

A PEN LIKE INPUT DEVICE FOR ONLINE CHARACTERS AND GESTURE RECOGNITION

G Sathvi

Dept. of Electronics and Communication Engineering
Vardhaman college of Engineering
Hyderabad, India

N.UmaMaheshwar Rao

Dept. of Electronics and Communication Engineering
Vardhaman college of Engineering
Hyderabad, India

Abstract— In this modern days using of digital pens in many scenarios from simple form filling and data capture to more advanced scenarios such as Interactive Surface Development. This digital pen contains components that only detect movement of the pen in contact with the writing surface (offline recognition). So we are going to present a pen like input device for online handwriting (3D) and gesture recognition applications like robot control. The entire system mainly includes two functional units. The one is pen type input device to write the alphabets or mnemonics in 3D space and the other is recognition algorithm which identifies the movement of input device. Here a dynamic time warping (DTW) algorithm applied to align the accelerations and search class templates for each alphabet. And also by using the same unit we can control the movement of robot

that they can be operated with low voltage The proposed accelerometer-based pen device is composed of a tri-axial accelerometer, lpc2148 microcontroller, zigbee module The accelerometer is used to detect accelerations of hand motions and its sensitivity was set from -4g to +4g in this paper. The microcontroller collects the digital signals that are generated from the accelerometer and wirelessly transmits the data to a PC main processor for further signal processing and recognition via the wireless transceiver. This digital pen mainly includes two sections. They are shown in fig 1

Index Terms— ARM, Dynamic Time Warping, Online Handwriting, Tri-axial Accelerometer, Zigbee.

I. INTRODUCTION

According to input signals, handwritten character recognition can be divided into online and offline recognition. Online recognition recognizes the stroke trajectories of handwritten characters, while offline recognition identifies the images of handwritten characters. Therefore, the input signals for online and offline recognition are the coordinate information of the pen tip as functions of time and the scanned image of the handwritten character, respectively. Since the online recognition can translate human's intentions to a computer more intuitively and effectively than the offline method, the input devices for the online handwriting recognition are widely developed in the last decade such as ultrasonic digital pens, infrared digital pens, and touch pads. However, the drawback of the abovementioned input devices is that they should be operated with ambit restrictions.

Pen based input devices embedded with MEMS sensors have been provided for hand gestures or hand writing. A silent application of MEMS sensors for general motion sensing is

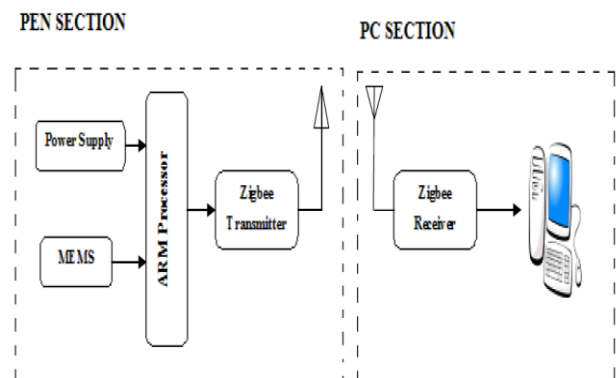


Fig 1 Digital pen block diagram

The accuracy of characters is more. We can also use this input unit for gesture recognition applications like robot control. The following figure is one of the examples.

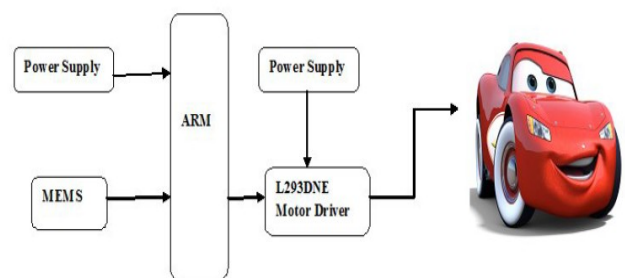


Fig 2. Gesture recognition robot module

II. SYSTEM HADWARE

A. LPC2147 Micro Controller (ARM7) Family

The ARM processor is 32-bit embedded RISC microprocessor. The ARM7 processor needs very low power, high performance and small size. Here in this paper I'm using LPC2148 microcontroller architecture LPC2148 is the widely used IC from ARM-7 family. It is manufactured by Philips and it is pre-loaded with many inbuilt peripherals making it more efficient and a reliable option for the beginners as well as high end application developer.

Pipeline techniques are employed so that all parts of the processing and memory systems can operate continuously. Typically, while one instruction is being executed, its successor is being decoded, and a third instruction is being fetched from memory. The ARM7TDMI-S processor also employs a unique architectural strategy known as Thumb, which makes it ideally suited to high-volume applications with memory restrictions, or applications where code density is an issue. It also includes A/D convertor which is required for our operation. The analog output from MEMS is given to microcontroller which inbuilt consists of ADC converts analog signal to digital form.

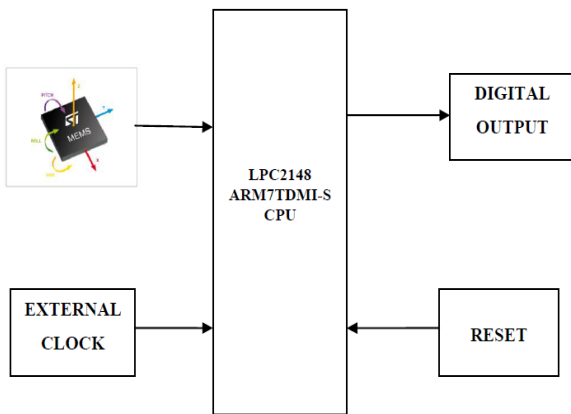


Fig 3 LPC2148 With all inputs and output

B. Wireless Zigbee Module

The XBee and XBee-PRO OEM RF Modules were engineered to meet IEEE 802.15.4 standards. There are wide range of wireless modules present in the market but Zigbee is used because it support unique needs like low-cost, low-power wireless sensor networks. The modules require minimal power and provide reliable delivery of data between devices. The modules operate within the ISM 2.4 GHz frequency band. In my paper this module is helpful to transmit data from pen unit to PC. We preferred to use Zigbee networks because they are secured by 128 bit symmetric encryption keys. In home automation applications, transmission distances range from 10 to 100 meters line-of-sight, depending on power output and environmental characteristics

III. MEMS TECHNOLOGY

Micro-electro-mechanical systems (MEMS) technology has contributed to the improved performance,

reliability and lower-cost sensors that support basic automobile functions within the automotive industry. Micro-Electro-Mechanical Systems (MEMS) is the integration of mechanical elements, sensors, actuators, and electronics on a common silicon substrate through micro fabrication technology. MEMS is an enabling technology allowing the development of smart products, augmenting the computational ability of microelectronics. In most cases, the physics behind the behavior of MEMS devices can be expressed by mathematical expressions. MEM Solver works by creating a mathematical model of the system and generates analytical solutions to explain the behavior of the MEMS device. The user just has to enter the input parameters like length and width of the beam for example in a user friendly GUI, and the software will immediately calculate the relevant results and plot graphs that fully explain the MEMS device or part of it.

The software is divided into five modules namely mechanics, sensing, actuation, and process and data analysis. Mechanics module is subdivided into three sub sections. The first subsection being structures where the most commonly used beams and diaphragm designs are examined. The second subsection discusses vibration of these structures, both free and forced vibrations. The third subsection discusses damping in the form of squeeze film and slide film damping.

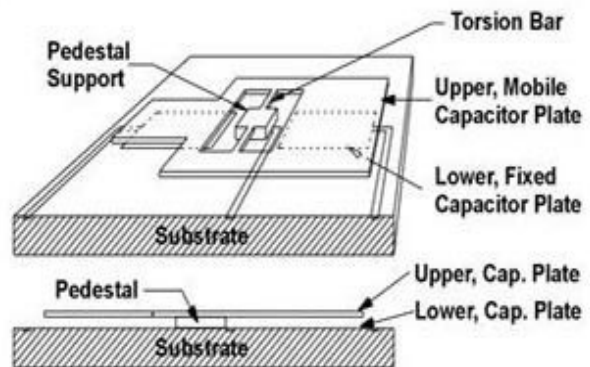


Fig 4 Mechanics module

A. MEMS accelerometer and its working

An accelerometer detects change in position. MEMS accelerometer differs from integrated circuits in that a "proof mass" is machined into the silicon. Any displacement of the component causes this mass to move slightly according to Newton's second law, and that change is detected by sensors. Usually the proof mass disturbs the capacitance of a nearby node; that change is measured and filtered. Although it may seem counterintuitive, an accelerometer can sense the inclination (tilt) of a device even when stationary. Since gravity is an acceleration of 1 g, tilt is proportional to the sine of the angle the accelerometer makes with the Earth's gravitational field. Much better results can be had using two or more sensors oriented orthogonally to each other. The most important specification is the number of axis. The MEMS proof mass can measure one parameter in each available axis, so a one axis device can sense acceleration in a single direction. Three axis units return sensor information in the X, Y, and Z directions.

IV. AUTOMATIC RECOGNITION ALGORITHM

An automatic recognition algorithm has been developed to perform 3D handwritten digit recognition task using the acceleration signals measured by the tri axial accelerometer embedded in the input device. The proposed automatic recognition algorithm shown in Fig. 4 consists of the following procedures: 1) signal acquisition, 2) signal preprocessing, and 3) DTW recognizer. We now introduce the detailed procedures of the proposed automatic recognition algorithm as follows.

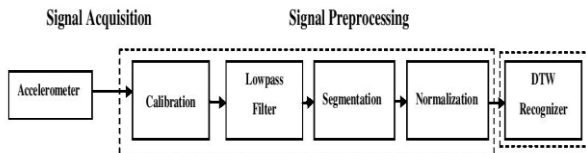


Fig 5 Block diagram of the recognition algorithm

A. Signal Acquisition and Preprocessing

In this paper, the acceleration signals of the hand motions are measured by a tri axial accelerometer. At the beginning of the procedure, a PC receives the accelerations via the transceiver. Subsequently, signal preprocessing is used to eliminate the intrinsic error sources of the accelerometer and users' unconscious trembles. The signal preprocessing procedure is composed of calibration, a low pass filter, segmentation, and normalization. Firstly, we need to calibrate the accelerometer to reduce its errors of sensitivity and offset before using the accelerometer-based pen device. Secondly, we utilize a low pass filter to remove high-frequency noise from the raw data. Then, an adaptive magnitude threshold is used to segment the acceleration patterns of hand movements when writing numerals in a 3-D space. Finally, the amplitude of each acceleration pattern has been normalized to the interval [0, 1] to avoid extreme amplitude scaling.

(a) Calibration: To perform the calibration we have to place the tri axial accelerometer on a leveled surface and continuously align each axis to earth's surface. The tri-axial accelerometer measures the gravitational acceleration when the pen device is in stationary state. Depending on this gravitational acceleration we can obtain the scale factor (SF) and bias (B) in each axis of the accelerometer from the measurements as follows.

$$SF = \frac{V(+g) - V(-g)}{2g} \tag{1}$$

$$B = \frac{V(+g) + V(-g)}{2} \tag{2}$$

Here V(+g) and V(-g) are the voltage outputs in each axis of the accelerometer when it is aligned with the direction of the Earth's gravity and with the opposite direction of Earth's gravity, respectively. From the above values we can obtain calibrated accelerometer measurements using the below formula

$$A_c = \frac{V - B}{SF} \tag{3}$$

Here V is the output voltage in each axis of the accelerometer.

(b) Low pass Filter: The calibrated output is filtered in order to reduce the high frequency noise of the calibrated accelerations, and the filter is expressed as

$$A_f[n] = \frac{1}{N} \sum_{i=1}^N A_c[n-i] \tag{4}$$

Here Ac[n] is the calibrated accelerations, Af[n] is the filtered accelerations, and N is the number of points in the average filter (N = 7 is used in this paper).

(c) Segmentation: segmentation is done in order to obtain accurate locations of the start and end points of each pattern based on an adaptive magnitude threshold.

The adaptive magnitude threshold is the mean of the filtered accelerations. These filtered accelerations are collected by keeping the accelerometer stationary.

$$TH = mean_k (|\sqrt{A^2_{fx}(k) + A^2_{fy}(k) + A^2_{fz}(k)} - 1|) \tag{5}$$

Here k denotes the time steps. The start and end points of the motion interval can be determined when the magnitudes are higher and lower than the threshold, respectively.

(d) Normalization: We normalize each segmented acceleration pattern into the interval [0, 1] via the following equation:

$$A_{norm} = \frac{A - \min(A)}{\max(A) - \min(A)} \tag{6}$$

Here max(A) and min(A) is the maximum and minimum amplitude among the segmented acceleration signals of the three axes in the motion interval, respectively.

B. DTW Recognizer

The Dynamic time warping (DTW) algorithm looks for an optimal alignment, which ensures a minimized cumulative distance measurement between the aligned sequences, to find the similarity between two time temporal sequences. Let H and R be two similar time sequences with the same sampling rate and different lengths, where H = [h1, h2, ..., hm] and R = [r1, r2, ..., rn]. The optimal warping path can be found effectively based on dynamic programming by using the following formulation:

$$D_{p,q} = d(h_p, r_q) + \min\{D_{p,q-1}, D_{p-1,q}, D_{p-1,q-1}\} \tag{7}$$

Here $d(h_p, r_q) = \sqrt{(h_p - r_q)^2}$ is the Euclidean distance, which is used to measure local distances between the two

time sequences. The cumulative distance DTW (H, R) between the two time sequences is then calculated by summing the local distances over the optimal warping path and can be defined as follows.

$$DTW(H, R) = D_{m,n} \tag{8}$$

The more detailed information about the DTW algorithm can be found in [7]. The recognition performance greatly depends on the quality of the selected class templates of the DTW recognizer. Hence, to select reliable training class templates for each class from all templates within the same class to be recognized is the most important task in the training stage of the DTW recognizer. In this paper, the minimum selection method presented by [8] is used to perform the template selection task. At first, the sum of the DTW distance between the template and all other patterns within the same class is calculated. Then, the pattern with the minimum intra-class DTW distance is selected as the class template. In other words, there is only one class template for each digit by using the DTW recognizer. Finally, in the testing stage of the DTW recognizer, the recognition results are outputted through the DTW recognizer by measuring the similarity between the testing data and the selected class templates. Since the accelerations of each digit is composed of three acceleration waveforms (X-, Y-, and Z-axis), the similarity between the class template $C \in R^{m \times 3}$ and the testing acceleration pattern $T \in R^{n \times 3}$ can be computed as

$$DTW(C, T) = \sqrt{D_{m,n}^2(x) + D_{m,n}^2(y) + D_{m,n}^2(z)} \tag{9}$$

where $D_{m,n}(x)$, $D_{m,n}(y)$, $D_{m,n}(z)$ are the DTW cumulative distance computed between the traces in the X-, Y-, and Z-axis, respectively. Finally, the minimal $DTW(C, T)$ representing that the testing sequence T_n and the class template C_m are within the same class.

V. EXPERIMENTAL RESULT

The following figures shown are the final output displaying the characters C and S and we can obtain the output simply by running the MATLAB code. The process that involved in getting the output is that by varying the position of MEMS different tilting angle values are generated this values are wirelessly transmitted through zigbee module to display on PC. The supporting MATLAB code which we used recognizes the values and displays the output.

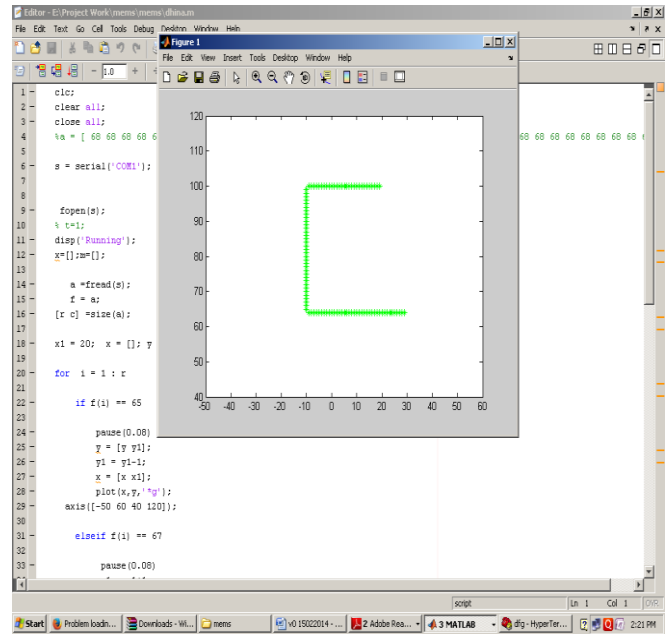


Fig 6 Screen shot of displaying letter 'C'

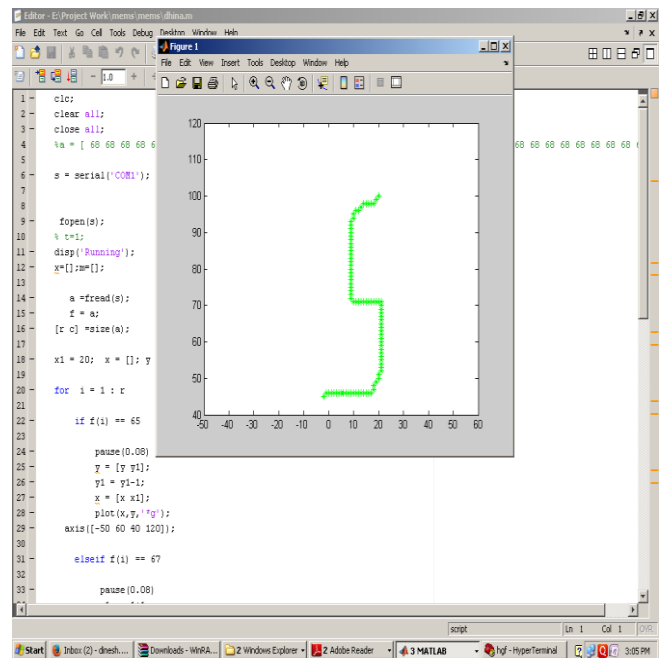


Fig 7 Screen shot of displaying letter 'S'

By this experiment we can display all continuous characters, numbers and symbols. This system not only used for displaying alphanumeric values but we also use this for gesture recognition applications like robot controlling.

The robot module can move in any direction just by moving the MEMS the extra thing all we required is motor driver. The motor driver we used is L293DNE IC. Due its size it is very much used in robotic application for controlling DC motors. The following figure given consists of photo shots of robot module while working. In (a) glowing of front light indicates the starting of the robot car, in (b) the front wheel is in straight position indicating that the robot car is

moving in either forward or backward direction, in (c) the front wheel of the car moves toward right indicating that the car is turning right and in (d) the front wheel of the car moves toward left indicating that the car is turning left.



(a)



(b)



(c)



(d)

Fig 8 Photo shots of robot module while working

VI. CONCLUSION

This paper consist of a pen like input device that can display all continuous characters, digits, symbols and not only that it can also used for controlling of robots, which comes under gesture applications. The entire operation of this pen unit and movement of robot depends upon movement of sensor and its tilting angles. For this digital pen different experiments were conducted with number of users and we obtained recognition rate up to 90.6% and we can also control the movement of any robotic modules. Finally we can conclude that by making further investigations there is a possibility of using our accelerometer-based pen device as an effective tool for many more HCI applications.

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