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A statistical pattern analysis approach for rapid coin identification based on Eddy-current sensors

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Abstract

We present an effective approach based on eddy-current sensors enabling rapid identification of different coin classes in this work. The employed Eddy-current sensing technique aims to detect the induced signals which are transponded back to the induction coil so that the system can promptly process the characteristic signals and recognize authenticity and classes of inspected coins. The training and identification program in this recognition system are developed by LabVIEW® interface and thus data accuracy can be secured. The experimental results have proven the proposed eddy-current sensing method an efficient way to rapidly identify authentic coins. It is found that the maximum identification rate can achieve 14 coins per second provided a coin feeding mechanism can be appropriately designed.

Keywords: Coin recognition; Eddy-current.

1. Introduction

Current automatic coin recognition approaches employed in vending and auto-ticketing machines (ATMs) use several different physical properties including coin diameter, thickness, weight, material,

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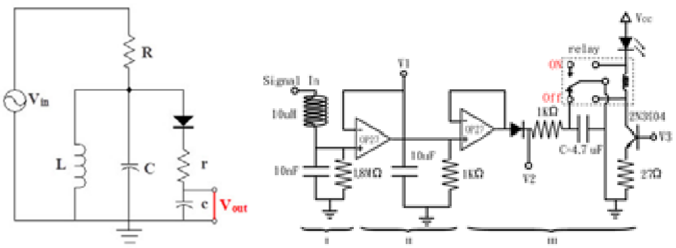
conductivity [1], magnetism [2], acoustics [3], and optical reflectivity. In addition, many systems also employ neural-like pattern recognition to identify coins which show the same image under a coin scanner. On the other hand, when the physical properties of coins are very similar such as diameter, weight and thickness, the coin sorter can barely reject the counterfeit coin. In practice, many vending machines only apply cheap sensors to coin detection and may induce fault identification. In this paper we intend to develop a method for rapid but reliable coin identification based on only Eddy-current sensors due to low-cost consideration, we aim to present an effective method based on low-cost Eddy-current sensors. We present a statistical pattern analysis approach for rapid coin identification including two Eddy-current sensors, resonance circuits, peak detection circuits, and a LabVIEW® instrument interface, to apply in a very fast coin classification module that will be embedded in the design of vast insertion of coins rather than traditionally one-by-one machines.

2. Experimental procedures

Figure 1 (a) shows the resonance circuit which is used to generate Eddy-current signal. When coin passes the Eddy-current sensors (coils), the inductance of sensor will change, resulting in the impedance variation of parallel inductance L and capacitance C. This will result in the output voltage (Vout in Figure 1 (a)), which is considered the characteristic voltage of coins. To find the best location of the recognition rate for these sensors, we refer to a 2D eddy-current signal map scanned from a 10-dollar coin and a forged token. The experimental result shows that the location with the largest signal difference of 2D eddy-current signal map between them appears at about 7 to 12.5 mm away from the center of the coin, and the distance from the sensor to the passing coin surface is 1 mm. We use two Eddy-current sensors located at both sides of coin to measure the diameter, thickness and material property of coins. The characteristic voltage of coin is acquired by NI DAQ-6008 and the voltage resolution is 0.01V in our module. Figure 1 (b) shows the peak detection circuits applied to process the input signal and recover the system. Whenever the coin passes the sensor 1 (located at the back side of coin feeding machine), the DAQ will output a 5V signal to V3 port (in part III) leading to ON state of relay. The high frequency noise of sensing signal will be filtered by the second-order low-pass filter (in part I). Afterwards the capacitance (in part III) will be charged by the buffer in part II and DAQ will read the characteristic voltage of the coin and send the voltage reading value to the coin identification program simultaneously. After that, DAQ will output a 0V signal to V3 leading to OFF state of relay discharging the capacitance in part III.



(a) (b)

Fig. 1. Schematics of (a) Resonance circuits; (b) peak detection circuits.

Each time the coin passes the two Eddy-current sensors will generate two characteristic voltage values of a coin's head-side and tail-side. Figure 2 shows the NI LabVIEW® interface of coin identification program. In voltage distribution map, we set X-axis as coordinate of sensor 2 (located at the front side of coin feeding machine) and Y-axis as coordinate of sensor 1. This map is built from a 900 x 900 matrix where the index of from 0 to 900 is corresponding to 0 - 9.00 V of sensing value. For example, the index 626 represents the sensing value of 6.26V. The value along the Z-axis (perpendicular to the paper) in the matrix represents the probability of matrix position where the voltage point may fall on. The currency we discuss here consists of NT 1-, 5-, 10-, 50-dollar coins and two tokens which are with same diameter as 10- and 50-dollar coins respectively (see Table 1). Considering two sides of the authentic coins, there are 8 coin cases (for 4 legal coins) of training process in our study. Therefore, each type of coins has its own characteristic voltage and the voltage distribution map is built by using the training process for ten thousand times for each case.

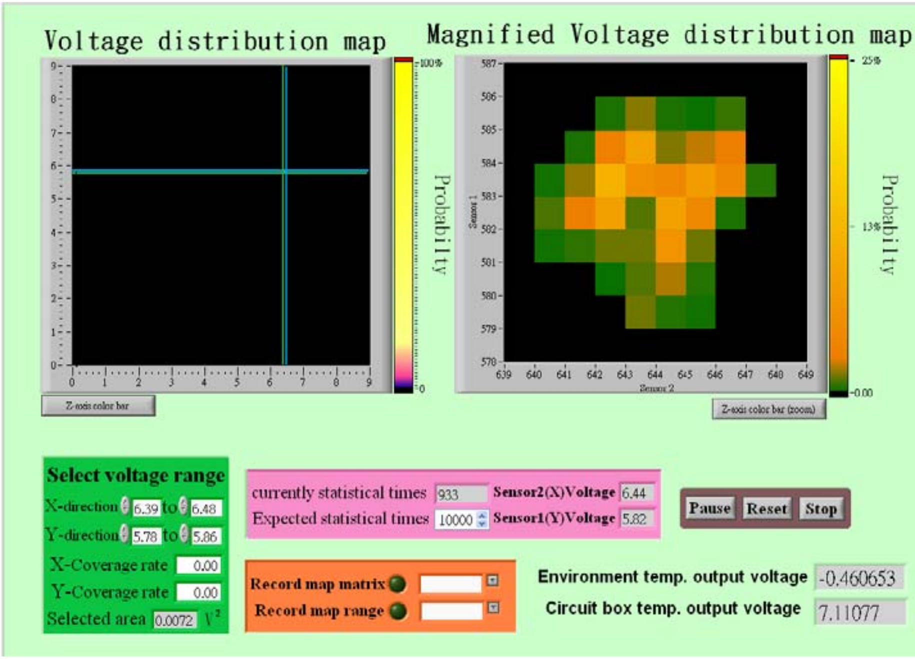
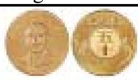
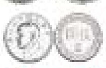
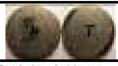
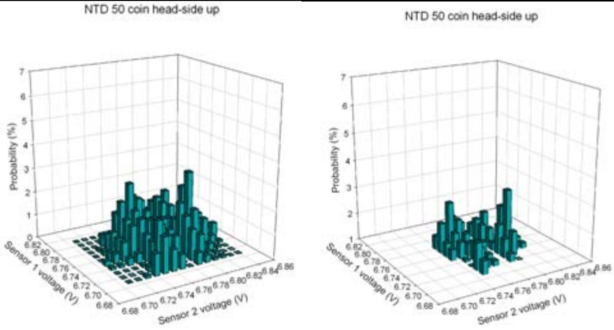


Fig. 2. The LabVIEW® interface of coin training and identification program

Table 1. The specifications of real currency and tokens

Coin	Image	Diameter	Thickness	Material
Legal 50-dollar coin		28 mm	2.4 mm	Cu:92%, Ni:2%, Al:6%
Legal 10-dollar coin		26 mm	1.85 mm	Cu:75%, Ni:25%,
Legal 5-dollar coin		22 mm	1.55 mm	Cu:75%, Ni:25%
Legal 1-dollar coin		20 mm	1.55 mm	Cu:92%, Ni:6%, Al:2%
Token minted with a Chinese character "Da"		28 mm	2.05 mm	Unknown

Token with smooth surface on both sides		26 mm	1.6 mm	Unknown



(a) (b)

Fig. 3. The 3D voltage distribution map of a NT 50-dollar coin (a)without threshold; (b) with 1% threshold setting.

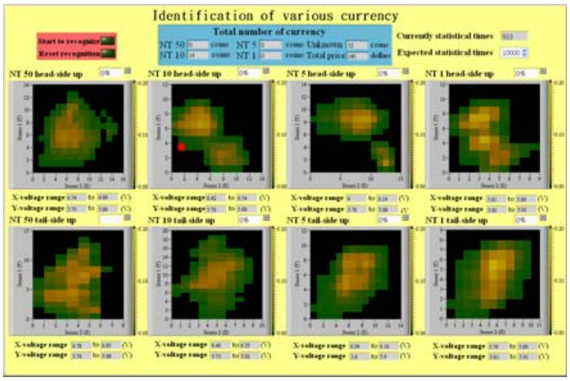


Fig. 4. Interface of voltage distribution map of various currency. The red spot represents that the new coming voltage spot falls onto the map.

3. Results and discussion

By placing the sensors at the specific position, the sensor 2 measures four kinds of coin mainly by their different diameter and thickness and the sensor 1 very close to the coin surface measures their material property. In classification experiments, the coin feeding machine employed here is a rotation mechanism with four blades which rotates the coin and is driven by a 12 V DC motor. If the coin feeding mechanism can be appropriately designed further, the maximum identification rate is estimated as 14 coins per second based on electronic signal processing rate. In classification experiment, we put 4 types of coins on the feeding machine at the same time and process for ten thousand times. Without any threshold setting, the measured result shows that the classification rate is greater than 98% and the rejection rate is less than 3% for each class of coin. On the other hand, as we set 1% threshold, the classification rate becomes lower than the result without threshold setting. It is because that the voltage distribution area is thus reduced in 1% threshold map and this restricts the new voltage points to fall onto the voltage distribution map of all 8 operations Moreover, in identification experiments, we adopt two forged tokens which have same diameters as those of NT 50-dollar and 10-dollar coins to identify with authentic coins. Each operation repeats for ten thousand times. Table 2 and 3 exhibit the results of identification and it is indicated that the successful rates of identification for these cases are very close to 100%.

Table 2. Identification of NTD 10 coin and token with smooth surface

Coin	Acceptance times	identification rate
NTD 10 (head-side)	5000	100%
Token with smooth surface (head-side)	5000	100%
NTD 10 (tail-side)	5000	100%
Token with smooth surface (tail-side)	5000	100%

Table 3. Identification of NTD 50 coin and token minted with a Chinese character "Da" (tail-side)

Coin	Acceptance times	identification rate
NTD 50 (head-side)	4999	99.99%
Token minted with a Chinese character "Da" (head-side)	5001	100%
NTD 50 (tail-side)	5000	100%
Token minted with a Chinese character "Da" (tail-side)	5000	100%

4. Conclusion

Experimental results have proven the use of Eddy-current method an effective way to rapidly identify coins. The rise of threshold setting in the program can reduce the classification rate; however, it is considered to be a useful factor when dealing with the token featured with similar characteristic voltage of authentic coins. During the statistical process, it is found that the sensing voltage varies with temperature slightly. This is because the system temperature in the circuit box is elevated during the operation or the variation of ambient temperature. Therefore it is possible to further improve the classification and identification module in consideration of temperature compensation.

Acknowledgements

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