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Study of the similarity and recognition between volatiles of brown rice plant hoppers and rice stem based on the electronic nose

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ABSTRACT

The volatiles of Brown rice plant hopper (BRPH) itself is an important evidence for BRPH electronic nose detection. However, during infestation, BRPH always sucks the juice from the rice stem, therefore, a study on the similarity between BRPH's volatiles and undamaged rice stem volatiles might help determine whether the volatile contents of BRPH would be influenced by the sucking of the rice stem juice. If so, recognizing BRPH from rice stem should be a crucial step to reduce the misjudgment of BRPH occurrence prediction by using electronic nose, which has not been reported until now. This paper used an electronic nose (PEN3) sample of the volatile of U3IN (under the 3th-instar nymphs), O3IN (over the 3th-instar nymphs) and healthy rice stem. Hierarchical clustering analysis (HCA), Loading analysis (Loadings), principal component analysis (PCA), k-nearest neighbor (KNN), probabilistic neural network (PNN), and support vector machine (SVM) were used for data analysis. HCA, Loadings, and PCA results proved that certain similarities exist between volatiles of rice stem and BRPH, Loadings and PCA results also indicated the volatile similarity between O3IN and rice stem is stronger than the volatile similarity between U3IN and rice stem. To reduce the redundant information and improve computation efficiency, according to Loadings and PCA results, sensor R5 of electronic nose has been be removed, then, the fist four principle components has been kept as the feature values. KNN, PNN and SVM all can recognize rice stem, O3IN, and U3IN effectively, however, KNN and PNN are more fit to solve the problem of rice stem and BRHP recognition than SVM. This experiment results proved that certain similarities exist between volatiles of rice stem and BRPH, also figured out the feasible way to recognize rice stem and BRPH, which could provide a reference for further research of BRPH prediction.

1. Introduction

Rice is an important food crop in China, as it constitutes the staple diet of approximately 65% of the total population (Xin and Li, 2009). Biohazards are one of the main factors that influence the stable and high rice yields. Despite insect pest control and treatment, still 4–5 billion tons of rice grain might be damaged by biohazards every year in China (Wang, 2006). The brown rice plant hopper (BRPH), *Nilaparvata lugens* (hemiptera: delphacidae), is one of the main insect pests in Asia's rice-growing area, and it migrates with monsoon (Gao et al., 2006). The prevention and amelioration of BRPH have become a research hotspot and posed a challenge for experts. The abuse of chemical pesticides in many countries since the 1960s has caused damage to the ecological system and weakened the natural restriction factors such as the natural enemies of BRPH, therefore, causing improved conditions for BRPH to thrive and have accelerated outbreaks (Wang and Wang, 2007). So far, chemical pesticide spraying is still the primary control method for BRPH.

The accurate acquisition of pest information can improve the efficiency of pest prevention and treatment effectively. Pest information can not only help predict pest occurrence and its control in the first stage but also decide the quantity of pesticide to be sprayed, which improves the service efficiency of the pesticide and protects the natural restriction factors of insect pests. Many BRPH information acquisition methods are currently available including the manual work detection method (Qi et al., 1995), the acoustical signal detection method (Butlin,

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1993; Claridge and Morgan, 1993), the radar observation method (Riley et al., 1991), the image recognition method (Shariff et al., 2006), and the near-infrared spectroscopy method (Yang et al., 2007). The manual work detection method mainly involves using people's senses to detect pest information artificially, however, it has some limitations such as high detection cost, low detection efficiency, massive labor intensity and sampling influence. The machine detection methods such as acoustical signal detection method, radar observation method, image recognition method and near-infrared spectroscopy method can reduce labor intensity to some extent. However, the field environment is complex, noise, illumination, pest mobility and masking are among the factors affecting detection efficiency. Thus, all detection methods above cannot meet the practical production requirements.

Electronic nose, namely smell scanner, was first suggested by Persanand and Dodd at the Warwick University in England (Yan et al., 2010). The special sensor array and pattern recognition system in the electronic nose can acquire sample information quickly and analyze sampling data in real time after modeling (Huang and Tian, 1999). The detection principle of electronic nose was as follows: when volatile compounds contacted the active material of the sensor, it created a transient response (a series of physical and chemical changes occur). This response from the voltage signal translated into the figure signal via an interface circuit, which was then recorded via a computer and sent to a signal processing unit for analysis. Afterwards, a comparison was made with a large number of volatile compounds information in a database that could compare and identify the type of volatiles (Jia et al., 2006). The electronic nose works without solvent, allows a quick analytical response, and is easy to carry. It is also a labor force saving and objective detection method compare with manual work detection method, and barely influenced by noise, illumination, pest mobility and masking which affect other machine detection methods a lot. Currently, the electronic nose is extensively used for many applicative purposes such as environmental monitoring (Baby et al., 2000; Staples and Viswanathan, 2006), food quality detection (Saevels et al., 2004; Zheng et al., 2009), medical treatment and health (Fend et al., 2006; Turner and Magan, 2004), and plant pests and diseases monitoring (Ghaffari et al., 2012; Lampson et al., 2014). This innovative technique may provide a new method for BRPH information acquisition. In 2005, Ye and Hu used an electronic nose (PEN2) to detect the volatile blends in paddy rice and classify the volatile odors of BRPHs. The experiment indicates that the best opportunity for detecting pest information using an electronic nose is from 15 to 36 h after pest damage, demonstrating that electronic noses are an efficient method to obtain rice pest information (Ye and Hu, 2005). In 2006, Hu detected BRPH information based on the obtained electronic nose sensor array data. The feature parameters from each sensor curve, such as maximum, max differential value, the mean value and stable value, were extracted and used for pattern recognition input; principal component analysis (PCA) was adopted to analyze the test sample. The experiments revealed that the electronic nose was able to detect whether rice plants were attacked by insect pests, the extent of rice damage and the amount of pests on each stem of paddy rice (Hu, 2006). Zhou and Wang used an electronic nose (PEN2) to discriminate between the volatile profiles emitted by uninjured rice plants and rice plants exposed to different numbers of BRPH adults. The results indicated that it was possible to separate differently treated rice plants using electronic nose signals, and the electronic nose technology was an effective insect monitoring method (Zhou and Wang, 2011a). In 2011, Zhou and Wang used an electronic nose (PEN2) to analyze rice plants that were subjected to different types of treatments causing damage, including damage caused by the rice Striped Stem Borer, damage caused by the BRPH, mechanical damage, and the results were compared with those of undamaged control plants. The results indicated that e-nose could successfully discriminate among rice plants with different types of damage (Zhou and Wang, 2011b). The volatiles of BRPH itself is an important evidence for BRPH electronic nose detection. However, during infestation, BRPH always pierces into the vascular tissue of rice stem and sucks the juice from the rice plant by its stylet (Huang and Feng, 1993). Therefore, a study on the similarity between BRPH's volatiles and undamaged rice stem volatiles might help determine whether the volatile contents of BRPH would be influenced by the sucking of the rice stem juice. If so, recognizing BRPH from rice stem should be a crucial step to reduce the misjudgment of BRPH occurrence prediction by using electronic nose, which has not been reported until now.

This paper used electronic nose technology for BRPH and rice stem (the same variety on which the experimental BRPH had been feeding) sampling. Then, we used hierarchical clustering analysis (HCA), Loading analysis (Loadings), principal component analysis (PCA), k-nearest neighbor (KNN), probabilistic neural network (PNN), and support vector machine (SVM) for data analysis. Our study will provide a reference for further research of BRPH detection.

2. Materials and methods

2.1. Experimental materials

All the experimental BRPHs and Rice plants were provided by the Institute of Plant Protection of the Academy of Agricultural Sciences in Guangzhou, Guangdong province, China. Overall, 6 identical plastic buckets were used for the control cultivation of rice seedlings (Meixiangzhan) under same growth condition. Six rice seedlings were planted in each bucket. To ensure good growing conditions, rice plants were grown in a pest-free outdoor environment with sufficient sunlight. After all of the rice seedlings grew to the tillering stage, 3 buckets were moved to a rearing cage for BRPH feeding and the others were moved to a pest-free rearing cage. On the BRPH feeding cage, 10 at least the third generation adult BRPH individuals (always fed by Meixiangzhan rice plant) were added to each bucked, the next generation BRPH was used for experiment, 30 of BRPH nymph individuals under third instar (U3IN) and over third instar (O3IN) was determined.

2.2. Sampling methods

This experiment was performed using the electronic nose (PEN3, Airsense Analytics GmbH). This electronic nose system sampling by its 10 metal oxide semiconductor gas sensors, the performances of sensors in PEN3 are listed in Table 1. The output signal of each sensor is G/G_0. G_0 represents the electronic conductivity (resistance) of sensor during the zero gas (ambient air after filtered by activated carbon) detection, and G represents the electronic conductivity (resistance) of sensor during the sample gas detection. To make electronic nose achieve the operating temperature, we warmed it up for 10 s before sampling. The working parameter settings were as follows: sampling interval was 1 s;

Table 1
Response features of the sensors in electronic nose (PEN3).

Number in array	Sensor name	Object substances for sensing	Threshold Value ($mL \cdot m^{-3}$)
R1	W1C	Aromatics	10
R2	W5S	Nitrogen oxides	1
R3	W3C	Ammonia and aromatic molecules	10
R4	W6S	Hydrogen	100
R5	W5C	Methane, propane and aliphatic non-polar molecules	1
R6	W1S	Broad methane	100
R7	W1W	Sulfur-containing organics	1
R8	W2S	Broad alcohols	100
R9	W2W	Aromatics, sulfur-and chlorine-containing organics	1
R10	W3S	Methane and aliphatics	10