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51. 基于加速度信号的走路模式多级分类算法

走路模式识别属于步态研究范畴 ．步态是人的一种 生物特征 ，在身份识别 、运动监测 、临床 医学等领域有着 重要 的研究意义 ．主流的步态研究方 法有两种 ，一种是 基 于图像 的方法 ，另一 种是基于运动传 感器 (主要是加 速度传感器)的方法 ．目前 国内的步态研 究主要是 基于 图像的身份识别l1l2 J．基于图像的方法对设备要求高、 资金投人大，而且限于在特定场所使用 ．近年来随着传 感器技术 的发展及制作工艺 的改进 ，具有 尺寸小 、精度 高、功耗低等优点的微型加速度传感器已经进入了应用 领域 ，使得基于运动传 感器 的步态研 究更为方 便 ，不受 运 动环境 的限制 ，这方 面远远优于基 于 图像 的方法 ，因 此将具有更为广阔的应用前景．

基于加速度传感器 的步态研究有两大分支 ：身份识 别和运动分析．其 中运 动 分 析 对 于 运 动 状 态 识 别 、能量 消耗 评估[、室 内导航 系统等研究都 有 着重要意义 ．以往 的运动分析研究 中大多采用 了加速度 信号的时域和频域特征．例如 Mathie等人利用加速度信 号的时域信息，如信号幅度区(signal magnitude area，简 称 SMA)的大小、垂直加速度信号的反余弦值(即人的倾 斜角)等，提出了一种基于决策二叉树 的多级分类算 法 5．6 J，实现人 的各种运动状态 的识别 ． Nishkam等人依据加速度传感器输 出的三维加速度 信号，提取平均值，标准差，能量值等特征L7 J进行运动状 态识别．其中平均值、标准差为时域特征，能量值是对信 号的 FFt频谱成分求平方和后得出的一种频域特性． 本文所设计的基于多级分类 模型 的非 特定人走 路模式分类算法，融合了时频、频域和时域三类特征 ，仅 提取少量特征就可快速有效地识别出不同运动速度下 的水平行走和上、下楼梯三种走路模式．

1. 一种基于自适应波峰检测的 MEMS 计步算法

In view that conventional peak detection algorithm and self-correlation analysis algorithm have poor adaptability to sensor attitudes and motion states of MEMS measurement system pedometer using single axis data and fixed threshold, an adaptive peak detection algorithm is proposed. According to inherent correlation of maximum acceleration and motion states, the algorithm gets peak detection experi- ence thresholds of different motion states, and realizes adaptive step counting. Experiments show that the adaptive peak detection step counting accuracy reaches above 99% for both different sensor attitudes and pedestrians motion states. In contrast, the accuracies of conventional peak detection and self-correlation analysis algorithms reach 97% and 99% under normal state, but only 70% and 50% under abnormal state. The results show that the adaptive peak detection algorithm has strong adaptability to sensor attitudes and motion states, and achieves reliable step counting under various conditions of sensor attitudes and motion states. In addition, the time calculation efficiencies of the adaptive, conventional peak detection and self-correlation analysis algorithms are 0.036 s, 0.046 s and 0.131 s, respectively, which prove that the adaptive peak detection algorithm is significantly superior to the other two algorithms.

1. 一种Android加速度传感器应用的通用解决方案

The acceleration sensor is the most popular sensor on mobile devices. More and more applications are developed using acceleration sensor, but there is not a general method for 25 implementation. This paper provides a general solution to acceleration sensor application based on Android platform, in order to improve design and implementation efficiency and save time. This paper analyzes the principles of the Android acceleration sensor in depth, describes how to design the movement style in detail according to different application scenes and different screen orientations, and implements a general program framework of acceleration sensor application. 30 Besides, this paper uses gravity induction phenomenon of a ball as an example, shows the entire workflow of how to develop an acceleration sensor application using this program framework. Key words: Android; acceleration sensor; gravity induction; mobile application framework.

1. Accelerometry Based Classiﬁcation of Walking Patterns Using Time-frequency Analysis

In this work, 33 dimensional time-frequency domain features were developed and evaluated to detect ﬁve different human walking patterns from dataacquiredusing a triaxial accelerometer attached atthe waist above the iliac spine. 52 subjects were asked to walk on a ﬂat surface along a corridor, walk up anddown a ﬂight of a stairwayand walk up anddown a constant gradient slope, in anunsupervised manner. Time-frequency domain features of accelerationdata in anterior-posterior (AP), medio-lateral (ML) and vertical (VT) direction were developed. The acceleration signal in each direction was decomposed to six detailed signals at different wavelet scales by using the wavelet packet transform. Therms values and standarddeviations ofthe decomposed signals at scales 5 to2 corresponding to the 0.78–18.75 Hz frequency band werecalculated. Theenergies in the 0.39–18.75 Hz frequency band of acceleration signal in AP, ML and VT directions were also computed. The back-end ofthe system was a multi-layer perceptron (MLP) Neural Networks (NNs) classiﬁer. Overall classiﬁcation accuracies of 88.54% and 92.05% were achieved by usinga round robin (RR) and random frame selecting (RFS) train-test method respectively for the ﬁve walking patterns.

1. AUTO-ENCODER BOTTLENECK FEATURES USING DEEP BELIEF NETWORKS

Neuralnetwork (NN)bottleneck(BN)featuresaretypicallycreated by training a NN with a middle bottleneck layer. Recently, an alternative structure was proposed which trains a NN with a constant number of hidden units to predict output targets, and then reduces the dimensionality of these output probabilities through an auto-encoder, to create auto-encoder bottleneck (AE-BN) features. The beneﬁt of placing the BN after the posterior estimation network is that it avoids the loss in frame classiﬁcation accuracy incurred by networks that place the BN before the softmax. In this work, we investigatetheuseofpre-trainingwhencreatingAE-BNfeatures. Our experiments indicate that with the AE-BN architecture, pre-trained and deeper NNs produce better AE-BN features. On a 50-hour English Broadcast News task, the AE-BN features provide over a 1% absolute improvement compared to a state-of-the-art GMM/HMM with a WER of 18.8% and pre-trained NN hybrid system with a WER of 18.4%. In addition, on a larger 430-hour Broadcast News task, AE-BN features provide a 0.5% absolute improvement over a strong GMM/HMM baseline with a WER of 16.0%. Finally, system combination with the GMM/HMM baseline and AE-BN systems provides an additional 0.5% absolute on 430 hours over the AE-BN system alone, yielding a ﬁnal WER of 15.0%.

1. 基于三维加速度传感器的人体运动识别运动能耗检测系统

Caj复制不下来

1. Jogging and Walking Analysis Using Wearable Sensors

Gait analysis is a process of learning the motion of human and animal by using wearable sensor approach and vision approach. This analysis is mainly used in medical and sports field where the study of body parts is crucial. 3-space sensor is a sensor consists of accelerometer, gyroscope sensor and compass sensor, built in one device. In this study, 3-space sensor is used to collect data of walking and jogging motion, of a test subject running on a treadmill. Angular velocity of the test subject’s arm and the angle of subject’s leaping motion are the two main components under investigation. Data are analyzed and processed with Principal of Component Analysis (PCA) technique. This method aims to combine and reduce the number of variables of the raw data. The Quiver function is used in order to generate feature vectors for both motions. Furthermore, the output of the process was used to create a system that can recognize human motion on any given data. The system is highly able to differentiate both of the motions.

1. Activity Recognition with Smartphone Sensors

The ubiquity of smartphones together with their ever-growing computing, networking, and sensing powers have been changing the landscape of people’s daily life. Among others, activity recoginition, which takes the raw sensor reading as inputs and predicts a user’s motion activity, has become an active research area in recent years. It is the core building block in many high-impact applications, ranging from health and fitness monitoring, personal biometric signature, urban computing, assistive technology, and elder-care, to indoor localization and navigation, etc. This paper presents a comprehensive survey of the recent advances in activity recognition with smartphones’ sensors. We start with the basic concepts such as sensors, activity types, etc. We review the core data mining techniques behind the main stream activity recognition algorithms, analyze their major challenges, and introduce avariety of real applications enabled by activity recognition.

1. Feature Selection and Activity Recognition from Wearable Sensors

Wedescribe our data collection and results on activity recognition with wearable, coin-sized sensor devices. The devices were attached to four diﬀerent parts of the body: right thigh and wrist, left wrist and to a necklace on 13 diﬀerent testees. In this experiment, data was from 17 daily life examples from male and female subjects. Features were calculated from triaxial accelerometer and heart rate data within diﬀerent sized time windows. The best features were selected with forward-backward sequentialsearch algorithm. Interestingly,acceleration mean values from the necklace were selected as important features. Two classiﬁers (multilayer perceptrons and kNN classiﬁers) were tested for activity recognition, and the best result (90.61 % aggregate recognition rate for 4-fold cross validation) was achieved with a kNN classiﬁer.

1. Body Motion Recognition Based on Acceleration Sensor

Acceleration, one of basic parameters of motion, can be measured using acceleration sensor, the values of the corresponding displacement and velocity can be obtained by mathematical computation. A system which can recognize the motion of human body is developed using a 3-axis acceleration sensor, and can complete information collection and data analysis of up to 5 sensors network nodes. The system is used in the control of the computer games with motion recognition rate of 95%, and can also be used in the training of physical rehabilitation, auxiliary diagnosis of medical clinic, physical training, and so on.

1. Deep belief networks using discriminative features for phone recognition

Deep Belief Networks (DBNs) are multi-layer generative models. They can betrained to model window sofco efﬁcient sex tracted from speech and they discover multiple layers of features that capture the higher-order statistical structure of the data. These features can be used to initialize the hidden units of a feed-forward neural network that is then trained to predict the HMM state for the central frame of the window. Initializing with features that are good at generating speech makes the neural net work perform much better than initializing with randomweights. DBNshavealreadybeenusedsuccessfully for phone recognition with input coefﬁcients that are MFCCs or ﬁlterbank outputs [1, 2]. In this paper, we demonstrate that they work even better when their inputs are speaker adaptive, discriminative features. On the standard TIMIT corpus ,they give phone error rates of 19.6% using monophone HMMs and a bigram language model and19.4%usingmonophoneHMMsandatrigramlanguagemodel.

1. FeatureLearningforActivityRecognitioninUbiquitousComputing ThomasPl¨otz,NilsY.Hammerla,andPatrickOlivie

Feature extraction for activity recognition in context-awareubiquitouscomputingapplicationsis usually a heuristic process, informed by underlying domain knowledge. Relying on such explicit knowledge is problematic when aiming to generalize across different application domains. We investigate the potential of recent machine learning methods for discovering universal features for context-aware applications of activity recognition. We also describe an alternative data representation based on the empirical cumulative distribution functionoftherawdata,whicheffectivelyabstracts from absolute values. Experiments on accelerometer data from four publiclyavailable activityrecognitiondatasetsdemonstratethesigniﬁcantpotential of our approach to address both contemporary activity recognition tasks and next generation problems such as skill assessment and the detection of novel activities.

1. A Survey of Mobile Phone Sensing

Mobile phones or smartphones are rapidly becoming the central computer and communication device in people’s lives. Application delivery channels such as the Apple AppStore are transforming mobile phones into App Phones, capable of downloading a myriad of applications in an instant. Importantly, today’s smartphones are programmable and come with a growing set of cheap powerful embedded sensors, such as an accelerometer, digital compass, gyroscope, GPS, microphone, and camera, which are enabling the emergence of personal, group, and communityscale sensing applications. We believe that sensor-equipped mobile phones will revolutionize many sectors of our economy, including business, healthcare, social networks, environmental monitoring, and transportation. In this article we survey existing mobile phone sensing algorithms, applications, and systems. We discuss the emerging sensing paradigms, and formulate an architectural framework for discussing a number of the open issues and challenges emerging in the new area of mobile phone sensing research.

1. Accelerometer’s position independent physical activity recognition system for long-term activity monitoring in the elderl

Mobility is a good indicator of health status and thus objective mobility data could be used to assess the health status of elderly patients. Accelerometry has emerged as an effective means for long-term physical activity monitoring in the elderly. However, the output of an accelerometer varies at differentpositions on a subject’s body, even for the same activity, resulting in high within-class variance. Existing accelerometer-based activity recognition systems thus require ﬁrm attachment of the sensor to a subject’s body. This requirement makes them impractical for longterm activity monitoring during unsupervised free-living as it forces subjects into a ﬁxed life pattern and impede their daily activities. Therefore, we introduce a novel singletriaxial-accelerometer-based activity recognition system that reduces the high within-class variance signiﬁcantly and allows subjects to carry the sensor freely in any pocket without its ﬁrm attachment. We validated our system using seven activities: resting (lying/sitting/standing), walking, walking-upstairs,walking-downstairs, running, cycling,and vacuuming, recorded from ﬁve positions: chest pocket, front

left trousers pocket, front right trousers pocket, rear trousers pocket, and inner jacket pocket. Its simplicity, ability to perform activities unimpeded, and an average recognition accuracy of 94% make our system a practical solution for continuous long-term activity monitoring in the elderly.

1. Activity identiﬁcation using body-mounted sensors—a review of classiﬁcation techniques

Withtheadventofminiaturizedsensingtechnology,whichcanbebody-worn,it isnowpossibletocollectandstoredataondifferentaspectsofhumanmovement undertheconditionsoffreeliving. Thistechnologyhasthepotentialtobeused in automated activity proﬁling systems which produce a continuous record of activitypatternsoverextendedperiodsoftime. Suchactivityproﬁlingsystems aredependentonclassiﬁcationalgorithmswhichcaneffectivelyinterpretbodyworn sensor data and identify different activities. This article reviews the different techniques which have been used to classify normal activities and/or identify falls from body-worn sensor data. The review is structured according to the different analytical techniques and illustrates the variety of approaches whichhavepreviouslybeenappliedinthisﬁeld. Althoughsigniﬁcantprogress has been made in this important area, there is still signiﬁcant scope for further work, particularly in the application of advanced classiﬁcation techniques to problems involving many different activities.

1. Activity Recognition and Monitoring Using Multiple Sensors on Different Body Positions

Thedesignofanactivityrecognitionandmonitoringsystem based on the eWatch, multi-sensor platform worn on different body positions, is presented in this paper. The system identiﬁes the user’s activity in realtime using multiple sensors and records the classiﬁcation results during a day. We compare multiple time domain feature sets and sampling rates, and analyze the tradeoff between recognition accuracy and computational complexity. The classiﬁcation accuracy on different body positions used for wearing electronic devices was evaluated

1. Activity Recognition from acceleration data Based on Discrete Consine Transform and SVM

This paper developed a high-accuracy human activity recognition system based on single tri-axis accelerometer for use in a naturalistic environment. This system exploits the discrete cosine transform (DCT), the Principal Component Analysis (PCA) and Support Vector Machine (SVM) for classification human different activity. First, the effective features are extracted from accelerometer data using DCT. Next, feature dimension is reduced by PCA in DCT domain. After implementing the PCA, the most invariant and discriminating information for recognition is maintained. As a consequence, Multi-class Support Vector Machines is adopted to distinguish different human activities. Experiment results show that the proposed system achieves the best accuracy is 97.51%, which is better than other approaches

1. Activity Recognition from Accelerometer Data

Activity recognition ﬁts within the bigger framework of context awareness. In this paper, we report on our efforts to recognize user activity from accelerometer data. Activityrecognitionisformulatedasaclassiﬁcationproblem. Performanceofbase-levelclassiﬁersand meta-level classiﬁers is compared. Plurality Voting is foundtoperformconsistentlywellacrossdifferentsettings.

1. Activity Recognition from User-Annotated Acceleration Data

In this work, algorithms are developed and evaluated to detect physical activities from data acquired using ﬁve small biaxial accelerometers worn simultaneously on diﬀerent parts of the body. Acceleration data was collected from 20 subjects without researcher supervision or observation. Subjects were asked to perform a sequence of everyday tasks but not told speciﬁcally where or how to do them. Mean, energy, frequency-domain entropy, and correlation of acceleration data was calculated and several classiﬁers using these features were tested. Decision tree classiﬁers showed the best performance recognizing everyday activities with an overall accuracy rate of 84%. The results show that although some activities are recognized well with subject-independent trainingdata,othersappeartorequiresubject-speciﬁctrainingdata.The results suggest that multiple accelerometers aid in recognition because conjunctions in acceleration feature values can eﬀectively discriminate many activities. With just two biaxial accelerometers – thigh and wrist – the recognition performance dropped only slightly. This is the ﬁrst work to investigate performance of recognition algorithms with multiple, wire-free accelerometers on 20 activities using datasets annotated by the subjects themselves.

1. Applications of Mobile Activity Recognition

Activity Recognition (AR), which identifies the activity that a user performs, is attracting a tremendous amount of attention, especially with the recent explosion of smart mobile devices. These ubiquitous mobile devices, most notably but not exclusively smartphones, provide the sensors, processing, and communication capabilities that enable the development of diverse and innovative activity recognitionbased applications. However, although there has been a great deal of research into activity recognition, surprisingly little practical work has been done in the area of applications in mobile devices. In this paper we describe and categorize a variety of activity recognition-based applications. Our hope is that this work will encourage the development of such applications and also influence the direction of activity recognition research.

1. Cell Phone-Based Biometric Identification

Mobile devices are becoming increasingly sophisticated and now incorporate many diverse and powerful sensors. The latest generation of smart phones is especially laden with sensors, including GPS sensors, vision sensors (cameras), audio sensors (microphones), light sensors, temperature sensors, direction sensors (compasses), and acceleration sensors. In this paper we describe and evaluate a system that uses phone-based acceleration sensors, called accelerometers, to identify and authenticate cell phone users. This form of behavioral biometric identification is possible because a person’s movements form a unique signature and this is reflected in the accelerometer data that they generate. To implement our system we collected accelerometer data from thirty-six users as they performed normal daily activities such as walking, jogging, and climbing stairs, aggregated this time series data into examples, and then applied standard classification algorithms to the resulting data to generate predictive models. These models either predict the identity of the individual from the set of thirty-six users, a task we call user identification, or predict whether (or not) the user is a specific user, a task we call user authentication. This work is notable because it enables identification and authentication to occur unobtrusively, without the users taking any extra actions—all they need to do is carry their cell phones. There are many uses for this work. For example, in environments where sharing may take place, our work can be used to automatically customize a mobile device to a user. It can also be used to provide device security by enabling usage for only specific users and can provide an extra level of identity verification.

1. Classification Algorithms in Human Activity Recognition using Smartphones

Rapid advancement in computing technology brings computers and humans to be seamlessly integrated in future. The emergence of smartphone has driven computing era towards ubiquitous and pervasive computing. Recognizing human activity has garnered a lot of interest and has raised significant researches’ concerns in identifying contextual information useful to human activity recognition. Not only unobtrusive to users in daily life, smartphone has embedded built-in sensors that capable to sense contextual information of its users supported with wide range capability of network connections. In this paper, we will discuss the classification algorithms used in smartphone-based human activity. Existing technologies pertaining to smartphone-based researches in human activity recognition will be highlighted and discussed. Our paper will also present our findings and opinions to formulate improvement ideas in current researches’ trends. Understanding research trends will enable researchers to have clearer research direction and common vision on latest smartphone-based human activity recognition area.

1. Cross-PeopleMobile-PhoneBasedActivityRecognition

Activity recognition using mobile phones has great potential in many applications including mobile healthcare. In order to let a person easily know whether he is in strict compliance with the doctor’s exercise prescription and adjust his exercise amount accordingly, we can use a smart-phone based activity reporting system to accurately recognize a range of daily activities and report the duration of each activity. A triaxial accelerometer embedded in the smart phone is used for the classiﬁcation of several activities, such as staying still, walking, running, and going upstairs and downstairs. The model learnt from a speciﬁc person often cannot yield accurate results when used on a different person. To solve the cross-people activity recognition problem, we propose an algorithm known as TransEMDT (Transfer learning EMbedded Decision Tree) that integrates a decision tree and the k-means clustering algorithm for personalized activity-recognition model adaptation. Tested on a real-world data set, the results show that our algorithm outperforms several traditional baseline algorithms.

1. Physical Activity Recognition  from Accelerometer Data Using  a Multi‐Scale Ensemble Method

这篇没有摘要

1. Fast Time Series Classification Using Numerosity Reduction

Many algorithms have been proposed for the problem of time series classification. However, it is clear that one-nearest-neighbor with Dynamic Time Warping (DTW) distance is exceptionally difficult to beat. This approach has one weakness, however; it is computationally too demanding for many realtime applications. One way to mitigate this problem is to speed up the DTW calculations. Nonetheless, there is a limit to how much this can help. In this work, we propose an additional technique, numerosity reduction, to speed up one-nearestneighbor DTW. While the idea of numerosity reduction for nearest-neighbor classifiers has a long history, we show here that we can leverage off an original observation about the relationship between dataset size and DTW constraints to produce an extremely compact dataset with little or no loss in accuracy. We test our ideas with a comprehensive set of experiments, and show that it can efficiently produce extremely fast accurate classifiers.

1. Gesture Recognition with a 3-D Accelerometer

Gesture-based interaction, as a natural way for human-computer interaction, has a wide range of applications in ubiquitous computing environment. This paper presents an acceleration-based gesture recognition approach, called FDSVM (Frame-based Descriptor and multi-class SVM), which needs only a wearable 3-dimensional accelerometer. With FDSVM, firstly, the acceleration data of a gesture is collected and represented by a frame-based descriptor, to extract the discriminative information. Then a SVM-based multi-class gesture classifier is built for recognition in the nonlinear gesture feature space. Extensive experimental results on a data set with 3360 gesture samples of 12 gestures over weeks demonstrate that the proposed FDSVM approach significantly outperforms other four methods: DTW, Naïve Bayes, C4.5 and HMM. In the user-dependent case, FDSVM achieves the recognition rate of 99.38% for the 4 direction gestures and 95.21% for all the 12 gestures. In the user-independent case, it obtains the recognition rate of 98.93% for 4 gestures and 89.29% for 12 gestures. Compared to other accelerometer-based gesture recognition approaches reported in literature FDSVM gives the best resulrs for both user-dependent and user-independent cases.

1. Human Action Recognition Using Dynamic Time Warping

Human action recognition is gaining interest from many computer vision researchers because of its wide variety of potential applications. For instance: surveillance, advanced human computer interaction, content-based video retrieval, or athletic performance analysis. In this research, we focus to recognize some human actions such as waving, punching, clapping, etc. We choose exemplar-based sequential singlelayered approach using Dynamic Time Warping (DTW) because of its robustness against variation in speed or style in performing action. For improving recognition rate, we perform body part tracking using depth camera to recover human joints body part information in 3D real world coordinate system. We build our feature vector from joint orientation along time series that invariant to human body size. Dynamic Time Warping is then applied to the resulted feature vector. We examine our approach to recognize several actions and we confirm our method can work well with several experiments. Further experiment for benchmarking the result will be held in near future.

1. Human Activity Recognition on Smartphones using a Multiclass Hardware-Friendly Support Vector Machin

Activity-Based Computing [1] aims to capture the state of the user and its environment by exploiting heterogeneous sensors in order to provide adaptation to exogenous computing resources. When these sensors are attached to the subject’s body, they permit continuous monitoring of numerous physiological signals. This has appealing use in healthcare applications, e.g. the exploitation of Ambient Intelligence (AmI) in daily activity monitoring for elderly people. In this paper, we present a system for human physical Activity Recognition (AR) using smartphone inertial sensors. As these mobile phones are limited in terms of energy and computing power, we propose a novel hardware-friendly approach for multiclass classiﬁcation. This method adapts the standard Support Vector Machine (SVM) and exploits ﬁxed-point arithmetic for computational cost reduction. A comparison with the traditional SVM shows a signiﬁcant improvement in terms of computational costs while maintaining similar accuracy, which can contribute to develop more sustainable systems for AmI.

1. Impact of Sensor Misplacement on Dynamic Time Warping Based Human Activity Recognition using Wearable Computers

Daily living activity monitoring is important for early detection of the onset of many diseases and for improving quality of life especially in elderly. A wireless wearable network of inertial sensor nodes can be used to observe daily motions. Continuous stream of data generated by these sensor networks can be used to recognize the movements of interest. Dynamic Time Warping (DTW) is a widely used signal processing method for time-series pattern matching because of its robustness to variations in time and speed as opposed to other template matching methods. Despite this flexibility, for the application of activity recognition, DTW can only find the similarity between the template of a movement and the incoming samples, when the location and orientation of the sensor remains unchanged. Due to this restriction, small sensor misplacements can lead to a decrease in the classification accuracy. In this work, we adopt DTW distance as a feature for real-time detection of human daily activities like sit to stand in the presence of sensor misplacement. To measure this performance of DTW, we need to create a large number of sensor configurations while the sensors are rotated or misplaced. Creating a large number of closely spaced sensors is impractical. To address this problem, we use the marker based optical motion capture system and generate simulated inertial sensor data for different locations and orientations on the body. We study the performance of the DTW under these conditions to determine the worst-case sensor location variations that the algorithm can accommodate.

1. Design Considerations for the WISDM Smart Phone-based Sensor Mining Architecture

Smart phones comprise a large and rapidly growing market. These devices provide unprecedented opportunities for sensor mining since they include a large variety of sensors, including an: acceleration sensor (accelerometer), location sensor (GPS), direction sensor (compass), audio sensor (microphone), image sensor (camera), proximity sensor, light sensor, and temperature sensor. Combined with the ubiquity and portability of these devices, these sensors provide us with an unprecedented view into people’s lives—and an excellent opportunity for data mining. But there are obstacles to sensor mining applications, due to the severe resource limitations (e.g., power, memory, bandwidth) faced by mobile devices. In this paper we discuss these limitations, their impact, and propose a solution based on our WISDM (WIireless Sensor Data Mining) smart phone-based sensor mining architecture.

1. Recognizing Human Activities Userindependently on Smartphones Based on Accelerometer Data

Smart phones comprise a large and rapidly growing market. These devices provide unprecedented opportunities for sensor mining since they include a large variety of sensors, including an: acceleration sensor (accelerometer), location sensor (GPS), direction sensor (compass), audio sensor (microphone), image sensor (camera), proximity sensor, light sensor, and temperature sensor. Combined with the ubiquity and portability of these devices, these sensors provide us with an unprecedented view into people’s lives—and an excellent opportunity for data mining. But there are obstacles to sensor mining applications, due to the severe resource limitations (e.g., power, memory, bandwidth) faced by mobile devices. In this paper we discuss these limitations, their impact, and propose a solution based on our WISDM (WIireless Sensor Data Mining) smart phone-based sensor mining architecture.

1. Online Pose Classiﬁcation and Walking Speed Estimation using Handheld Devices

Wedescribeandevaluatetwomethodsforposeclassiﬁcation and walking speed estimation that generalize well to new users, compared to previous work. These machine learning based methods are designed for the general case of a person holding a mobile device in an unknown location and require only a single low-cost, low-power sensor: a triaxial accelerometer. We evaluate our methods in straight-walking experiments as well as in natural indoor walking settings. Experiments with 14 human participants to test user generalization show that our pose classiﬁer correctly selects among four device poses with 94% accuracy compared to 82% for previous work, and our walking speed estimates are within 1215% (straight/indoor walk) of ground truth compared to 1722% for previous work. Implementation on a mobile phone demonstrates that both methods can run online.

1. Personalization Algorithm for Real-Time Activity Recognition Using PDA, Wireless Motion Bands, and Binary Decision Tree

Inactiveandsedentarylifestyleisamajorproblemin manyindustrializedcountriestoday.Automaticrecognitionoftype ofphysicalactivitycanbeusedtoshowtheuserthedistributionof his daily activities and to motivate him into more active lifestyle. In this study, an automatic activity-recognition system consisting of wireless motion bands and a PDA is evaluated. The system classiﬁes raw sensor data into activity types online. It uses a decision tree classiﬁer, which has low computational cost and low battery consumption.Theclassiﬁerparameterscanbepersonalizedonline by performing a short bout of an activity and by telling the system which activity is being performed. Data were collected with seven volunteers during ﬁve everyday activities: lying, sitting/standing, walking, running, and cycling. The online system can detect these activities with overall 86.6% accuracy and with 94.0% accuracy after classiﬁer personalization.

1. PhysicalActivityRecognitionfromAccelerometer DataUsingaMulti-ScaleEnsembleMethod

Accurate and detailed measurement of an individual’s physical activity is a key requirement for helping researchers understand the relationship between physical activity and health. Accelerometers have become the methodofchoiceformeasuringphysicalactivitydueto their small size, low cost, convenience and their ability to provide objective information about physical activity.However,interpretingaccelerometerdataonceithas been collected can be challenging. In this work, we applied machine learning algorithms to the task of physicalactivityrecognitionfromtriaxialaccelerometerdata. We employed a simple but effective approach of dividing the accelerometer data into short non-overlapping windows,convertingeachwindowintoafeaturevector, and treating each feature vector as an i.i.d training instance for a supervised learning algorithm. In addition, weimprovedonthissimpleapproachwithamulti-scale ensemble method that did not need to commit to a single window size and was able to leverage the fact that physical activities produced time series with repetitive patternsanddiscriminativefeaturesforphysicalactivity occurred at different temporal scales.

1. Pocket, Bag, Hand, etc. - Automatically Detecting Phone Context through Discovery

Most top end smart phones come with a handful of sensors today. We see this growth continuing over the next decade with an explosion of new distributed sensor applications supporting both personal sensing with local use (e.g., healthcare) to distributed sensing with large scale community (e.g., air quality, stress levels and well being), population and global use. One fundamental building block for distributed sensing systems on mobile phones is the automatic detection of accurate, robust and low-cost phone sensing context; that is, the position of the phone carried by a person (e.g., in the pocket, in the hand, inside a backpack, on the hip, arm mounted, etc.) in relation to the event being sensed. Mobile phones carried by people may have many diﬀerent sensing contexts that limit the use of a sensor, for example: an air-quality sensor oﬀers poor sensing quality buried in a person’s backpack. We present the preliminary design, implementation, and evaluation of Discovery, a framework to automatically detect the phone sensing context in a robust, accurate and low-cost manner, as people move about in their everyday lives. The initial system implements a set of sophisticated inference models that include Gaussian Mixture Model and Support Vector Machine on the Nokia N95 and Apple iPhone with focus on a limited set of sensors and contexts. Initial results indicate this is a promising approach to provide phone sensing context on mobile phones.

1. Classiﬁcation of Mobile Device Accelerometer Data for Unique Activity Identiﬁcation

Accelerometer datasets from 36 smartphones were analyzed in order to distinguish between diﬀerent user activities. Training data from jogging, walking, standing, stair climbing (ascending and descending) and sitting were collected for each device at a sampling rate of 20Hz. The spectrogram for each activity was transformed using PCA to reduce the dimensionality of the dataset, and the eigenvalues of three dimensions (X, Y, and Z coordinates of the accelerometer) were used as inputs for Gaussian Discriminant analysis to label the recorded activity. Kwapisz et. al. explored the possibility of using accelerometer data to classify user activity, and achieved a 90% success rate in their classiﬁcation. Using our methodology, we achieved a global success rate over 92%, however, our results are generated using a direction-agnostic approach which increases the practicality of such a system for real-world use.

1. Real-Time Activity Classiﬁcation Using Ambient and Wearable Sensor

New approaches to chronic disease management within a home or community setting offer patients the prospect of more individually focused care and improved quality of life. This paper investigates the use of a light-weight ear worn activity recognition device combined with wireless ambient sensors for identifyingcommonactivitiesofdailyliving.Atwo-stageBayesian classiﬁer that uses information from both types of sensors is presented. Detailed experimental validation is provided for datasets collected in a laboratory setting as well as in a home environment. Issuesconcerningtheeffectiveuseoftherelativelylimiteddiscriminative power of the ambient sensors are discussed. The proposed frameworkbodeswellforamulti-dwellingenvironment,andoffers apervasivesensingenvironmentforbothpatientsandcare-takers.

1. Semantic Activity Classiﬁcation Using Locomotive Signatures from Mobile Phones

We explore the use of mobile phone-generated sensor feeds to determine the high-level (i.e., at the semantic level), indoor, lifestyle activities of individuals, such as cooking & dining at home and working & having lunch at the workplace. We propose and evaluate a 2-Tier activity extraction framework (called SAMMPLE1) where features of the low-level accelerometerdataareﬁrstusedtoidentifyindividuallocomotive micro-activities (e.g., sitting or standing), and the micro-activity sequence is subsequently used to identify the discriminatory characteristics of individual semantic activities. Using 152 days of real-life behavioral traces from users, our approach achieves an average accuracy of 77.14%, an improvement of 16.37% from the traditional 1-Tier approach, which directly uses statistical features of the accelerometer stream, towards such activity classiﬁcation tasks.

1. Sensor Placement Modes for Smartphone Based Pedestrian Dead Reckonin

These days, most of the smartphones come with integrated MEMS (Microelectromechanicalsystems) sensors like accelerometer, magnetometer, gyros etc. It has opened the ways to use them for location based applications. The big advantage of these sensor based navigation system is that they are environment independent in contrast to other existing positioning technologies. A lot of work is already done on ﬁxed position sensor based systems where sensors are either attached to foot or belt. This work is focussed on developing a smartphone based pedestrian dead reckoning (PDR) system. The big issue with smartphone’s sensor based PDR system is that the position of mobile is not deterministic in contrast to ﬁxed position inertial measuring unit. In this work, three different modes of smartphone placement (Idle, Handheld and Listening) are investigated and accelerometer and magnetic sensors are used for step detection and heading determination respectively. Various step detection and stride length estimation methods are implemented and a comparison is given at the end.

1. Simple and Complex Activity Recognition Through Smart Phones

Due to an increased popularity of assistive healthcare technologies activity recognition has become one of the most widely studied problems in technology-driven assistive healthcare domain. Current approaches for smart-phone based activity recognition focus only on simple activities such as locomotion. In this paper, in addition to recognizing simple activities, we investigate the ability to recognize complex activities, such as cooking, cleaning, etc. through a smart phone. Features extracted from the raw inertial sensor data of the smart phone corresponding to the user’s activities, are used to train and test supervised machine learning algorithms. The results from the experiments conducted on ten participants indicate that, in isolation, while simple activities can be easily recognized, the performance of the prediction models on complex activities is poor. However, the prediction model is robust enough to recognize simple activities even in the presence of complex activities.

1. Toward PhysicalActivityDiary: Motion Recognition Using SimpleAcceleration Features with MobilePhone

In this paper, we perform physical motion recognition using mobile phones with built-in accelerometer sensors. Sensor data processing and smoothing techniques are discussed ﬁrst to reduce the special noise present in phone-collected accelerometer data. We explore orientation-independent features extracted from vertical and horizonal components in acceleration as well as magnitudes of acceleration for six common physical activities, such as sitting, standing, walking, running, driving and bicycling. We ﬁnd decision tree achieves the best performance among four commonly used static classiﬁers, while vertical and horizonal features have better recognition accuracy than magnitude features. Furthermore, a well-pruned decision tree with simple time domain features and less over-ﬁtting on the training data can provide a usable model for inferencing a physical activity diary, reﬁned by a similarity match from 𝑘-means clustering results and smoothed by an HMM-based Viterbi algorithm.

1. PBN: Towards Practical Activity Recognition Using Smartphone-Based Body Sensor Networks

Thevastarrayofsmallwirelesssensorsisaboontobody sensornetworkapplications,especiallyinthecontextawareness and activity recognition arena. However, most activity recognition deployments and applications are challenged to provide personal control and practical functionality for everyday use. We argue that activity recognition for mobile devices must meet several goals in order to provide a practical solution: user friendly hardware and software, accurate and efﬁcient classiﬁcation, and reduced reliance on ground truth. To meet these challenges, we present PBN: Practical Body Networking. Through the uniﬁcation of TinyOS motes and Android smartphones, we combine the sensing power of on-body wireless sensors with the additional sensing power, computational resources, and user-friendly interface of an Android smartphone. We providean accurate and efﬁcient classiﬁcation approachthroughthe use of ensemble learning. We explore the properties of different sensors and sensor data to further improve classiﬁcation efﬁciency and reduce reliance on user annotated ground truth. We evaluate our PBN system with multiple subjects over a two week periodanddemonstratethatthe systemis easy touse, accurate, and appropriatefor mobile devices.

1. USC-HAD: A Daily Activity Dataset for Ubiquitous Activity Recognition Using Wearable Sensors

Many ubiquitous computing applications involve human activity recognition based on wearable sensors. Although this problem has been studied for a decade, there are a limited numberofpubliclyavailabledatasetstouseasstandardbenchmarks to compare the performance of activity models and recognition algorithms. In this paper, we describe the freely available USC human activity dataset (USC-HAD), consisting of well-deﬁned low-level daily activities intended as a benchmarkforalgorithmcomparisonparticularlyforhealthcare scenarios. We brieﬂy review some existing publicly available datasets and compare them with USC-HAD. We describe the wearable sensors used and details of dataset construction. We use high-precision well-calibrated sensing hardware such that the collected data is accurate, reliable, and easy to interpret. The goal is to make the dataset and research based on it repeatable and extendible by others.

1. 基于 Android 智能手机内置传感器的人体运动识别

In this paper, built-in sensors were described to automatically detect human daily activities. In contrast to the previous work, this paper intends to recognize the physical activities when the phone’s orientation and position are varying. The data collected from six positions of seven subjects were investigated and two signals that are insensitive to orientation were chosen for classification. Decision trees (J48), Naive Bayes and sequential minimal optimization (SMO) were employed to recognize five activities: static, walking, running, walking upstairs and walking downstairs. The classification results of three classifiers were compared. The results demonstrates that the J48 classifier produces the best performance (average recognition accuracy: 90.7%). Then we chose the J48 classifier as online classifier.

1. 一种基于三维加速度传感器的人体行为识别方法

提出了一种基于单个三维加速度传感器的人体行为的特征提取及识别方法,主要识别了站立、走、跑、 上楼和下楼五种动作. 该方法提取了多种统计特征包括标准差、偏度、峰度和相关系数实现多层分类. 实验表明, 本文采用的方法能够有效地识别这五种动作.

1. 基于加速度传感器的放置方式和位置无关运动识别

传统基于加速度传感器的运动识别方法通常假设传感设备是固定放置的，当传感设备的放置方式或位置偏离预定设置时识别性能会受到极大影响。然而，在普适计算环境下使用最为广泛的传感设备———智能手机，通常无法预先固定其放置方式和位置。为解决此问题，提出了一种基于加速度传感器、与放置方式和位置无关的运动识别方法。该方法首先基于一种降维算法将原始三维加速度信号处理成与放置方式无关的一维信号，然后借鉴生物信息学中的“模体”（Ｍｏｔｉｆ）概念抽取一维信号中与放置位置无关的模式特征，最后基于模式特征构建向量空间模型（ＶＳＭ）对运动进行识别。实验结果表明，该方法在不固定传感设备放置方式和位置条件下的运动识别率达到８１．４１％。

1. 基于单个加速度传感器的人体运动模式识别

基于加速度传感器的人体运动模式识别是模式识别领域一个新兴的研究方向，其本质是首先通过一个或多个加速度传感器获取人运动时产生的加速度信号并通过蓝牙无线传输技术将数据传送到移动设备中，然后对数据进行预处理、特征提取和选择，最后根据提取的特征对运动进行分类和识别。但是，早期的研究工作为了能够获取较为全面的人体运动信息，使用多个加速度传感器放置在人身体的不同部位同时进行数据采集。由于需要在身体的多个部位穿戴传感器，大大地降低了佩戴者的舒适度。为了提高佩戴者的舒适度，也为了更好的降低系统的制造成本和数据的运算成本，本文采用单个加速度传感器进行人体运动模式识别。 目前，基于加速度传感器的人体运动模式识别研究还处在一个相对基础的阶段, 尽管基于加速度传感器的人体运动模式识别技术在近十多年来已经取得了极大的发展，但是，由于客观环境的多样性以及人体运动的复杂性使得人体运动模式识别研究还有很多亟待解决的问题摆在研究者面前，包括如何针对不同运动模式的细致分类及三维手写识别进一步研制新的识别技术，解决数据库的建立、有效特征提取、高效分类算法设计等识别难题。本文围绕着这些难点对基于加速度传感器的人体运动模式识别技术展开了一系列研究，主要工作包括： 1．基于加速度传感器的人体运动识别是一个新兴发展起来的识别技术，目前还没有一个标准的数据库。本文构建了一批支持人体运动模式识别的基础数据，包括三维手写数据和人体动作数据。其中，支持人体动作识别研究的数据被命名为华南理工大学自然的基于加速度传感器的人体动作数据库(South China University of Technology-A Naturalistic 3D Acceleration-Based Activity Dataset)，下文缩写为 SCUT-NAA 库。SCUT－NAA 库的主页为：http://www.hcii-lab.net/data/scutnaa/。SCUT-NAA 库为基于加速度传感器的动作识别研究提供了基本的训练和测试数据，也为不同算法性能的比较提供了一个标准的数据库。并且，SCUT-NAA 库是第一款公开的基于三轴加速度传感器的人体动作数据库。该数据库包括 44 个不同采集者（34 个男性，10 个女性）的 1278 个样本。该数据库是在完全自然的件下，仅用一个三轴加速度传感器，分别放置在采集者的腰带、裤子口袋、上衣口袋三个位置采集的数据。每类动作每个采集者只执行一遍，共采集了 10 类动作。而三维手写数据则含 60 个不同采集者的 180 套数据样本。每套数据包括阿拉伯数字 0 到 9，每个采集者每套数据书写三遍。

2．提出了基于加速度传感器的三维手写识别的两种解决方法，即三维轨迹恢复和统计模式识别。第一种解决方法，利用无陀螺仪的惯性导航系统(INS)理论恢复手写字符的三维轨迹。因为没有陀螺仪，INS 理论中的三个 Euler 角度只能由三轴加速度信号来估计。又由于速度传感器的精度会随时间而发散，而在用 INS 估计位置nP 时，不可避免的要对时间 t 积分 3 次，从而使精度误差随时间快速增大。为了更正这种加速度传感器固有的误差，采零速度补偿(ZVC)方法。最后，通过创造一个假想平面和旋转变换，把书写字符的三维轨迹投影到二维平面。第二种解决方法：利用统计模式识别的方法分类三维手写字符。提出了一基于加速度传感器的虚拟手写数字特征提取及识别方法。该方法首先对书写时产生的三轴加速度信号投影，获得三个二维矢量。然后基于每个二维矢量提取反映加速度信号顺时针和逆针旋转变化的特征点，并进行数字编码得到旋转特征码。接着采用归一化编辑距离来度量不样本的旋转特征码间的差异，最后结合旋转特征和基于编辑距离的旋转特征码的距离测度，给出虚拟手写数字识别算法。与传统的时域原始特征、峰值谷值特征、FFT 特征的识别性能对比实验表明本文方法的有效性。

3．针对 SCUT-NAA 数据库，分别基于四种不同的特征和四种常用的分类器进行了基准评价。四种特征是 FFT 系数、DCT 系数、时域特征(TF)以及自回归(AR)系数。其中，时域特征包括均值、标准差、能量和两轴的相关系数。四种常用的分类器分别是C4.5 决策树(Decision Tree)、k 近邻(k-NN)、朴素贝叶斯(Naive Bayes)以及 SVM。四种特征的提取都是采用滑动时间窗的方法，将一个窗口长度为 512 个样本点的矩形窗滑过原始的加速度信号，相邻的窗之间重叠半个窗长。四种分类器都是采用留一交叉证法(Leave-one-subject-out cross-validation测试数据。实验结果发现：相比于跑、跳和静坐这三种动作 95%以上的高识别率，有些动作则很难识别，而照成难识别的原因是相似动作之间的混淆分类。如上楼和下楼动作的混淆，走、快走及原地踏步之间的混淆。

4．提出了一种解决上楼和下楼动作混淆问题的分类算法。首先，由于加速度传感器在随人一起运动时会随机的旋转，导致加速度信号的竖直方向和重力方向不一致，为了有效地从竖直方向的加速度信号中提取特征，提出利用重力方向动态校正加速度信号的竖直方向。然后，从校正后的竖直分量中提取了四分位间距(IQR)和小波能量(WE)两种特征。并利用 wrapper特征子集选择算法对提取的特征进行特征选择。用 SVM 分类器分类的结果表明：基于 IQR 和 WE 特征的分类算法能有效的区分上楼和下楼这两种动作，而且该特征对传感器的放置位置不敏感。利用 IQR 和 WE 特征，传感器放置在不同位置的平均识别率为 95.64%，比传统时域特征的识别率提高了 8.34%，比 FFT 系数的识别率提高了 4.37%。即使将不同位置传感器的数据混合在一起，基于 IQR 和 WE 特征的平均识别率也达到了 94.84%。

5．提出了基于小波变换和分形分析的步态模式识别算法，重点是细分类三种走路模式，正常走、快走和原地踏步。首先采用小波多分辨率分析的方法，对信号进行小波分解，然后从分解后的小波系数中提取了三种类型的特征。小波能量分布(Wavelet Energy Distribution)

特征可以衡量三种步态模式在不同小波分解层的能量分布情况。基于小波系数估计的分形维数(Fractal Dimension)特征量化了不同小波尺度下细节系数的方差变化过程，因此利用分形维数可以衡量原始加速度信号的复杂性。小波峰(Wavelet Peak)特征反映了三种步态模式加速度信号的幅度。利用不同类型特征的互补特性，对于三种相似的步态模式，能达到 98.41%的平均识别率，与时域和频域特征相比，本文提出的方法能显著提高识别性能。此外，本文还初步研究了上楼、下楼、正常走、快走和原地踏步这五种步态模式的识别问题。最后，提出了一种新颖的基于三轴加速度信号的应用——跳高高度估计。实验结果说明基于加速度传感器进行跳高高度估计是可行的，也是有效的。

总的来说，基于加速度传感器的人体运动模式识别研究是穿戴式计算和普适计算的

重要研究内容之一。该课题的研究具有重要的理论价值和实用意义，值得人们继续进行

更细致、深入的研究。

1. 基于三维加速度传感器的人体行为识别

In this paper, a method for activity recognition based on 3D acceleration sensor is introduced.We recognized five activity including standing,walking, running,upstair and downstair with this method. Many statistical features are extracted such as standard deviation, skewness, kurtosis and correlation coefficient for classification. The result of experiments for testing the effectiveness of the proposed method is presented.

1. 基于三轴加速度传感器的人体行为识别研究

基于加速度传感器的人体行为识别是模式识别领域中的一个新兴的研究方向，它的迅速发展受惠于微电子和传感器技术的不断进步以及模式识别理论的深入研究。随着人们对智能交互和健康监护等方面需求的日益增长，基于加速度传感器的人体行为识别在医疗保健、运动检测、能耗评估等领域受到了广泛的关注。与基于计算机视觉的行为识别不同，基于加速度传感器的方法更能体现人体运动的本质，而且不受特定的场景和时间限制，能量消耗少，成本较低，更适合推广应用。虽然近年来基于加速度传感器的行为识别取得了极大的进展，但仍面临不少急需解决的问题，包括如何提取具有较强表征能力的信号特征，如何面向实际应用设计合理的

跌倒识别方法，如何构建高精度、泛化能力强的行为分类器等问题。围绕这些问题，本

文主要进行了如下的研究工作：

1)总结了现有的行为识别方法，比较了基于计算机视觉和基于加速度传感器两种方法，详细分析了基于加速度信号的行为识别具有的优势，系统研究了该类方法的实现过程和相关技术。

2)针对行为识别过程中的特征提取问题，从加速度信号的时频分析和分布特点的角度出发，利用小波分析等技术手段，提取了基于角度的小波能量和关键点连线斜率两种新颖特征，从不同方面对加速度信号进行刻画。利用独立检测法和交叉验证法对不同特征集合的识别率进行了比较，表明了这两种特征的有效性。

3)在跌倒识别方面，常用分类器往往需要大量的训练样本，现有的方法常采用故意反复跌倒的方式获取训练样本，但对于用户而言非常不便。针对这一问题，提出了一种基于隐马尔科夫模型和身体倾角的跌倒识别方法。该方法将跌倒识别问题转换为对已学模型的偏差问题进行处理，减小跌倒样本量对识别结果的影响。而且基于时序分析的方法，可以有效保留研究对象前后的状态信息，更加符合物理规律。

4)在日常行为识别方面，为了提高分类器的泛化能力和识别正确率，采用递阶遗传算法训练

RBF神经网络，对其结构和参数同时寻优。以降低分类器结构复杂度和提高正确率为目的，设计了新的适应度函数，利用四分位间距改进参数基因的交叉方式，并结合两种变异操作，提高寻优效率。实验结果表明，采用改进递阶遗传算法训练的RBF网络分类器，同时具备结构精简和误差较低的优点，对7种行为的识别率可达91.54%。

5)从识别系统的底层出发，设计了一种加速度信号采集平台，实现了对运动加速度

数据的采集。

1. 人体运动信息获取及物理活动识别研究

人的物理活动具有可感知性、非侵犯性以及受环境影响小等特点,在上下文环境中能体现人的意图,是生物特征研究的一个新兴领域,在普适计算、虚拟现实、运动训练和医疗保健等众多领域有广阔的应用前景。人体运动信息可通过加速度等惯性传感器采集,经过特征提取和活动建模后,运用统计和机器学习算法进行物理活动识别。其中,将大量的低层传感器数据转换为高层的物理活动信息是物理活动识别的关键问题。本文重点研究了人体运动信息的获取方法、基于步态加速度的步态识别、物理活动特征的自动选择、短时物理活动识别和基于多传感器的物理活动识别等内容。运动环境的多样性及物理活动的复杂性影响人体运动信息的准确获取。为有效提取人体运动信息,设计了基于加速度传感器的可穿戴人体运动信息采集系统。通过对人体运动信号的检测与分析,研究了运动数据的位置校正与加速度信号去噪等数据预处理方法,保证了人体运动信息获取的准确度。通过分析步态加速度的无偏自相关特性,研究了步态参数计算和步态对称性评估方法,给出了行走速度与步频、步长和步幅之间的关系。提出了一种混合时频域特征的最近邻步态识别算法,该方法对单步态切分得到步态代码,采用混合时频域特征匹配实现身份的识别。实验结果显示,最近邻步态识别方法能消除人体行走的步态周期不确定性问题,提高了身份识别的准确率。从运动数据中提取有效特征是物理活动识别的关键。针对短时物理活动中加速度信号的相似性和不稳定性等问题,提出了基于聚类特征选择的姿势识别方法。该方法运用聚类算法自动提取物理活动特征,并将多维特征输入离散隐马尔可夫模型,通过模型训练和似然度计算,识别出不同的姿势动作。实验结果表明,聚类特征选择降低了隐马尔可夫模型的复杂度,提高了短时物理活动的识别性

育旨。

在多个传感器节点的物理活动识别中,需要融合多特征参数以减少节点传送的信息量。本文采用机器学习算法得到各节点的分类混淆概率,然后采用贝叶斯规则融合多节点上的分类信息,将物理活动分类为具有最大后验概率的类别,提高了物理活动的识别率。为了减少各传感器节点的训练样本数量,研究了在多个未标识活动中选择特定实例的主动学习方法,从而提高了系统的分类效率。最后对全文进行总结,并指出今后需要进一步研究的工作。