Automatic Detection of Situational Context Using AI from Minimal Sensor Modality

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***Abstract*—There is a vast improvement in the sector of human healthcare and education delivery using artificial intelligence (AI) such as recommender system. For this purpose, many modern technology are being used like smart wearable device to make the diagnosis of different types of human disease and automated tutoring systems. For these AI algorithms, there can be high error rates if situational contexts are ignored. Currently there is no automated approach to detect situational context. In this work, we propose a novel approach to automatically detect situational context using clustering algorithm type AI from minimal sensor modality. We begin the process by converting a few sensor data to a multitude of axes, then determine situational context from these axes by using clustering algorithm. Here, we evaluated the machine learning Clustering algorithm performance on the simulated data and compared the characteristics of their performance. The results show 89.4% accuracy for Seven situational contexts and 89.8% accuracy for eight situational contexts. This preliminary work shows the feasibility of detecting situational context automatically from a few sensor data by converting the sensor data to multiple axes and applying clustering algorithm.**

Keywords: KMEANS algorithm, machine learning, situational context detection

I. Introduction

Early detection and continuous monitoring can help reduce the complexity of treatment and recovery. Also nowadays the technology have developed a lot in various sectors in our day to day life without which we cannot think of our life. For instance, artificial intelligence (AI) based recommender system can revolutionize education system. In today's world with the advancements in health monitoring technologies, we envision that future smart devices would monitor not only our environment, but also our vital signs, such as breathing, heartbeat, and body temperature. Future Smart and Connected Communities (SCC) will utilize distributed sensors and embedded computing to seamlessly generate meaningful data that can assist individuals, communities, and society with interlocking physical, social, behavioral, economic, and infrastructural interaction [1]. Mobile Health (mHealth) technology has enabled a revolution in computerized health interventions through mobile (smart) phones. It is desirable to have an automated adaptation of the behavior of a mobile device depending on a change of user context to spare him additional effort or unwanted behavior in different situations. The availability of sensors in wearable devices can accurately measure the status of patient. These can help to track physiological changes of human and the progress of treatments on a continuous basis. Sensors are also used to monitor, periodically and assess to improve patient compliance. To enable such an automatic adaptation the mobile user's context needs to be determined by the mobile device itself. In future, we might be able to interpret the physical situation of the user and alert the physician about it if we have automated system. This type of automated systems are data dependent and data can be misleading sometimes, so it will have pitfall. So if we use AI without Context aware system, error rates can be high, and it can loose the trust of usage. In this case context detection is very useful to reduce the error rate. AI tutoring is also an automated system where AI searched literature and provide the user all the information. So for this auto-tutoring we also need context detection.

To date most of the wearables studies are limited in tracking one or two health-related variables, and have yet to produce accurate measurement of many markers of health status that they attempt to assess such as heart rate , movement, speed [2]. Sometimes they cannot use all the sensor data from our wearables and accumulate them to be used for our health monitoring. Previous research suggests that knowledge is limited regarding all the factors that may drive successful implementation of wearables sensors as they need extra steps to identify them into the healthcare environment. Deficits in knowledge and also taking extra steps into generalizing the reading also sometimes shows that it can cause a rise to concerns that wearables could pose health risks by paradoxically reducing healthy behavior rather than promoting it, either through a false assurance of healthy behavior or through discouragement from failure to achieve goals [3] [4]. In this study, we tried to implement our knowledge how we can use the wearbles sensor reading without taking anymore extra steps to complicate our life in our health monitoring.

The context-aware systems are intelligent systems which recommend users with adaptive service choices that are appropriate to their individual preferences and contextual situations. However, the main challenges in these systems are extracting different context information and updating user's profile information. Recently by the popularity as well as the availability of the sensors, a massive volume of data is available to gain useful insights into user profile which contains dynamic contextual information. IoT sensors continuously generate enormous amounts of data. In ubiquitous computing situational context is often derived from one specialized sensor either attached to a person or located in several different places across so called smart rooms [5]. To get the data for these systems, we can target some of the smart objects such as smart watches/wristbands, smartphones/tablets, Google Home and personal computers for detecting several contexts. An activity of the user, by other means, what he/she is doing, such as sleeping, eating, driving, or walking is referred to as a context. A category or metric values of collected data from sensors, such as a user's heart rate, location, speed, or acceleration is referred to as an axis. For instance, heart rate axis and location axis are collected from wristband heart-rate sensor and GPS respectively.

In this study, we aim at extracting useful information from the user's wearable devices. This work also explores the novel concept of detecting situational context from a few sensor data from sensors. Then the sensor data can be converted to multiple axis data, which will improve accuracy of situational context detection. By analyzing these axes data and situational contexts we will work on the procedure which can help us understanding the condition of the patient. Then we will apply Gaussian distribution and machine learning algorithm to process these data to characterize our human condition and try to take initial steps to health care.

II. Methods

A. Simulated Data

In this work we have worked with sensor data and converted them into multiple axes data. Wearable devices have a feature, which is very suitable for collecting body information. In the field of medical and health segmentation, smart wristband have heart rate monitoring, sleep monitoring and other different function, which can meet the needs of users to monitor daily life indicators. The advantages of these wearable devices can be extended to disease detection and surveillance through reliable data collection. Like from the pulse-oximetry we can get the value of person's heart-rate and from GPS we can get the speed of a person. This data conversion is explained in fig 1. The statistics language identifies numerical data as two

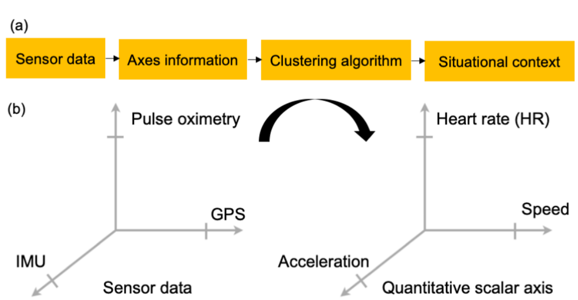

Fig. 1. (a) Process of analyzing sensor data to automatically detect context using AI, (b) Illustration example of converting 3 sample data to 3 axes data, which must be quantitative scalar values

types: Continuous data and Categorical data. Continuous data describes the quantity measured on a scale. And categorical data tells about the quality of the data and is expressed in proportions. The representation of data is inclusive of two parameters: The measure of central tendency and the measure if dispersion. The measure of central tendency is direction towards the central most value of the data set which is known as the mean or median. The measure of dispersion includes standard deviation (SD), standard error and confidence interval [6]. Now in this work we need to work with a large sets of data which are categorized under different axes and context to prepare them for machine learning algorithm. So, for this reason we chose Gaussian Distribution and Gaussian-based distribution of data sets seems to be the best fit for collecting large amount of data for testing. The Gaussian distribution is known as a general state of appropriation with a specific symmetrical level of bunching around the mean, which resembles a bell curve. This distribution is also known as the Normal distribution. Normal distribution was first used as part of astronomical perceptions, where the errors of estimation was discovered. This distributions are very important in statistics and randomly used in the natural and social sciences to represent real-valued random variables whose distributions are not known [7]. In probability theory, a normal distribution is a type of continuous probability distribution for a real-valued random variable. The general form of probability density function of Gaussian distribution [8] is

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

The parameter μ is known as the mean of the distribution which can also be called as its median and mode and the parameter is its standard deviation or SD [9]. A random variable which has a Gaussian distribution is said to be normally distributed and known as a normal deviate. The shape of the normal distribution is a function of SD. The shape is broader and flatter when SD is high and narrower when SD is low.

B. KMEANS Algorithm

Clustering analysis method is one of the main analytical methods in data mining and influence the results directly. Clustering is a way that classifies the raw data reasonably and searches the hidden patterns that may exist in datasets [10]. It is a process of grouping data objects into disjointed clusters so that the data in the same cluster are similar, but data in different cluster differ. This makes clustering techniques widely applied in many application areas as artificial intelligence, data compression, data mining etc. KMEANS is a typical clustering algorithm in data mining which is widely used for clustering large set of data. MacQueen firstly proposed the KMEANS algorithm It was one of the most simple, non-supervised learning algorithms, which was applied to solve the problem of cluster [11]. This method classifies the given date objects into k different clusters through the iterative, converging to a local minimum. So, the results of generated clusters are compact and independent. The process of k-means algorithm as follow:

Input: Number of desired clusters, k, and a database containing n data objects.
Output: A set of k clusters
The way KMEANS algorithm works is as follows:

1) Number of clusters K is specified.
2) Initialization of centroids by first shuffling the data set and then randomly selecting K data points for the centroids without replacement.
3) The distance between each data object needs to be calculated and compute the sum of the squared distance
4) Each data point needs to be assigned to the closest cluster (centroid). Compute the centroids for the clusters by taking the average of the all data points that belong to each cluster.
5) Iterating until there is no change to the centroids. i.e, assignment of data points to clusters is not changing [12].

Here, we tried to increase the context and axes number in respect to human body position and state, because when the number is limited we can't get a clear view of the clustering and we can't predict their position and state. For example, in the figure 2 we can see a 2D presentation of 2 axes, but as we can see all the clusters are combined together and they can't be differentiate. So we can't predict their status and it can cause problem in our data inspection.

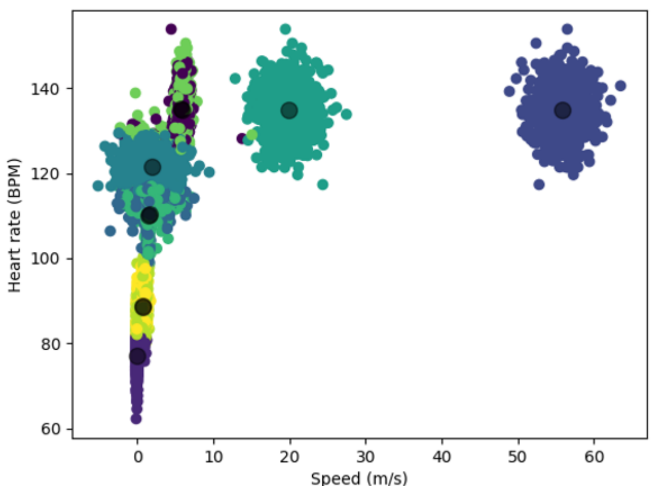

Fig. 2. 2D presentation of clustering data

III. Results

In this paper, we selected to work with 10 Axes and 8 situational context which can be observed from human body to get an idea of the human position by using wearable sensors of daily life. These Axes and context are shown below in the table 1

How we can collect these axes from wearable sensors is illustrated in the fig 3.

After collecting data from wearable sensors, we worked on processing those data. For fitting the Data in to machine learning we need a large set of data to cluster and differentiate them. So, we chose Gaussian Distribution and Gaussian-based distribution of data sets seems to be the best fit for collecting large amount of data for testing. For each context, 1000 data of an axis is generated by using Gaussian Distribution. For example, we generated 1000 data of speed axes or 1000 data of hand acceleration magnitude for sitting context. We have used MATLAB gaussian function to generate these data sets and then saved them in a mat file under each axes for each context . After generating the sets, we used the gaussian function in MATLAB to generate graphs with respect to each axis. In MATLAB we will use those mat file to access the data sets and then produce the graphs which we can see in figure 4 a) and 4 b) for sitting context and with this process we can generate all the distribution.

TABLE I
Axes and Situational Context listing

Axes
Speed(m/s)
Heart Rate(BPM)
Hand Movement Amplitude(m)
Distance from Home(m)
Altitude(m)
Time of Day(hr)
Hand Movement periodicity(Hz)
Hand Acceleration Magnitude(m/s^2)
Hand Rotation
Hand Jitter

Context
Sitting
Walking
Running
Cycling
Driving
At Train
At Gym
At Work

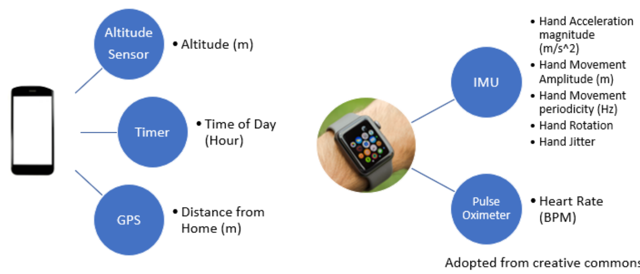

Fig. 3. Axes Data collection from devices

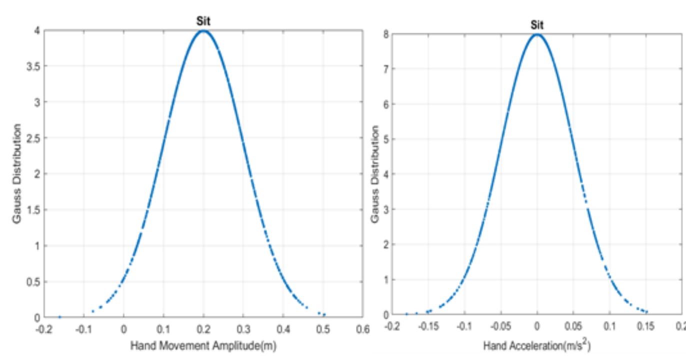

Fig. 4. Example of simulated axes data with Gaussian distribution of a)Hand Movement amplitude and b)Hand acceleration for sitting position

From these figures, we can see the data is properly distributed and properly generated for the machine learning application. Now, as our data is an unsupervised set and for this reason we chose KMEANS algorithm because they can cluster/group similar data without the need to be trained. Now there are some other algorithm by which we can cluster our data like affinity propagation but the main difference between KMEANS and Affinity Propagation is that we can specify the number of clusters/classifications for our data sets in KMEANS, whereas in Affinity Propagation, the algorithm automatically chooses a suitable number of clusters for the data. We first worked with 7 situational contexts and then 8 situational contexts with KMEANS algorithm to see the data set clustering and results, compare the performance and accuracy of them. Here we have optimized the parameters of KMeans algorithm to work better with our data set, which is shown in table 2.

TABLE II
PARAMETER OPTIMIZATION OF KMEANS ALGORITHM

Parameter	**Value**
Algorithm	Auto
'copy_x'	True
'initialization'	'k-means++'
'max_iteration'	300
'n_clusters'	10
'n_init'	10
'n_jobs'	Deprecated
'precompute_distances'	Deprecated
'random_state'	0
tol	0.0001
'verbose'	0

As we increased the situational context number of human position then the accuracy was increased as they processed more data.

A. Seven Situational Contexts

So by increasing the number of Axes and contexts we increase out data clustering. Prediction of our position can be more accurate with more situational context of the human body. We can get more understandable and clear perception of our data. At first, we chose 7 situational contexts from our human body perspective and try clustering the data by using KMEANS. We saw the true classification and predicted classification of the data and it is shown in table 3

Here we can get a clear view from the position and how the data are distributed as most of the data from true class and predicted class matched. Also these values are clustered in a 3D view to see how they are divided, shown in the fig 5 We got an accuracy level of how they are calculated properly as comparison with the true data and the predicted data. The accuracy is as high as 89.4%. These are shown in table 4 and 5 below

B. Eight Situational Contexts

After situational contexts, we increased the data as we increased the context number to get more clear position of

TABLE III
TRUE CLASS AND PREDICTED CLASS PRESENTATION OF 7 CONTEXTS

Prediction → / True class	Sit	Walking	Run	Bike	Car	Train	Gym
Sit	662	0	0	0	0	0	338
Walking	0	944	46	1	0	0	9
Run	0	245	719	36	0	0	0
Bike	0	1	40	959	0	0	0
Car	0	0	0	3	997	0	0
Train	0	0	0	0	0	1000	0
Gym	18	3	0	0	0	0	979

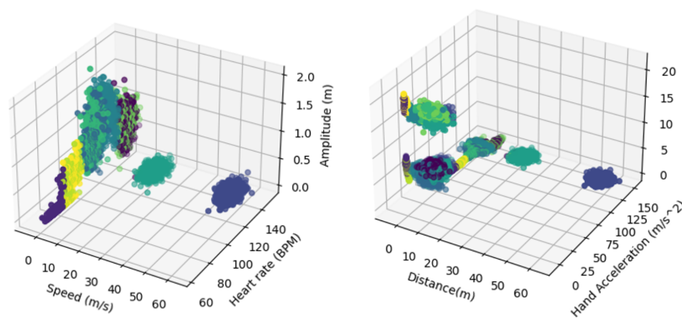

Fig. 5. 3D presentation of the clustering data in case of 7 Contexts

the body. In 8 situational contexts, we can see that the accuracy and results was more accurate and the data are more synchronized. The 3D presentation is shown in fig 6 We saw the true classification and predicted classification of the data after running the KMEANS algorithm for 8 contexts and that can be shown in 6 table.

Then we calculated the accuracy where we can see the performance is better than 7 contexts which was our goal of increasing the context situational contexts number, and the accuracy is 89.8% and this is shown in the table 7 and 8. So,

TABLE IV
PRECISION LEVEL OF 7 CONTEXTS

Situational Context	precision	recall	f1-score	support
Car	1	0.997	0.998	1000
Biking	0.96	0.959	0.959	1000
Gym	0.738	0.979	0.842	1000
Running	0.893	0.719	0.797	1000
Sit	0.974	0.662	0.778	1000
Train	1	1	1	1000
Walking	0.791	0.944	0.861	1000

TABLE V
ACCURACY LEVEL OF 7 CONTEXTS

	precision	recall	f1-score	support
accuracy			0.894	7000
macro avg	0.908	0.894	0.892	7000
weighted avg	0.908	0.894	0.892	7000

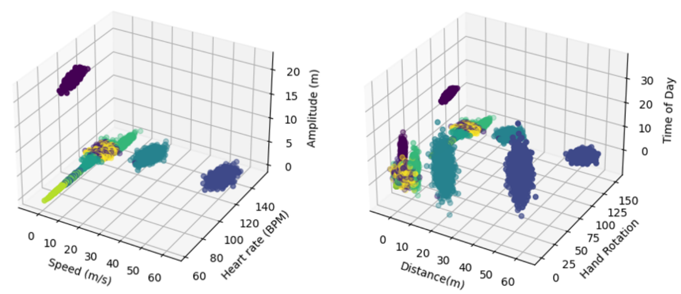

Fig. 6. 3D presentation of the clustering data in case of 8 Contexts

as the goal of our work was to increase the performance to identify the condition and state of the body with respect to different axes by increasing the number of context, we got our results better and more accurate from our analysis and we can say our algorithm worked well in these circumstances.

TABLE VI
TRUE CLASS AND PREDICTED CLASS PRESENTATION OF 8 CONTEXTS

Prediction	Sit	Walk	Run	Bike	Car	Train	Gym	At Work
True Class								
Sit	658	0	0	0	0	0	342	0
Walk	0	654	339	1	0	0	6	0
Run	0	39	932	29	0	0	0	0
Bike	0	0	45	955	0	0	0	0
Car	0	0	1	0	999	0	0	0
Train	0	0	0	0	0	1000	0	0
Gym	14	3	0	0	0	0	983	0
At Work	0	0	0	0	0	0	0	1000

TABLE VII
PRECISION LEVEL OF 8 CONTEXTS

Situational Context	precision	recall	f1-score	support
Car	1	0.999	0.999	1000
Biking	0.97	0.955	0.962	1000
Gym	0.739	0.983	0.842	1000
Running	0.708	0.932	0.804	1000
Sit	0.979	0.658	0.787	1000
Train	1	1	1	1000
Walking	0.94	0.654	0.771	1000
At work	1	1	1	1000

TABLE VIII
ACCURACY LEVEL OF 8 CONTEXTS

	precision	recall	f1-score	support
accuracy			0.898	8000
macro avg	0.917	0.898	0.896	8000
weighted avg	0.917	0.898	0.896	8000

IV. CONCLUSION

A novel approach to automatically detect situational context using minimal sensor is proposed and the comparison between different number of situational context is presented in this paper. The sensor data can be collected from wearable devices and converted them into multiple axes data. In this work, we used simulated axes data to automatically determine situational contexts using AI. The presented accuracy result shows the advantages of increasing the number of situational context as it gives higher accuracy. As a result, the proposed approach suggest that this method can be used to optimize the error rates in various automated algorithms for disease detection and recommender system.

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