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Identification of baled materials through capacitive sensing and data driven modelling

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ABSTRACT

Recycle and reuse of waste materials are important measures in achieving circular economy, reducing resource waste, and protecting environment. However, current recycling rate is low and a key issue causing low recycling rate is the uncertainty in the quality of baled materials. In this study, a new method based on a capacitive sensor and a data driven model is proposed for identifying baled materials. A novel capacitive sensor with satisfactory sensitivity and sensitivity distribution is designed for this purpose using finite element method. The transmitter and receiver units as well as advanced signal conditioning circuit are developed. To achieve automated identification of the baled materials based on the sensor outputs, the support vector machine algorithm is used. To verify the proposed method, experiments were carried out to measure different baled materials. Experimental results suggest that the proposed method is able to successfully identify these baled materials with satisfactory accuracy.

1. Introduction

Currently, around millions of tonnes of plastic waste are generated worldwide every year [1]. To reduce environmental impact and resource depletion, recycle and reuse are the main waste-management strategies to deal with plastics. However, the current recycling rate is low due to the uncertainty in the quality of recycled plastic bales. The baled material to be recycled may be mixed with bales with other materials, making effective recycling difficult. Therefore, material identification and quality assessment of baled materials is essential to enhance the recycle and reuse of waste materials.

The existing approach for examining baled materials is core sampling, where samples are extracted using a specialised drill and their characteristics are analysed off line. However, this method is time-consuming to obtain material compositions and lacks accuracy when the tested samples are not truly representative. Hence, there is a pressing need for an automated and non-destructive inspection technology to identify and quantify material types in baled materials. A range of methods, including X-ray [2], ultrasound [3], microwave [4], near infrared spectroscopy [5], hyperspectral imaging [6] and capacitive sensing [7,8], have been investigated for sorting different materials. However, all such methods are not developed towards baled materials and have various limitations. The X-rays are considered as being environmentally hazardous with regards to radiation protection and high energy consumption, in addition to high capital cost and administratively inconvenience. When using the ultrasound method, the acoustic properties and reflective behavior are influenced by multiple factors. The microwave method is usually expensive and it is difficult to develop their hardware. The near infrared spectroscopy and hyperspectral imaging have low penetration depth which limits their application in the material identification within bales. The existing capacitive sensors also have low penetration depth because of their structures, which make them unsuitable for identifying baled materials. Due to the advantages of rapid response, low cost, and design flexibility offered by the capacitive method [9,10], designing a new capacitive sensor that meets the measurement requirement for baled materials can provide an economical and effective method for identifying baled materials.

In this study, a new method based on a capacitive sensor and a data driven model is proposed to realize identification of baled materials for the first time. The sensor configuration is optimised and designed using finite element method. The transmitter and receiver units as well as advanced signal conditioning circuit are developed. To achieve automated identification of the baled materials based on the sensor outputs, the support vector machine (SVM) algorithm is used as this algorithm has several advantages including wide applicability, strong generalization ability, and suitability for modelling with a small dataset [11,12]. Experiments were carried out to measure different bales made from plastic foam, paper, cardboard, polyethylene terephthalate (PET), wood chip, sand, and mixed materials, respectively. Experimental results suggest that the sensor is able to differentiate these bales based on the measured capacitance and the SVM algorithm can realize automated identification of the baled materials. This outcome provides a new approach to the automated and non-destructive identification of baled materials, which contributes to the recycle and reuse of waste materials.

2. Methodology

2.1. Sensor system

In this study, a capacitive sensor consisting of two measurement channels is proposed. As shown in Fig. 1 (a), the sensor has two identical square transmitter units and two identical square receiver units. They are installed around the conveyor belt which transports the bales. Each transmitter unit and its corresponding receiver unit form a measurement

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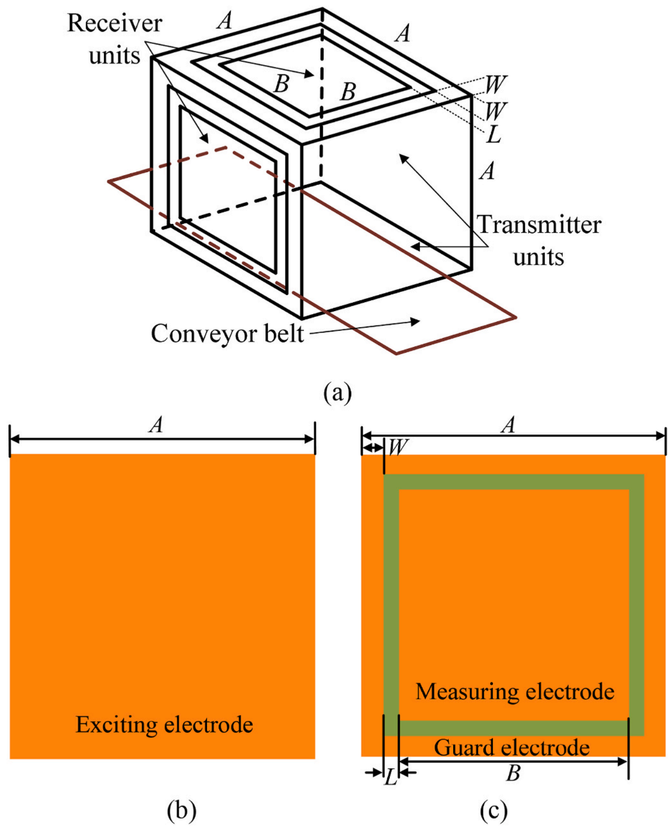

Fig. 1. (a) Structure of the capacitive sensor; (b) Front of the transmitter unit; (c) Front of the receiver unit.

channel, and thus the sensor has two measurement channels. The front of the transmitter unit, as shown in Fig. 1 (b), is an exciting electrode and a ground plane at the back. The exciting electrode and the ground plane are arranged on both sides of the rectangular substrate with the thickness of 1.6 mm and side length A. As shown in Fig. 1 (c), the front of the receiver unit consists of a measuring electrode with side length B and a guard electrode. The back of the receiver unit is a ground plane with side length A. The guard electrode surrounds the exciting electrode and they are on the same side of the substrate. The width of the guard electrode is W and the spacing between the exciting electrode and the guard electrode is L. The ground planes arranged at the back of the transmitter units and receiver units form a shielding layer, and the guard electrode surrounding the exciting electrode is used to reduce the fringe field effect. To design a capacitive sensor with high sensitivity and uniform sensitivity distribution, parameters A, B, W and L should be optimised and determined.

Considering the dimensions of the baled materials to be tested in this study, the side length of the measuring electrode B is set to range from 85 mm to 110 mm with a step size of 5 mm, the width of the guard electrode W from 3 mm to 13 mm with a step size of 2 mm, and the spacing between the exciting electrode and the guard electrode L from 1 mm to 6 mm with a step size of 1 mm. Once B, W and L are optimised, A is determined as well. The finite element method is applied to optimise and determine these parameters. To evaluate the optimisation result of the sensor configuration, two parameters which are average sensitivity $\overline{S}$ and non-uniformity index SVP are considered. $\overline{S}$ and SVP are defined as [13]

$$\overline{S} = \frac{1}{M}\sum_{k=1}^{M} S_{i,j}(k) \tag{1}$$

$$SVP = \frac{\left(\frac{1}{M}\sum_{k=1}^{M}\left(S_{i,j}(k)-\overline{S}\right)^2\right)^{\frac{1}{2}}}{\overline{S}} \tag{2}$$

where $S_{i,j}(k)$ is the sensitivity of the kth element at point (x, y, z) in region P (x, y, z) and M is the number of the elements. $S_{i,j}(k)$ is defined according to [14]

$$S_{i,j}(k) = -\int_{P(x,y,z)} \frac{E_i(x,y,z)E_j(x,y,z)}{U_0^2}\mathrm{d}x\mathrm{d}y\mathrm{d}z \tag{3}$$

where $E_i\,(x, y, \mathrm{z})$ is the electrical field strength when electrode i is excited by voltage U_0 and $E_j\,(x, y, \mathrm{z})$ is the electrical field strength when electrode j is excited. In general, higher sensitivity of the sensor results in larger $\overline{S}$. The more uniform the sensitivity distribution, the smaller SVP is. To determine optimal B, W and L, both average sensitivity $\overline{S}$ and non-uniformity index SVP are calculated and considered in this study.

From Fig. 2 (a) we can see that with the increase of L, both $\overline{S}$ and SVP decreases. These results mean that when the spacing L between the exciting electrode and the guard electrode increases, the sensitivity of the sensor decreases and the uniformity of the sensitivity increases. In this study, the sensitivity is the primary factor we consider because the differences in the permittivity of different materials are small in some cases, which require a sensor with high sensitivity to identify these materials. Therefore, the value of L is determined as 1 mm. In Fig. 2 (b), the effects of W on $\overline{S}$ and SVP are investigated. With the increase of W, both $\overline{S}$ and SVP decrease. This suggests that when the width W of the guard electrode increases, the sensitivity of the sensor decreases while the uniformity of the sensitivity increases. To design a sensor with high sensitivity and satisfactory uniformity, W is determined as 3 mm. Fig. 2 (c) shows the influences of B on $\overline{S}$ and SVP. With the increase of B, both $\overline{S}$ and SVP decrease. These results demonstrate that when the side length B of the measuring electrode increases, the sensitivity decreases while the uniformity of the sensitivity increases. To keep high sensitivity of the sensor with acceptable uniformity of the sensitivity, B is determined as 85 mm. Finally, the parameters A, B, W and L are determined as 93 mm, 85mm, 3 mm and 1 mm, respectively. Based on the optimised configuration, the transmitter units and the receiver units are fabricated on printed circuit boards (PCBs) and the developed capacitive sensor is shown in Fig. 3.

To measure the capacitances which are usually in small values, an AC-based capacitance measuring circuit is designed for the capacitive sensor. This circuit can achieve fast response, high signal-to-noise ratio and stray capacitance immunity [15]. The circuit diagram of the sensor system is shown in Fig. 4. The exciting electrodes of the transmitter units are excited by the sinusoidal signal V_s. The measuring electrodes of the receiver units are connected to the capacitance-to-voltage (C/V) module and the resulting output voltage V_c is defined as [15].

$$V_c = -V_s\left(\frac{\mathrm{j}\omega C_m R_f}{1+\mathrm{j}\omega C_f R_f}\right) \tag{4}$$

where C_m is the measured capacitance, and R_f and C_f are the values of the resistor and capacitor in the C/V module, respectively. An amplifier is used to amplify the voltage V_c and the amplified signal V_a with amplitude of A and phase of φ_1 is fed into the demodulation module which is a multiplier. The other input of the multiplier is the signal V_p with amplitude of B and phase of φ_2 from the phase shifter. Therefore, the output V_m of the multiplier is described as

$$\begin{aligned} V_m &= V_a V_p = A\sin(\omega t+\varphi_1)B\sin(\omega t+\varphi_2) \\ &= \frac{1}{2}AB[\cos(\varphi_1-\varphi_2)-\cos(2\omega t+\varphi_1+\varphi_2)] \end{aligned} \tag{5}$$

Afterwards, a low-pass filter is designed to eliminate high-frequency components from V_m, and the remain part V_o, as shown in equation (6),

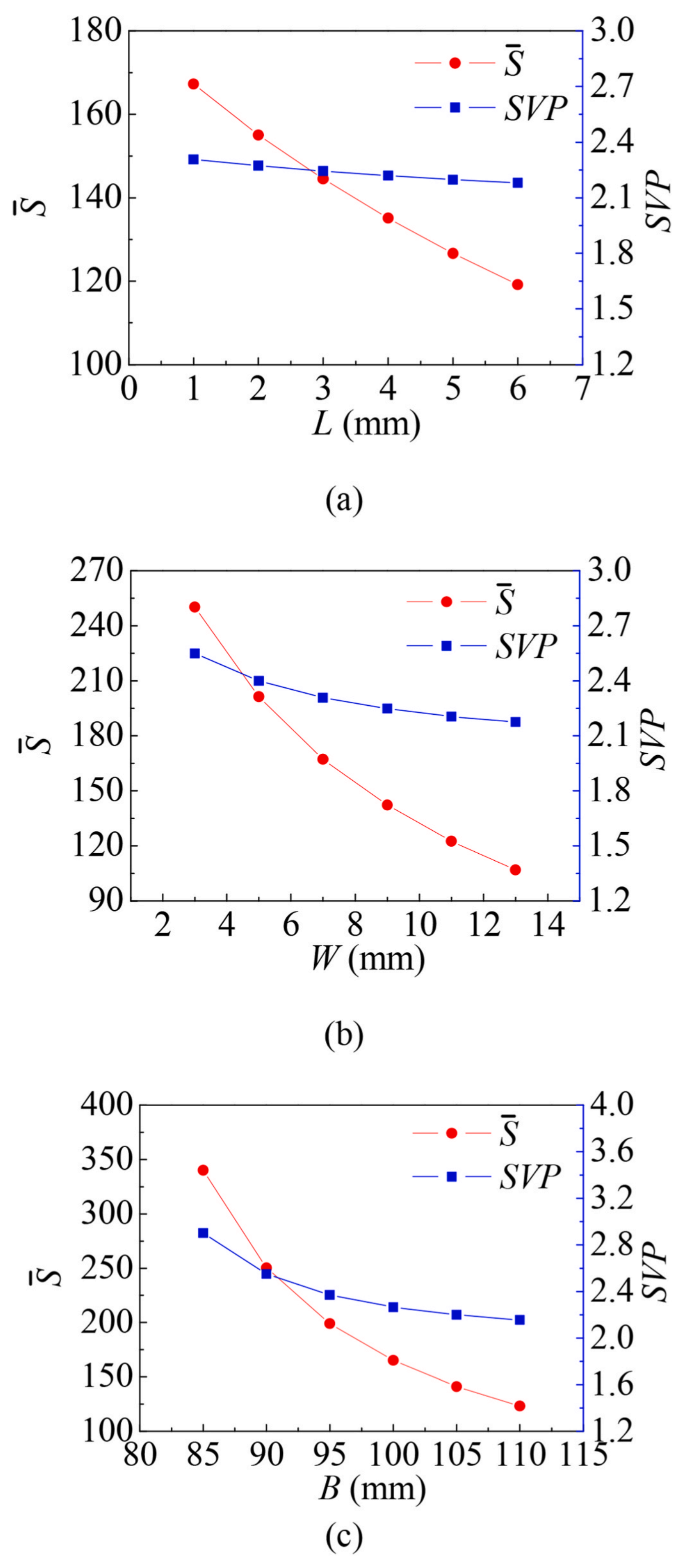

Fig. 2. $\bar{S}$ and SVP with the change of (a) L; (b) W; (c) B.

reflects the measured capacitance.

$$V_o = \frac{1}{2} AB \cos(\varphi_1 - \varphi_2) \tag{6}$$

The phase shifter can adjust the phase φ_2 to be equal to φ_1 which makes the V_o larger. Since the measured capacitance depends on the permittivity, the sensor output V_o has relationship F with the permittivity.

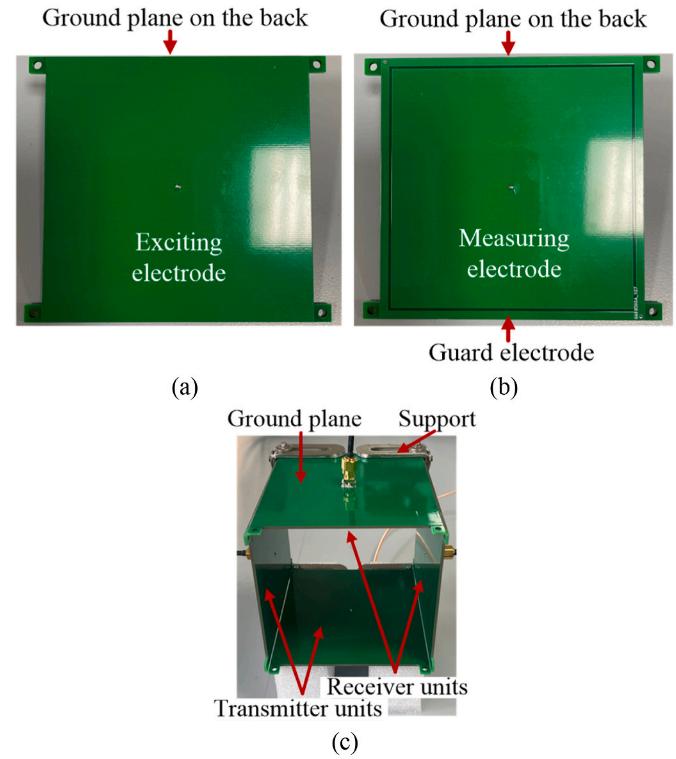

Fig. 3. (a) Transmitter unit; (b) Receiver unit; (c) Capacitive sensor.

$$\mathbf{V_o} = \mathbf{F}\,(\boldsymbol{\varepsilon}_\mathbf{m}) \tag{7}$$

The sensor has two-channel outputs which reflect the permittivity of the baled materials, and they are used for identifying the baled materials.

2.2. Data driven modelling

To achieve automated identification of the baled materials based on the sensor outputs, the SVM algorithm is adopted. Utilizing statistical learning theory and the concept of structural risk minimization, SVMs have the capability to address classification problems [11]. SVM is a powerful supervised learning model that excels in classification tasks by finding the optimal hyperplane that separates different classes in the feature space. X= (x_1, x_2, …,x_n) is the training samples and each sample is a vector x=(x_1, x_2, …,x_n). $\phi(\mathrm{x})$ is a transfer function that maps the input vectors into an L-dimensional feature space. $\frac{2}{\|\omega\|}$ is the distance between two different classes in the feature space. To minimize the training error ξ_i and maximize the separating margin is equivalent to [16,17]

$$\begin{gathered} \min \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}\xi_i \\ s.t. \begin{cases} y_i(\langle \omega, \phi(\mathrm{x}_i)\rangle + b) \geq 1 - \xi_i \\ \xi_i \geq 0 \end{cases} \end{gathered} \tag{8}$$

where C is user-specified parameter and ξ_i is the slack variable. According to the Karush-Kuhn-Tucker (KKT) theorem, the problem is tantamount to solving the subsequent dual problem:

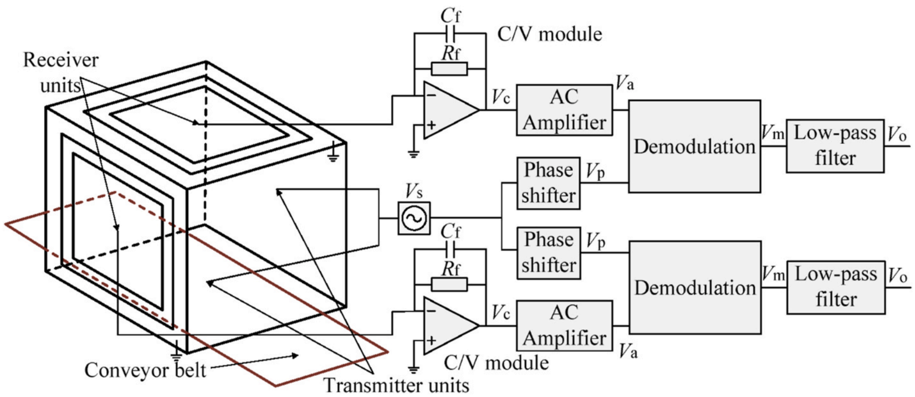

Fig. 4. Circuit diagram of sensor system.

$$\min \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} y_i y_j a_i a_j \langle \phi(\mathrm{x}_i), \phi(\mathrm{x}_j) \rangle - \sum_{i=1}^{n} a_i$$

$$s.t. \begin{cases} \sum_{i=1}^{n} y_i a_i = 0 \\ 0 \le a_i \le C \end{cases} \tag{9}$$

In the equation, each Lagrange multiplier α_i is associated with a training sample (x_i, y_i) and $K(\mathrm{x}_i, \mathrm{x}_j) = \langle \phi(\mathrm{x}_i), \phi(\mathrm{x}_j) \rangle$ is a kernel function. The optional kernel functions for SVM are linear kernel function, polynomial kernel function, RBF kernel function and the sigmoid kernel function. The decision function of the SVM is formulated as

$$y = f(\mathrm{x}) = \mathrm{sign}\left(\sum_{i=1}^{n} a_i y_i K(\mathrm{x}_i, \mathrm{x}_j) + b\right) \tag{10}$$

Fig. 5 shows the structure of the data-driven model. In this study, the input of the data-driven model includes the voltage output of channel 1 and the voltage output of channel 2, and the output of the model is the type of bale.

3. Experimental tests and results

3.1. Experimental tests

To verify the proposed method, experiments were carried out to measure baled materials using the developed capacitive sensor. In this study, different types of baled materials including plastic foam, paper, cardboard, PET, wood chip, sand, the mixture of paper and plastic foam, and the mixture of cardboard and wood chip were tested. The materials are filled into a thin-walled plastic boxes with side length of 80 mm and taken as a bale. The sensor system is shown in Fig. 6 (a) and baled materials to be tested are presented in Fig. 6 (b). Channel 1 of the sensor system measures the capacitance using the bottom and top electrodes, while channel 2 uses the left and right electrodes. By placing the baled materials into the sensing area, the capacitance between the exciting electrode and measuring electrode of each channel is converted into a voltage signal by the hardware. The voltage outputs of the sensor reflect the capacitance of the bale being measured.

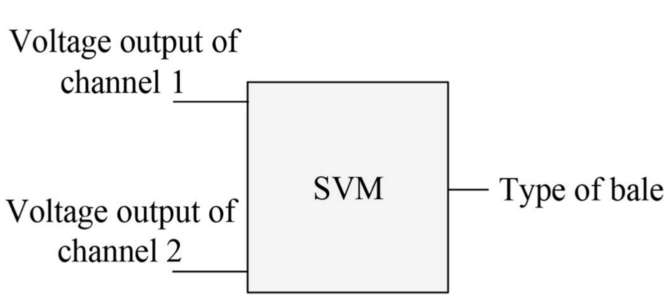

Fig. 5. Structure of the data-driven model.

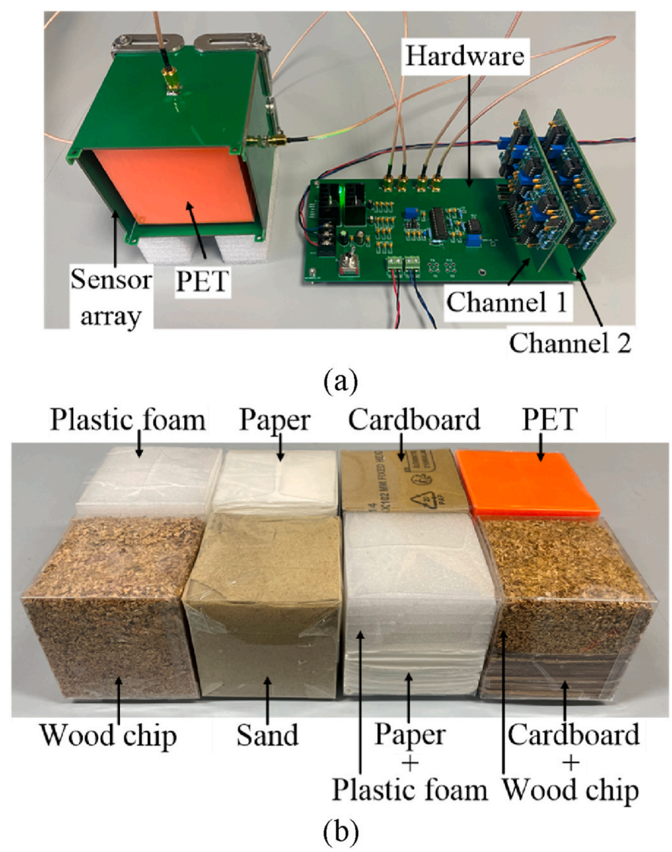

Fig. 6. (a) Sensor system; (b) Different baled materials.

3.2. Results and discussion

The baled materials shown in Fig. 6 (b) are measured by channel 1 of the sensor from bottom to top and by channel 2 from left to right, and the dual-channel voltage outputs of the sensor are shown in Fig. 7. In addition, the voltage outputs in the case of only air inside the sensing area are also given in Fig. 7. As air has lowest permittivity compared with the materials under test, the voltage outputs of both channels are the smallest (less than 4.4 V). With the increase of the permittivity, the voltage outputs of the sensor increase. Compared with other baled materials, plastic foam has lowest voltage outputs because of its small permittivity and sparse material distribution. While, sand has the largest

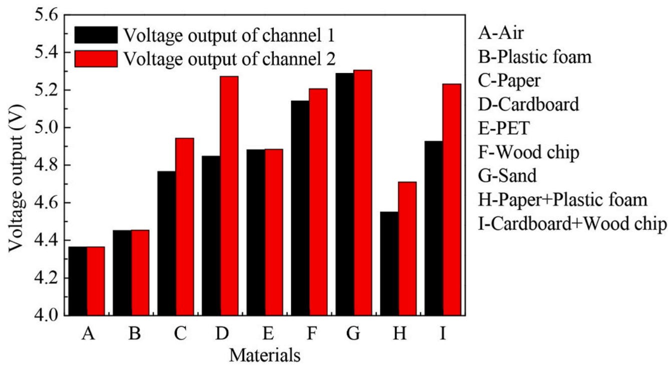

Fig. 7. Dual-channel voltage outputs of the sensor when measuring the bales with different materials.

voltage outputs due to its large permittivity and dense material distribution. For the bale with paper and plastic foam, the voltage outputs fall between the sensor outputs of the paper bale and plastic foam bale. For the bale with cardboard and wood chip, the voltage outputs fall between the sensor outputs of the cardboard bale and the wood chip bale. These results indicate the effectiveness of the sensor system.

For the same material, the voltage outputs of two channels are almost the same when measuring plastic foam, PET, and sand. This is because the distribution of these materials is relatively uniform. Therefore, the voltage outputs of two channels are similar though they are measured from two different directions. However, for the baled paper, cardboard, wood chip, mixture of paper and plastic foam, and mixture of cardboard and wood chip, the voltage outputs of two channels are different. This is because the distribution of these materials is relatively non-uniform. Due to dual-channel measurements, the dual-channel voltage outputs also contain the information of the material distribution. Based on the dual-channel voltage outputs, it is capable of differentiating the bales with different materials.

The SVM algorithm is used to achieve automated identification of the baled materials based on the sensor outputs. As shown in Fig. 7 that the voltage outputs of channel 1 and the voltage outputs of channel 2 are different when the different baled materials are measured. In this study, the voltage outputs of channel 1 and the voltage outputs of channel 2 are the input data, and the type of bale is the output. The baled material has 6 faces, and which faces correspond to the four faces of the sensor electrodes is unknown. For a bale with 6 faces, the bale and the sensor can have 24 different relative positions, resulting in 24 capacitance data from two channels. Repeated experiments were conducted in all 24 relative positions, and the sensor outputs are obtained. 80 % of the obtained dataset are used for training the model and the remaining 20 % of the obtained dataset are used for testing the model. The polynomial kernel function is used after comprehensive comparisons. The parameters named accuracy, precision, recall, F1-score, and support are used to evaluate the performance of this method. The accuracy is calculated as the ratio of the number of correct predictions to the total number of predictions made. The precision is the ratio of correctly predicted positive observations to the total predicted positives. It indicates the accuracy of the positive predictions. The recall measures the ratio of correctly predicted positive observations to all actual positives. It indicates the ability of model to find all the positive samples. The F1-score is the harmonic mean of precision and recall. The support is the number of actual occurrences of the type in the specified dataset. For each type of baled material, the precision, recall, F1-score and supports are shown in the Table 1.

This method can accurately identify the plastic foam, paper, PET, wood chip, sand, and mixture of paper and plastic foam, respectively. However, there were misclassifications for the cardboard and the mixture of cardboard and woodchip, leading to a decrease in precision, recall and F1-score. This can be attributed to the fact that the two-channel outputs of the sensor to these two kinds of baled materials are a little similar in some circumstances. The accuracy is 0.97 which means that the overall prediction accuracy is high and the baled materials can be accurately identified based on the proposed method.

Table 1
Classification results.

Type of baled material	Evaluation metrics			
	Precision	Recall	F1-score	Support
Plastic foam	1	1	1	10
Paper	1	1	1	12
Cardboard	1	0.80	0.89	10
PET	1	1	1	11
Woodchip	1	1	1	9
Sand	1	1	1	9
Paper + Plastic foam	1	1	1	8
Cardboard + Woodchip	0.80	1	0.89	8

4. Conclusions

In this study, a new method for identifying baled materials based on a capacitive sensor and a data driven model has been proposed for the first time. The capacitive sensor has been designed using finite element method to achieve satisfactory sensitivity and sensitivity distribution. An effective hardware of the sensor including transmitter and receiver units and signal conditioning circuit has been developed. Experimental results have demonstrated that the dual-channel voltage outputs of the sensor are both sensitive to the change of permittivity. For different baled materials, the voltage outputs of sensor presented differently due to their permittivity and material distribution. For the same material, the voltage outputs of two channels depend on the distribution of materials. In the case of the bales with uniform material distribution, the outputs of two channels are almost the same. For the bales with non-uniform distribution, an obvious difference is seen from the outputs of two channels. Based on the dual-channel voltage outputs, it is feasible to differentiate different baled materials. To achieve automated identification of the baled materials based on the sensor outputs, the SVM algorithm is adopted. By using the proposed method, the baled materials can be accurately identified. Future work will be conducted to investigate the proportions of different materials in a bale.

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