A Review On An Inertial Pen for Handwriting and Gesture Recognition Using Adaptive DTW Algorithm

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ABSTRACT

In this review paper we are going to discuss a systematic adaptive dynamic time wrapping algorithm framework that can construct effective classifier for hand writing & gesture recognition. Review of digital pen for handwritten digit and gesture recognition using adaptive DTW algorithm based on accelerometer is discuss for the identification of 2-d handwriting and 3-d gesture. For this implementation we are going to use tri-axial accelerometer, tri-axial magnetometer, gyroscope, microcontroller, and RF wireless transmition module for sensing and collecting acceleration of handwriting and gesture. The proposed adaptive dynamic time wrapping algorithm includes the procedure of inertial signal acquisition, single pre-processing, motion detection, template selection and recognition. We integrate signals collected from accelerometer, a gyroscope, which might reduce the accuracy of the orientation estimation. We also have developed minimal inter-class to maximal inter-class based template selection method for ADTW recognizer to obtain a superior class separation for improved recognition.

Keyword: - *Inertial Pen, Adaptive Dynamic Time Wrapping Algorithm (ADTW), Human Computer Interface (HCI).*

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1. INTRODUCTION

With the rapid development of computer technology human computer interaction technique/devices have become indispensable in individuals daily lives. The ease with which an HCI device or technique can be understood and operate by users has become one of the major consideration when selecting such devices. Recently, an attractive alternative, a portable device embedded with inertial sensor, has been proposed to sense the activities of human and to capture their motion acceleration for recognizing gesture or handwriting among those methods pen based input device embedded with accelerometer, gyroscope can most easily provide intuitive expression through capturing translation acceleration and angular velocity generated. This inertial sensing based input device can be operated without ambit limitation such as writing range, directions, dimensions, while other pen may limit the writing space. The major challenge of inertial-sensing based hand-written and gesture recognition using acceleration or angular velocity signals is misrecognised since different users have different preferred style and speed. Models such as hidden markov model and neural network approaches are effective at increasing the recognition rate of inertial pen. However the computational complexity of HMM and neural network are directional proportional to dimension of the feature vector and both required more than one training sample to obtain acceptable rate. While some researches' have demonstrated the effectiveness of ADTW algorithm, which select the best match from many samples for each class for recognition, the ADTW enhance the capacity of supervised learning for time series data.

In this paper, an inertial-sensor based pen and an adaptive dynamic time wrapping (ADTW) based recognition algorithm are presented for both handwriting and gesture recognition task. The portable inertial pen is composed of a triaxial accelerometer, a triaxial gyroscope, a triaxial magnetometer, a microcontroller, and an RF wireless transmission module. User can utilized this inertial pen to write numerical or English letter, and make hand gesture at their preferred speed without space limitation. Measured acceleration, angular velocity and magnetic signals are transmitted to a pc via RF wireless module. The proposed ADTW based recognition algorithm is composed of the procedures of inertial signal acquisition, signal pre processing, motion detection template selection, and recognition. In the proposed recognition algorithm, we utilize the zero velocity compensation (ZVC) method and a quaternion-based complementary filter to reduce the integral errors caused by the intrinsic noise/drift of the accelerometer and gyroscope, which worsen the accuracy of the velocity, position, and orientation estimations. We have developed a minimal intra-class to maximal inter-class based template selection method (Min-Max template selection method) for an ADTW recognizer to obtain a superior class separation for improved recognition. The accelerometer, gyroscope, and magnetometer are used to detect accelerations, angular velocities, and magnetic signals generated by hand movements.

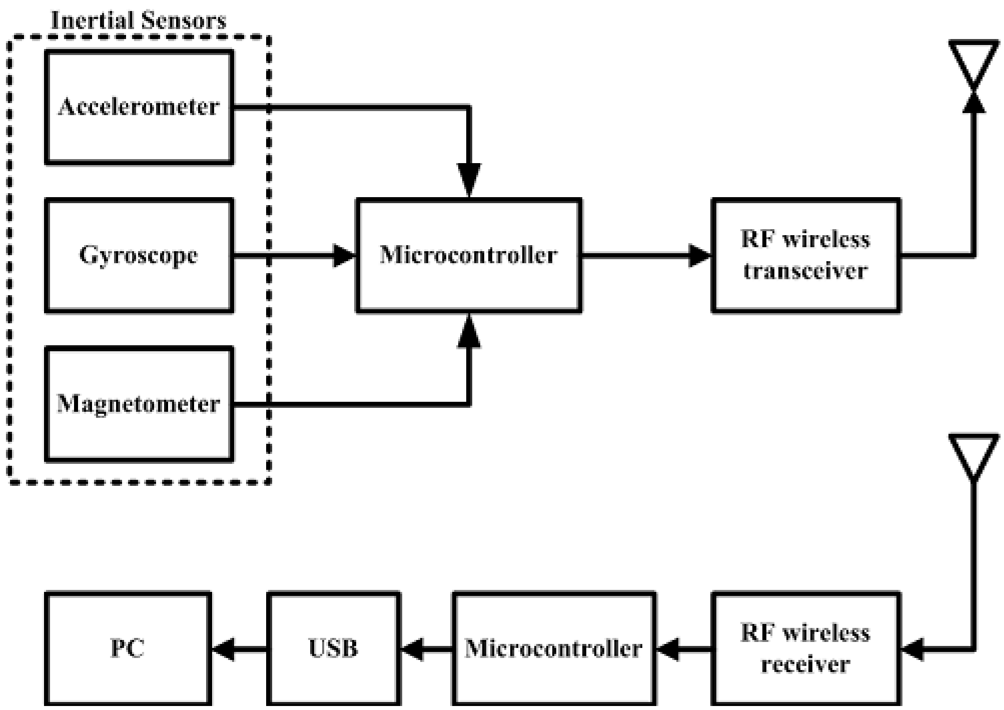

Fig.1: Block Diagram of Digital Pen

2. ADAPTIVE DYNAMIC TIME WRAPPING ALGORITHM:-

Pattern developed from time series is of fundamental importance. If information about this structure of a pattern is incomplete, than for such incomplete pattern. An algorithm discovers specific patterns or shapes automatically from the time series data if required. The dynamic time warping is a technique that allows local flexibility in aligning time series. Because of this, it is widely used in many fields such as science, finance, medicine, industry and others. However, a major problem of the dynamic time warping is that it is not able to work with structural changes of a pattern. This problem arises when the structure is influenced by noise, which is a common thing in practice for almost every application. This problem of pattern structure variation which arise the structure due to influence of noise, which is a common thing in practice for almost every application. The standard DTW approach uses only information about fixed pattern points and not structural elements between these points. Throughout this paper, the term ‘structural element’ will refer to linear or nonlinear part, which connects two adjacent fixed points in a pattern and the term ‘fixed point’ will refer to a point of a pattern. This paper addresses this problem by means of developing a novel technique called adaptive dynamic time warping. The DTW algorithm cannot use these elements because there are an infinite number of possible solutions to the initial problem of pattern matching.

This algorithm deal with inertial-sensing-based handwriting and gesture recognition, and is composed of the following process: 1) Signal Preprocessing, 2) Inertial Signal Acquisition 3) Motion Detection, 4) Template Selection, and 5) Recognition

The signals which are generated by hand movements are measured by the accelerometer, gyroscope, and magnetometer assembled on the inertial pen and then they are transmitted to a PC via the RF wireless transceiver. The effects of sensor uncertainty are removed using signal pre processing. The motion detection is used to extract an exact location by segmenting inertial signal. Next the min-max template selection method is used for reliable class template for each class of sequence.

2.1. Signal Preprocessing -

Since the measured signals are always contaminated not only by the sensors error sources but also with users' unconscious trembles, signal preprocessing composed of i) Calibration and ii) Moving average filter, are essential procedure for inertial signal preprocessing

2.1.1 Calibration: The acceleration, angular velocity, and magnetic signal are calibrated to reduce sensitivity and offset error from the raw signal. When the inertial pen is stationary the triaxial accelerometer measures the gravitational acceleration only. On the basis of this fact, we align each axis of the triaxial accelerometer with the Earth's gravity to calibrate the accelerometer. To execute the calibration, we first place the triaxial accelerometer on a level surface and then point each axis alternately upward and downward. For the calibration of the triaxial gyroscope, the scale factor (SFgyro) for each axis of the gyroscope can be obtained from the datasheet. In ideal situations, the output of each axis of the gyroscope should be zero when the inertial pen is stationary. Therefore, the bias (Bgyro) in each axis of the gyroscope is calculated as the mean of the angular velocities for each axis when the inertial pen is stationary at the beginning.

2.1.2 Moving average filter: The second step of the signal preprocessing procedure is to reduce the high-frequency noise from the calibrated signals by using a moving average filter.

2.2. Signal Acquisition –

The signal acquisition process includes 3 steps as follows.

2.2.1 Orientation Estimation: - The purpose of the orientation estimation for the non-motion interval is to obtain the initial orientation angles for the motion interval. The signals measured from the accelerometer and magnetometer are utilized to estimate the orientation angles during the non-motion interval since the initial orientation angles cannot be directly obtained from the signals of the gyroscope

2.2.2. Coordinate Transformation: - Complementary filter is used to estimate orientation of the inertial pen and once this is done, we will first derive a transformation matrix based on the quaternion to transfer all the filtered acceleration signals from the body coordinate to the reference coordinate. And we know the fact that the transformed acceleration in the reference coordinate is consist of both, the gravitational acceleration and motion acceleration. The gravitational acceleration must then be subtracted from the transformed acceleration to obtain the compensated acceleration generated by the movements alone.

2.2.3. Velocity and position estimation: - The estimated velocity of the inertial pen during a motion can be obtained through the single integral of the compensated acceleration in the motion interval

2.3. Motion Detection –

This process involves 2 steps; Segmentation, and Normalization

2.3.1. Segmentation: After filtering the reading each signal are segmented properly to extract a precise motion interval, as the size of measurement differs for fast and slow writer hence to study this difference, we segment the motion intervals of all inertial signals to obtain the accurate locations of the start and end points of each measurement based on an adaptive magnitude threshold generated from the filtered acceleration signal.

2.3.2. Normalizations: - The signal amplitude biases of the filtered accelerations, compensated accelerations, velocities, and positions are generally inconsistent due to individual differences of writing speeds or styles. In order to avoid extreme amplitude scaling, normalization of the amplitude of the above mentioned movement signals is required to ensure that the ADTW distance calculated by utilizing the local distance measurement is representative. Z-score method to normalize the movement signals.

2.4. Template Selection –

Recognition performance greatly depends on the quality of the selected class templates. During the training phase of the ADTW recognizer, it is most important to select reliable training, for classification problems with small training sets, we suggest selecting features adaptively. Thus we do not predefine a single subset of the relevant features but rather select a specific one for every new testing sample. The proposed feature selection scheme is a sequential feed forward algorithm. Every next feature added to the subset should be discriminative together with the already selected features, which take particular values observed on the current testing sample. Sequential feed forward feature selection algorithms use a greedy search strategy; such feed forward algorithms start from the empty set and add features one by one so that every next feature maximizes some selection criterion S considering features selected on the previous steps. Thus, conventionally the feature $F\alpha i+1$ selected on the (i+1)the step should satisfy.

2.5. Recognition –

Once each class template of each digit, English lowercase letter, gesture is selected, the similarity between each class template and the movement patterns will be measured through the ADTW recognizer. Since each movement pattern, including the filtered accelerations, compensated accelerations, velocities, and positions, is composed of three signal sequences (X-, Y -, and Z-axis), the distance ADTW, which denotes the similarity between the class template Ci of size i ×3andthe testing pattern Tj of size j × 3.

3. RELATED WORK:-

Recently some studies have focused on the development of digital pens for hand gesture recognition and HCI applications. Yu-Liang Hsu, Cheng-Ling Chu (1) has presented an inertial-sensor-based digital pen (inertial pen) and it's associated dynamic time warping (DTW)-based recognition algorithm for handwriting and gesture recognition. DTW recognize to obtain a superior class separation for improved recognition. Experimental results have successfully validated the effectiveness of the DTW-based recognition algorithm for online handwriting and gesture recognition using the inertial pen. Jeen-Shing Wang, Yu-Liang Hsu (2) presents an inertial-measurement unit-based pen (IMUPEN) and its associated trajectory reconstruction algorithm for motion trajectory reconstruction and handwritten digit recognition applications. The IMUPEN is composed of a tri-axial accelerometer, two gyroscopes, a microcontroller, and an RF wireless transmission module. A trajectory reconstruction algorithm composed of the procedures of data collection, signal preprocessing, and trajectory reconstruction has been developed for reconstructing the trajectories of movements. In order to minimize the cumulative errors caused by the intrinsic noise/drift of sensors, they used an orientation error compensation method and a multi-axis dynamic switch; Mariano Lopez Garcia, Rafael Ramos-Lara, (3) describes the implementation on field programmable gate arrays (FPGAs) of an embedded system for online signature verification a dynamic time warping algorithm is used to align this processed signature with its template previously stored in a database. Finally, a set of features are extracted and passed through a Gaussian Mixture Model, which reveals the degree of similarity between both signatures. The implemented system consists of a vector floating-point unit (VFPU), specifically designed for accelerating the floating-point computations involved in this biometric modality; Zhong Cheng Wu, Fei Shen,Yong Yun (4) design a force Tablet (F-Tablet) for human-computer-interaction (HCI), which can acquire the kinematics and kinetics information of human handwriting, including strokes of pen-up and pen-down, pen nib trajectory and three-axis forces of pen tip directly and simultaneously. Any stylus- and pen-like device can be used to write on it. To InkML format an improved DTW (Dynamic Time Warping) algorithm is also put forward to verify the online signatures based on the digital handwriting forces vector ink. (5) Presented an accelerometer-based digital pen for handwritten digit and gesture trajectory recognition applications. The digital pen consists of a tri-axial accelerometer, a microcontroller, and an RF wireless transmission module for sensing and collecting accelerations of handwriting and gesture trajectories. The algorithm is capable of translating time-series acceleration signals into important feature vectors. The algorithm first extracts the time- and frequency-domain features from the acceleration signals and, then, further identities the most important features by a hybrid method: kernel-based class separability for selecting significant features and linear discriminate analysis for reducing the dimension of features. The reduced features are sent to a trained probabilistic neural network for recognition (PNN).

4. EXPECTED RESULT:-

For both the recognition i.e.1) handwritten digit recognition and 2) gesture recognition. We are going to collect about ten acceleration signals from females & males, to calculate the effectiveness of proposed algorithm. The ADTW recognition algorithm consist of the following procedures: acceleration acquisition, signal preprocessing, feature generation, feature selection, and feature extractions explain in early section. we also expect result towards the Total CPU time comparatively less than other algorithms, also as the recognition rate of tablet digitizer pen is 97.2% while IMUPEN gives the recognition rate about 90.4?% [5]. Our expectation is to improve this in all aspect. We are going to used different combinations of feature selection and extraction methods and employed ADTW to recognize handwritten digits and hand gestures. In addition, we are training for the better results of the recognition using ADTW in case of all features than different feature engineering methods.

5. CONCLUSION:-

In this paper we are going to present an inertial pen with adaptive dynamic time wrapping algorithm for inertial sensing based handwriting and gesture recognition. The proposed algorithm consists of signal acquisition; signal preprocessing, motion detection, template selection, and recognition. To obtain better movement signal we will be utilizing complementary filter to reduce orientation error and the ZVC method to minimize the undesirable error. All movement signals will be normalized using Z-score method and class templates are selected, during experimental validation 2D, 3D handwriting digit, English lower case upper case latter, 3D gesture will be collected to evaluate effectiveness of our inertial pen.

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