{x}_1,\mathbf{x}_2,...,\mathbf{x}_L\}$ from the 31-dimensions, where L is number of pixels. First, the covariance matrix $\Sigma = 1/\mathrm{L}(\mathbf{SS}^{\mathrm{T}})$ is calculated from the input vectors, where $\mathbf{S}=\{\mathbf{s}_1,\mathbf{s}_2,...,\mathbf{s}_L\}$ for the deviation $\mathbf{s}=\mathbf{x}-\boldsymbol{\mu}$, and $\boldsymbol{\mu}$ is the 31-dimensional mean vector of the input spectral reflectance data. Second, the eigenvectors and eigenvalues are computed and sorted according to the decreasing order of eigenvalues. Some eigenvectors from the largest are then chosen to form low dimension from the original high dimension. Third, let $\mathbf{Y}=\{\mathbf{y}_1,\mathbf{y}_2,...,\mathbf{y}_L\}$ be n dimensional vector (<31) representations. The output vectors are obtained by the linear orthonormal projection

$$\mathbf{y}_i = \mathbf{M}^{\mathrm{T}}\mathbf{x}_i + \mathbf{b}\,, (i=1,2,...,L)\,, \qquad \textbf{(2)}$$

where the projection matrix $\mathbf{M}$ [31×n] contains the n eigenvectors of the sample covariance matrix Σ. The bias vector $\mathbf{b}$ [n×1] equals to $-\mathbf{M}^{\mathrm{T}}\boldsymbol{\mu}$. Finally, $\mathbf{Y}$ can be used as feature vectors for segmentation purpose.

Figure 5 shows the cumulative contribution rate for the estimated spectral reflectance data. More than 99% of the percent variance is performed by the first three principal components. Therefore, we can reduce the original 31-dimension into three-dimension.

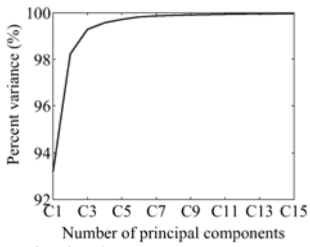


Figure 5. Principal component percent variance.

5. Classification Algorithms

We use the normalized cut and k-means clustering techniques for the material classification based on the reduced spectral reflectance data. Both algorithms are summarized for solving the present problem.

In the normalized cut [5], a weighted graph $G=(V,E)$ is constructed for the input image by talking each pixel as a node (set V) and connecting each pair of pixels by an edge (set E). Calculating the weights on edges to reflect similarity between nodes i and j

$$w(i,j)=\exp\left(-\frac{\|\mathbf{F}(i)-\mathbf{F}(j)\|_2^2}{\sigma_I^2}\right)\exp\left(-\frac{\|\mathbf{Z}(i)-\mathbf{Z}(j)\|_2^2}{\sigma_Z^2}\right),$$

$$\text{if } \|\mathbf{Z}(i)-\mathbf{Z}(j)\| < r\,, \qquad \textbf{(3)}$$

where $\mathbf{F}(i)\in[0,1]^3$ is the feature vector of a node i corresponding to the three principal components resulted from the PCA-based spectral reflectance. $\mathbf{Z}(i)$ is the spatial location that effectively connects different regions to the same class. The parameter r considering local area, if $\|\mathbf{Z}(i)-\mathbf{Z}(j)\| \geq r$, then $w(i,j)=0$.

Color sensitivity σ_I depends on the materials appearance. Location sensitivity σ_Z depends on the size of tested PCB image and minimum distance between different materials. For pixel apart r, it controls radius of weight calculations. Larger r gives better segmentation and the smaller gives faster segmentation.

Then, the splitting point is found such that the resulting partitions have the best $Ncut(A,B)$ value for two disjoint sets A, B, $A\cup B=V, A\cap B=\varphi$ using the following:

$$Ncut(A,B)=\frac{cut(A,B)}{assoc(A,V)}+\frac{cut(A,B)}{assoc(B,V)} \qquad \textbf{(4)}$$

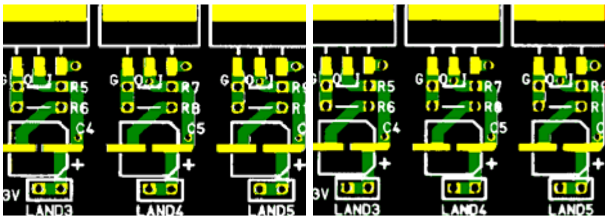
where $cut(A,B)$ is the total weight of connections that will be removed between partition A and partition B. The symbol $assoc(A,V)=\sum_{u\in A, v\in V} w(u,v)$ denotes the total weight of connections from nodes in A to all nodes in the graph. Also $assoc(B,V)$ is similarly defined. Finally, the algorithm decides if the current partition should be subdivided and recursively repartition the segmented parts if necessary.

In the k-means algorithm [4], the high dimension of the spectral images makes it difficult to apply such algorithm to the present problem. Therefore, we apply the k-means clustering algorithm to the dimension-reduced data with the same initial seed points (k=4) as the number of material classes of the raw PCBs in this study.

6. Experiments

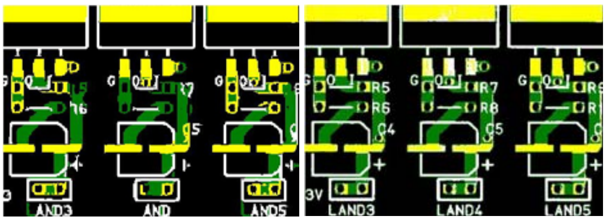
We have examined the performance of material classification by the proposed method in comparison with the method based on the RGB-based reflectance images. The scene of the raw circuit board shown in Fig. 2 was captured with the present spectral imaging system under incandescent lamps. Two data sets of surface-spectral reflectances were estimated from the two spectral images at two different light sources. We combined these reflectance images into one reflectance image by comparing the relevant reflectances at the same pixel point and applying the above rules to all pixels. These spectral reflectance data were transformed into the three-dimensional reflectance feature space, where the clustering was executed. In the normalized cut, the parameter values used for calculating the weight matrix were the spectral sensitivity σ_I=0.03, the spatial distribution σ_Z=100, and the radius r=15. The parameter values were also used for the classification using RGB color images.

Figure 6 shows the classification results for both normalized cut and k-means algorithms based on the three-dimensional reduced spectral data. In the figure, the classified regions are painted in different colors for silk-screen, metal, resist-coated metal, and substrate. The normalized cut and k-means achieved noticeable quality in classifying observed PCB image into four material regions. Specular highlights areas around PCB holes also were well classified.



(a) PCA+Ncut (b) PCA+k-means

Figure 6. Classification results by the proposed method.



(a) RGB+Ncut (b) RGB+k-means

Figure 7. Classification results by the RGB method.

To confirm reliability of the proposed spectral-based method, the spectral camera system was replaced with a digital still camera. We used a Canon camera, EOS-1Ds MarkII to capture color images of the same PCB under the same illumination environment. The RGB images with the same size 1280x1024 as the spectral images were obtained. The normalized color values were calculated as spectral reflectance from Eq. (1) for only RGB channels by eliminating illumination effect. The classification results of the normalized cut and the k-means algorithms using the RGB data are shown in Figs. 7 (a) and (b). We can notice from the classification results that the algorithms can not determine the material type in many pixels, especially in print and metal areas.

Moreover, to demonstrate the accuracy of the proposed method, we compare the resulting segmentations with a ground truth. Table 1 presents the classification quality for the whole regions using the following

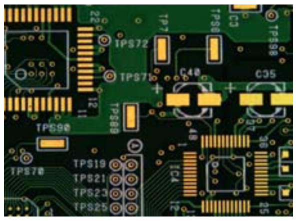
$$Quality\ rate = \frac{Number\ of\ correct\ classified\ pixels}{Total\ number\ of\ pixels}.$$

The classification quality is numerically evaluated in the table. It should be noted that the material classification based on the three-dimensional reduced spectral information achieves very high quality, compared with the RGB-based classification.

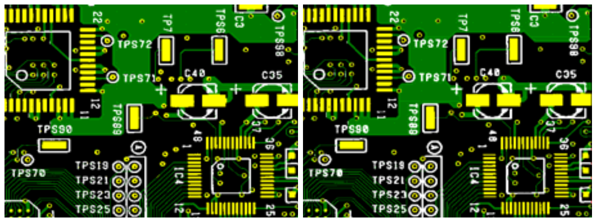
Table 1. Quality comparison using the ground truth.

	3 dim. signal (PCA)		3 dim. signal (RGB)	
Algorithm	Ncut	k-means	Ncut	k-means
Quality rate	99.17%	98.96%	74.37%	77.56%

We apply the algorithm on more complicated four materials PCB. Figure 8 shows segmentation result of a different board with four materials.



(a) Four materials PCB spectral image



(b) PCA+Ncut (c) PCA+k-means

Figure 8. Classification results by the proposed method.

7. Conclusion

This paper has proposed a method for unsupervised material classification of raw PCBs based on the dimension-reduced spectral information. A new spectral imaging system was constructed for acquiring accurate spectral reflectance images. For effective material classification, we considered extraction of low-dimensional spectral features from the original high-dimensional spectral reflectance data by using PCA. As a result, we showed that the original 31-dimensional spectral reflectance data could be reduced into only three-dimensional data. We applied the normalized cut and k-means clustering algorithms to the material classification based on the reduced spectral reflectance data. We compare the performance to the classification results by the relevant RGB imaging system. The material classification by the propose method achieves high quality, compared with the RGB-based classification, and still effective in five materials PCBs with quite similar appearance.

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