Effective Feature Extraction by Trace Transform for Insect Footprint Recognition

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***Abstract*—The paper discusses insect footprint recognition. Footprint segments are extracted from scanned footprints, and appropriate features are calculated for those segments (or cluster of segments) in order to discriminate species of insects. The selection or identification of such features is crucial for this classification process.**

This paper proposes methods for automatic footprint segmentation and feature extraction. First, we use a morphological method in order to extract footprint regions by clustering footprint patterns. Second, an improved SOM algorithm and an ART2 algorithm of automatic threshold selection are applied to extract footprint segments by clustering footprint regions regardless of footprint size or stride. Third, we use a trace transform technique in order to find out appropriate features for the segments extracted by the above methods. The trace transform builds a new type of data structure from the segmented images, by defining functions based on parallel trace lines.

This new type of data structure has characteristics invariant to translation, rotation and reflection of images. This data structure is converted into triple features by using diametric and circus functions; the triple features are finally used for discriminating patterns of insect footprints. In this paper, we show that the triple features found by applying the proposed methods are sufficient to distinguish species of insects to a specified degree.

I. Introduction

Modern transportation also means that various kinds of insects change places in vehicles, aircrafts, or ships. There are no problems in cases where native insects travel within their habitat, but it may cause harm to the ecosystem or the environment if insects enter an area outside of their habitat. In order to monitor movements or presence of insects (e.g., in containers in airplanes or ships, or in defined areas such as an island), special methods have been designed for the monitoring of insects, taking their characteristics into account.

Tracking tunnels and inked cards[1] have been used for monitoring small animals or insects [1]. Such tunnel devices are widely used for collecting footprints of various species of insects. The acquired footprints are visually inspected or scanned for automated reading; they are used for solving monitoring tasks, for example for verifying the presence of some insects, or for more detailed ecological or biological studies as supported by those footprints [2].

Insect footprints, acquired by using such tracking tunnels and cards for collection, are then typically identified by entomologists' expert knowledge about insect morphology [3]. The identification requires that individual footprints are extracted (e.g., by using morphological features of each specie of insects [4]) and then clustered into meaningful track patterns, but it may be hard to extract, analyze and classify insects footprints even for the experienced human specialist if available knowledge about entomology and visible patterns do not match (e.g., if too many insects left traces on the same card).

For automated reading of such cards, we start with a method to extract segments automatically for later classification, with the aim to remove unnecessary human preprocessing, improve time efficiency, and increase accuracy for insect footprint recognition, possibly even for situations where expert knowledge about entomology is not accessible.

Insect footprints are represented as dispersed patterns, ranging from isolated dots to areas of partly connected regions. It is a challenge to extract exact segments from scanned insect footprints having various deformations. Conventional research for extracting individual footprint segments are using morphological information such as expected insect species, sizes of insects, positions of legs, strides, and so on [5]. Alternatively, the research reported in [6] used an ART2 algorithm to set an initial threshold value automatically for extracting footprint segments as basic areas, to be used in insect recognition. [6] reported about a problem that the number of appropriate segments for insect classification may be decreased because noisy spots also can be clustered into acceptable segments,

[1]These tunnels use Black Trakka$^{\mathrm{TM}}$ tracking cards, and cards and tunnels are available from Connovation Ltd., an eco-related company in New Zealand.

and such segments of noisy spots are later on excluded from being a segment group for further feature extraction.

In order to overcome this difficulty, we propose in this paper a new segment extraction method for extracting appropriate segments and also proposed a feature extraction method having characteristics invariant to translation, rotation and even reflection of segment images. The proposed segment extraction method uses a morphological method, an improved Kohonen's SOM algorithm, and an ART2 neural network algorithm to increase extraction rate of appropriate segments.

The feature extraction method, proposed in this paper, uses a trace transform technique that has several procedural processing stages for extracting suitable features for classification of insect footprint segments. Ideally, insects would leave symmetrical footprint tracks by left and right feet centering on the body. Because of this fact, independently extracted features (say, for left-hand or right-hand segments only), using conventional methods, can not be mapped on each other, and extracted features (even for some symmetric segments) lead to a low performance of classification [7]. However, this paper shows that the proposed feature extraction method produces (about) identical feature values for all segments extracted from the same insect regardless of deformations caused by translation, rotation, or (especially) reflection.

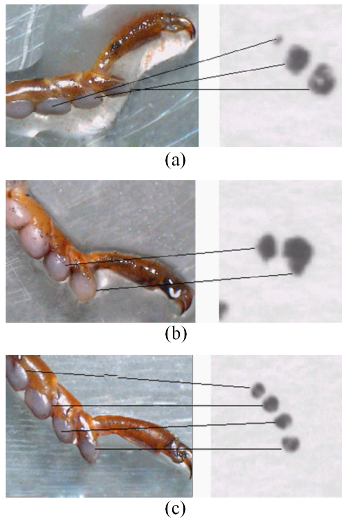

Fig. 1. Illustration of the foot structure of an insect; (a) front, (b) mid, and (c) hind foot.

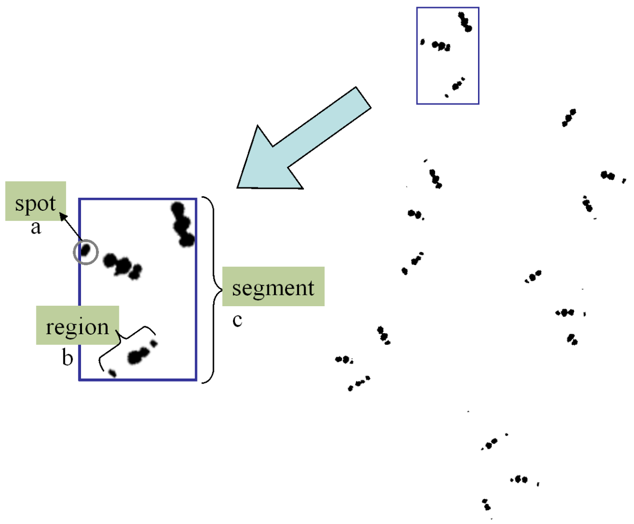

Fig. 2. Definition of spot, region, and segment, illustrated for a scanned track.

II. The Proposed Segment Extraction Method

First, we define three terms for describing our methodology. We define a *spot* to be a set of connected pixels in a binarized footprint image, and a *region* to be a set of spots, (ideally) for each foot of an insect. We define a *segment* to be a set of three regions, for front, mid, and hind foot. See Eq. (1) for a sketch. An illustration of biological structures of insect's feet and of those three defined terms is shown in Fig. 1 and Fig. 2, respectively. In this paper, segments are the basic units for classification of species of insects.

$$\begin{aligned} spot &= \{connected\ pixels\} \\ region &= \{spots\ for\ each\ foot\} \\ segment &= \{region_1,\ region_2,\ region_3\} \end{aligned} \tag{1}$$

Insect footprint patterns are composed of sets of segments produced by insect feet, and these segments appear in the footprint image repeatedly and dispersedly. In general, it is a challenge to detect segments which identify a footprint (from a scanned footprint image). Meaningful groups of regions, or segments identifying a single footprint, can be extracted using specific morphological characteristics defined by species, body size, leg positions, or stride of an insect (see conventional research reported in [3][4][5]).

In this paper, we propose a method for extracting footprint segments automatically without any complex morphological features. In order to extract segments as basic units for insect footprint recognition from scanned and binarized footprint images, the most basic areas (called *spot*) are clustered to extract region areas, and then the regions are clustered again to extract segment areas. In the first process stage, to extract regions, we use a morphological method, and in the second process stage (to extract segments), we use Kohonen's SOM algorithm, but improved in this paper, and an ART2 algorithm of automatic threshold selection.

A. A Morphological Method for Region Growing

Morphological methods are used for extracting some objects from an image by utilization of geometrical information about those objects. Various kinds of morphological information are used in image processing and computer vision [8], [9], [10]. Morphological methods use structural elements called *masks* for the extraction of specific objects from an image, and there are four basic operators called dilation, erosion, opening and closing in conventional morphological methods [9].

Regions that form a segment in a scanned footprint image have 'characteristics of linear direction', because the disposition of soles of an insect's foot is linear. For this reason, we can easily extract region areas by collecting spots in a certain linear direction, and so we use the closing operator (one of the four operators mentioned above) having a $1 \times n$ linear mask in order to group each spot. The mask structure for the closing operation is a linear structure for connecting neighboring spots by taking into consideration the spot's direction, as shown in Fig. 3. The mask rotates from 0 to 2π, centering on a certain spot, for finding adjacent spots, and the initial spot is merged with an adjacent spot by a rotation operation as shown in Fig. 4 (B in Fig. 4 means the mask as shown in Fig. 3). The length of the mask changes according to the size of spots in a scanned footprint image in order to provide for processing of various kinds of insects having different sizes of body, foot, or stride. Fig. 5 shows the results of region growing when using the closing operator with a linear mask.

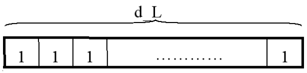

Fig. 3. Structure of the $1 \times n$ mask in the closing operator.

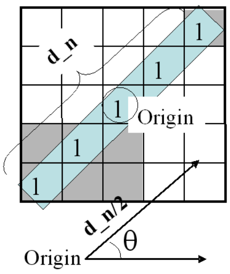

Fig. 4. The rotational mask, $R_\theta(B)$.

Fig. 5. Results of region growing using a closing operation.

B. An Improved SOM Algorithm for Region and Spot Grouping

In the process of insect footprint recognition, it is required to extract segments defined by "correct" regions or spots, and to exclude noise or useless spots for recognition. If noisy spots or useless spots still remain near the regions detected by the morphological method, it is difficult to extract the correct segments because of the influence of those spots. In order to solve this difficulty, we improve Kohonen's SOM (Self-Organizing Map) algorithm [11][12] that meaningful regions or spots have to be close to each other while noisy or less meaningful spots, are not to be close to meaningful regions or spots.

Kohonen's SOM algorithm is a kind of a neural network algorithm, and it is used to cluster complex data by mapping multi-dimensional data onto a 2-dimensional space, and correlating the mapped 2-dimensional data with each other. SOM uses an unsupervised learning method for analyzing data without a pre-defined number of clusters or correlation between data. The SOM algorithm is a suitable algorithm for clustering large and complex multi-dimensional data because it is easy to visualize the clustered data, and it is time-efficient.

In order to improve the SOM algorithm, we define all the found regions and not yet grouped spots to be *nodes* used in a conventional neural network algorithm, and we propose a function called Heavy function for adjusting the nodes altered by the weight adjustment function in a conventional SOM algorithm. In the improved SOM algorithm, weight is given to every region or spot in proportion to the size of those, and the connection weights of the SOM algorithm are adjusted by the weights of the spots.

So, weights of less meaningful or noisy spots are decreased through the Heavy function in order not to cluster such spots, while weights of correct regions or meaningful spots are increased, in order to cluster those more easily. By this function, all of the regions and spots in the binarized footprint image are rearranged to improve clustering at the next processing stage. The improved SOM algorithm, with adjusted weights by the proposed Heavy function, is shown in Table I.

Equation (4) is the formula for updating the weights in the SOM algorithm with the Heavy function, $H(t)$ is defined as in Eq. (3). In Eq. (3), m represents a weight value of winning node j^* and m_{ij} represents weight values of adjacent nodes. The illustration of a sample of a binarized footprint image

TABLE I
THE IMPROVED SOM ALGORITHM

The Improved SOM
Input : Set of N dimensional vectors, X
Output : Subsets of input data, K

begin
$InitializeW_i = (w_{i1}, w_{i2}, \cdots, w_{iN})$ foreachnode
for *(increase t)*
for *(for all input X)*
for *(i=0 to K)*

$$compute\ \ d_j = \sum_{i=0}^{N-1} (x_i(t) - w_{ij}(t))^2 \qquad (2)$$

endfor
*Find ($d_i$is minimum) then winner j**
Update the winner j(and its neighbors)*

$$H(i) = \frac{g_i}{Max(g_i)}, g_i = m_i - m_{ij}, g_i > 0 \qquad (3)$$

$$w_{ij}(t+1) = w_{ij}(t) + a(t) \cdot H(i) \cdot (x_i(t) - w_{ij}(t)) \qquad (4)$$

endfor
endfor
end

(after adjusting weights of spots using the improved SOM algorithm) is shown in Fig. 6. In the figure, the spots depicted by outline are moved spots by adjustments of their weights.

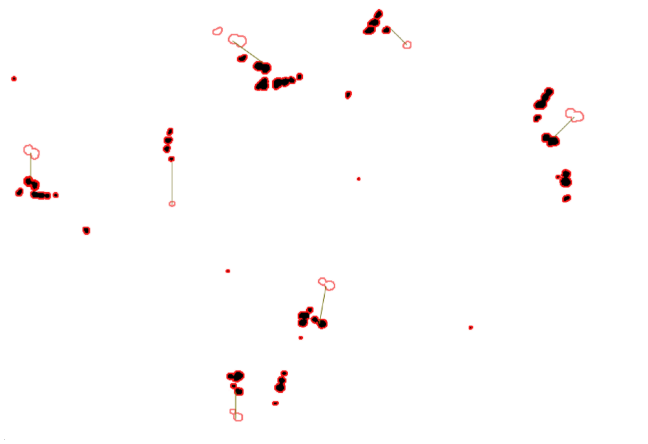

Fig. 6. Adjustments of weights by the improved SOM algorithm.

C. Segment Extraction by an ART2 algorithm

An ART2 algorithm is an unsupervised learning neural network algorithm that has a good performance in clustering [13][14]. The ART2 algorithm can cluster footprint regions easily without any morphological features. With the ART2 algorithm, the clustering process can be performed in real time, regardless of the number of massively generated data, as clusters are created dynamically. But the threshold value (σ) in the ART2 algorithm is defined by heuristic characteristics of the input data, and the threshold value is of crucial importance for the performance of clustering.

When we cluster insect footprint regions by the ART algorithm, it is difficult to pre-select an initial threshold value because the sizes of feet and strides vary with the species of insects. In order to solve this difficulty, we use the method for extraction of footprint segments using the ART2 algorithm of automatic threshold selection proposed by [6]. The proposed ART2 algorithm in [6] uses the contour shape of the graph created by accumulating distances between all spots of a footprint pattern image for an automatic setting of a threshold value, used in the ART2 algorithm. But we use the ART2 algorithm of automatic threshold selection to cluster regions extracted by the morphological method for extracting segments, while the ART2 algorithm in [6] is applied for clustering of spots from the beginning (i.e., for extracting segments). Thus, the ART2 algorithm is the same algorithm as in [6], but the inputs of the ART2 algorithm are different now in this paper.

Figure 7 shows a graph of common contour shape by accumulating distances between all the regions found by the morphological method. The figure represents stride and feet density of an insect. In the ART2 algorithm, the distance interval represented by 'segment area' is used for determining an initial threshold value. A more detailed description of this processing method is given in [6].

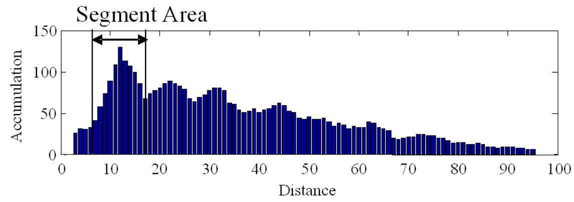

Fig. 7. Graph created by accumulating distances between all the regions.

III. The Proposed Feature Extraction Method

Insects always leave symmetrical footprint tracks by their left set or right set of feet, as shown in Fig. 2. Because of this fact, it is expected to extract the same feature values from the left-side segments and the right-side segments if all the segments are extracted from footprint images of the same insect.

In this paper, we use a trace transform technique for extracting features from clustered segments. The trace transform method can produce feature values of an input image, invariant to translation, rotation and even reflection of an input image [15], [16], [17]. Accordingly, it is suitable to extract feature values from various shapes of insect footprint segments, even if deformed by translation, rotation, or reflection.

A. Trace Transform

Let F denote an image. A method to represent the characteristics of image F decided by $l(\theta, p)$ onto the horizontal axis θ and the vertical axis p, is called the *trace transform*. The trace-line l is decided using the distance from the origin to l denoted by p, and the directional vector denoted by θ, as shown in Fig. 8(a). The trace-line l is represented by the formula $l = \{(x, y) : x \cos\theta + y \sin\theta = p\}$, and a function used in the trace transform is represented as $g(F : \theta, p, l) = T(F : \theta, p, l)$. A matrix (or image) generated by the trace transform is called trace image as shown in Fig. 8(b).

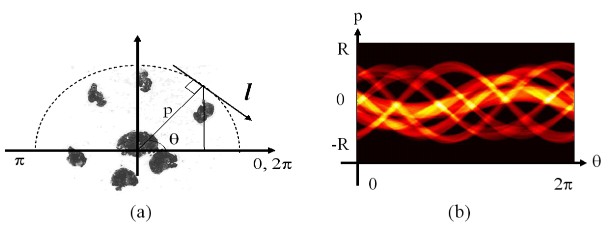

Fig. 8. (a) Parameters of the trace transform. (b) A trace image visualized in 3D space.

The trace image generated by the trace transform method has the following characteristics. If the original image rotates, its trace image shifts along the horizontal axis θ. If the original image translates to a certain vector, its trace image undergoes changes as follows. For convenience they are stated in terms of a trace matrix. Columns remain unchanged and stay in their places, though may shift up or down. A shift vector specifies numbers a and b such that a column with coordinate θ_i shifts vertically to $a\cos(\theta_i - b)$. Because of the characteristics, feature values extracted from an input image by the trace transform are always invariant to translation and rotation.

B. Extraction of Triple Features

Feature values for classifying insect footprints are calculated by the combination of values in a trace image decided by the trace transform using three functions called *trace function* T, *diametric function* P, and *circus function* Φ. The trace function T is used to produce a trace image using an input image; the diametric function P is used to produce a diametric matrix using the trace image; the circus function Φ is used to produce the final feature values using the diametric matrix.

A 2-dimensional image represented by $(F;\theta,p,l)$ having the structure of $F(x,y)$ and parameters of θ,p,t, is processed to extract the final feature values called *triple features* using a combination of the above mentioned three functions. The triple features are represented by Eq. (5), and the procedural processing steps to extract the triple features, are as follows:

$$\Pi(F) = \Phi(P(T(F:\theta,p,l) \tag{5}$$

Step 1: Trace function, $T = T(F:\theta,p,l)$

- Trace transform is determined by the trace function T.
- A trace image is generated by the trace transform. The range of θ is $[0,2\pi]$ and the range of p is $[p_{\max}, p_{\min}]$.

Step 2: Diametric function, $P = P(T(F:\theta,p,l))$

- Feature values are acquired by the diametric function P using the column values of the trace image.
- A diametric matrix is generated by the diametric function P using the parameter p of diametric moving direction.

Step 3: Circus function, $\Phi = \Phi(P(T(F:\theta,p,l)))$

- The final feature values are acquired by the circus function Φ using the diametric matrix and the parameter θ.

In this paper, we compose equations selectively from equations in Table II for the three functions, T,P and Φ, in order to produce the triple features for a classification of insect footprints.

IV. Experimental Results and Analysis

We used three footprint images (called B1, B2, B3) of Black Cockroach and two footprint images (called N1, N2) of Native Bush Cockroach for experiments. Table III shows the comparison of the segmentation results of the proposed method against those of the conventional method. In the conventional method, the performance of segment extraction was worse than the proposed method because extracted segments are degraded by the influence of noise spots, but in the proposed method, the performance of segment extraction was better than the conventional method because of the improved SOM algorithm. In the case of sample image N1, there were lots of noise spots, so we could see a big difference between both segmentation results.

TABLE II
Characteristic functions for Triple features.

$$F_1 = \int \xi(t)dt$$

$$F_2 = \int t^2\xi(t)dt, t = x - c, andc = median_x\{x, \xi(x)\}$$

$$F_3 = \max(\xi(t)), \quad F_4 = F_3 - \min(\xi(t))$$

$$F_5 = median(\xi(t)), \quad F_6 = FFT(\xi(t))$$

$$F_7 = Variance(\xi(t))$$

$$F_8 = Amplitudeof1stharmonicof\xi(t)$$

$$F_9 = Amplitudeof2ndharmonicof\xi(t)$$

$$F_{10} = Amplitudeof3rdharmonicof\xi(t)$$

$$F_{11} = Amplitudeof4thharmonicof\xi(t)$$

TABLE III
Comparison of segmentation results.

Kinds of insects		Native Bush Cockroach		Black Cockroach		
		N1	N2	B1	B2	B3
Conventional method[6]	# of extraction	14	11	19	15	15
	# of correct extraction	4	11	17	14	8
	Success ratio	29%	100%	89%	93%	53%
The proposed method	# of extraction	7	8	17	11	12
	# of correct extraction	6	8	17	11	8
	Success ratio	86%	100%	100%	100%	67%

Figure 9 shows three trace images of the trace transform method using an extracted segment image, the segment image after rotation, and the segment image after translation and rotation. We could verify that the trace image is shifted along the horizontal axis θ by rotation of the segment image, and it is also shifted along the vertical axis p by translation of the segment image. We also verified that all the distributions of triple features, computed from the three trace images, are exactly the same in the experiments. Figure 10 shows trace images and a set of triple features using a segment

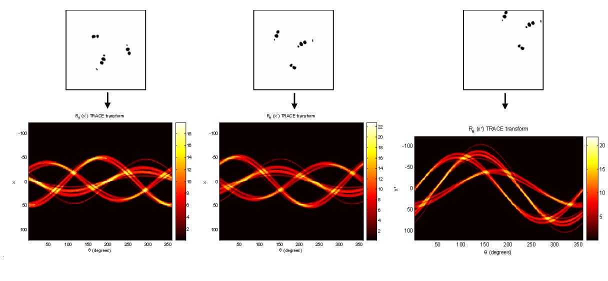

Fig. 9. A comparison of trace images by rotation and translation.

image and its reflection. We verified that the extracted triple features generated by the combination of three characteristics functions, are the same in the segment image and its reflection.

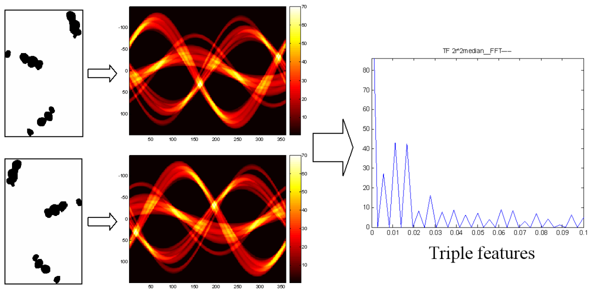

Fig. 10. A comparison of trace images by reflection and its triple features.

Figure 11 shows distributions of triple features extracted from the segments of Black Cockroach and Native Bush Cockroach using the trace transform with the combination of F_1, F_2, F_6 functions of Table II. We could verify that the distribution of triple features of Black Cockroach is located on a higher level than the distribution of triple features of Native Bush Cockroach. We conclude that the triple features, as extracted by the proposed method in this paper, are very promising because of this meaningful difference in the distribution of the triple features.

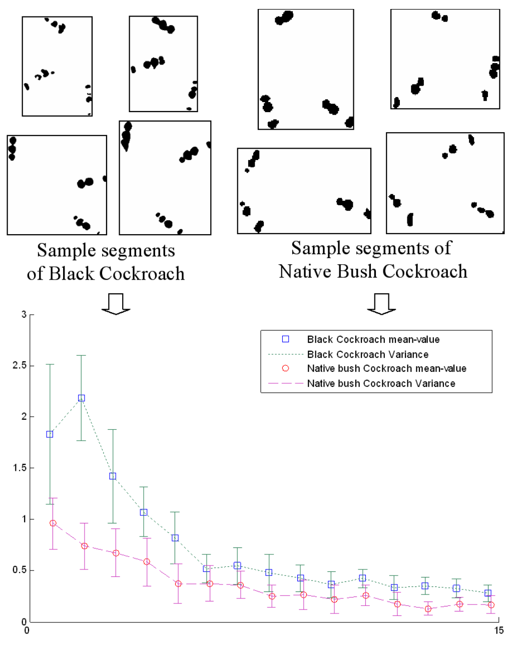

Fig. 11. Distribution of triple features for two different insects.

V. Conclusions

In this paper, we proposed a new method for extracting segments from binarized insect footprint images, which is robust to deformation or noisy spots. In the proposed method, the morphological method, the improved SOM algorithm, and the ART2 algorithm of automatic threshold selection are utilized. We also proposed a feature extraction method based on the trace transform in order to find appropriate feature values invariant to translation, rotation, and reflection. We verified that the proposed new method for extracting segments has better performance than the previous (say, conventional) method, and the triple features computed by the proposed feature extraction method provide sufficient distinguishable feature distributions for the species of insects used in the experiments.

Regarding future research, a classification method suitable for the characteristics of the triple features should be studied to increase the recognition rate. Also various kinds of insects should be considered to verify the usefulness of the proposed methods.

Acknowledgment

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