

## MEMS-BASED DIGITAL PEN WITH A TRAJECTORY RECOGNITION ALGORITHM FOR HANDWRITTEN DIGIT AND ALPHABET RECOGNITION

S. Iswarya, PG Student\*

Mr. T. Rajesh, Assistant professor\*\*

**Abstract---**This paper presents an accelerometer-based digital pen for handwritten digit and gesture trajectory recognition applications. The digital pen consists of a triaxial accelerometer, a microcontroller (with A/D converter), and a ZigBee wireless transmission module for sensing and collecting accelerations of handwriting and gesture trajectories. The triaxial accelerometer measures the acceleration signals generated by a user's hand motions. The microcontroller collects the analog acceleration signals and converts the signals to digital ones via the A/D converter. Using this project we can do human computer interaction. Users can use the pen to write digits or make hand gestures, and the accelerations of hand motions measured by the accelerometer are wirelessly transmitted to a computer for online trajectory recognition. So, by changing the position of mems (micro electro mechanical systems) we can able to show the alphabetical characters in the PC. The acceleration signals measured from the triaxial accelerometer are transmitted to a computer via the wireless module.

**Index Terms---**Accelerometer, ZigBee, gesture, recognition, MEMS, A/D converter

\* PG Student, M.E (EST), PSN College of Engineering and Technology, Tirunelveli,

\*\* M.E, Assistant Professor, PSN College of Engineering and Technology, Tirunelveli,

## I. INTRODUCTION

The increase in human-machine interactions in our daily lives has made user interface technology progressively more important. Physical gestures as intuitive expressions will greatly ease the interaction process and enable humans to more naturally command computers or machines. Recently, an attractive alternative, a portable device embedded with inertial sensors, has been proposed to sense the activities of human and to capture his/her motion trajectory information from accelerations for recognizing gestures or handwriting. Use of inertial sensors has an advantage that they can be operated without any external reference and limitation in working conditions. However, motion trajectory recognition is relatively complicated because different users have different speeds and styles to generate various motion trajectories.

In this work, a miniature MEMS accelerometer based recognition system which can recognize seven hand gestures in 3-D space is built. The system has potential uses such as a remote controller for visual and audio equipment, or as a control mechanism to Command machines and intelligent systems in offices and factories. There are mainly two existing types of gesture recognition methods, i.e., vision-based and accelerometer and/or gyroscope based. Due to the limitations such as unexpected ambient optical noise, slower dynamic response, and relatively large data collections/ processing of vision-based method, our recognition system is implemented based on an inertial measurement unit based on MEMS acceleration sensors. Since heavy computation burden will be brought if gyroscopes are used for inertial measurement, current system is based on MEMS accelerometers only and gyroscopes are not implemented for motion sensing.

In this paper, developed a pen-type portable device and a trajectory recognition algorithm. The pen-type portable device consists of a triaxial accelerometer, a microcontroller, and an RF wireless transmission module. The acceleration signals measured from the triaxial accelerometer are transmitted to a computer via the wireless module. Users can utilize this digital pen to write digits and make hand gestures at normal speed. The measured acceleration signals of these motions can be recognized by the trajectory recognition algorithm. The recognition procedure is composed of acceleration acquisition, signal preprocessing, feature generation, feature selection, and feature extraction. The acceleration signals of hand motions are measured by the pen-type portable device. The signal preprocessing procedure consists of calibration, a

moving average filter, a high-pass filter, and normalization. First, the accelerations are calibrated to remove drift errors and offsets from the raw signals. These two filters are applied to remove high frequency noise and gravitational acceleration from the raw data, respectively. The features of the preprocessed acceleration signals of each axis include mean, root mean square (rms), VAR, standard deviation (STD), and energy. Before classifying the hand motion trajectories, that perform the procedures of feature selection and extraction methods. Therefore, the criterion of kernel-based class separability (KBCS) with best individual N (BIN) is to select significant features from the original features and that of linear discriminate analysis (LDA) is to reduce the dimension of the feature space with a better recognition performance. The objective of the feature selection and feature extraction methods is not only to ease the burden of computational load but also to increase the accuracy of classification. The reduced features are used as the inputs of classifiers. In this paper, we adopted a probabilistic neural network (PNN). The rest of this paper is organized as follows. In Sections II, the survey related work on digital pen trajectory recognition and similar HCI applications and introduce the hardware components of the digital pen in detail, respectively. The proposed trajectory recognition algorithm consisting of acceleration acquisition, signal preprocessing, feature generation, feature selection, feature extractions are presented.

## II. RELATED WORKS

Existing gesture recognition approaches include template- matching [1], dictionary lookup [2], statistical matching [3], linguistic matching [4], and neural network [5]. For sequential data such as measurement of time series and acoustic features at successive time frames used for speech recognition, HMM (Hidden Markov Model) is one of the most important models [6]. It is effective for recognizing patterns with spatial and temporal variation [7]. In this paper, we present three different gesture recognition models, which are: 1) sign sequence and Hopfield based gesture recognition model; 2) velocity increment based gesture recognition model; and 3) sign sequence and template matching based gesture recognition model. In these three models, in order to find a simple and efficient solution to the hand gesture recognition problem based on MEMS accelerometers, the acceleration patterns are not mapped into velocity, displacement or transformed into frequency domain, but are directly segmented and recognized in time domain. By extracting a simple feature based on sign sequence of acceleration, the recognition system achieves high accuracy and efficiency without the employment of HMM.

Some studies have focused on the development of digital pens for trajectory recognition and HCI applications. For instance, an alternative method of conventional tablet-based handwriting recognition has been proposed by Milner [8]. In his system, two dual-axis accelerometers are mounted on the side of a pen to generate time-varying x- and y-axis acceleration for handwriting motion. The author employed an HMM with a band pass filtering and a down-sampling procedure for classification of seven handwritten words. The best recognition rate is 96.2% when the number of states of the HMM is equal to 60. Oh. [9] Presented a wand like input device embedding a triaxial accelerometer and a triaxial gyroscope for online 3-D character gesture recognition. Fisher discriminate analysis was adopted, and different combinations of sensor signals were used to test the recognition performance of their device. When all six axes raw signals were used as inputs of the recognition system, the recognition rate was 93.23%. In addition, they proposed an ensemble recognizer consisting of three sub recognizers with the following signals as inputs: acceleration, angular velocity, and estimated handwriting trajectory. The recognition rate of the recognizer was 95.04%. Similarly, a gesture recognition system consisting of a gesture input device, a trajectory estimation algorithm, and a recognition algorithm in 3-D space was proposed by Cho. [10]. The trajectory estimation algorithm based on an inertial navigation system was developed to reconstruct the trajectories of numerical digits and three hand gestures, and then, a Bayesian network was trained to recognize the reconstructed trajectories. The average recognition rate was 99.2%. Zhou. [11] Proposed a  $\mu$ IMU for 2-D handwriting applications. They extracted the discrete cosine transform features from x- and y-axis acceleration signals and one angular velocity and used an unsupervised self-organizing map to classify 26 English alphabets and ten numerical digits. The recognition rate of 26 English alphabets and ten numerical digits achieved 64.38% and 80.8%, respectively.

### III. SYSTEM DESIGN

Digital pen consists of a triaxial accelerometer (LIS3L02AQ3), a microcontroller (PIC16F87A with a 12-b A/D converter), and a wireless transceiver. The triaxial accelerometer measures the acceleration signals generated by a user's hand motions. The microcontroller collects the analog acceleration signals and converts the signals to digital ones via the A/D converter. The wireless transceiver transmits the acceleration signals wirelessly to a personal computer (PC). The dimension of the pen-type circuit board is 14 cm  $\times$  2 cm  $\times$  1.5 cm. The LIS3L02AQ3 is a low-cost capacitive micro machined accelerometer with a temperature

compensation function. The accelerometer's sensitivity is set from  $-2\text{ g}$  to  $+2\text{ g}$ . The PIC16F87A integrates a high-performance 12-b A/D converter on a signal chip. The output signals of the accelerometer are sampled the 12-b A/D converter. Then, all the data sensed by the accelerometer are transmitted wirelessly to a PC by an RF transceiver.

- A. Sensor Description:** The sensing system utilized in our experiments for hand motion data collection and is essentially a MEMS 3-axes acceleration sensing chip integrated with data management and ZIGBEE wireless data chips. The algorithms described in this paper were implemented and run on a PC.
- B. System work flow:** When the sensing system is switched on, the accelerations in three perpendicular directions are detected by the MEMS sensors and transmitted to a PC via ZIGBEE protocol.

In this project consist of mainly two sections, one is Pen section & second is PC section as shown in fig.1 and fig.2. PIC Microcontroller is control all the operation in this system. The triaxial accelerometer measures the acceleration signals generated by a user's hand motions. The microcontroller collects the analog acceleration signals and converts the signals to digital ones via the A/D converter. The wireless transceiver transmits the acceleration signals wirelessly to a personal computer (PC). The acceleration signals measured from the triaxial accelerometer are transmitted to a computer via the wireless module.

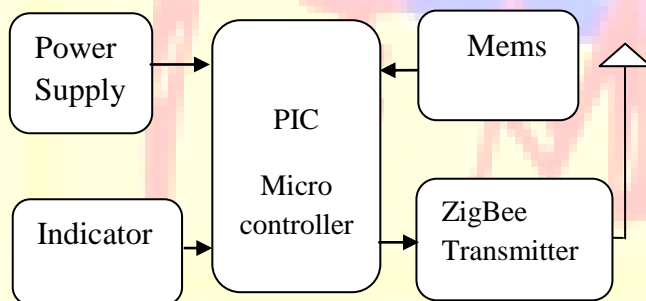


Fig.1. PEN Section

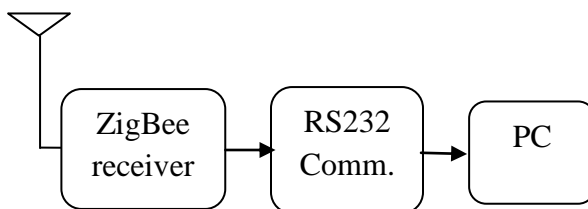


Fig.2. PC Section

#### IV. TRAJECTORY RECOGNITION ALGORITHM

The proposed trajectory recognition algorithm consisting of acceleration acquisition, signal preprocessing, feature generation, feature selection, and feature extraction. In this paper, the motions for recognition include numerals and hand gestures. The acceleration signals of the hand motions are measured by a triaxial accelerometer and then preprocessed by filtering and normalization. Consequently, the features are extracted from the preprocessed data to represent the characteristics of different motion signals, and the feature selection process based on KBCS. To reduce the computational load and increase the recognition accuracy of the classifier, uses LDA to reduce the dimension of the selected features. The reduced feature vectors are fed into a PNN classifier to recognize the motion to which the feature vector belongs. We now introduce the detailed procedure of the proposed trajectory recognition algorithm as follows.

**A. Signal Preprocessing:** The raw acceleration signals of hand motions are generated by the accelerometer and collected by the microcontroller. Due to human nature, their hand always trembles slightly while moving, which causes certain amount of noise. The signal preprocessing consists of calibration, a moving average filter, a high-pass filter, and normalization. First, the accelerations are calibrated to remove drift errors and offsets from the raw signals. The second step of the signal preprocessing is to use a moving average filter to reduce the high-frequency noise of the calibrated accelerations, and the filter is expressed as

$$y[t] = \frac{1}{N} \sum_{i=1}^{N-1} x[t + i]$$

Where  $x[t]$  is the input signal,  $y[t]$  is the output signal, and  $N$  is the number of points in the average filter.

**B. Feature Generation:** The characteristics of different hand movement signals can be obtained by extracting features from the preprocessed x-, y-, and z-axis signals, and can extract some features from the triaxial acceleration signals, including mean, STD, VAR, rms, and energy. They are explicated as follows.

**1) Mean:** The mean value of the acceleration signals of each hand motion is the dc component of the signal

$$\text{Mean} = \frac{1}{|W|} \sum_{i=1}^{|W|} x_i$$

where  $W$  is the length of each hand motion.

2) **STD:** STD is the square root of VAR

$$\text{STD} = \sqrt{\frac{1}{|W| - 1} \sum_{i=1}^{|W|} (x_i - m)^2}$$

3) **VAR:**

$$\text{VAR} = \frac{1}{|w| - 1} \sum_{i=1}^{|W|} (x_i - m)^2$$

where  $x_i$  is the acceleration instance and  $m$  is the mean value of  $x_i$ .

4) **rms:**

$$\text{rms} = \sqrt{\frac{1}{|W|} \sum_{i=1}^{|W|} x_i^2}$$

where  $x_i$  is the acceleration instance and  $m$  is the mean value of  $x_i$

5) **Energy:** Energy is calculated as the sum of the magnitudes of squared discrete fast Fourier transform (FFT) components of the signal in a window. The equation is defined as

$$\text{Energy} = \frac{1}{|W|} \sum_{i=1}^{|W|} |F_i|^2$$

Where  $F_i$  is the  $i$ th FFT component of the window and  $|F_i|$  is the magnitude of  $F_i$ . When the procedure of feature generation is done, some features are then generated. Because the amount of the extracted features is large, we adopt KBCS to select most useful features and then use LDA to reduce the dimensions of features.

**C. Feature Selection:** Feature selection comprises a selection criterion and a search strategy. The adopted selection criterion is the KBCS. The KBCS can be computed as follows: Let  $(\mathbf{x}, y) \in (\mathbb{R}^d \times \mathbf{Y})$  represents a sample, where  $\mathbb{R}^d$  denotes a  $d$ -dimensional feature space,  $\mathbf{Y}$  symbolizes the set of class labels, and the size of  $\mathbf{Y}$  is the number of class  $c$ . This method projects the samples onto a kernel space, and  $\mathbf{m}_i$  is defined as the mean vector for the  $i$ th class in the kernel space,  $n_i$  denotes the number of samples in the  $i$ th class,  $\mathbf{m}$  denotes the mean vector for all classes in the kernel space,  $\mathbf{S}_B$  denotes the between-class scatter matrix in the kernel space,

and  $S_{\emptyset W}$  denotes the within-class scatter matrix in the kernel space. Let  $\emptyset(\cdot)$  be a possible nonlinear mapping from the feature space  $R^d$  to a kernel space  $\kappa$  and  $\text{tr}(\mathbf{A})$  represents the trace of a square matrix  $\mathbf{A}$ . The class separability in the kernel space can be measured as

$$j^{\emptyset} = \frac{\text{tr}(S_B^{\emptyset})}{\text{tr}(S_W^{\emptyset})}$$

To maintain the numerical stability in the maximization of  $J^{\emptyset}$ , the denominator  $\text{tr}(S_{\emptyset W})$  has to be prevented from approaching zero.

**D. Feature Extraction:** For pattern recognition problems, LDA is an effective feature extraction which uses a linear transformation to transform the original feature sets into a lower dimensional feature space. The fundamental concept of LDA is to maximize the following Fisher criterion to search for the most efficient projection matrix  $\mathbf{W}$

$$J(\mathbf{W}) = \frac{\mathbf{W}^T \mathbf{S}_B \mathbf{W}}{\mathbf{W}^T \mathbf{S}_W \mathbf{W}}$$

in order to achieve maximal discrimination in the new feature space, transformation matrix  $\mathbf{W}$  is utilized to maximize the ratio of the between-class distance to the within class distance. After feature extraction, these reduced features

## V. CONCLUSION

Designed a MEMS-based digital pen for handwritten digit and alphabet recognition applications. The digital pen consists of a triaxial accelerometer, a microcontroller (with A/D converter), and an ZigBee wireless transmission module. Users can use the pen to write digits or make hand gestures, and the accelerations of hand motions measured by the accelerometer are wirelessly transmitted to a computer for online trajectory recognition. So, by changing the position of mems (micro electro mechanical systems) we can able to show the alphabetical characters in the PC. The proposed method is to be more efficient than the existing method. Moreover, using ZigBee technology, we can reduce the power and cost of the system.



## REFERENCES

- [1] J. S. Lipscomb, "A trainable gesture recognizer," *Pattern. Recognition.* vol. 24, no. 9, pp. 895–907, 1991.
- [2] W. M. Newman and R. F. Sproull, *Principles of Interactive Computer Graphics.* New York: McGraw-ill, 1979.
- [3] D. H. Rubine, "The Automatic Recognition of Gesture," PhD dissertation, Computer Science Dept., Carnegie Mellon Univ., Pittsburgh, PA, Dec. 1991.
- [4] K. S. Fu, *Syntactic Recognition in Character Recognition.* New York: Academic, 1974, vol. 112, *Mathematics in Science and Engineering.*
- [5] S. S. Fels and G. E. Hinton, "Glove-talk: A neural network interface between a data glove and a speech synthesizer," *IEEE Trans. Neural Netw.*, vol. 4, no. 1, pp. 2–8, Jan. 1993.
- [6] C. M. Bishop, *Pattern Recognition and Machine Learning*, 1st ed. New York: Springer, 2006.
- [7] T. Schlomer, B. Poppinga, N. Henze, and S. Boll, "Gesture recognition with a Wii controller," in *Proc. 2nd Int. Conf. Tangible and Embedded Interaction (TEI'08)*, Bonn, Germany, 2008, pp. 11–14.
- [8] B. Milner, "Probabilistic neural networks," in *Proc. Inst. Elect. Eng.—Colloq. Doc. Image Process. Multimedia*, 1999, pp. 5/1–5/6.
- [9] J. K. Oh, S. J. Cho, W. C. Bang, W. Chang, E. Choi, J. Yang, J. Cho, and D. Y. Kim, "Inertial sensor based recognition of 3-D characters gestures with an ensemble of classifiers," in *Proc. IEEE 9th Int. Workshop Frontiers Handwriting Recognit.*, 2004, pp. 112–117.
- [10] S. J. Cho, J. K. Oh, W. C. Bang, W. Chang, E. Choi, Y. Jing, J. Cho, and D. Y. Kim, "Magic wand: A hand-drawn gesture input device in 3-D space with inertial sensors," in *Proc. IEEE 9th Int. Workshop Frontiers Handwriting Recognition.*, 2004, pp. 106–111.
- [11] S. Zhou, Z. Dong, W. J. Li, and C. P. Kwong, "Hand-written character recognition using MEMS motion sensing technology," in *Proc. IEEE/ASME Int. Conf. Adv. Intell. Mechatron.* 2008, pp. 1418–1423.

**Author's Detail:**



**S. Iswarya** is doing her ME in Embedded System Technologies at PSN College of Engineering And Technology, Tirunelveli. She received her B.Tech in Electronics and Communication from College of Engineering Attingal, Kerala in 2008. Her research interests include Embedded System.



**T. Rajesh** was born in Nagercoil at 1982. He received the BE degree in 2003 from PET Engineering College, and master degree from Anna University-Chennai in 2006. He is currently pursuing the Ph.D degree in Anna University Chennai. He is currently Assistant Professor at PSNCET in Tirunelveli. His field of research interests includes DIP, Soft Computing Techniques and Grid Computing.