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Evaluation of Complex Human Activity Monitoring and Recognition Techniques

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Abstract: The most important and challenging research area in proactive and ubiquitous computing is Human activity recognition. Automatic classification of human activity milieu (from simple activities to more complex ones) are crucial for applications like monitoring elderly people in assisted living, activity aware media content delivery, designing smart homes and appliances, quantified self, smart health care etc. Physical activity recognition using wearable sensors is capable of providing priceless information regarding an individual's degree of operative ability and lifestyle. During the old age periods, falls are a major problem.so they are forced to depend on others. To monitor the way of walking of elderly people development of a technology that analyzes the relationship between the possibility of fall with the fitness and the total number of daily living activities of the elderly person that looks for precursors to falls. As we are surrounded by a lot of IoT devices, and efficient communication between man and machine are important for the proper working of these devices. So, activity recognition can be used to make our life easier through these IoT devices. There are several models for recognizing activities that use different techniques. We aim to analyze various models of human activity recognition and to propose a model for secure activity monitoring.

Keywords: IoT, Automatic Classification, Ubiquitous Computing, Quantified Self.

I. INTRODUCTION

Everyday activities of people are composite and comprise of more than one sub-activities. There are several models for activity recognition, some of them suffer from high infrastructure cost and privacy concerns. Also, major works are only able to recognize more coarse-grained activities of daily living and a few complex instrumental activities of daily living. Coarse-grained ADL's are generally fundamental self-supporting skills that people learn during their early childhood which include physical and postural activities. While IADL's are complex chores needed for independent living and it requires an amalgamation physical and cognitive efficiency. Several models use different kinds of devices for activity sensing. These sensing devices include video camera, wearable sensors, In-home Wi-Fi, some electrode on neck, chest etc., smartphone accelerometer and gyroscope ,ceiling-mounted infrared motion sensor, motion detectors ,break beam sensors, pressure mats and contact switches ,Microsoft Kinect RGB ,IR video camera,3d video camera, active sonar and Bluetooth beacon in physical environment. The main aim of this paper is to analyses different models for activity recognition and to propose a new and secure way for activity recognition which can be applied to areas that need more security. The proposed model uses an accelerometer, gyroscope, flex sensors, vibration sensors, ultrasonic sensor, temperature sensor atmospheric pressure sensor, humidity sensor and Wi-Fi module to recognize complex human activities. For security, we use DNA encryption scheme. The paper is divided into four main categories in which in first section we are giving a brief introduction about various activity recognition models, in the second section we are analyzing the general features that should be considered on developing an activity recognition model, in section three we are taking into account various activity recognition models and in section four we concludes..

II. THEORY

A. Devices for activity recognition

The three main types of work for activity recognition which differ from each other depending on the devices used are : (I) only with wearable devices (ii) combining wearable devices and external infrastructure-based system (iii) with non-wearable technologies. With wearable devices, the activities can be classified by learning from the data selected by smartphones, wearable health tracker devices, smartwatches, Near Field Communication (NFC) based gadgets,

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augmented reality devices (e.g., Google Glass), etc. There also occur a body of literature that perform activity recognition by combining data sensed from wearable devices and additional static infrastructures. Finally, there also occur works in activity recognition by non-wearable devices such as combination of motion detectors, break-beam sensors, pressure mats, and contact switches, Active Sonar technologies, Microsoft Kinect RGB, infrared (IR) and 3D depth cameras, in-home WIFI, kinetic energy harvesting techniques.

B. Feature Selection Techniques

Feature selection is an essential element of a machine learning algorithm. It determines a mapping function between input features and output class depends on the data from input features. But not every input feature produces useful information about the output class. Immaterial features can cause problems like over-fitting, overhead, and inefficient to anticipate the feature map to glean insights on the data.

1) Filter-based feature selection using Relief-F: This algorithm depends on contingent information and dependencies between the features to evaluate the quality of features. Initially, it provides a default weight to each feature .Then, during iterating through each data point, it increments the weight of those features which illustrate important difference in values for various classes, and then decrement the weight for those that are consistent for different classes. The process is continuing for p times, where p is a user-defined parameter, and at last it determines the average weight for each feature. A higher weight for a feature defines more utility for classification.
2) Wrapper-based feature selection using SFFS: The main difference between the filtering and wrapper methods is that the filtering method estimate subsets by their information content, (e.g., interclass distance, nearest neighbor, statistical dependence), while the wrapper-based method adopts a classifier to estimate subsets by their predictive accuracy (on test data) by statistical re-sampling or cross-validation. One of the disadvantages of a wrapper-based method is its lack of generality when enforced on multiple classifiers.
3) Correlation-based feature selection using greedy method: Correlation based methods determine the quality of a subset of features by considering the predictive capability of each feature as well as the degree of redundancy between them. Subsets of features that are highly coordinated with the class although having low interconnection between other features are adopted. The method uses Pearson’s correlation coefficient to determine the subset connection. Finally, a greedy forward or backward search is built over the space of feature subsets. It initiates with no/all features or from a random point in the space, and ends when the addition/deletion of any resting features results in a decrement in the final estimation.

C. Classifier

Naive Bayes:
Naïve Bayes classifiers are a collection of group algorithms based on Bayes theorem. This is not an individual algorithm but a group of an algorithm where all of them share a general principle. Every combination of a feature being organized is independent of each other. These classifiers are highly scalable wanting a vast abundance of parameters extended in the representation of variables in a learning problem.
Artificial Neural Network:
Artificial neural networks or connectionist methods are calculating methods that are stimulated by, but not alike to a vital neural network that organizes animal brains. Such techniques to determine to perform tasks by interpreting examples, usually without being programmed with task-specific rules.
Conditional Random Field:
CRF is a group of arithmetical modeling techniques regularly used in pattern recognition and machine learning and applied for a structured forecast.CRFs slip toward the array modeling family. Whereas a discrete classifier predicts a design for a single example without examining neighboring samples.
Support Vector Machine:
An SVM model is a symbol of the examples as points in space, outlined so that the examples of the separate divisions are separated by a clear gap that is as far-flung as possible. In addition to performing linear classification, SVMs can efficiently execute a non-linear classification, essentially drafting their data into high-dimensional feature spaces.
Hidden Markov Model:
Hidden Markov Models (HMMs) are a form of probabilistic graphical design that empowers us to predict a series of concealed (hidden) variables from a set of perceived variables. A simple example of an HMM is foretelling the weather (hidden variable) based on the kind of outfits that someone wears (observed). An HMM can be inspected as a Bayes Net uncovered through time with remarks made at an array of time steps being used to predict the best sequence of hidden states.

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D. Attacks in wireless sensor networks

Sensor networks are pregnable to security menaces. Attacks can occur at each layer such as physical, link, network, transport and application etc. Most of the routing protocols are not devised to have security mechanisms and this makes it even easier for an attacker to hiatus the security. The attacks are

1.Physical layer attacks

Jamming: This is affected due to the intrusion with the radio frequencies of the network devices. This is an attack on the availability of sensor networks. And it is distinct from normal radio transmission in the way that it is undesirable and troublesome, thus resulting in DoS(Denial of Service) conditions.

Tampering: This is also known as node capturing in which a node is jeopardized. These attacks are easy to accomplish and it is very harmful. Tampering involves physically abating and ruining the sensor nodes.

2. Link Layer Attacks

Collision: This is affected in the link layer that manages neighbor to neighbor communication together with channel arbitration. The entire packet will be distorted when an opponent can generate collision as a part of the transmission, CRC discord and probably need retransmission that is caused by a single bit error.

Exhaustion: Enervation of a network's battery power can be incited by an interrogation attack. An imperiled node could frequently send which drains battery power more than needed.

Layers	Attacks
Physical Layer	Jamming, Tampering
Link Layer	Collision, Exhaustion
Network Layer	HelloFlood,Wormhole Attack,Sybil,Sinkhole
Transport Layer	Flooding
Application Layer	DoS,Cloning

3.Network Layer Attack

Hello Flood Attack : This is instigated when an invader with high broadcasting power can send or reply "HELLO" packets which are utilized for identifying neighboring nodes. Thus, the invader generates a delusion of being a neighbor to other nodes and underlying routing protocol can be disturbed which eases additional types of attacks.

Wormhole Attack: This is produced due to creation of a low latency link that is designed so that packets can travel from one end to the other end quicker than usual via a multihop route. This attack is a menace against the routing protocol and is perplexing to notice and avert. By using this type of attack an opponent can persuade the distant nodes that are only one or two hops away through the wormhole instigating misperception in the network routing techniques.

Sybil attack : This is caused when an assailant utilizes a malevolent device to generate a huge quantity of entities in order to gain domination over the network traffic. The ID of these malevolent nodes can be the outcome due to false network accompaniments or replication of existing genuine identities. The sybil attack frequently targets fault lenient schemes incorporating disseminated storage, topology sustentation, and multi-hop routing.

Sinkhole attack : This is caused when an invader averts the base station of the network from gaining ample and precise sensing data, thus ensuing in a serious threat to higher-layer applications. By Sinkhole attack, invader can entice almost all the traffic from a definite area. It works in the way by molding malevolent node look particularly attractive to other nearby nodes with respect to routing protocols inferior routing algorithm.

4.Transport Layer Attacks

Flooding Attacks: This is a denial of service attack intended to lead a network or service down by flooding it with huge quantities of traffic. Flood attacks frequently happens when a network or service becomes oppressed with packets, thus starting half-finished connection requests that it cannot, longer procedure Bonafede connection request. Through flooding a server with connections that unable to be completed ,flood attack ultimately fills up the server's memory buffer and when this buffer is full, no additional connections can be completed and thus results in a denial of service.

5.Application Layer Attacks

Denial of Service: This attack is generally mentioned as the envisioned attack of the adversary to damage or ruin the sensor network. DoS attack will result in restricting or confiscating the sensor network functionality than anticipated attack will occur at any layer of OSI layers of WSN.DoS pierces the efficiency of the targeted network by perpetuating its related protocol by overwhelming the resources, destroying or changing the infrastructure configuration, physically damaging the network components.

Cloning Attack: This is caused when opponents may simply arrest and concedes sensors nodes and arrange unlimited no of clones in the sensor network of the conceded nodes. As the clones have genuine access to the sensor network procedures in the same way as a genuine node resulting in a large diversity of insider attacks or even taking over the entire network. if these clones in the sensor network are left hidden, the network is unfortified to attackers thus tremendously pregnable. Thus, clone attacks are gravely disparaging, operative and well-organized solutions are needed for clone attack recognition to reduce the damage.

III. RELATED WORK

Here we introduce each papers based on the number activities recognized by them. And these models are arranged in increasing order of activities recognized by them

The work in [1] uses a combination of motion detectors, pressure mats, break beam sensors and contact switches to fulfil motion tracking and limited activity recognition such as sleeping. Here they use Bayes filter which provides a familiar way to estimate the state of a dynamic system from noisy sensor data. In this paper, they introduce the STAR problem and shows the capability of a simple sensor for concurrent location awareness and activity recognition. Automatic health monitoring eventually requires recognition of complex activities of daily living and they aim to incorporate new sensors and models as required to meet the goal.

The work in [2] uses Microsoft Kinect RGB, Infra-Red and 3D depth camera for activity recognition. The Kinect experiences a limited range angular coverage distortion in skeletal joint estimation and inaccurate multiplexing dissimilar subjects' estimations to one. This paper addresses these restrictions including a set of features that create a unique "Kinect signature". The Kinect signature enables recognition of several subjects in the scene, automatically allocate the kinematics feature estimations only to the subject of interest, and supply information about the standard of the Kinect -based estimations. The work provided a finite set of fixed skeleton-based features of ratio and length of diverse BPs that can be used depending on their time- invariance features to identify subjects. Comparatively a small number of these features were given to build a KS Kinect signature of the subjects of interest(SoIs). Distorted estimations were noticed and avoided from the feature domain based on feature prior knowledge of constancy over time and permitted the identification of the KIs of the SoI using K-means classification algorithm. Then, Kinematic features based upon the SoI's joints estimation were extracted to illustrate a kinematics analysis.

The work in [3] used an Active sonar technology for activity recognition and classification. The above technique is not pervasive in the sense that the hardware utilized for classification are costly and it is not able to cover an entire home. As usual, the hardware is fixed in a certain location(for example in one room), and repositioning them to other rooms as the subject moves off is too difficult and not pragmatic.

Furthermore, in works using camera privacy concerns are also embossed. The work in[4] uses in-home Wi-Fi signals for activity recognition. But Wi-Fi based techniques are not able to differentiate activities which need no to minimal body motion or activities which are in contextually very similar in location and body motion.

The work in [5] used a belt clip accelerometer attached to the waist to recognize 6 activities such as walking, jumping, running, sit to stand /stand to sit, stand to kneel to stand and being stationary. Feature selection is performed with a filter-based approach using Relief-F and wrapper-based approach using Sequential forward floating search (SFFS). For error calculation, K-NN and Naïve Bayes classifiers are used. The system classifies several activities with high accuracy and also it requires minimum training of users and gives the least errors due to orientation and positioning offsets. This model can be used in a more realistic environment and also recognize activities independent of the position of an accelerometer. The main drawback of this model is that it can only recognize 6 activities.

The work in [6] places an accelerometer sensor in the subject's prepotent wrist to recognize 7 human activities. This paper introduces a portable device for real-time activity recognition. The suggested portable device is recognized by an embedded system that combines a triaxial accelerometer, a microprocessor and a wireless transceiver module. An online activity recognition algorithm was developed for daily activity recognition of humans based on the acceleration signal collected from the triaxial accelerometer. The proposed algorithm consists of data collection, data preprocessing, feature extraction, feature reduction and classifier construction. The model uses fuzzy basis function-based classifier. The disadvantage of the paper is that it only recognizes 7 activities.

Recognizing human activities in [7] is a hard problem for context-aware systems and applications. This system uses Accelerometer and GPS for activity recognition. The model recognizes 10 activities with higher accuracy. The techniques based on supervised learning algorithm experiences scalability problems regarding some considered activities and contextual data. This model proposes a solution based on the use of ontologies and ontological ratiocinating merging with statistical inference. The main contribution of this model is the design of hybrid reasoning algorithm running on the mobile devices and also an ingenious architecture and its complete enforcement. The model uses location as the only data used to ratify ontological reasoning.

In [8] the model does not require any costly framework like a network of sensors and cameras. For activity recognition, multi-sensor fusion scheme is used. This system uses accelerometer, gyroscope, magnetometer and temperature sensor for activity recognition. In this system, they propose a human daily activity recognition technique by combining the data from two wearable inertial sensors placed on one foot and waist of subject, respectively. The data from these two sensors are combined for coarse-grained classification, to decide the type of activity: zero displacement

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activity, translation activity and strong displacement activity. Second, the fine-grained classification module based on heuristic discrimination or Hidden Markov models is applied to a greater extent to differentiate the activities.

In this paper [9] an automatic activity recognition system combining both accelerometers and a first-person view camera in traditional glasses called "smart glasses". It is having a smartphone connected on top of safety goggles. It focuses to develop a model capable to identify a broad range of human activities consisting of dynamic and stationary states. Here uses multi-class support vector as a classifier which is having a binary sub classifier and concludes the final forecasting based on the voting process. By using a conditional random field, it constructs a structured classification application for contextual activity recognition.

In this paper[10] it presents a work which guarantees a novel sensing mechanism that takes effort to make use of information from inside the body. It modifies the physical principle of capacitive sensing utilizing in the industry to wearable activity sensing. Here examines a capacitor constructed as a conductive textile electrode and the human body as a dielectric. It further evaluates the capacitance variations due to tissue replacement, electrode distortion. By using the sensing principle, the analogue hardware required to gain and preprocess the signals and sample signals from disparate body locations and actions. It also evaluates estimative determination of the recognition accuracy, based on collar combined electrodes and actions such as chewing and swallowing, speaking, sighing and also various head movements and locations.

There exist a lot of work that fulfil activity recognition by fusing data sensed from the wearable device and ancillary static infrastructures. For example, the work in [11] amalgamates data sensed from infrared motion sensors fixed on the ceiling of different rooms, with data produced from a smartphone sensor which is placed in the pocket of a user for recognizing locomotive/postural states of different humans occupying in a home.

Automated recognition of human activities is one among the principal and exacting research areas in proactive and ubiquitous computing. The work in [12] recognizes 4 human activities utilizing augmented features extricated from the activity signals calculated using a single triaxial accelerometer sensor and artificial neural networks. The features cover autoregressive(AR) modelling coefficients of activity signals, signal magnitude areas(SMA) and tilt angles(TA). It gives an accuracy of 99%. The accuracy reduced in adding new activities.

The work in [13] uses a single triaxial accelerometer sensor attached to the subject's chest to recognize and classify 3 states and 15 activities with an accuracy of 97.9%.In this, the recognition method uses a hierarchical scheme. For state recognition features including the standard deviation, mean, spectral entropy and correlation, as state features are extricated from the noise reduced acceleration signal and is utilized by a classifier. For activity recognition features including SMA, TA, AR Coefficient(Signal magnitude area, Tilt angle, Autoregressive coefficient) are applied to the classifier. The model uses LDA(Linear Discriminant Analysis) which takes the augmented feature vector as input and make use of class-specific information increase the ratio of the between and within-class scatter information. The model uses an artificial neural network based on a feedforward backpropagation algorithm as a classifier. The model is capable of recognizing a broad set of daily physical activities using a single triaxial accelerometer. The accuracy of the system remained the same even after adding new activities. The main disadvantage of the model is that when the system was tested with the accelerometer sensor at five different positions then the accuracy of the system was reduced to 47%.

In [14] a new model is proposed by the authors in [28], that can recognize activities independent of the accelerometer sensors position. The system had an accuracy of 94.4%. But the model was not able to recognize transitional activities.

The development of cost-effectiveness and easy operation depth cameras has added a diverse of visual recognition tasks including human activity recognition. The work in [15] introduces a unique framework for recognizing human activities from video sequences captured by depth cameras. We expand the surface normal to polynormal by collecting local neighboring hypersurface normal from a depth sequence to mutually distinguish confined motions and shape information. The system introduced a well-established scheme called Super Normal vector(SNV) to agglomerate the low-level polynormals into discriminative representation, which can be observed as an uncomplicated version of the Fisher Kernel Representation. To globally detain the spatial layout and temporal order, an adaptive spatiotemporal pyramid is established to divide a depth video into a set of space-time cells.

The work in [16] introduces a technique for recognizing human activities using information extracted by an RGB-D camera, that is Microsoft Kinect. The technique is based on the evaluation of some pertinent joint of the human body using the Kinect. In this model, three different machine learning techniques are used. In this, the three machine learning techniques such as K-Means clustering, SVM(Support Vector Machines) and HMM(Hidden Markov Model) are combined to detect the postures involved while doing an activity.to categorize them and to model each activity as a spatiotemporal evolution of well-known postures. This model is able to capture a general model of the activity regardless of the user. The model can recognize activities independent of who performs the action and the speed at which the actions are performed. The model is scalable to a large number of actions and is expandable with new actions. The drawbacks of this model are the lesser capacity of Kinect in providing a stable video stream, unreliable joint detection mechanism and less efficient pose estimation process in order to deal with frame loss and body occlusion.

The work in [17] combined multi-sensor data from a smartphone(used as wearables kept on multiple body positions) and Bluetooth beacons to recognize 19 human activities. This model uses conditional random field classifier to recognize 19 activities. For activity recognition, they are using accelerometer and gyroscope, for ambient environment sensing they are using temperature, humidity and atmospheric pressure sensor and for location context they use a Bluetooth beacon. This work was not able to recognize complex activities related to ambient sensing(Moving from outdoors to indoors and indoors to outdoors).The feature selection used here is primitive which leads to a lower accuracy of only 80%in activity recognition for a single user.

The work in [18] inspects deep learning techniques for human activity recognition by fusing sensor data from smartphones and Bluetooth beacons. The major limitation of this model is the complexity of deep learning algorithm on smartphones.

The work in [19] introduces a watchdog system, to inscript the problem of recognizing self-harming activities when endeavored in-patients in clinical settings. Watch dog consists of three components -data extracted from tiny accelerometer sensors attached on the wrist of the person, an effective algorithm to classify whether a user is active or dormant(performing a physical activity or not performing any activity) and a novel decision selection algorithm based on random forest and continuity indices for fine-grained activity recognition. The model can only recognize self-harming activities.

In [20] a new model is proposed by the authors in [17] which uses superior feature extraction techniques, noise reduction and parameter tuning to significantly enhance the accuracy of activity classification. The model uses wearable(body multi-positional) multimodal sensors such as accelerometer, a gyroscope for body locomotion, temperature, atmospheric pressure, humidity sensors for ambient environment sensing and GPS, Bluetooth reception for location context. The model uses filter-based, wrapper based and correlation-based feature selection techniques. The system uses conditional random field classifier to recognize 21 complex human activities. The drawback of this model is that it is less energy efficient. The challenges are wireless packet loss, network delays and jitter.

In order to solve the problems faced by the above model, we propose a model which is capable of recognizing complex human activities which include both ADL and IADL using multimodal multi positional wearable sensing.The model utilizes accelerometer, gyroscope, flex sensors, vibration sensors, ultrasonic sensor, temperature sensor atmospheric pressure sensor, humidity sensor and Wi-Fi module. For security purpose we use DNA encryption algorithm. This paper is meant for analyzing various models of activity recognition and to propose a model for activity recognition. This model consists of three modules that is one for activity recognition, one for ambient environment sensing and the other for location context. This model is able to recognize static, dynamic and transitional activities. The model uses conditional random field classifier for activity classification.

IV. CONCLUSION

There exist several models for activity recognition and monitoring which uses different technologies and devices for activity recognition. These models utilize wearable devices, wearable devices with external static infrastructure and non-wearable technologies. Most of these models have high infrastructure cost and direct privacy concern. And these models are not able to recognize complex instrumental activities of daily living. Some of these models suffers from packet loss and packet delay that may occur due to some attacks in sensor networks. Our proposed system is capable of solving such problems. This model uses multimodal wearable sensors which are placed at multiple body positions to recognize and classify complex human activities with a high degree of security. For activity recognition we use accelerometer, gyroscope, flex sensors, vibration sensors, ultrasonic sensor, temperature sensor atmospheric pressure sensor, humidity sensor and WIFI module. For security purpose we use DNA encryption algorithm. This paper is meant for analyzing various models of activity recognition and to propose a model for activity recognition.

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