Change Point Detection Used in smart homes to predict Human Activity

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Abstract** -A Sensor is attached to aSmart Homeswhich send message now and then about the inmates or the old people. Whether they had taken food or not and other activities performs in proper time or not. Change Point Detection (CPD) is the problem which discovers any abnormal changes within the inmates. Any changes in the inmates have been detected by the time points. The unequal changes happened called SeparationDistance (SEP). It will not coincide at any points.Change Point Detection is the problem of discovering time points at which the behavior of a time series changes abruptly. A novel real-time nonparametric change point detection algorithm called SEP, which uses Separation distance as a divergence measure to detect change points in high-dimensional time series.Change points in smart home are valuable for identifying activity transitionDetection.The artificial and real-world data indicate that SEP performs as well as or better than existing methods at classical CPD.**

***Keywords:*Change Point Detection, Separation Distance, Smart Homes, Time Series Data, Activity Transition Detection.**

I. INTRODUCTION

Change point detection is a well-known area and has been studied for the last few years in the fields of computer science. Change point detection finds application in real-world problems such as medical checkups, climate change prediction, speech recognition, image analysis and human activity analysis. So many algorithms have been designed and adapted for change point detection. Supervised and unsupervised methods are used to detect change points. Change point detection is more recent investigated field and it is rare. Real time change point detection algorithm runs concurrently in the process. The goal is to find a change point before it occur the next data point arrives.

Now a day’s direct densities ratio change point detection algorithm have been challenged. These algorithms detect change points between two successive windows of data. Any changes in the windows may be noted by the sensor. Changes happening in the inmates may be noted in few seconds through the sensor. The unsupervised algorithm to detect change points in time series data names as SEP and also known as separation change point detection.

II. LITERATURE SURVEY

In [1], introduces a set of scalable algorithms to identify patterns of human daily behaviors. These patterns are extracted from multivariate temporal data that have been collected from smartphones. It has exploited sensors that are available on these devices, and have identified frequent behavioral patterns with a temporal granularity, which has been inspired by the way individuals segment time into events. These patterns are helpful to both end-users and third parties who provide services based on this information.Drawbacks in this method are it cannot be reduce the false positive ratio. The prediction accuracy is low.

In [2], Smart homes offer an unprecedented opportunity to unobtrusively monitor human behavior in everyday environments and to determine whether relationships exist between behavior and health changes. Behavior change detection (BCD) can be used to identify changes that accompany health events, which can potentially save lives.Drawbacks: It cannot be reduce the processing time. It cannot be accurately predict the change point.

III. EXISTING SYSTEM

The supervised and unsupervised concepts to detect change point problems. Supervised algorithm can be classified into two classifiers such as binary and multi-class problem and also trained by machine learning algorithm and change point detection. The change point detection detects each state boundary and produces a multi-class problem. A sliding window passes the data obtaining each division between the two data points in the state boundary or to detect change point as a possible state. The simpler training phase and the diversity of training data and it represent individual state class and all possible transition and also it can be from one state to another. To provide sufficient information finds the nature and the detected change of each state. Change point detection algorithm can be classified into two different types that are supervised methods and unsupervised methods.

IV. PROPOSED SYSTEM

DATASET COLLECTION Using embedded sensors, the CASAS smart homes collect information about the state of the home and the resident(s) to monitor and analyze daily activities. Sensors generate “events” to report their state. An event contains a date, time, sensor identifier, and message sent from the sensor. Each of the CASAS smart homes has at least one bedroom, a kitchen, a dining area, a living area, and at least one bathroom. All of the CASAS smart homes have different sizes and layouts, yet they all include the standard sensor setup.

Each of the smart apartments is equipped with a network of wireless motion and door sensors and houses a single older adult resident who performs normal daily routines. Sensor labels starting with “M” indicate motion sensors and “D” indicates door sensors.The motion sensors are used to determine when motion is occurring in the area covered by the sensor. The motion sensor reports an ON message when motion is detected, followed by an OFF message when the movement stops. When the resident is walking under the motion sensor to some other location, the motion sensor has a gap between the ON and OFF messages that is roughly 1.25 seconds. The activity results in continuous movement under the motion sensor, (e.g., dancing near the motion sensor), the sensor will not generate an OFF message until 1.25 seconds after the activity has stopped.

CHANGE POINT DETECTION:

The activity classes that usefor analyses are Bathe, Enter Home, Wash Dishes, Personal Hygiene, Relax, Work, Sleep, Leave Home, Cook, Bed Toilet Transition, Eat, and Other Activity. Because all events that do not fit into the 11 predefined activity classes are labeled as “Other Activity”, the activities are skewed toward this activity class.

Activity transitions are time in the sensor event data sequence when the activity changes from one label to a different label. These represent the change points want to detect using CPD algorithms.

SEP:

In the training phase, the parameters θ are determined for each window so that a chosen dissimilarity measure is minimized. A density-ratio estimator, a dissimilarity measure between windows is calculated during the test phase as a change point score. The higher the change point score is, the more likely the point is a change point, these methods identify change points by comparing scores to a threshold.

First, transition detection can be used to segment smart home sensor data into non-overlapping activity sequences and provide insights on the start time, stop time, and duration of activities performed in the home. This segmentation can also boost the performance of activity recognition because the feature vector does not contain information from more than one activity and can include features such as activity start time and duration so far. The detection of activity transitions facilitates activity-aware delivery of notifications, automation and behavioral intervention technologies.

PERFORMANCE METRICS:

True Positive Rate (TP Rate) this refers to the portion of a class of interest (in this case, change points) that was recognized correctly. TP denotes the number of change points that were correctly detected and FN denotes the number of change points that were not detected.

False Positive Rate (FP Rate) this refers to the ratio of negative examples (in this case, the number of data points in a time series which are not changing points) which are recognized as change points to the total number of negative examples.

FP denotes the number of non-change points that were incorrectly identified as change points and TN denotes the number of non-change points that were not labeled as change points.

A supervised learning algorithm that attempts to perform change point detection typically faces an imbalanced class distribution because the ratio of changes to total data is usually small. This utilizes both Sensitivity and Specificity measures to assess the performance of the algorithm in terms of the ratio of positive accuracy (Sensitivity) and the ratio of negative accuracy (Specificity). This directly measures how close the time value of each correctly-predicted CP is to the actual CP time value in the series. The absolute value of the time difference between the true predicted and actual CP time points is summed and normalized over the total number of change points.

The proposed system detects change point in real time dimensionality. SEP includes new probability metrics and density ratio to detect change point and it is highly sensitive change point. Change point detection method constructs the separation distance and the existing change point detection concepts. The set of relationships explained the existing probability metrics and Pearson metrics. SEP includes artificial datasets and benchmark datasets. SEP finds changes in sensor based Human Activity Data. Change point detection includes Health detection, Breakpoint detection and Activity data. The smart home sensor data detects change point in health detection and other activities. Separation Change point detection performs far better than the existing system.

The person who lives in the casas smart home where noted through the sensor. Whether the movement is not predicted in the sensor the message can be reached in the concerned person through sensor. A sensor is a device to detect and responds to some type of input from the physical environment. The specific input is light, heat, motion, moisture, pressure, or any one of a great number of other environment phenomena. Sensors are sophisticated devices that are frequently used to detect and responds to signals. A sensor converts the physical parameter such as temperature, blood pressure, humidity, and speed into a signal which can be measured automatically whether the sensor is on mode. The sensor readings are collected by a computer network and stored in a database that an intelligent agent uses to generate useful knowledge such as patterns, predictions and trends. On the basis of this information, a smart home can select and automate an action that meets the goal of the smart home.

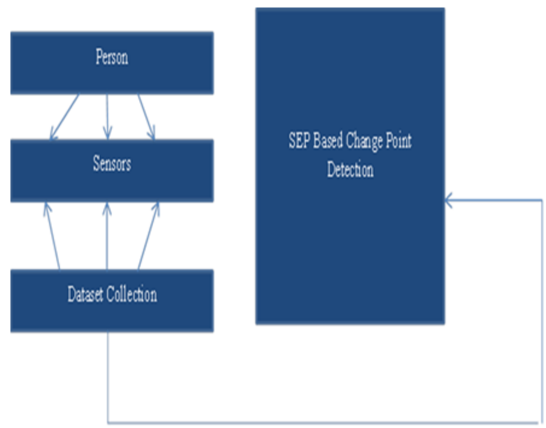

Fig 1.HUMAN ACTIVITY PREDICTED BY THE SENSORIN THE CASAS SMART HOME

There are several ways to collect data from the environment in the existing researches. One of which is using infrared-based motion detectors or reed switches placed on doors. Also, some researches are using data from video cameras monitoring. Sensors are cheaper, unobtrusive and models needed for activity recognition, in general, are less complex. There are also some challenges with video-based activity recognition researches need to overcome like illumination variations, occlusion, and background changes.

DATASET COLLECTION IN THE CASAS SMART HOME

There are several research projects that focused on gathering data in real settings. In the dataset from CASAS Smart Home Project Advanced Studies in Adaptive Systems was used. CASAS Smart Home plan and sensor location in the dataset collection. There are three types of sensors presented in current research: motion sensors these sensor IDs represented as “M”, door sensors these sensor IDs represented as “D”, and temperature sensors these sensor IDs represented as with “T”. Sensor will be activated all over the time.

Segmentation

In each sensor define this problem as multiclass classification. To create training set divide the data on windows. There are 3 different ways in the existing system.

An activity-based segmentation to divide the dataset on windows in the case of detection of changing activity, so each of the windows must contain one activity. But ordinary activities are not well distinct in the boundaries are not detailed and specific. And it’s not applicable for online recognition and also to wait for the future data to make a decision.

Next type of segmentation is **time-based segmentation**. To divide the data in fixed time windows whether selected the too small window size, it may not contain certain information for making a decision. And the window size is big there can be huge activities, and activity that dominates will be more represented compared to other activities, which badly affects the decision.

The Final method is **sensor-based windowing**. By using the sliding windows divide the stream on windows with an identical number of sensor activations. This method also has some disadvantages. One window can contain activations from few activities. So the idea is to classify final sensor activation, other activations are window context. And also use this method.

Feature extraction the forming dataset applicable for learning models. Using the sensors window method lets extract from each window such features as begin time, final time, time difference, and the number of activations of each sensor in current window, weighted using mutual information method. To add the id's of last two sensor activations. So our feature number is 5 + number of sensors in the dataset. As consequence of addressing the existing drawback of the method, And also calculate the shared information matrix, which defined as the idea is that we have to reduce the influence of sensor activations in the window that occurs low frequently within activities together with the final sensor event.

V. CONCLUSION

The problem of change point detection to the existing change point detection methods and difference standard used in density ratio-based concept, that metrics with larger range of difference value perform better for reliable predicting change points in complex data to introduce a change point algorithm based on Separation distance for real-time detection of change points. The artificial and real-world datasets, that the proposed algorithm outperforms existing methods such as smart home activity transition detection.

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