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DIGITAL ART DRAWING IN THE AIR THROUGH CAMERA

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Abstract

Gesture Recognition is a technology which is used to identify human gestures with the help of mathematical algorithms. Gesture recognition recognizes the hand, tracks the hand movements & also provides information about hand position orientation and flux of the fingers. The colour markers are placed at the tip of the user fingers. This helps the webcam to identify the movement of hand and the gesture recognition. The drawing application allows the user you to draw on any surface by tracking the fingertip movements of the user's index finger. The pictures that are drawn by the user can be stored and replaced on any other surface. The user can also shuffle through various pictures and drawing by using the hand gesture movements.

Keywords: Inertial pen, dynamic time warping, colour makers,web camera, handwriting recognition, gesture recognition.

1. INTRODUCTION

With the rapid development of computer technology, contemporary human-computer interaction (HCI) devices/techniques have become indispensable in individuals' daily lives. HCI devices/techniques have also dramatically altered our living habits with computers, consumer electronics, and mobile devices. The ease with which an HCI device or technique can be understood and operated by users has become one of the major considerations when selecting such a device. Therefore, it is necessary for researchers to develop advanced and user-friendly HCI technologies which are able to effortlessly translate users' intentions into corresponding commands without requiring users to learn or accommodate tothe device. Technologies are being developed which are able to intuitively express users' intentions, such as handwriting, gestures, and human body language, to naturally control HCI devices. These technologies have many applications in the fields of remote control, virtual reality, sign language, sig-nature authentication, sport science, health care, and medical rehabilitation .

Recently, a number of researchers have developed diverse technologies for inertial-sensing-based HCI methods such as activity recognition, gesture recognition, hand-writing recognition , and motion tracking . Among inertial-sensing-based HCI methods, pen-based input devices embedded with accelerometers and/or gyroscopes can most easily provide intuitive expressions through capturing trans-lational accelerations and/or angular velocities generated by hand movements. Most importantly, inertial-sensing-based pen-based input devices for recognizing handwritten characters and hand gestures can be operated without ambit limitations such as writing ranges, directions, or dimensions , while other pen-based devices such as electromagnetic and pressure types must limit the writing space. The major challenge of inertial-sensing-based hand-writing and gesture recognition using acceleration or angular velocity signals is misrecognition, since different users have different preferred speeds and styles.

Recent studies have shown that hidden Markov model (HMM) and neural network approaches are effective at increasing the recognition rate of the inertial-sensing-based handwriting and gesture recognition. However, the computational complexity of HMMs and neural classifiers are directly proportional to the dimension of the feature vectors, and both require more than one training sample to obtain acceptable recognition rates. While some researchers have demonstrated the effectiveness of the DTW algorithm, which selects the best match from many samples for each class for recognition, most of these studies were based on accelerometer-based gesture recognition alone. gesture recognition. Over 4000 samples with eight gestures collected from eight users were utilized for user-dependent recognition with 98.6% accuracy.

In this paper, an inertial-sensor-based digital pen (inertial pen) and a dynamic time warping (DTW)-based recognition algorithm are presented for both handwriting and gesture recognition tasks. The portable inertial pen is composed of a triaxial accelerometer, a triaxial gyroscope, a triaxial mag-netometer, a microcontroller, and an RF wireless transmission module. Users can utilize this inertial pen to write numerals or English lowercase letters, and make hand gestures at their preferred speed without any space limitations. Measured accelerations, angular velocities, and magnetic signals are transmitted to a personal computer (PC) via the RF wireless module. The proposed DTW-based recognition algorithm is composed of the procedures of inertial signal acquisition, signal preprocessing, motion detection, template selection, and recognition. In the proposed recognition algorithm, we utilize the zero velocity compensation (ZVC) method and a quaternion-based complementary filter to reduce the integral errors caused by the intrinsic noise/drift of the accelerometer and gyroscope, which worsen the accuracy of the veloc-ity, position, and orientation estimations. Furthermore, we have developed a minimal intra-class to maximal inter-class based template selection method (Min-Max template selection method) for a DTW recognizer to obtain a superior class separation for improved recognition. The advantages of this approach include the following:

1) with the inertial pen, users can deliver diverse commands through hand motions to control electronic devices anywhere without space limitations;
2) the DTW-based recognition algorithm only requires one training sample or class template for each class for highly accurate motion recognition; and
3) the DTW-based recognition algo-rithm can effectively reduce the integral errors of inertial signals.

The remainder of this paper is organized as follows. In Section II, we introduce the hardware components of the inertial pen in detail. The DTW algorithm is introduced in Section III. The proposed DTW-based recognition algorithm, consisting of inertial signal acquisition, signal preprocessing, motion detection, template selection, and recognition pro-cedures, is presented in Section IV. In Section V, experi-mental results are presented and discussed to validate the proposed approach. Finally, conclusions are given in the last section.

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2. INERTIAL PEN

Our inertial pen consists of a triaxial accelerometer (LSM303DLH, STMicroelectronics), a triaxial gyroscope (L3G4200D, STMicroelectronics), a triaxial magnetome-ter (LSM303DLH, STMicroelectronics), a microcontroller (STM32F103T8, STMicroelectronics), and an RF wireless transceiver (nRF24L01, Nordic). The accelerometer, gyro-scope, and magnetometer are used to detect accelerations, angular velocities, and magnetic signals generated by hand movements. The LSM303DLH possesses a linear acceleration full scale of ±2*g*, ±4*g*, and ±8*g*, with data output rates from 0.5 Hz to 1 kHz for all axes, and a magnetic field inertial pen is replaceable and rechargeable. The schematic diagram of the inertial pen hardware system is shown in Fig. 2.

3. DYNAMIC TIME WARPING ALGORITHM

Dynamic time warping (DTW) algorithm is developed to ensure a minimal cumulative distance between the aligned sequences, and to find the similarity for the optimal alignment between two temporal sequences [25]. The DTW algorithm in the current paper is used to classify time sequences (movement signals) of different digits, letters, or gestures based on the nature of the movement signals generated from the

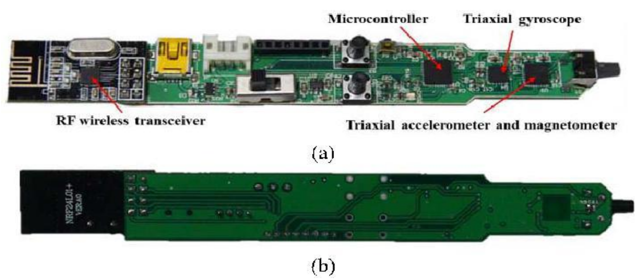

Fig. 1.Inertial pen. (a) Front view of the circuit. (b) Back view of the circuit.

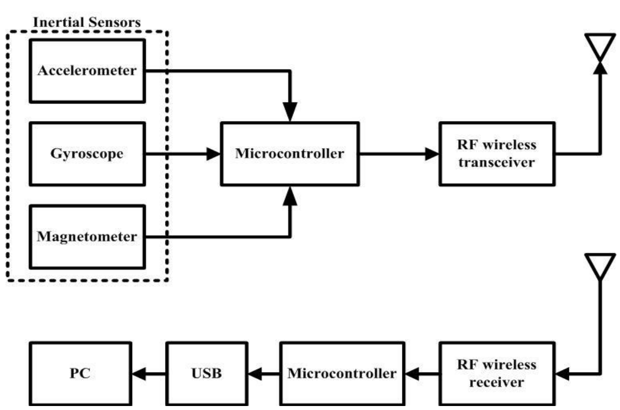

Fig. 2.Schematic diagram of the inertial pen.

full scale of ±1.3, ±1.9, ±2.5, ±4.0, ±4.7, ±5.6, and ±8.1 gauss, with data output rate from 0.75 Hz to 75 Hz. The accelerometer's sensitivity is set from $-4g$ to $+4g$ in this study. The L3G4200D gyroscope simultaneously detects the X -, Y -, and Z -axis angular rates of the inertial pen, possesses a full scale of ±250, ±500, and ±2000 degree per second (dps) with data output rates from 100 Hz to 800 Hz, and is capable of measuring rates with a user-selectable bandwidth. The microcontroller collects the digital accelerations, angular velocities, and magnetic signals, and transmits wirelessly the abovementioned inertial signals to a PC main processor via the RF wireless transceiver for further signal processing and analysis. The sampling rate of the abovementioned measure-ment signals is set at 75 Hz. The size of the pen-type board is 130 mm × 15 mm × 8 mm (Fig. 1). Note that all signal processing procedures are performed on a PC. The overall power consumption of the hardware device is 30 mA at 3.7 V. The battery of the

4. BLOCK DIAGRAM EXPLANATION

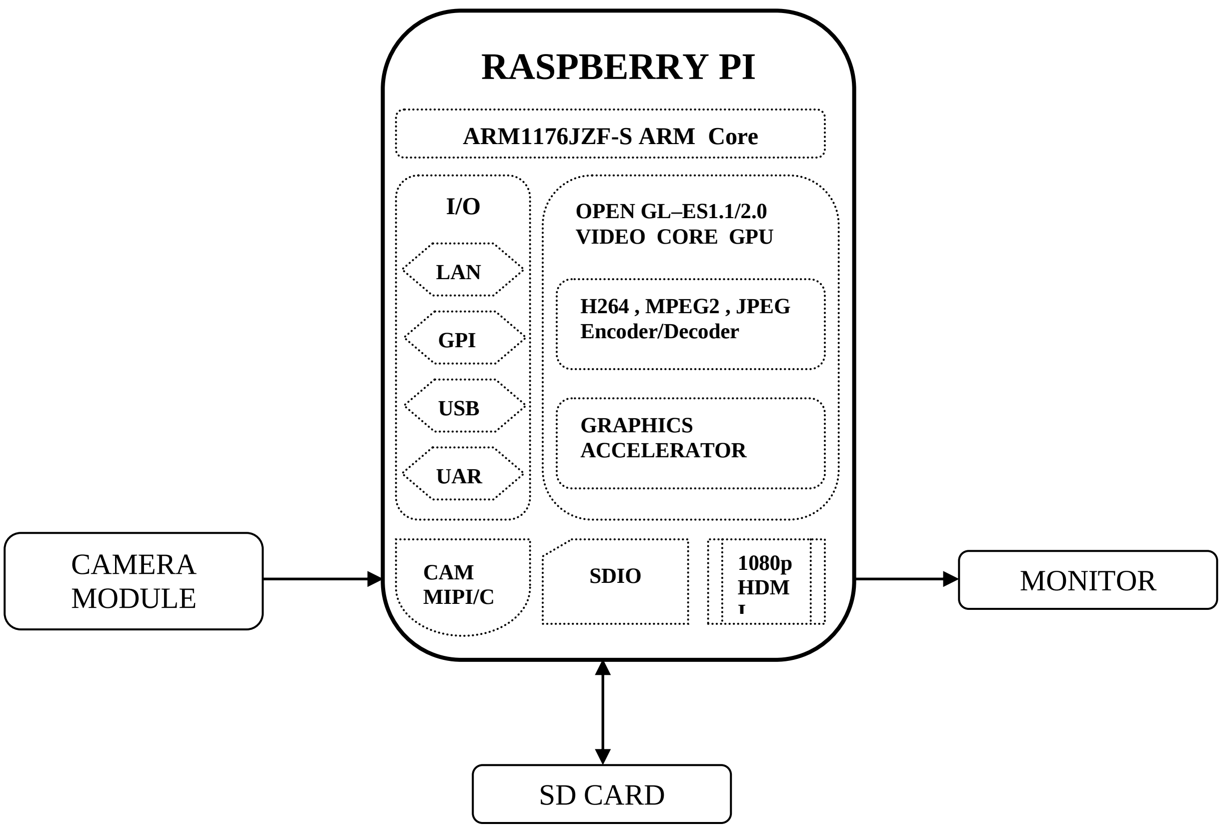

Fig.3. Block Diagram

The system consists of ARM11 RaspberryPi device, camera and Projector. There are colour markers placed at the tip of users fingers. Marking the user's fingers with red, yellow, green and blue coloured tape helps the camera to recognize the hand gestures. Captured gesture image is transferred to the ARM11 Raspberry Pi device for further processing. Projector receives the information from the ARM11 Raspberry Pi device & projects on to any particular surface

B. 2D Handwritten English Character Recognition

This experiment was designed to demonstrate the effec-tiveness of the proposed inertial pen and its associated DTW-based recognition algorithm for recognizing handwritten English lowercase letters. Ten participants were asked to hold the inertial pen and to draw English lowercase letters in a 2D space. Pictorial trajectories of English lowercase letters are shown in Fig. 8. Each participant was asked to write 26 letters (from a to z), and each letter was to be written 5 times for this experiment. Therefore, a total of 1300 *(*= 26×10×5) data were collected for this experiment. Table II shows that the best recognition rate was achieved through the use of velocity signals with 92.0% accuracy by leave-one-out cross-validation.

The results shown in Table III demonstrate that the pro-posed Min-Max template selection method with the DTW recognizer can obtain better recognition results compared to the random and minimum template selection methods. The recognition rates obtained by 2-fold cross-validation, 5-fold cross-validation, 10-fold cross-validation, and leave-one-out cross-validation strategies were 70.3%, 72.5%, 81.4%, and 92.0%, as shown in Table IV. In addition, the user-dependent recognition rate for 2D handwritten English lowercase letter recognition evaluated by leave-one-out cross-validation was 94.3%, as shown in Table V.

In addition, recognition performance was evaluated when 2D digits and 2D English characters were written simulta-neously. Ten participants were asked to hold the inertial pen and draw Arabic numerals and English lowercase letters in a 2D space. Each digit and letter was to be written 5 times. Therefore, a total of 1800*(*= 36 × 10 × 5) data were collected for this experiment. From Table II, the best recognition rate obtained by leave-one-out cross-validation was about 92.1% for 2D handwritten digit and 2D English characters recognition using the velocities. The recognition rate of the proposed Min-Max template selection method with the DTW recognizer *C. 3D Gesture Recognition*

In the third experiment, the participants were invited to hold the inertial pen and perform eight hand gestures in a 3D space. The trajectories of the eight hand gestures are shown in Fig. 9. The participants were asked to repeat each of the hand gestures 10 times. Hence, a total of 800 *(*= 8 × 10 × 10) hand gestures were generated. The same vali-dation procedure as that of the first experiment was conducted for the gesture motion signals. Table II shows that the proposed DTW-based recognition algorithm using velocities can effec-tively recognize different hand trajectories that can be defined as various commands for HCIs. From Table III, the recognition rate of the proposed Min-Max template selection method with the DTW recognizer using velocity signals is superior to alternative methods. The overall user-independent and user-dependent recognition rates evaluated by leave-one-out cross-validation were 98.1% and 99.8%, as shown in Tables II and V. As shown in Table IV, the recognition rates obtained by mul-tiple cross-validation strategies ranged from 82.3% to 98.1%.

CONCLUSION

This paper has presented an inertial pen with a system-atic time alignment algorithm framework for inertial-sensing-based handwriting and gesture recognition. The proposed DTW-based recognition algorithm consists of inertial signal acquisition, signal preprocessing, motion detection, template selection, and recognition. To obtain better movement signals, we have utilized a quaternion-based complementary filter to reduce orientation errors and the ZVC method so as to minimize the undesirable error accumulation of velocity signals. Subsequently, to improve the performance of the DTW recognizer, all movement signals are normalized via the Z-score method and the class template is selected via the proposed Min-Max template selection method. During exper-imental validation, 2D handwritten digits, 3D handwritten digits, 2D handwritten English lowercase letters, 2D hand-written digits and English letters, and 3D hand gestures were collected to evaluate the effectiveness of the proposed inertial pen and algorithm. The user-independent recognition rates for the abovementioned experiments were 97.9%, 87.3%, 92.0%, 92.1%, and 98.1%, respectively. In addition, the user-dependent recognition rates of the experiments were 99.4%, 94.6%, 94.3%, 93.0%, and 99.8%, respectively. Based on the above experimental results, we believe that the inertial pen and its associated DTW-based recognition algorithm can be considered an innovative and effective HCI device.

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