Bark Rubber Tree Crack Detection and Classification using Fractal Dimension

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Abstract: - The amount of latex from rubber tree (Hevia Brasiliensis) depends on the quality of the bark surface in the cutting area. The major sign for a low quality surface is a cracking bark which can results in empty latex. This paper proposes a vision-based method for crack detection and classification of bark surfaces. First, candidate regions are detected using threshold-based boundary detection method. Then, the maximum area region each candidate region is computed by fractal dimension method finally, these features are used as the inputs to discriminate statistic to classify whether or not it is a cracking bark. Any surface with a cracking bark is considered as a bad surface. The experiments on 30 cracking surfaces and 30 normal surfaces were carried out. The results showed overall errors at 10 % of which 16.7 % is the negative faults (i.e. bad surfaces are graded as good ones) and 3.3 % is the positive faults (i.e. good surfaces are graded as bad ones).

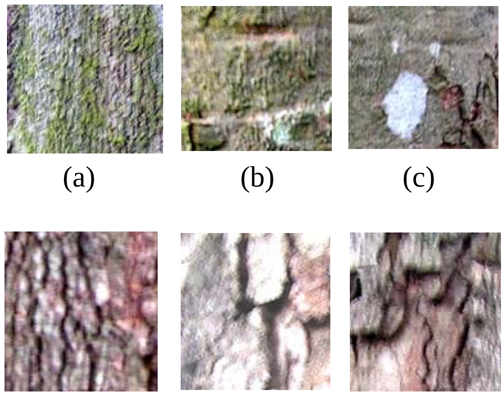
Key-Words: - Crack detection, Bark, Classification, Boundary Region, Fuzzy Logic, Inspection, and Fractal Dimension

1 Introduction

The rubber tree (Hevia Brasiliensis) is a kind of trees that generate natural latex, which becomes very important in the rubber market because of the increasing prices of the petrochemical-based rubbers. In the past, natural rubbers produced from rubber trees had a hard time competing with the synthetic rubbers produced from petrochemical materials. However, the cost of the synthetic rubbers is increased because of the continuous increasing of the crude oils price. As a result, the natural rubbers can complete very well now and in the future as the fossil-based crude oils become depleted. To this end, rubber trees become precious to the rubber industry because it can reproduce the latex for a period of time, but the most important thing is that they can be grown to replace the unproductive ones. In February of 2006, the selling prices of processed and unprocessed rubbers in Thailand are about 75.25-77.77 and 67.75-68 Baht/kg, respectively. In 2004 and 2005, Thailand had exported 3,021,618 and 2,952,191 tons of rubbers for the values of 137,604 and 148,868 million baths, respectively [1]. Notice that the exporting amount of tons reduced while the values increased. This indicates that the rubber price is increasing while its productivity decreases. To this end, many attempts are being carried out to increase the rubber productivity. The chain of rubber producing includes harvesting, processing, marketing, industry and development [2]. We focus our work in the harvesting phase where the latex is extracted from the tree by cutting a bark surface in an appropriate angle so that the latex will flow to a container. One of the main problems for low productivity during this phase is that the quality of the bark surface is not in a good condition for latex producing due to natural causes. However, we will emphasize on how to avoid bad bark surfaces especially for future robot labours. The bark characteristic can illustrate as physical properties including smoothness, coarseness and regularity of a region. All of these are visible; therefore, a vision-based classification method is chosen. A couple of research works involving bark classification have been reported. Song [3] proposed to combine grey-scale and binary texture features for classification of barks. Wavelet transform had been applied to improve the feature extraction for better accuracy in classification. At the same conference, Wan [4] considered feature extraction based on a statistical texture analysis. Although these works showed good results in feature extraction, but their main goal is for surface and object recognition. On the other hands, cracks in rubber tree barks possess clear tracks. Therefore, we try to investigate a simpler appropriate method for the rubber tree bark classification. The rest of this paper is organized as follows. Problem and basic concept is discussed in Section 2. The detail method then explained in Section 3. Section 4 gives experimental results. Finally, concluding remarks are made in Section 5.

2 Problem Analysis

The problem of detecting cracking bark is that the cracks have random shapes. However, they have some distinction. Fig. 1 shows two groups of bark surfaces; i.e. (a), (b) and (c) shows good surfaces (d), (e) and (f) shows barks with cracks. The bark surface in (a) is a sample of a perfect bark surface while (b) and (c) show some bad regions but have enough cutting areas.



(a) (b) (c)

(d) (e) (f)

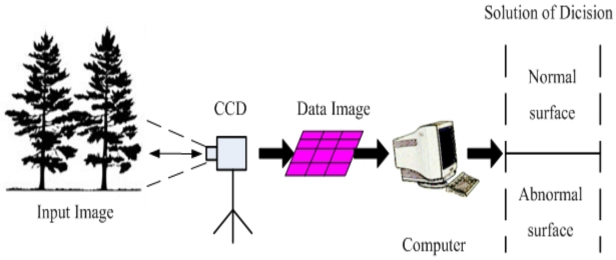
Fig.1 Samples of bark surfaces; (a) – (c) are good surfaces while (d) – (f) are bad ones

2.1 Basic Concept

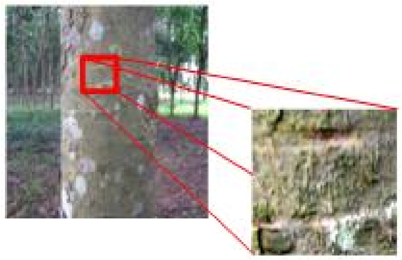
Comparing the properties of good and bad surface we found that bad barks possess deeper, wider and longer tracks with dark color. Based on these properties, we can use grayscales threshold to filter out smooth surface area keeping only areas that can be a crack. The boundary diction method [5] is adapted to detect only possible cracking region. Then, the width and length of each remaining region is detected. These two values are important properties of a crack as it shows that a crack usually is longer and wider; i.e. which we created to areas and generate scale box in close boundary region by fractal dimension. That are feature extensions input to classified from box counting with discriminate statistic is applied

3 System and Method

3.1 System



(a)



(b)

Fig. 2 (a) Functional system (b) Crop Image region

3.2 Method

Following the concept, we propose a method for classification as follows:

1. Take an input image
2. Pre-processing:

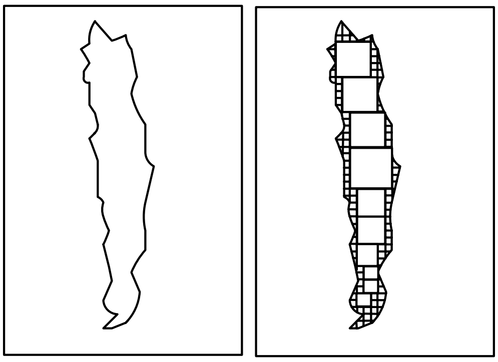
Pre-processing includes a noise filter by thresholding using histogram of gray-level intensity. Then, the gray level image is converted to binary image for edge detection.

3. Crack candidate identification:

Crack candidates are closed boundary regions which can be found by tracing the exterior boundary of objects using the 8-connected neighborhoods [5]. Then, the candidate regions are marked and labeled.

4. Feature extraction:

After cracks detection from boundary region, that we chosen maximum the crack for input to fractal dimension method generate to scale box from sizes 256, 128, 64, 32, 16, 8, 4, 2 and 1 respectively in close boundary region follow in Fig.3



(a) (b)

Fig.3 (a) Crack Boundary Detect and (b) Feature extraction by fractal dimension method.

$$N_{(r)} = \left(\frac{1}{r}\right)^{D_s} \quad For\ r \to 0 \tag{1}$$

$$D_{Sk} = \lim_{k\to\infty} \frac{\log(N^k)}{\log\left[1/(1/r^k)\right]} = \frac{\log(N)}{\log(1/r)} \tag{2}$$

3.3 Classification

As mentioned in the section 2 that a crack must have long enough length and wide enough width, but some regions are long but narrow and vice versa. Therefore, classified to area box counting base on statistical discriminate are sample and train data comparative group from data expert with boundary area are applied as shown in table 1:

4 Experiment and Result

The proposed method is evaluated by experimenting it using 30 good bark images and 30 bad bark images taken by CCD camera with resolution of 1536×2048 pixels. These images are cropped to become 256×256 pixels. Using a computer with Pentium IV processor 2.4GHz 256MB and the Matlab program, we collect the result as follows: Fig. 4 Illustrates samples of the result in each step of the proposed method. Fig.5 (a), (c) and (e) show the original and boundary regions of good bark and bad bark image, respectively. Table 1 shows the classification accuracy. Totally, we can achieve 90% accuracy. However, the negative fault errors are about 16.7 % and the positive errors are 3.3 %.

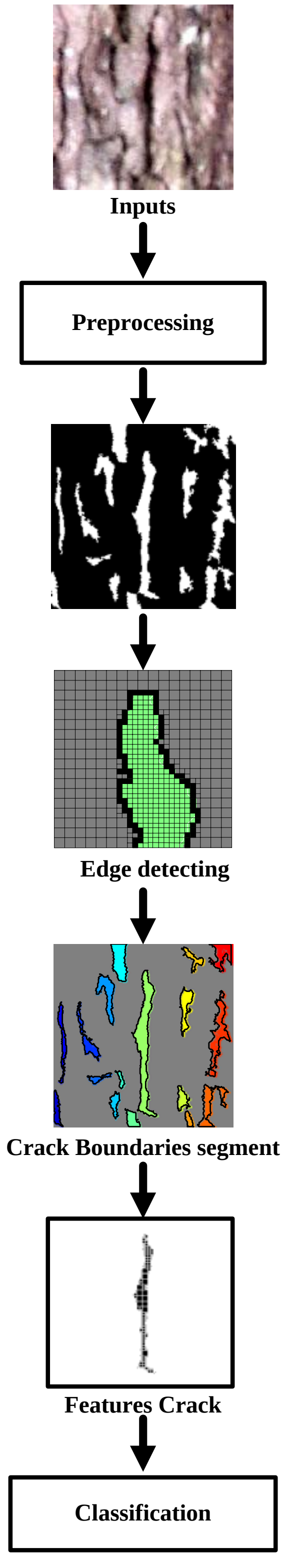


Fig.4 A sample in each step of the proposed algorithm

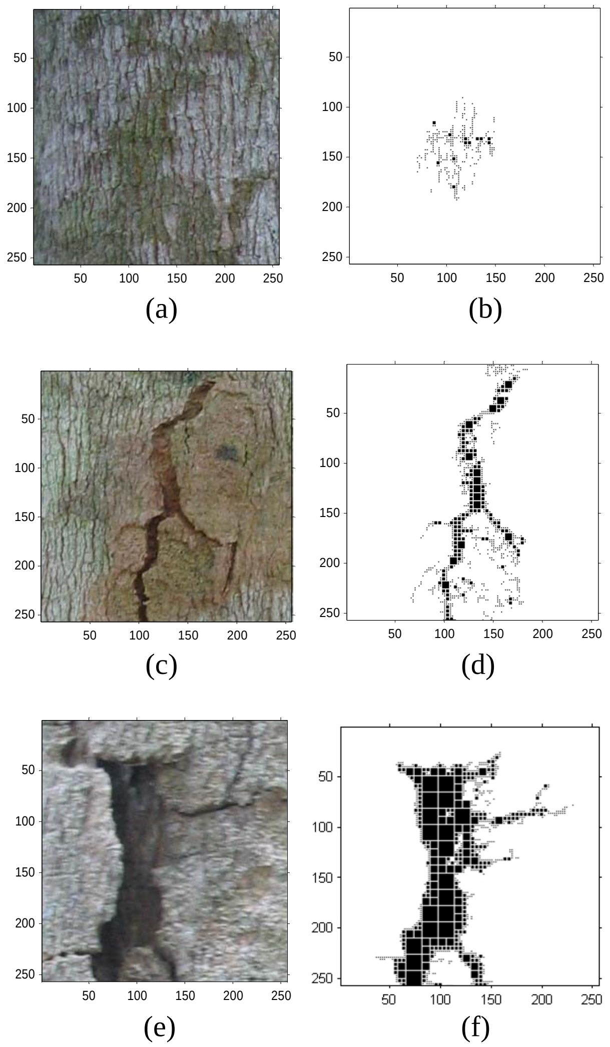


Fig .5 Boundary detection and Feature extraction

Table 1 Classification result

Pattern Bark	Result			
	Sample	Positive errors	Negative errors	Accuracy
Good Bark	30	3.3%	-	96.6%
Bad Bark	30	-	16.6%	83.3%
Total Bark				90%

5 Conclusion

We propose a simple but effective method for detecting cracks in bark and classifying them into good and bad barks. Experiments with 60 samples show good accuracy.

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