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Research Article

Review of an Accelerometer Based Digital Pen with Trajectory recognition Algorithm for Handwritten Digit and Gesture Recognition

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Abstract

In the office automation area, many handwritten documents are digitized for ease of backup and transmission. The demand for digital writing instruments is thus expected to grow rapidly in coming years. There are many different types of systems already available on the market. Recently, we have developed a prototype of a MEMS (Micro-Electro-Mechanical Systems) based digital writing instrument which makes use of a micro inertial measurement unit (µIMU) constructed from MEMS accelerometers and gyroscopes for real-time capture of handwriting. We have proposed an accelerometer digital pen for handwritten digit & gesture recognition. In this pen type device consist of a triaxial accelerometer, a microcontroller, and RF wireless module. The acceleration signals measured by this transmitter are transmitted to the computer by using wireless module. After measurement of this acceleration signals we can recognize it by using trajectory recognition algorithm. In the recognition algorithm basically we are using acceleration acquisition, signal preprocessing, feature generation, feature selection and feature extraction. In this project we are using the KBCS (Kernel-based class separability) for selecting the significant features from the original features. After selection of the feature it can reduce by using the LDA (Linear Discriminant Analysis) because it gives the better recognition performance

Keywords: *RF wireless module, Microcontroller, Accelerometer, KBCS (Kernel- based class separability) for the feature selection, LDA (Linear Discriminant Analysis) for the feature reduction*

1. Introduction

The “Electronic Whiteboard” and “Digital Pen” are new instruments in the office automation industry that may someday completely replace the computer keyboard, which is still the preferred alphanumeric human-to-computer input device. These new devices aim to capture human handwriting or drawing motions in real-time and store motion strokes for digit recognition or information retrieval at a later time. For sensing this acceletions of the humans and capture the motion trajectory information has been proposed the inertial sensors in this portable device So the advantage of inertial sensors for general motion sensing is 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. Thus, many researchers have tried to narrow down the problem domain for increasing the accuracy of handwriting recognition systems

In 1964, the first graphics tablet was launched, the RAND Tablet (Malcolm Davis and T. O. Ellis, 1964) also known as the Grafacon (Graphic Converter). It makes use of electromagnetic resonance to digitize pen motion. In the next 40 years of development, many different well-developed methodologies to digitize handwriting have been proposed. Targeting business and academic institutions, ultrasonic, infrared and optical sensing are currently the most popular technologies for detecting the position of a digital pen on a large area electronic whiteboard. Luidia Inc. and Sanford LP have separately proposed systems, eBeam and mimior respectively, that can modify a conventional whiteboard by placing a receiver in its corner. The receiver uses infrared and ultrasound technologies to translate pen movement into positions which are recorded on a computer. However, the price of the overall system is very expensive, and the active area is limited.

Recently, some researchers have focused on reducing the error of handwriting trajectory reconstruction by manipulating acceleration signals and angular velocities of inertial sensors However, (Z. Dong, U. C. Wejinya, and W. J. Li, 2010; J. S.Wang, Y. L. Hsu, and J. N. Liu,2010)the reconstructed trajectories suffer from various intrinsic errors of inertial sensors. Hence, many researchers have focused to improve effective algorithms for error compensation of inertial sensors to improve the accuracy of recognition.

Dong *et al.*(Z. Dong, G. Zhang, Y. Luo, C. C. Tsang, G. Shi, S. Y. Kwok, W. J. Li, P. H. W. Leong, and M. Y. Wong, 2007) proposed an optical tracking calibration

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method based on optical tracking system (OTS) to calibrate 3-D accelerations, angular velocities, and space attitude of handwriting motions. The OTS was developed to obtain accelerations of the proposed ubiquitous digital writing instrument (UDWI) by calibrating 2-D trajectories and to obtain the accurate attitude angles by using the multiple camera calibration. However, in order to recognize or reconstruct motion trajectories accurately, the aforementioned approaches introduce other sensors such as gyroscopes or magnetometers to obtain precise orientation. It increases additional cost for motion trajectory recognition systems as well as the algorithm of the trajectory recognition is also becomes complicated.

In this project we have proposed an accelerometer digital pen for handwritten digit & gesture recognition. In this pen type portable device consist of a triaxial accelerometer, a microcontroller, and RF wireless module. The acceleration signals measured by this transmitter are transmitted to the computer by using wireless module.

After measurement of this acceleration signals we can recognize it by using trajectory recognition algorithm. In the recognition algorithm basically we are using acceleration acquisition, signal preprocessing, feature generation, feature selection and feature extraction. The signal preprocessing procedure consists of calibration, a moving average filter, a high-pass filter, and normalization. In the feature generation it includes the preprocessed acceleration signals of each axis include mean, correlation among axes, interquartile range (IQR), mean absolute deviation (MAD), root mean square (rms), VAR, standard deviation (STD),Range ,Zero crossing and energy. After this third step is feature selection. In general, feature selection aims at selecting a subset of size m from an original set of d features ($d > m$). 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 for the better recognition performance (i.e., to reduce the size of m).By using the feature selection and feature extraction methods we can reduce the burden of computational load and increase the accuracy of classification. The reduced features are given to the as the inputs of classifiers. In this paper, we proposed a probabilistic neural network (PNN) as the classifier for handwritten digit and hand gesture recognition.

The main aim of this paper to develop the portable digital pen with a trajectory recognition algorithm, i.e. with the digital pen, users can deliver diverse commands by hand motions to control electronics devices anywhere without space limitations, and an effective trajectory recognition algorithm, i.e., the proposed algorithm can efficiently select significant features from the time and frequency domains of acceleration signals and project the feature space into a smaller feature dimension for motion recognition with high recognition accuracy.

After this in this paper we will see the details of hardware components of the digital pen in detail, respectively. The trajectory recognition consisting of acceleration acquisition, signal preprocessing, feature generation, feature selection, feature extraction, and a PNN. Then we will see the simulation results of the digit and gesture recognition. Finally conclusion is given in the last section.

2. System Overview

This is the schematic diagram of system which is the digital pen. We will develop 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 by using the wireless module. Users can use this digital pen to write digits and make hand gestures at normal speed. The measured acceleration signals of these motions can be recognized from the trajectory recognition algorithm.

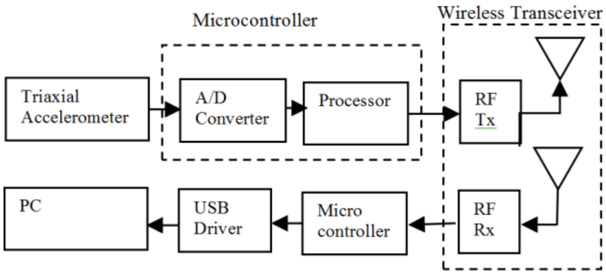


Fig.1 Schematic diagram of digital pen

3. Hardware Part of Digital Pen

In the hardware part, it includes the AVR microcontroller, MEMS Accelerometer; RF wireless module, Power supply

AVR Microcontroller

The ATmega16 is a low-power CMOS 8-bit microcontroller based on the AVR enhanced RISC Architecture. By executing powerful instructions in a single clock cycle, the ATmega16 achieves throughputs approaching 1 MIPS per MHz allowing the system designed to optimize power consumption versus processing speed. The AVR core combines a rich instruction set with 32 general purpose working registers. All the 32 registers are directly connected to the Arithmetic Logic Unit (ALU), allowing two independent registers to be accessed in one single instruction executed in one clock cycle. The resulting architecture is more code efficient while achieving throughputs up to ten times faster than conventional CISC microcontrollers

MEMS Accelerometer

In this project used the MEMS –ACCELEROMETER - MXA 2300 The MEMS IC device is a complete dual-axis acceleration measurement system fabricated on a monolithic CMOS IC process. The device operation is based on heat transfer by natural convection and operates like other accelerometers having a proof mass except it is a gas in the MEMSIC sensor. A single heat source, centered in the silicon chip is suspended across a cavity.

Equally spaced Aluminum/poly-silicon thermopiles (groups of thermocouples) are located equidistantly on all four sides of the heat source (dual axis). Under zero acceleration, a temperature gradient is symmetrical about the heat source, so that the temperature is the same at all four thermopiles, causing them to output the same voltage. Acceleration in any direction will disturb the temperature profile, due to free convection heat transfer, causing it to be asymmetrical.

RF Wireless Module

RF communication works by creating electromagnetic waves at a source and being able to work up those electromagnetic waves at a particular destination. Higher frequencies result in shorter wavelengths. The wavelength for a 900 MHz device is longer than that of a 2.4 GHz device. In general, signals with longer wavelengths travel a greater distance and penetrate through, and around objects better than signals with shorter wavelengths. Transmit power refers to the amount of RF power that comes out of the antenna port of the radio. Transmit power is usually measured in Watts, mill watts or dBm. Receiver sensitivity refers to the minimum level signal the radio can demodulate. It is convenient to use an example with sound waves; Transmit power is how loud someone is yelling and receive sensitivity would be how soft a voice someone can hear. Transmit power and receive sensitivity together constitute what is known as “link budget”. The link budget is the total amount of signal attenuation you can have between the transmitter and receiver and still have communication occur. Data rates are usually dictated by the system - how much data must be transferred and how often does the transfer need to take place. Lower data rates, allow the radio module to have better receive sensitivity and thus more range. In the XStream modules the 9600 baud module has 3dB more sensitivity than the 19200 baud module. This means about 30% more distance in line-of-sight conditions. Higher data rates allow the communication to take place in less time, potentially using less power to transmit.

Power supply

Our project requires +5V for microcontroller and sensors and 3.3V for AVR and RF transceiver module. +5 volt power supply is based on the commercial 7805 voltage regulator IC. This IC contains all the circuitry needed to accept any input voltage from 8 to 18 volts and produce a steady +5 volt output, accurate to within 5% (0.25 volt). It also contains current-limiting circuitry and thermal overload protection, so that the IC won't be damaged in case of excessive load current; it will reduce its output voltage instead.

4. Trajectory Recognition Algorithm

This is the block diagram of the trajectory recognition algorithm. In this block diagram it includes the acceleration acquisition, signal preprocessing, feature generation, feature selection, and feature extraction. By using this algorithm we can measure the acceleration signals of hand motions measured by triaxial accelerometer. We will discuss the detail block by block procedure of the trajectory recognition algorithm.

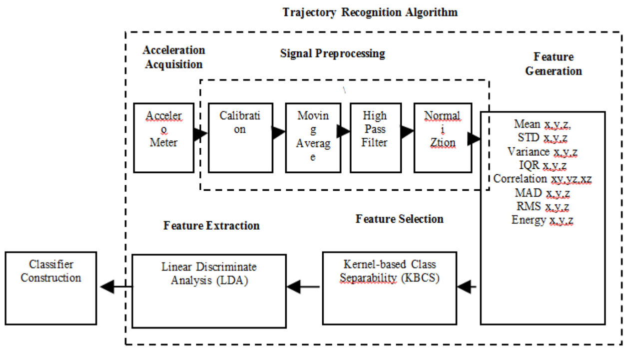


Fig.2 Trajectory Recognition Algorithm

1) Acceleration Acquisition

In this the acceleration signals of the hand motions are measured by a triaxial accelerometer. After measurement of this signal given to the microcontroller. Due to human nature, our hand always trembles slightly while moving, which causes certain amount of noise.

2) Signal Preprocessing

The acceleration signals of hand motions are generated by the accelerometer and collected by the microcontroller. The signal Preprocessing consists of calibration, a moving average filter, a high-pass filter, and normalization. In the signal preprocessing calibration is used to remove the drift errors. And offset error of accelerations signals. After this signal preprocessing is to use a moving average filter to reduce the high-frequency noise of the calibrated accelerations.

Then, we use a high-pass filter to remove the gravitational acceleration from the filtered acceleration to obtain accelerations caused by hand movement. In general, the size of samples of each movement between fast and slow writers is different. Therefore, after filtering the data, we first segment each movement signal properly to extract the exact motion interval. Then, we normalize each segmented motion interval into equal sizes via interpolation. Once the preprocessing procedure is completed, the features can be extracted from the preprocessed acceleration signals.

3) Feature Generation

In the feature generation the characteristics of different hand movement signals obtained from the accelerometer. We can obtained this by extracting features from the preprocessed *x*-,
y-, and *z*-axis signals and we extract eight features from the triaxial acceleration signals, including mean, STD, VAR, IQR
(S. J. Preece, J. Y. Goulermas, L. P. J. Kenney, and D. Howard, 2005), correlation between axes(L. Bao and S. S. Intille,2009),MAD, rms, energy(Y. P. Chen, J. Y. Yang, S.

N. Liou, G. Y. Lee, and J. S. Wang,2008),Range, Zero crossing in this study. When the procedure of feature generation is done, 24 features are then generated. Because the amount of the extracted features is large, we used KBCS to select most useful features and then use LDA to reduce the dimensions of features.

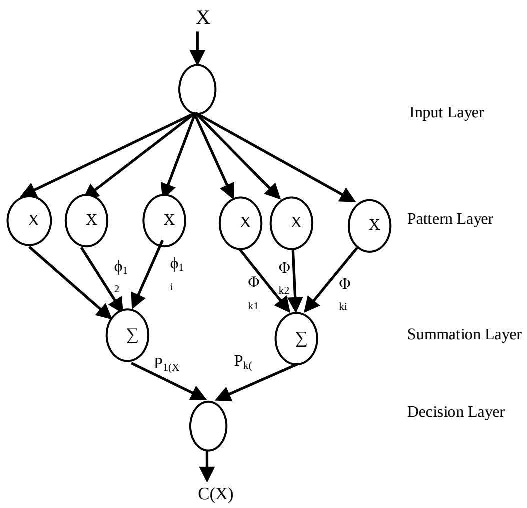
4) Feature Selection

In the feature selection we selecting a subset of size m from an original set of d features ($d > m$). Therefore, the criterion of kernel-based class separability (KBCS) with best individual N (BIN) is to select significant features from the original features Feature selection comprises a selection criterion and a search Strategy.

5) Feature Extraction

For solving the pattern recognition problems used LDA (A.M. Martinez and A. C. Kak, 2001)LDA is an effective feature extraction (or dimensionality reduction method) which uses a linear transformation to transform the original feature sets into a lower dimensional feature space. The advantage of LDA is to divide the data distribution in different classes and minimize the data distribution of the same class in a new space.

6) PNN (Probalistic Neural Network) Classifier



After feature extraction, these reduced features will be fed into the PNN classifier to recognize different hand movements. The PNN was first proposed by Specht (D. F. Specht, 1990) The PNN is very useful to converge to a Bayesian classifier, and thus, it has a great work for making classification decisions accurately and providing probability and reliability measures for each classification. In the training procedure of the PNN only needs to adjust the weights and biases of the network architecture. Therefore, the most important advantage of using the PNN is its high speed of learning. Basically, the PNN consists of an input layer, a pattern layer, a summation layer, and a decision layer as shown in Fig. The function of the each layer of the PNN is given as follows.

Layer 1: The first layer is the input layer, and this layer performs no computation. The neurons of this layer given to the input features **x** to the neurons of the second layer

$\mathbf{x} = [x1, x2, \ldots, xp]$T

p is the number of the extracted features.

Layer 2: The second layer is the pattern layer, and the number of neurons in this layer is equal to NL. Once a pattern vector **x** from the input layer arrives, the output of the neurons of the pattern layer as shown in fig.

Layer 3: The third layer is the summation layer. The work of this layer is inputs are summed in this layer to produce the output as the vector of probabilities. Each neuron in the summation layer represents the active status of one class.

Layer 4: The fourth layer is the decision layer. If the a priori probabilities and the losses of misclassification for each class are all the same, the pattern **x** can be classified according to the Bayes' strategy in the decision layer based on the output of all neurons in the summation layer. In this paper, the output of the PNN is represented as the label of the desired outcome defined by users. For example, in our handwritten digit recognition, the labels "1," "2," "3," "4," "5,""6," "7," "8," "9," and "10" are used to represent handwriting digits 1, 2, . . ., 9, and 0, respectively.

5. Overview of the Trajectory Recognition Algorithm

We will discuss the trajectory recognition algorithm in the following steps.

Step I: Capture the acceleration signals from the pen type accelerometer module.

Step II: After this filter out the high-frequency noise of the accelerations by the moving average filter in and then remove the gravity from the filtered accelerations by a high-pass filter. In the last ,we normalize each segmented motion interval into equal sizes via interpolation.

Step III: Generate the time- and frequency-domain features from the preprocessed acceleration of each axis including meanx,y, STDx,y, VARx,y, IQRx,y, corrxy,, MADx,y rmsx,y,, rangex,y, zero crossing,y and energyx,y

Step IV: Select significant features by using the KBCS.

Step V: Reduce the dimension of the selected features by LDA.

Conclusion

In this paper we developed a MEMS accelerometer-based digital writing instrument. The accelerometer picks up the acceleration generated during handwriting which is transmitted to a host computer to compute the position of the pen tip. However, as random noise degrades the acceleration readings, a positional drift results when double integration of acceleration is applied. We used the trajectory recognition algorithm framework that can construct effective classifiers for acceleration-based handwriting and gesture recognition. The trajectory recognition algorithm consists of acceleration acquisition, signal preprocessing, feature generation, feature selection, and feature extraction. With the reduced features, a PNN can be quickly trained as an effective classifier. The overall handwritten digit recognition rate was 98%, and the gesture recognition rate was also 98.75%.The remaining proposed work is to achieve 99 % accuracy for handwritten digit and the gesture recognition rate.

References

Malcolm Davis and T. O. Ellis (1964), The RAND Tablet: A Man-Machine Graphical Communications Device.

Z. Dong, U. C. Wejinya, and W. J. Li (2010), An optical-tracking calibration method for MEMS-based digital writing instrument, *IEEE Sens. J*, vol. 10, no. 10, pp. 1543–1551.

J. S.Wang, Y. L. Hsu, and J. N. Liu(2010), An inertial-measurement-unit-based pen with a trajectory reconstruction algorithm and its applications, *IEEE Trans. Ind. Electron.*, vol. 57, no. 10, pp. 3508–3521.

S.-H. P. Won, W. W. Melek, and F. Golnaraghi(2010.), A Kalman/particle filter-based position and orientation estimation method using a position sensor/inertial measurement unit hybrid system, *IEEE Trans. Ind. Electron.*, vol. 57, no. 5, pp. 1787–1798.

S.-H. P. Won, F. Golnaraghi, and W. W. Melek(2009), A fastening tool tracking system using an IMU and a position sensor with Kalman filters and a fuzzy expert system, *IEEE Trans. Ind. Electron.*, vol. 56, no. 5, pp. 1782–1792

Y. S. Suh (2006.), Attitude estimation by multiple-mode Kalman filters, *IEEE Trans. Ind. Electron.*, vol. 53, no. 4, pp. 1386–1389.

Z. Dong, G. Zhang, Y. Luo, C. C. Tsang, G. Shi, S. Y. Kwok, W. J. Li, P. H. W. Leong, and M. Y. Wong(2007), A calibration method for MEMS inertial sensors based on optical tracking in *Proc, IEEE Int. Conf. Nano/Micro Eng*, pp. 542–547.

S. J. Preece, J. Y. Goulermas, L. P. J. Kenney, and D. Howard (2005), A comparison of feature extraction methods for the classification of dynamic activities from accelerometer data, *IEEE Trans. Biomed. Eng.*, vol. 56.

L. Bao and S. S. Intill(2009), Activity recognition from user-annotated acceleration data, *Pervasive*, *Lecture Notes in Computer Science*, no. 3001 pp. 1–17, 2004. no. 3, pp. 871–879.

Y. P. Chen, J. Y. Yang, S. N. Liou, G. Y. Lee, and J. S. Wang(2008.), Online classifier construction algorithm for human activity detection using a triaxial accelerometer, *Appl. Math. Compute*, pp. 849–860.

A.M. Martinez and A. C. Kak (2001), PCA versus LDA, *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 23, no. 2, pp. 228–233.

D. F. Specht(1990), Probabilistic neural networks, *Neural Net.*, vol. 3, no. 1,pp. 109–118.