

## Accelerometer based Handwritten Digit Recognition using Trajectory Algorithm

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### Abstract-

Accelerometer based digit recognition is one of the widely implemented method in the recognition scenario. In this paper we have discuss various classifier techniques used for a trajectorybased digit recognitionsystem. Accelerometer embeds in a digital pen which consists of a tri-axial accelerometer, a microcontroller, RF wireless transmitter module for sensing and collecting accelerations of handwriting trajectories. The triaxial accelerometer measure acceleration signal along all the 3 axis. MEMS (micro electro mechanical systems) position change can be detected and displayed on the PC. Accelerated signal process through microcontroller and serially transmitted through RF transmitter which can be received at remote place RF receiver. With the help of MATLAB tool, feature vector are generated from received accelerated signal using to recognize handeritten numeric digit and PNN classifier technique for the best accuracy purpose. Our experimental results shows that the PNN has best accuracy than any other classifier.

**KEYWORDS**—MEMS,PNN

### I. INTRODUCTION

Handwriting Recognition is generally used for security ,authentication purpose. There are two types recognition offline recognition & on-line recognition[7]. Pen based input devices embedded with MEMS sensors have been provided for hand gestures or hand writing. In this paper, we have proposed a pen-type portable device and a trajectory recognition algorithm. 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. Before classifying the hand motion trajectories, we perform the procedures of feature selection and extraction methods for not only to ease the burden of computational load but also to increase the accuracy of classification.

The recognition procedure is composed of acceleration acquisition, signal preprocessing, feature generation, feature selection, and feature extraction[9]. Trajectory algorithm is capable of translating time-series acceleration signal into a feature vector. The trajectory recognition algorithm first extract the time-and frequency-domain feature from the acceleration signal and then further identifies the important feature by KBCS (Kernal- based class separability) for selecting significant feature and then for reducing the dimension of feature used as LDA(linear discriminant analysis). The reduced features are used as the inputs of classifiers[9]. Block Diagram Of Accelerometer based Digital Pen is as shown in following fig.1[2]

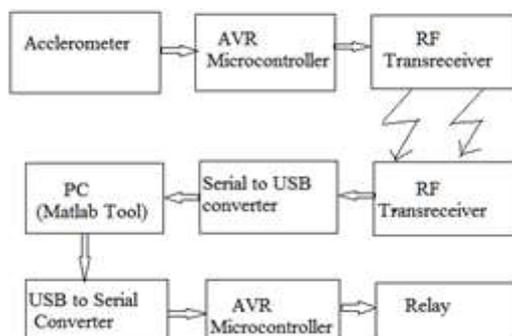


fig1:BlockDiagram Of Accelerometer based Digital Pen[2]

## II. TRAJECTORY ALGORITHM

The block diagram of the proposed trajectory recognition algorithm consisting of acceleration acquisition, signal preprocessing, feature generation, feature selection, and feature extraction is shown in fig[2]

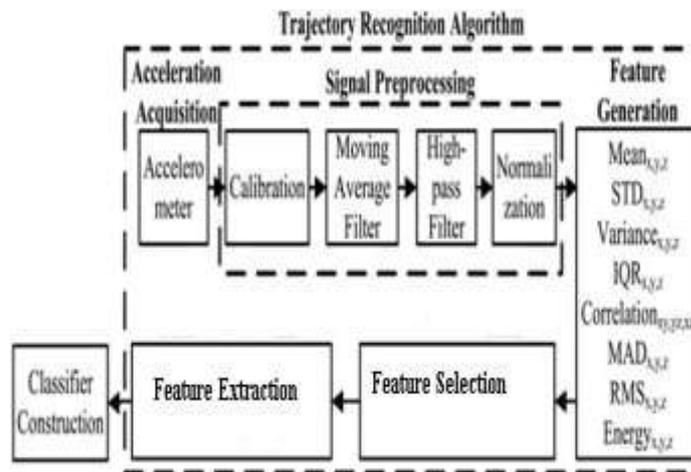


fig2:Block Diagram Of Trajectory Recognition System[2]

We now introduce the detailed procedure of the proposed trajectory recognition algorithm as follows.

### *Signal Preprocessing*

The raw acceleration signals of hand motions are generated by the accelerometer and collected by the microcontroller. Due to human nature, our 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

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

Where  $x[t]$  is the input signal,  $y[t]$  is the output signal, and  $N$  is the number of points in the average filter. In this paper, we set  $N = 8$ . The decision of using an eight-point moving average filter is based on our empirical tests. From our experimental results, we found that the ideal value of the moving average filter to achieve the best recognition result is eight. Then, we utilize 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.

### *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 we extract eight features from the triaxial acceleration signals, including mean, STD, VAR, IQR, Correlation between axis, MAD, rms & energy[2].

### *Feature Selection*

Feature selection comprises a selection criterion and a search strategy. The mostly used selection criterion is the KBCS which is originally developed by Wang. The KBCS can be computed as follows:

Let  $(x, y) \in (R^d \times Y)$  represents a sample,

where  $R^d$  denotes a d-dimensional feature space,  $Y$  symbolizes the set of class labels, and the size of  $Y$  is the number of class.

This method projects the samples onto a kernel space, and  $m_i^0$  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,  $m^0$  denotes the mean vector for all classes in the kernel space,  $S_B^0$  denotes the between-class scatter matrix in the kernel

Let  $\phi(\cdot)$  be a possible nonlinear mapping from the feature space  $R^d$  to a kernel space  $\kappa$  and  $\text{tr}(A)$  represents the trace of a square matrix  $A$ . The following two equations are used in the class separability measure:

$$\begin{aligned} \text{tr}(S_B^0) &= \text{tr} \left[ \sum_{i=1}^c n_i (m_i^0 - m^0) (m_i^0 - m^0)^T \right] \\ &= \sum_{i=1}^c n_i [(m_i^0 - m^0) (m_i^0 - m^0)^T] \end{aligned} \quad \dots(2)$$

$$\begin{aligned} \text{tr}(S_W^0) &= \text{tr} \left[ \sum_{i=1}^c \sum_{j=1}^{n_i} (\phi(x_{ij}) - m_i^0) (\phi(x_{ij}) - m_i^0)^T \right] \\ &= \sum_{i=1}^c \sum_{j=1}^{n_i} [(\phi(x_{ij}) - m_i^0)^T (\phi(x_{ij}) - m_i^0)] \end{aligned} \quad \dots(3)$$

The class separability in the kernel space can be measured as

$$J^0 = \frac{\text{tr}(S_B^0)}{\text{tr}(S_W^0)} \quad \dots(4)$$

To maintain the numerical stability in the maximization of  $J^0$ , the denominator  $\text{tr}(S_W^0)$  has to be prevented from approaching zero. In order to maximize class separability, we adopt the BIN as the search strategy. In the BIN, a selection criterion is individually applied to each of the features. The features with larger values of the given criteria are selected.

#### *Feature Extraction*

For feature extraction there are various type of various type of classifier like PNN , FNN, FDA, HMM, GMM, LDA. They have different recognition rates.

### **III. DIFFERENT CLASSIFIER FOR TRAJECTORY RECOGNITION**

#### *PNN Classifier*

The PNN was initial projected by Specht , the PNN is certain to converge to a Bayesian classifier, and thus, it's a good potential for creating classification selections accurately and providing chance and responsibility measures for every classification .additionally, the procedure of the PNN solely wants one epoch to regulate the weights and biases of the spec. Therefore, the foremost necessary advantage of mistreatment the PNN is its high speed of learning. Typically, the PNN consists of associate input layer, a pattern layer, a summation layer, and a choice layer as shown in Fig. 4. The operate of the neurons in every layer of the PNN is outlined as follows. defined as follows.

- 1) Layer 1: The primary layer is that the input layer, and this layer performs no computation. The neurons of this layer convey the input options  $x$  to the neurons of the second layer
- 2) Layer 2: The second layer is that the pattern layer, and therefore the variety of neurons during this layer is adequate to NL.
- 3) Layer 3: The third layer is that the summation layer. The contributions forevery category of inputs are summed during this layer to provide the output because the vector of possibilities.[7] where  $N_i$  is that the total variety of samples within the  $k$ th nerve cell.
- 4) Layer 4: The fourth layer is that the decision layer.

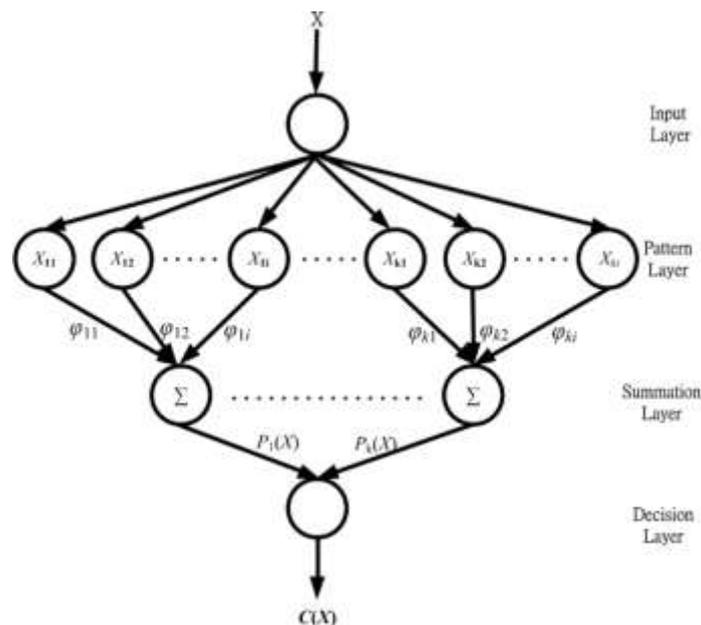


fig. 4: Topology of PNN classifier [2]

#### HMM Classifier

Markov model may be a mathematical model of framework wherever these processes generate a random sequence of outcomes per sure possibilities it's trainable and therefore the underlying framework is unperceivable, therefore we have a tendency to decision it hidden Markov model. each CHMM and DHMM square measure wideemployed in Pattern Recognition and lots of different fields. For DHMM, the evident states and invisible states square measure all separate. A HMM may be a assortment of finite states  $S =$  interconnected by transition every state includes a variety of distinct observation symbols  $V =$  reminiscent of the physical output of the system [1].

#### FDA Classifier

FDA is one of the linear projection methods that project the input point (a vector) in the input space to a point in the feature space. One motivation of using a linear method was that the training is easier, faster and requires relatively smaller amount of data for reasonable level of training than the more resource-intensive techniques like neural networks or hidden Markov models. Therefore it expedites, as a fast-running test-bed, one of our purposes, which is to explore the various sensor information combinations and see how the classifier behaves on each combination. One reason for such an exploration was that we wanted to determine the best performing combination of sensors. Another reason was to identify the most economical alternatives (yet performing acceptably) in terms of the number of sensors because the less sensors we use, the cheaper. Another motivation for linear method was to reinforce the overall performance via an ensemble of simple and fast classifiers. Yet another motivation was that the approach has a potential for making a user-tailored adaptation feasible because the training runs fast and demands less on the amount of training data. [9]

CLASSIFIER	RECOGNITION RATE
HMM	96.2%
PNN	98.5%
FDA	93.3%

Table 1: Recognition rate of Different Classifier [2,3,4]

#### IV CONCLUSION

In this paper we have studied and compared various classifier techniques and proposed trajectory recognition system and PNN for developing handwriting and gesture recognition also it is conclude that the recognition rate of PNN is greater than other classifier techniques.

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