Original Article

An Algorithm for Detecting the Location of Rodent-Made Holes through Aerial Filming by Drones

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Abstract

Order Rodentia is a massive group of animals. In case the population of which is not controlled, their sprawl and propagation will impose severe problems for humankind. One way to control and fight the growth of the Rodentia population is by poisoning their burrows, which requires finding the precise location of holes made. The present research provides a fast, intelligent algorithm to locate holes of rodent burrows. A quadcopter with a 1-m/s propeller speed at a constant 1-m height from the ground was used for aerial filming. Filming rate was 20 frames per second. Movies prepared by the camera were transmitted to a computer via wireless communications and converted into images by Aoao software. From images, red, green, blue, and gray surfaces, as well as co-occurrence matrices, were extracted, from which, in turn, 40 color and 44 texture features were extracted. Once top features, most of which related to the texture of images, were selected, they were used to train and implement the classifier of a support vector machine (SVW) with the radial base kernel. Classification accuracy decreased with an increase in Kernel breadth so that maximum classification accuracy was obtained with Kernel breadth of 0.1. Results showed 96.1% accuracy for the proposed method in locating the burrow holes.

Keywords: Burrow holes, Aerial filming, Image processing, Support-vector machines, Quadcopters

Introduction

As a broad group of animals, mice make up the largest order of mammals [1]. As defenseless animals with many enemies in nature, mice need burrows with multiple holes for protection against their enemies [2]. On the other hand, mice have great potential for reproduction so that their numbers never decrease, although they have a wide variety of enemies in nature. Mice are noxious animals causing several damages, which are considered a significant problem agriculturally [3]. Being active in the gardens and warehouses as well as on the crop fields, mice attack any kinds of agricultural products under different conditions, inflicting severe damages. In some regions, a temporary infestation of mice results in heavy damages to and even in the destruction of crops [4].

Based on estimations made by the World Health Organization (WHO), mice destroy about 33 million tons of food annually. This figure, according to FAO estimations and evaluations, is equal to 5% of total food production in the world, which suffices to feed 130 million people [5]. For mentioned reasons, to control mice is extremely important economically since, in addition to compensation of money spent, it increases profits and yields of crop production. It is necessary to locate and plant poison inside the mice burrows in order to prevent them from propagating and increasing, on the one hand, and to reduce damages they inflict on crop fields, on the other [9]. Typically, this technique is performed entirely traditionally, making the discussion of mice chemical control difficult. For the poison-planting technique, it is particularly important to locate burrow holes because in case some of which are not poisoned, mice escape through them, and poisoning will become fruitless practically [7].

In recent years, new technologies, including remote sensing and image processing systems, have found some uses increasingly in different areas of the agriculture industry. Machine vision systems play essential roles in precise agriculture applications, such as applications of automation to agriculture. [8]. The study target images were taken, image processing methods with specialized software, and an

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appropriate detection algorithm can be employed to identify intended target features (color, size, geometry, texture, pests) in order to arrange the next activities [9]. Researches done by Bennedsen et al., (2005), Unay & Gosselin (2006), Omrani et al., (2013), Taheri Gravand (2014), Tavakoli & Najagzadeh (2015), Doosti Irani et al., (2015), and Jidong et al., (2016) are among many investigations performed so far on applications of remote sensing and image processing systems in agricultural domains [10-16]. Also, the followings are among applications of aerial filming and image processing. (i) identification of cultivated crop types [17], (ii) quality control and monitoring of lettuce fields [18], (iii) monitoring the status of cultivation types to preserve biodiversity [19], (iv) identification of citrus orchards [20], and (v) identification of infected citrus orchards [21]. A review of the research background indicated no research on how to find the holes of burrows made by mice at the fields' level. This task can be realized by using remote sensing and image processing systems. However, given the material abovementioned, the main objective of the present research is to implement a system to locate the holes of mouse burrows on the fields via remote sensing and image processing systems.

Materials and Methods

This section presents the instruments and equipment required to do present research and describes the method provided to locate the mouse burrows.

Experimental Site

A lot with the surface area of 150m^2 located in Kermanshah city was considered as the experimental site to perform experiments and filming. The lot was 100m long and 1.5m wide with no vegetation or some particularly cultivated crop, being selected because of having many mouse burrow holes on the surface. Along the length of the lot, there existed 41 holes, the locations of which were identified exactly before filming. Two images of the same mouse burrow hole are shown below (2 successive frames). The field was filmed at about noon on entirely sunny days.

Figure 1. Status of a mouse burrow hole inside the soil.

Filming

A Xiaomi-made (A Chinese company) camera, Andoer sport, with filming rate of 20 frames per second, vision angle of 173°, and the image quality of 12 megapixels was used to film. This camera was used due to its high resolution, lightness, and the high number of frames, which was mounted on Cheerson CX-Quadcopter 22 to record aerial films. This device has a 2-km radio range and a brushless motor with 20200 rpm. Fixed 1-m height from the ground and 1-m/s propeller speed were set for filming by quadcopter. Low elevation was selected for quadcopter flight because we wanted to have more control over it and to record high-quality images [22]. Moreover, considering the filming rate, the slower the speed of quadcopter is, the higher the number of images it takes from a specified surface; therefore, the lowest speed of movement (1m/s) was considered. Our quadcopter traveled the length of test lot in 100s and took images, each of which covered the 1.5-m breadth of the lot surface.

The film taken by the camera was transmitted to a computer online via wireless communications and converted into pictures by Aoao Video to Picture Converter 4.2 software. Aoao software output included 2000 images of the ground surface because the camera filming rate was 20 frames per second, and the length of the film was 100s.

Image processing and feature mining

Here, acquired images were processed by Matlab R2017a software. In this section, data were divided into two general classes: locations of mouse burrow holes (T), and hole-free ground surface (F). It should be noted that the test lot was crop-free. Class T includes those studied images displaying more than 50% of mouse burrow holes. Class F includes those studied images displaying less than 50% of holes. Based on this classification, 86 images fell in class T and the remaining ones in class F.

Color features

Red, green, blue, and gray surfaces were extracted from any images (figure 2). Next, ten features were extracted from intensity (quantity) of pixels of different colored image surfaces, which included means, standard deviations, root square means, acuteness coefficient, variance, harmonic means, dispersion coefficient, skewness, slip, and kurtosis. Forty color features were extracted from each image. As shown in figure 2, images of red, green, blue, and gray surfaces are not very different; that is, color features provide us with no sufficient information about mouse holes.

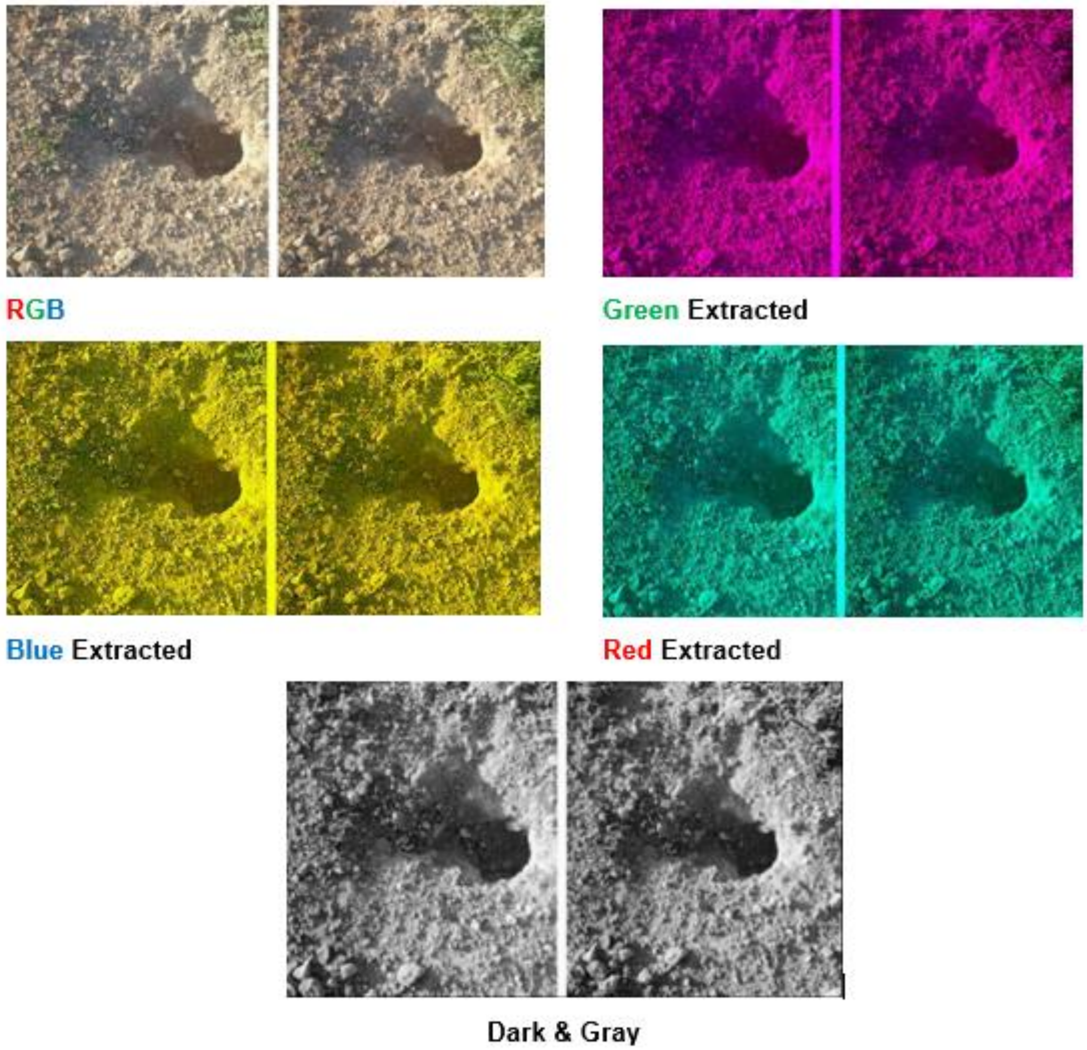

Figure 2. Image red, green, blue and gray surfaces

Texture Features

Q indicates spatial locations of 2 pixels relative to each other, and f is an image with an intensity level of L. Then co-occurrence matrix is one whose element gij denotes how many times a pair of pixels with the intensity of zi and zj lies on the position indicated by Q on image f. The size of matrix G is determined by the number of possible intensity levels on the image. For an 8-bit image, the size of G is equal to 256*256. Texture intensity patterns can be identified by using this matrix and selecting appropriate situational operators. To this end, 11 features from the co-occurrence matrix were extracted from images at angles of 0°, 45°, 90° and 135° with the distance of unity. Features such as probability maximum, correlations, contrast, uniformity, entropy, homogeneity, dissimilarity, means on axes X and Y, cluster shadow, and cluster nodes [23]. Forty-four texture features were extracted from each image.

Support-Vector Machines (SVMs)

Support-vector machines (SVMs) are among supervised classification methods, which predict one sample falls in which class. SVMs separate two classes directly via an optimization process using all bands constituting inter-classes following educational data, determining optimal decision borderline (hyperplane), and separating surface. Therefore the hyperplane is at the most distance to both classes on any side. The closest educational cases to this level are called support vectors [24].

Once top features have been selected, they were used to train SVM on the identification of mouse holes. The performance of SVMs depends on many such factors as multi-class methods, kernel types, penalty parameters, and selected kernel parameters [25]. The present research evaluated the effects of kernel breadth (σ) on the accuracy of classification.

Research Method

84 color and texture features were extracted from images divided into two classes T and F. Seventy percent of data were employed to educate SVM and to remain 30% to test it. After the images in both classes, T and F, were sufficiently accurately separated by SVM used, a program was written by

MATLAB software in order to separate images of both classes T and F. The general diagram of the program is shown by figure 3.

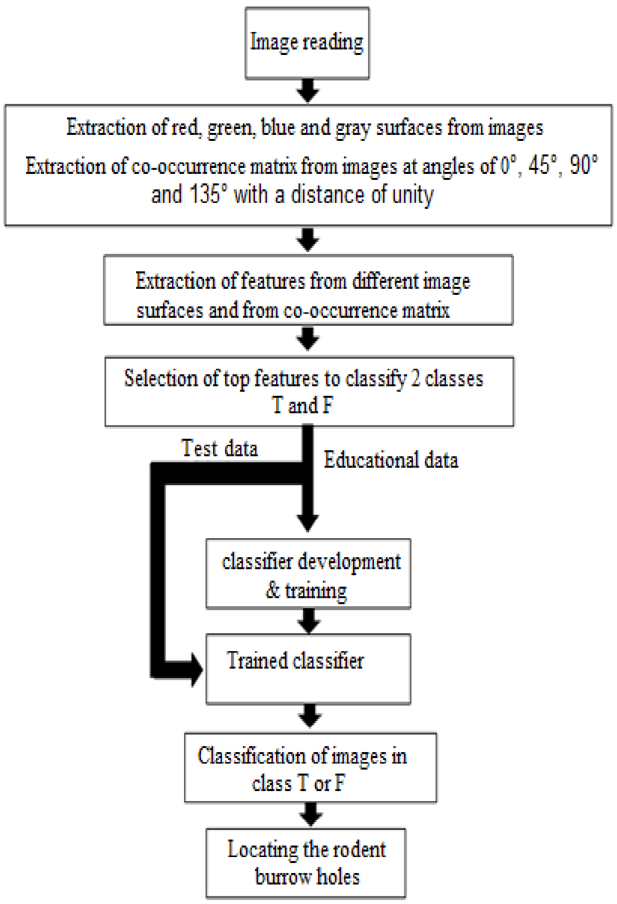

Figure 3. General diagram of the program detecting locations of mouse burrow holes

After the classifier of SVM was educated, the respective program was linked to the supplementary one of locating the holes, the generic algorithm of which is provided by figure 4. Given that 2000 images were obtained along the length of the lot studied, the algorithm in figure 4 was implemented in the form of one loop for all 2000 images. Any of the images placed by the classifier in class T took a number (i) indicating, based on Eq.1, that how far (in m) the image is from the ground borderline (since 2000 images were acquired along the studied lot 100m long, each image indicates 5cm).

Eq.1 can be solved by standard non-linear programming, the result of which is expressed as a linear combination of educational vectors.

$$X = 5i \qquad (1)$$

Where

i= image number

X= distance of each hole to the ground borderline (cm)

On the other hand, since the diameter of mouse burrow holes was 12.5 cm, each hole displayed itself on 3 to 4 images during filming. However, the program was written in such a way that it selected one as showing the location of the mouse hole from images with a difference of less than 5 in their numbers (i).

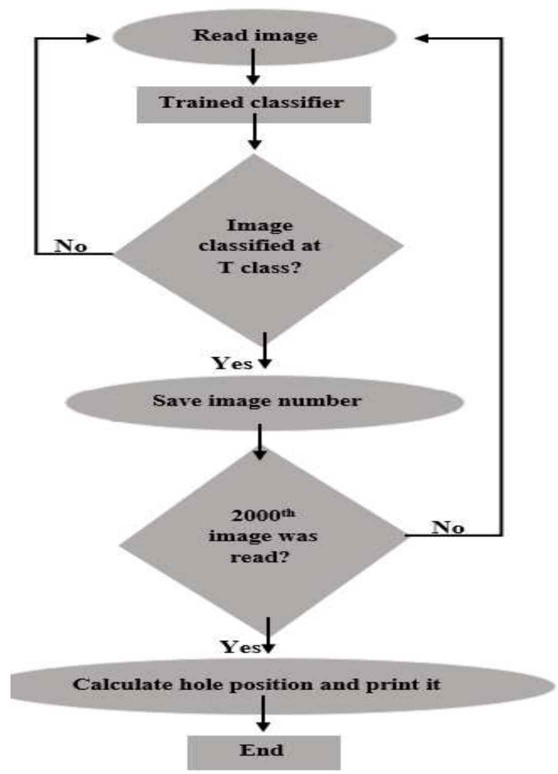

Figure 4. The algorithm implemented to locate mouse burrow holes

The supplementary algorithm shown in fig.4 identified the location of each burrow hole by linking to the trained classifier. In other words, the ultimate accuracy of the method proposed in the present research is the same as that of SVM used to separate images into class F and class T.

Results and Discussion

Results of data mining

Each image shows eighty-four statistical features. Since not all features contained beneficial information, it was essential to select top ones and consider them as inputs to the classifier. Therefore, the correlation-based feature selection (CFS) method was employed, which is one of the most important techniques of feature selection by Weka software. Figure 5 shows the results for feature selection. Out of 84 features extracted from images, 17 were selected as top ones, 16 of which were related to the texture or co-occurrence matrix, and one related to colors. Results presented in this section showed that the co-occurrence matrix contained useful information to classify images into class T and class F.

```
=== Attribute Selection on all input data ===
Search Method:
        Attribute ranking.
Attribute Evaluator (supervised, Class (nominal): 85 CLASS)
        Information Gain Ranking Filter
        Ranked attributes:
         1          55 C-45-F4
         1          56 C-45-F5
         1          54 C-45-F3
         1          74 C-135-F1
         1          59 C-45-F8
         1          67 C-90-F5
         1          46 C-0-F6
         1          45 C-0-F5
         1          70 C-90-F8
         1          50 C-0-F10
         1          81 C-135-F8
         1          48 C-0-F8
         1          49 C-0-F9
         1          53 C-45-F2
         1          10 R-F10
         1          47 C-0-F7
         1          78 C-135-F5
```

Figure 5. Top features used to classify two classes T and F

Classification

Table 1 shows the results from classification by SVM of 2 classes T and F for different values of kernel breadth. Of selected features, 70% and 30% were used to train and test, respectively, SVM employed. Results showed that the maximum accuracy of classifier was obtained for Kernel breadth of 0.1, which was 99.07% for educational data and 96.50% for test data.

Table 1. Accuracy of SVM for classifying images in class T and class F

Kernel breadth (σ)	Education/ training	Test
0.1	99.07`	96.5
0.2	90.93	91
0.3	87.71	84.33
0.4	84.57	82.67
0.5	86.93	83.67
0.6	78.14	68.5
0.7	82.43	79.33
0.8	70.43	75.17
0.9	65.5	64.83
1	59.14	57.83

Table 2 presents the confusion matrix resulting from training and testing SVM employed to classify two classes T and F. There were 86 and 1914 pieces of data for class T and class F, respectively, 70% of which was used to train SVM and 30% to test it. Examination of Table 2 indicates that the accuracy of SVM to distinguish class T from class F was 93.33% for educational data and 96.15% for test data.

Table 2. Classifier confusion matrix for the classification of images into two classes T and F

	Education data			Test data	
	T	F		T	F
T	25	1	T	56	4
F	20	554	F	9	1331

Results suggested high accuracy and reliability of classifier in distinguishing the images in class T from those in class F. Total accuracy of proposed method regarding the identification of hole locations was 96.15% so that suggested algorithm could detect accurately 25/26 of images selected to perform the test on the given day.

Conclusions

In the present research, an algorithm was provided to locate mouse burrow holes in the soil by using combined aerial image processing and SVM method. Some features related to the color and texture domains were extracted from images taken, from which top ones containing useful information for the classification were selected. The SVM used to classify images was of a radial base Kernel model. In this research, some evaluation was carried out on the effects of variations of the Kernel breadth parameter on the classifier accuracy. Results indicated a decrease in the classifier accuracy with an increase in the Kernel breadth. Finally, results showed that the proposed method could detect exact locations of holes with a 96.1% accuracy. It is recommended that integrated visible-thermal filming and a quadcopter equipped with GPS be used to film in order to improve the results from present research.

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