Asbestos Detection Method in Building Materials by Integration of Various Classifiers

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Abstract We propose a method of detecting asbestos in building materials by integrating various kinds of classifiers. Recently, asbestos-related illnesses have become a nationwide problem in Japan. Now, human inspectors check whether asbestos is contained in building materials. An asbestos detection method using a support vector machine (SVM) with a weight summation kernel of color and shape has been proposed. It was effective but it did not work well for asbestos with very thin and low contrast because only a single detector with $40 \times 40$ pixels was used. Since the color, shape, and size of asbestos vary in microscope images, it is difficult to detect them with a single classifier. Therefore, we train many classifiers with various region sizes and feature types, and integrate them along the orientation of asbestos. We collect the asbestos detection with high accuracy and a small number of false positives by considering the asbestos orientation in classifier integration.

Keywords: asbestos detection, classifier integration, support vector machine (SVM)

1. Introduction

In the last decade, health damages due to asbestos has become a major problem in the world. Asbestos is a fibrous mineral that is non-flammable, durable and inexpensive. For such reasons, asbestos was widely used as a building material. However, the use of asbestos has been banned or limited worldwide since the late 1980s, because it was discovered to cause cancer. However, there are many buildings made of materials containing asbestos. We must check whether or not asbestos is included when buildings are demolished. Currently, human inspectors check specimens of building materials using microscopes. This is inefficient and the human burden is large. In the near future, many old buildings will be rebuilt or demolished, and demand for inspection will be higher. Therefore, the efficient automatic inspection of asbestos is strongly desired.

Asbestos analysis by human inspectors employs the disperse dyeing method. In this method, three specimens are prepared from one sample, and an inspector counts 1,000 particles from each specimen. When more than four asbestos particles are contained among the 3,000 particles, the material is judged to be hazardous. Since asbestos has a polarization property as shown in Figure 1, it emits a characteristic color. In summary, unique colors and shapes are the main feature of asbestos; the inspectors count asbestos using these color and shape properties.
Since particle color and shape are effective for asbestos detection, image recognition is considered to be the most appropriate method for detecting and counting asbestos particles automatically by computer. Some asbestos detection methods using microscope images of building materials have been proposed [1,2]. Moriguchi et al. proposed an asbestos detection method using the support vector random field of local and global features [1]. Nomoto et.al proposed an asbestos detection method using an SVM with a weight summation kernel of color and shape [2]. These methods were effective but did not work well for asbestos with very thin and low contrast because only a single detector with $40 \times 40$ pixels was used.

Since the color, shape and size of asbestos vary in microscope images, it is difficult to detect them with a single classifier. Therefore, we train many classifiers with various region sizes and feature types, and integrate them [9]. When we integrate all the outputs of classifiers at each location simply, we has can not use neighborhood information. Since asbestos has a particular orientation, we use the orientation information for integration. To obtain the orientation of asbestos, we use the outputs of Sobel filters with four directions. We integrate classifiers along the orientation, and we realize asbestos detection with high accuracy and a small number of false positives.

This paper is organized as follows. In Sect. 2, we describe the proposed method. Section 3 shows experimental results. Conclusions and future works are described in Sect. 4.

### 2. Proposed method

Our method consists of the following three steps: training of classifiers, detection by classifier integration and counting. Figure 2 shows an overview of the proposed method. Since asbestos detection from microscope images is a two class classification problem similar to face or pedestrian detection [4-5], we use an SVM [6] which is a binary classifier with high generalization ability. We train many classifiers using an SVM with various region sizes and feature types. By applying classifiers to all regions in a test image, we obtain outputs of classifiers at each pixel. By integrating them, we obtain probability map that indicates the existence of asbestos at each location. Finally, the probability map is binarized, and asbestos particles are counted by labeling.

#### 2.1 Training various classifiers

This section explains feature extraction. Since asbestos particles have unique color and shape, we use color and shape features for detecting asbestos by computer. Color features are described in Sect 2.1.1 and shape features are explained in Sect 2.1.2.

##### 2.1.1 Extraction of color features

Since asbestos particles emit a particular color with specific polarization, color information is important. In general, histograms are effective for asbestos detection because the rotation and location of asbestos particles vary in microscope images. However, some non asbestos particles have similar features, as shown in Figure 3. To overcome this problem, we use the idea of a spatial pyramid histogram [7]. Since asbestos particles are thin, the center region is more effective than peripheral regions. Thus, we use overlapped spatial pyramid histograms as shown on the right side of Figure 3. We divide a training image into five regions, and a histogram is made for each region.

In this study, we use HSV and RGB color spaces. In the HSV space, we use only hue (H) and saturation (S) color features, and we make a histogram for H and S independently. The number of bins is set to 64. Therefore, we obtain $640 = 64 \times 2$ colors $\times 5$ histograms) dimensional features. The procedure to make the five histograms is shown in Fig. 4. For each region, a histogram with 64 bins is made. Finally, the five histograms for H and S are concatenated. In RGB space, we make a histogram for each color. The number of bin is also 64. Therefore, we obtain $960 = 64 \times 3$ colors $\times 5$ histograms) dimensional feature.
this paper, we train classifiers using an SVM with various region sizes from $3 \times 3$ pixels to $19 \times 19$ pixels at intervals of 2 pixels. Thus, we obtain 18 (= $9 \times 2$ colors) classifiers for color features.

![Fig. 3 Overlapped spatial pyramid histogram](image1)

**Fig. 3** Overlapped spatial pyramid histogram

2.1.2 Extraction of shape features

The needle-like shape of asbestos particles is also important. Since the direction and position of asbestos particles is not constant, we use the edge histogram, which is robust to changes. The edges are calculated using Sobel filters with four directions. However, the standard edge histogram is not effective, as shown in Figure 5. Since most regions do not have edges, the entire region is dark. If we use the edge histogram, asbestos edges are not represented well. This is because the area of asbestos particles is smaller than the background. Therefore, we use weighted voting,

$$w_{ij} = \frac{s_{ij}}{\sum_{l=1}^{4} \sum_{k=1}^{4} s_{kl}}$$  \hspace{1cm} (1)

where $w_{ij}$ is the voting weight, $s_{ij}$ indicates the edge strength of the $j$th direction at the $i$th pixel, $\sum_{l=1}^{4} \sum_{k=1}^{4} s_{kl}$ is the sum of all outputs of Sobel filters with four directions in the region and $HW$ indicates the area of the region. Since we apply Sobel filters with $3 \times 3$ pixels for training images to obtain edges, we cannot obtain the output for peripheral regions and the output region size becomes $38 \times 38$ pixels. By using weighted voting, we can obtain histograms in which edges are emphasized. We make a spatial pyramid histogram by weighted voting, and eight classifiers are trained using the SVM with various region sizes from $3 \times 3$ pixels to $17 \times 17$ pixels at intervals of 2 pixels.

![Fig. 4 Extraction of feature](image2)

**Fig. 4** Extraction of feature

2.2 Asbestos particle detection and counting

We apply all 26 classifiers to all regions in the test images. The outputs of classifiers are integrated. The simplest approach is to use the sum of all outputs at each location. We call this method simple integration. However, in simple integration, we cannot use neighborhood information. Since asbestos particles have a particular orientation, we attempt to use the orientation information for integration. We determine the orientation of asbestos particles using the outputs of Sobel filters with four directions, as shown in Figure 6. Then we integrate classifiers along the orientation direction. In the experiments, we evaluate two local regions for integration as shown in Figure 7. To integrate classifier outputs at the center pixel, we integrate outputs at the yellow pixels in Figure 7 according to the orientation.

![Fig. 5 Weakness of edge histogram](image3)

**Fig. 5** Weakness of edge histogram

![Fig. 6 Orientation determination](image4)

**Fig. 6** Orientation determination
In this section, we present experimental results. First, we describe image dataset in Sect. 3.1. In Sect. 3.2, we explain how to evaluate detection accuracy. Evaluation results are shown in Sect. 3.3.

3.1 Image dataset

In the experiments, we use 122 microscope images that contain 154 asbestos particles. To train the detector, we select 27 images. The 600 positive examples and 7000 negative examples without asbestos particles are extracted from 27 images. The remaining 95 images are used as test images. The test images include 145 asbestos particles.

3.2 How to evaluate accuracy

In general, the precision-recall (P-R) curve or receiver operating characteristic (ROC) curve is used for evaluating detection accuracy. However, since our method integrates the outputs of all classifiers at each pixel, P-R and ROC curves are not suitable. We explain the reasons for this.

In general, the numbers of true positives and false positives decrease when the threshold increases. However, in our method, the number of false positives increases while the number of true positives decreases. Figure 8 shows this phenomenon. In Figure 8, the graph is an example of the probability for the asbestos particle shown in the image below it. The red dotted line is the threshold. Red squares in the images are the results of detection by our method. Each classifier uses only the local color or shape feature, and we integrate the output of all classifiers. Thus, the integrated value is not uniform. Two local regions are detected as asbestos particles. As shown in Figure 8, if we increase the threshold, the number of true positives decreases and the number of false positives increases.

We evaluate our method by employing the optimal threshold value obtained using the SVM.

Next, we explain how to judge whether or not the detection result is correct. Figure 9 (a) shows our evaluation method. In the proposed method, if we detect the center of ground truth, we judge that the detection is true. This is different from the evaluation method in [2]. Nomoto et al. detected asbestos with high accuracy [2]. However, if a part of ground truth is detected, they judged that detection is true. If we use the same criterion in [2], our method gives nearly the same true positive rate with a lower false positive rate than theirs [2]. However, we consider that our
evaluation method is more effective for practical application, and we use our evaluation method.

3.3 Evaluation results

Evaluation results are shown in Table 1, in which # TP is the number of true positives and # FP is the number of false positives. The first and second rows show the results of integrating classifiers using the orientation of asbestos particles. The difference between two methods is the region size for integration. The third row is the result by simple integration without using the orientation of asbestos particles. The fourth row shows the results of simple integration without the use of overlapped spatial pyramid histograms. Lastly, the fifth row shows the results of using the best single classifier with the spatial pyramid histogram with 19×19 pixels in HSV color space. These results show that our method has high accuracy with the smallest number of false positives. Our method can reduce the number of false positives by considering the orientation of asbestos particles.

| #Asbestos | # TP (Rate) | # FP |
|-----------|------------|------|
| With orientation 5×5 | 145 | 134 (92.4%) | 6 |
| With orientation 3×3 | 145 | 135 (93.1%) | 11 |
| Simple integration | 145 | 136 (93.8%) | 18 |
| Simple integration standard histogram | 145 | 134 (92.4%) | 58 |
| Best single classifier overlapped spatial pyramid | 145 | 135 (93.1%) | 99 |

Figure 10 shows our detection result for asbestos particles that are very thin. The conventional method [2] cannot detect such asbestos particles because only a single detector with 40×40 pixels is used. This demonstrates the effectiveness of our method.

Figure 11 shows examples of detection results, where squares show the detection results; all asbestos particles are detected correctly. Figure 12 shows a typical failure of our approach. Almost all asbestos particles are detected, but one asbestos particle is detected as two particles. Since we estimate the asbestos particle orientation using four Sobel filters, the integration may not work well for asbestos particles whose orientation is intermediate between those of the four Sobel filters.

4. Conclusion

In this paper, we proposed a method of detecting asbestos in building materials. Our method can detect small and very thin asbestos particles by integrating various kinds of classifiers. The conventional method [2] cannot detect such asbestos particles. In addition, by using the orientation of asbestos particles in the integration, we can reduce the number of false positives while the number of true positives was slightly decreased.

Because we used Sobel filters with only four orientations to estimate the orientation of asbestos particles, we could not estimate the orientation of asbestos accurately. More accurate orientation determination is a subject of future work.

In the disperse dyeing method, we must count 3,000 particles that are not only those of asbestos. Some particle detection methods have already been proposed [8]. Thus, if we combine them with our method, we may realize an automatic disperse dyeing method. This is also a subject of future work.
Fig. 11 Example of asbestos particle detection

Fig. 12 Typical failure of our approach

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(Received May 14, 2013; revised August 27, 2013)