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AN ACCELEROMETER BASED DIGITAL PEN WITH TRAJECTORY RECOGNITION ALGORITHM FOR HANDWRITTEN DIGIT AND GESTURE RECOGNITION

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ABSTRACT
The paper aims is to design an accelerometer based digital pen with trajectory recognition algorithm for handwritten digit and gesture recognition by using Zigbee technology. This system uses a MEMS device for having all directions. The digital pen consists of a triaxial accelerometer, a microcontroller, and an Zigbee wireless transmission module for sensing and collecting accelerations of handwriting and gesture trajectories. The proposed trajectory recognition algorithm composes of the procedures of acceleration acquisition, signal preprocessing, feature generation, feature selection, and feature extraction. The algorithm is capable of translating time-series acceleration signals into important feature vectors. 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. The algorithm first extracts the time- and frequency-domain features from the acceleration signals and, then, further identifies the most important features by a hybrid method: kernel-based class separability for selecting significant features and linear discriminant analysis for reducing the dimension of features. The reduced features are sent to a trained probabilistic neural network for recognition. Our experimental results have successfully validated the effectiveness of the trajectory recognition algorithm for handwritten digit and gesture recognition using the proposed digital pen.

KEYWORDS: Accelerometer, gesture, handwritten recognition, linear discriminate analysis (LDA), probabilistic neural network (PNN). Micro Electro Mechanical Sensor (MEMS), Zigbee.

INTRODUCTION
EXPLOSIVE growth of miniaturization technologies in electronic circuits and components has greatly decreased the dimension and weight of consumer electronic products, such as smart phones and handheld computers, and thus made them more handy and convenient. Due to the rapid development of computer technology, human–computer interaction (HCI) techniques [1]–[3] have become an indispensable component in our daily life. 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. A significant 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. Recently, some researchers have concentrated on reducing the error of handwriting trajectory reconstruction by manipulating acceleration signals and angular velocities of inertial sensors [4]–[6]. However, the reconstructed trajectories suffer from various intrinsic errors of inertial sensors. Hence, many researchers have focused on developing effective algorithms for error compensation of inertial sensors to improve the recognition accuracy.

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BLOCK DIAGRAM-

Transmitter

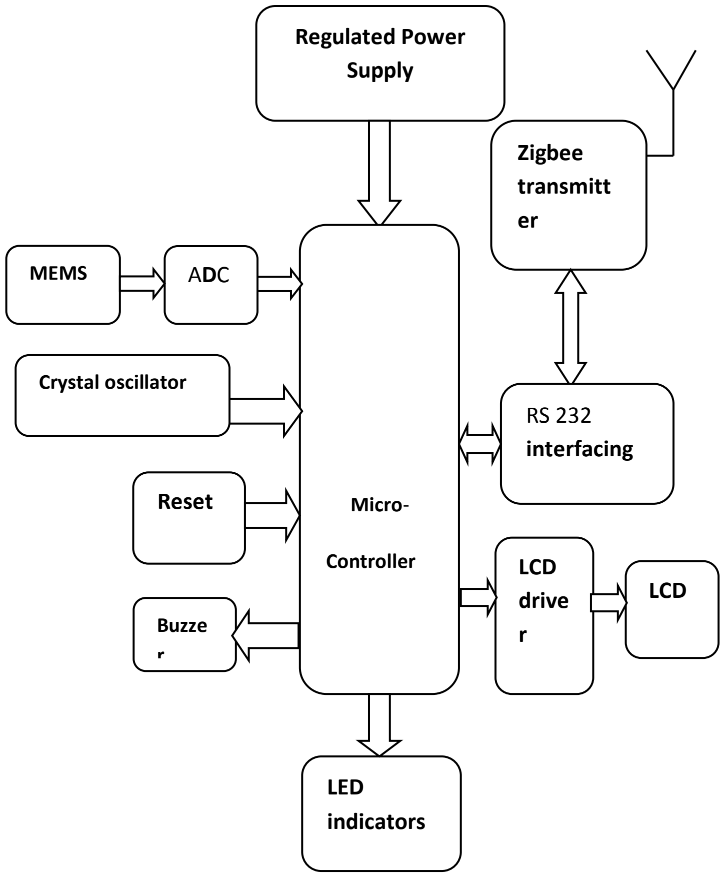

Fig 1. Transmitter section of system

Receiver

In this project, we are developing a pen-type portable device and a trajectory recognition algorithm. The pen-type portable device consists of a triaxial accelerometer, a microcontroller, and an Zigbee 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 [1]-[3].

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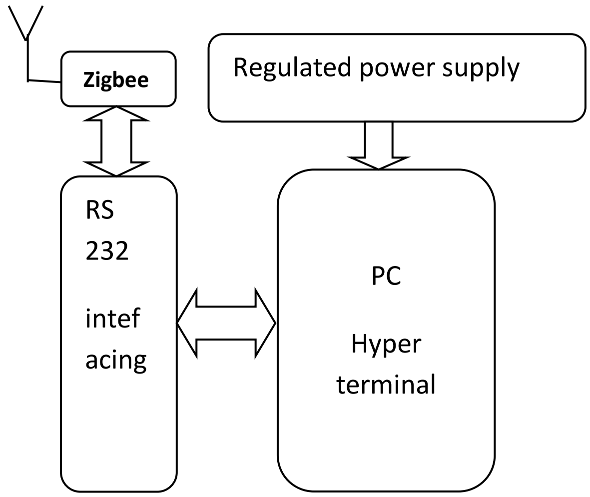

Fig 2 . Receiver section of system

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, correlation among axes, interquartile range (IQR), mean absolute deviation (MAD), root mean square (rms), VAR, standard deviation (STD), and energy. Before classifying the hand motion trajectories, we perform the procedures of feature selection and extraction methods. In general, feature selection aims at selecting a subset of size m from an original set of d features (d > m) [1]- [3].

Therefore, the criterion of kernel-based class reparability (KBCS) with best individual N (BIN) is to select significant features from the original features (i.e., to pick up some important features from d) and that of linear discriminate analysis (LDA) is to reduce the dimension of the feature space with a better recognition performance (i.e., to reduce the size of m). 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 project, I am going to adopt a probabilistic neural network (PNN) as the classifier for handwritten digit and hand gesture recognition. The contributions of this project include the following: 1) The development of a 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, 2) 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 [1]-[3].

TRAJECTORY RECOGNITION ALGORITHM

Trajectory recognition algorithm consisting of acceleration acquisition, signal pre-processing, feature generation, feature selection, and feature extraction. 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 [1].

Signal Pre-processing

The signal pre-processing procedure consists of calibration n, 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.

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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

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

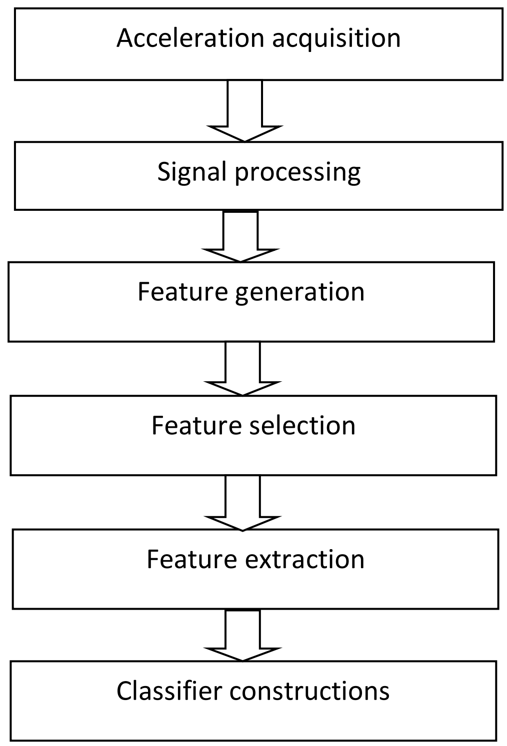

Fig 3. Step for trajectory Recognition Algorithm

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

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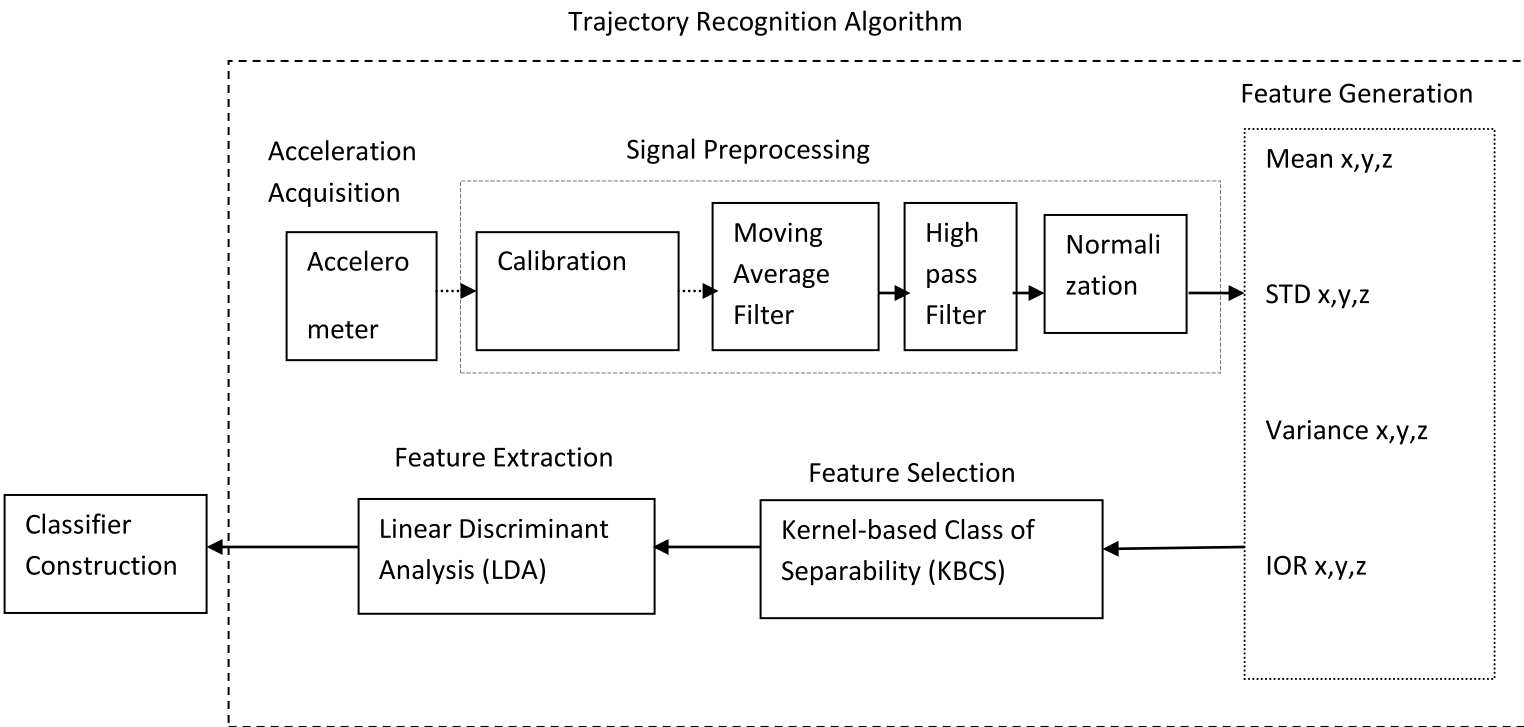

Fig 4. Block diagram of trajectory recognition algorithm

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 [1].

Feature Generation

The features of the pre-processed acceleration signals of each axis (three axis) include mean, correlation among axes, interquartile range (IQR), mean absolute deviation (MAD), root mean square (rms), VAR, standard deviation (STD), and energy. The characteristics of different hand movement signals can be obtained by extracting features from the pre-processed x, y, and z-axis signals, and we extract eight features from the triaxial acceleration signals, including mean, STD, VAR, IQR, correlation between axes,MAD, rms, and energy. Before classifying the hand motion trajectories, we perform the procedures of feature selection and extraction methods. They are explicated as follows, [1-5].

1) Mean:

The mean value of the acceleration signals of each hand motion is the dc component of the signal.

$$MEAN = \frac{1}{|W|} \sum_{i=1}^{|W|} \mathrm{x_i} \qquad (2)$$

Where W is the length of each hand motion.

2) STD:

STD is the square root of VAR

$$STD = \sqrt{\frac{1}{|W|-1} \sum_{i=1}^{|W|} (\mathrm{x_i} - \mathrm{m})^2} \qquad (3)$$

3) VAR:

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$$VAR = \frac{1}{|W|-1} \sum_{i=1}^{|W|} (\mathrm{x_i} - \mathrm{m})^2 \qquad (4)$$

Where *xi* is the acceleration instance and *m* is the mean value of *xi* in (3) and (4).

4) IQR:

When different classes have similar mean values, the interquartile range represents the dispersion of the data and eliminates the influence of outliers in the data.

5) Correlation among axes:

The correlation among axes is computed as the ratio of the covariance to the product of the STD for each pair of axes. For example, the correlation (*corrxy*) between two variables *x* on *x*-axis and *y* on *y*-axis is defined as

$$\mathrm{corr} = \frac{\mathrm{conv(x,y)}}{\sigma_x \sigma_y} = \frac{\mathrm{E((x-m_x)(y-m_y))}}{\sigma_x \sigma_y} \qquad (5)$$

where *E* represents the expected value, $\boldsymbol{\sigma x}$ and $\boldsymbol{\sigma x}$ are STDs, and *mx* and *my* are the expected values of *x* and *y*, respectively. Correlation is a useful feature in discriminating motions that involve translation in only one dimension.

6) MAD

$$MAD = \frac{1}{|W|-1} \sum_{i=1}^{|W|} |\mathrm{x_i} - \mathrm{m}| \qquad (6)$$

7) rms:

$$rms = \sqrt{\frac{1}{|W|} \sum_{i=1}^{|W|} \mathrm{x_i}^2} \qquad (7)$$

Where *xi* is the acceleration instance and *m* is the mean value of *xi* in (6) to (7).

8) Energy:

$$Energy = \frac{1}{|W|} \sum_{i=1}^{|W|} |\mathrm{F_i}|^2 \qquad (8)$$

Where *Fi* is the *i*th FFT component of the window and |*Fi*| is the magnitude of *Fi*.

When the procedure of feature generation is done, 24 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.

Feature selection:

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 [1-3].

Feature selection comprises a selection criterion and a search strategy. The adopted selection criterion is the KBCS which is originally developed by Wang. The KBCS can be computed as follows: Let (**x**, *y*) ∈(R*d* × ***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 *c*. This method projects the samples onto a kernel space, and $m^{\emptyset}$ is defined as the mean vector for the *i*th class in the kernel space, *ni* denotes the number of samples in the *i*th class, $m^{\emptyset}$ denotes the mean vector for all classes in the kernel space, $S_B^{\emptyset}$ denotes the between-class scatter matrix in the kernel space, and $S_W^{\emptyset}$ denotes the within-class scatter matrix in the kernel space. Let Ø (・) be a possible nonlinear mapping from the feature space R*d* to a kernel space *κ* and tr(**A**) represents the trace of a square matrix **A**. The following two equations are used in the class separability measure: [1-3].

$$tr(S_B^{\emptyset}) = tr\left[\sum_{i=1}^{c} \mathrm{n_i}(\mathrm{m_i^{\emptyset}} - \mathrm{m^{\emptyset}})(\mathrm{m_i^{\emptyset}} - \mathrm{m^{\emptyset}})^{\mathrm{T}}\right] = \left[\sum_{i=1}^{c} \mathrm{n_i}(\mathrm{m_i^{\emptyset}} - \mathrm{m^{\emptyset}})(\mathrm{m_i^{\emptyset}} - \mathrm{m^{\emptyset}})^{\mathrm{T}}\right] \qquad (9)$$

To maintain the numerical stability in the maximization of $J^{\emptyset}$ the denominator tr($S_W^{\emptyset}$)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 [1-3].

Feature extraction

For pattern recognition problems, LD 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 purpose of LDA is to divide the data distribution in different classes and minimize the data distribution of the same

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class in a new space. First, two scatter matrices, a within-class scatter matrix *SW* and a between-class scatter matrix *SB*, are introduced as follows: [1-3].

$$S_{W_i} = \frac{1}{\mathrm{n_i}} \sum_{j=1}^{\mathrm{n_i}} (x_j^i - m_i)\, (x_j^i - m_i)^T \qquad (10)$$

$$S_W = \sum_{i=1}^{\mathrm{N}} \mathrm{n_i X\, S_{W_i}} = \sum_{i=1}^{N} . \sum_{j=1}^{n_i} \left(\mathrm{x_j^{(i)}} - \mathrm{m_i}\right) \left(\mathrm{x_j^{(i)}} \right)^{\mathrm{T}} \qquad (11)$$

$$S_B = \sum_{i=1}^{N} \mathrm{n_i}\, (\mathrm{m_i} - \mathrm{m_{all}})\, (\mathrm{m_i} - \mathrm{m_{all}})^{\mathrm{T}} \qquad (12)$$

Where $\mathrm{n_i}$ is the number of samples in the *i*th class and $x(i)$ $j\in \mathrm{R}d$ represents the *j*th sample of the *i*th class. *d* is the dimension of the feature space, and *n* and *N* are the total numbers of the samples and classes, respectively. m_i is the mean of the *i*th class, and m all is the mean of all classes. Note that S_{W_i} is the covariance matrix of the *i*th class, S_W is the sum of the covariance matrices, and S_B is the sum of the squared distances between the mean of each class and the means of all classes. The fundamental concept of LDA is to maximize the following Fisher criterion to search for the most efficient projection matrix W.

$$J(W) = \frac{\mathrm{W^T S_B W}}{W^T S_W W} \qquad (13)$$

Where $W^T S_W W$ and $\mathrm{W^T S_B W}$ are the new within-class scatter and between-class scatter in the new feature space, respectively. That is, in order to achieve maximal discrimination in the new feature space, transformation matrix **W** is utilized to maximize the ratio of the between-class distance to the within class distance.

Classifier Construction

The PNN was first proposed by Specht. With enough training data, the PNN is guaranteed to converge to a Bayesian classifier, and thus, it has a great potential for making classification decisions accurately and providing probability and reliability measures for each classification. In addition, the training procedure of the PNN only needs one epoch 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. Typically, the PNN consists of an input layer, a pattern layer, a summation layer, and a decision layer as shown in Fig. 4. The function of the neurons in each layer of the PNN is defined as follows [1-3].

1) **Layer 1**:

The first layer is the input layer, and this layer performs no computation. The neurons of this layer convey the input features **x** to the neurons of the second layer directly

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

Where *p* is the number of the extracted features.

2) **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.

3) **Layer 3**:

The third layer is the summation layer. The contributions for each class of 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.

4) **Layer 4**:

The fourth layer is the decision layer

$$\mathrm{c}(\mathbf{x}) = \arg\max \{\mathrm{pk}(\mathbf{x})\},\ \mathrm{k}= 1, 2, \ldots, \mathrm{m}$$

Where m denotes the number of classes in the training samples and $c(\mathbf{x})$ is the estimated class of the pattern **x**. 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.

ADVANTAGES

-With the digital pen, users can deliver diverse commands by hand motions to control electronics devices anywhere without space limitations.

-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.

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- Digital pen is portable so that we can use this digital pen in any portable electronic device.

APPLICATIONS

1. E-Classes

In the E-classrooms there is need to change the picture, slides, play video, or write any words on the board. While teaching teacher may be walk into the classes so there is no need to come front of the board or near the key board. Teacher can change the slides or can give any commands to the PC, and also he can write on the board from anywhere from the class. So this digital pen can replace the keyboard and chalk and make easy and smart teaching learning process.

2. Conferences

Similar to the above we can use this pen to present our presentation and pen can replace the remote control and by using this pen we can change the slides or we can give any commands to the any portable device.

3. Easy for handicapped people

Those who have problem with their legs and cannot stand so this digital pen is very useful for those people.

4. To control the portable electronics devices

We can use this digital pen to give commands to the portable electronics devices. So by using this digital pen we can control the portable electronic device anywhere without any distance limitation

CONCLUSION

This paper has presented a systematic trajectory recognition algorithm framework that can construct effective classifiers for acceleration-based handwriting and gesture recognition. The proposed 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.

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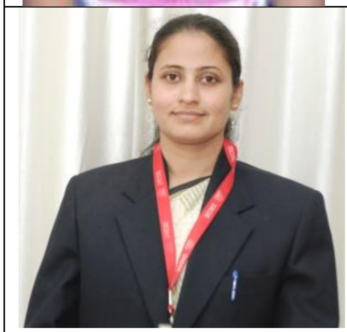	**AssoProf.K.Sujatha**, M.Tech PhD working as a PG coordinator in Shri Ramchandra College if Engineering, Lonikand, Pune, Maharashtra, India.