VOL. 15, NO. 24, DECEMBER 2020 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

SPATIO-TEMPORAL DATA ANALYSIS FOR HUMAN DAILY LIFE ACTIVITIES

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ABSTRACT

Pakistan currently has the largest percentage of young people in its history that makes Pakistan one of the youngest country in the world and second in Asia Pacific region. Understanding the macro level pattern of daily life activities for everyone can reveal significant information about people of a particular region. This information at the persons' own end can be used to adapt a desirable, more healthy and smart options to plan further. On the other hand, this information if used by mass planning and governments may help to promote and plan future strategies in wide range. This study entangles a case study for the daily life activities of Pakistani peoples. In Pakistan, there is no such platform exists where people can understand the life pattern of their daily life activities with respect to time and location. We used dynamic flowing bubble graph technique (Force Directed Graph) and scatter plots to observe and analyse human daily life activities. We used 20 volunteers of age group between 19 to 29 years, residents of Islamabad/ Rawalpindi. We modeled spatial and temporal features of data by catering 18 distinct daily life activities of each person. A dataset is generated with 6 attributes having 709 daily life activity instances of volunteers. This comprises of a web based application coupled with a mobile application to represent the human daily life activities using force-directed graph. Results show the desired offline analysis of Pakistani peoples' daily life activities.

Keywords: spatio-temporal, human activity analysis, mobile application, force directed graph.

1. INTRODUCTION

According to a report [1], Pakistan currently has the largest percentage of young people in its history. The report further says that 29 percent of the total population is between the ages of 15 years and 29 years while 64 percentage of the total population is below the age of 30 percent of the population. Participants' age bracket for this study, having 30 volunteers were also in the age group between 19 to 29 years. These participants are the residents of Islamabad/ Rawalpindi. As we observe people's activity that is people's movements and whereabouts. These observations can be valuable for studying mobility, people's movement patterns through the urban environment, their use of the urban space, and finally social interaction. So, for that purpose firstly, we are introducing a mobile based application to observe and gather the data of daily life people's activity (hiding their identity). Secondly, we introduce a web-based application. Its basic purpose is to graphically define the people's activity.

Nowadays, "Time" has become a central topic of debates in the academy. Time is punctuated by extraordinary events like birth and death, but it is also organized through a range of ordinary routine like, sleeping, eating, working and many others. These ordinary routines show the life style of a nation which must be represent in front of other nation that, who we are and how we behave? To represent the interest and trend of our people. Moreover, to watch how Pakistan runs, we got inspiration from [2] and reworked for said context. Where a similar system implemented to show life style of American people, where data collected by American Time Use Survey.

We purposed a mobile based application to gather the data from people. We develop a web-based application which will graphically represent daily life activity of people by using Force directed graph. There are two modes in this system one is mobile application and other is web-based application.

Mobile version of the application is supposed to collect the data of those people that will be registered. For that purpose, they must provide some information about themselves i.e. his/her email, name, password, gander, etc. User must allow to application to access his/her location. Application will store all the data in Database. Whereas, web application will graphically represent daily life activity of people by using Force-directed graph.

Through our study, it will become much easier to understand the lifestyle of our people, the ratio of people with any activity will suggest their habits (and future intentions) and this will show trend of people what they like to do.

The major purpose of this application may be the interest of organizations/government/ companies towards investment sector because they are much familiar with activities of people what they like.

However, much work has been done in the field of human activity recognition. We can promote a healthy life style that lack adequate physical activity by monitoring and analyzing the user's daily activity. Human activity recognition is a classical time series or sequencing classification difficulty, for which the task is to develop the part of data chain through which one of the activity is generated. Human activity recognition processing consist of three step: data collection, feature extraction, and data visualization. Information and communication

technologies such as mobile phones are spreading rapidly in modern society. There are many studies that have implemented human activity recognition for real time processing on mobile phones. In some studies, the goal is to show that the online identifier work on mobile phones while considering available resources. While in other studies the goal is to develop an application where user activity can be tracked. In this system we provide such environment for a user where user input his/her activity using mobile application. The purpose of human activity recognition is to identify a user's activity and to visualize these activity of user using force directed graph and scatter plot.

At First, we develop a mobile application where user enter his/her phone number for authentication. OTP will send to user and application automatically to logged into the system.

After logged in user register him/herself by providing information such as name, email, job, age, gender etc. That information is stored in database and that can be used for further classification.

After user register himself/herself activity page shown to user. Where total 18 activities user select his/her activity and that activity is stored in database with time.

Figure-1. List of activities.

When user enters his/her activity next page shown to user where user change his/her activity whenever user wants using change activity button and user back to activities page as we see in Figure-1 and Figure-2.

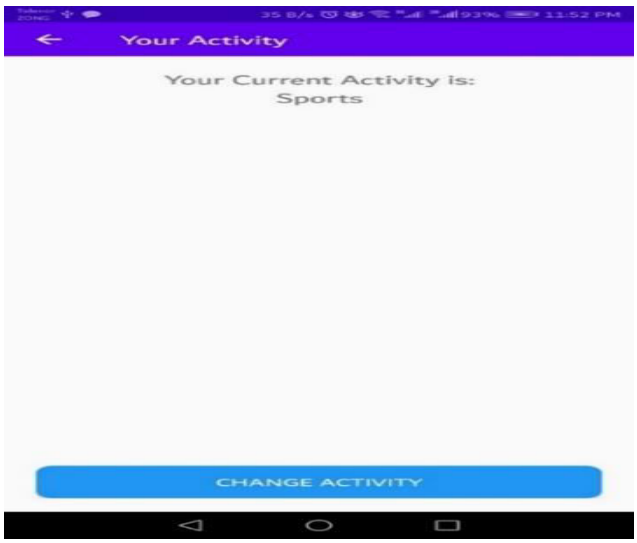

Figure-2. Change activity.

We use 30 user data who use mobile application. Dataset have 5 features id, start minute, stop minute, activity code and number of activities. When user logged into the system a specific id is assign to user. When user enter his 1st activity that activity is stored in database with time. This time is the start minute of activity. When user enter his 2nd activity the time of this activity is stop minute of previous activity and start minute of this activity. Activity code is fourth feature where we assign all 18 activities a specific code start from 1 to 18. And last feature is number of activities that how many activity users perform in 24 hours.

For visualization the data of mobile application we use Force Directed Graph. In Force Directed Graph we assign each user data a specific bubble. These bubbles move with respect to time. We also used Scatter plot to represent the data of user at specific time like how many users have same activity at 5pm or 10pm.

2. RELATED WORK

For the public, strategic and tactical planning is crucial in updating environmental policies, maintaining sustainable mobility and transportation. Therefore, it is important to use and understand the impact of information communication technologies in our current mobile information society. Information and communication Technology delivered a variety of spatio-temporal sources of data and information. This has a role of an immense importance in spatial as well as temporal exploration and discovery of data, information and knowledge to attain the level of wisdom. This can be utilised in our studies and daily life activities. For example, travelling behaviour and daily life patterns [3-6]. Human behaviour and mobility pattern plays an important role as well in dealing with catastrophic disasters, cities planning, diseases spreading, traffic forecasting, especially in decision making for rescue people with disabilities in emergencies [7-9]. Figure-3 displays a good piece of modeling and design that has been presented in [10] for online human activity recognition using smart phones.

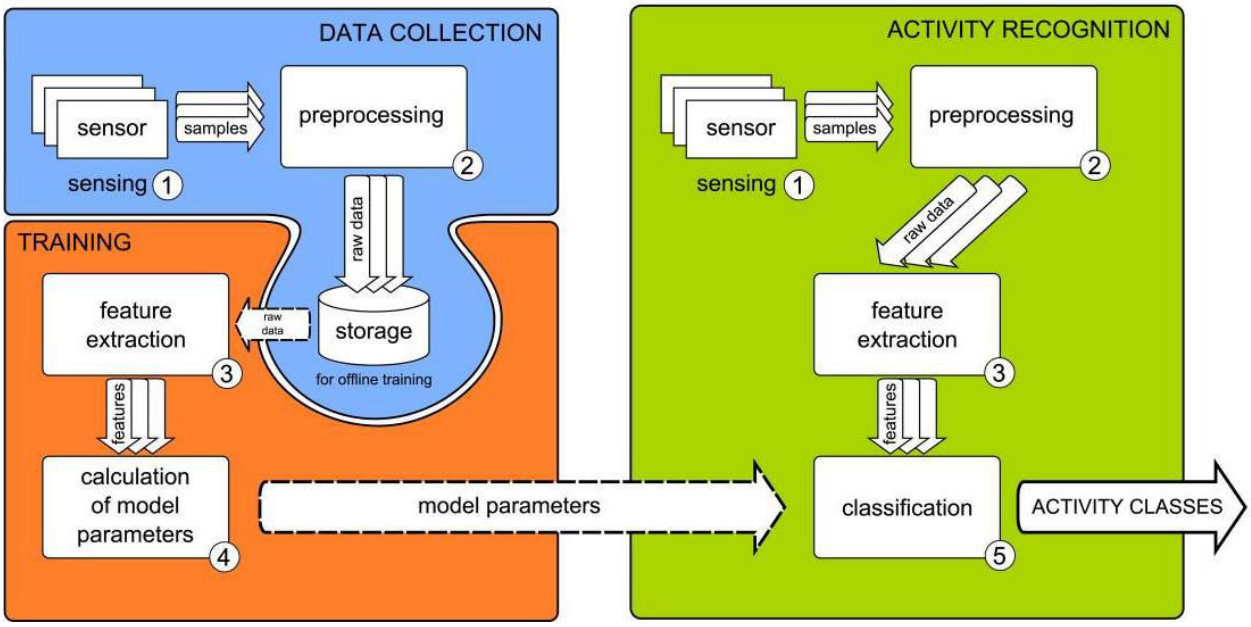

Figure-3. Data preparation and use model in online human activity recognition [10].

A dataset of 9 million mobile phone users from Harbin City, China is used that has the timestamp of last week of July in year 2007. Using ICT technologies provide more flexibility about when, where and how to travel.

Numerous studies have been conducted focusing on the extraction of spatio-temporal data in georeferenced mobile phones. The (SPM) Social Positioning Method introduced to combine the mobile phone location data and social attribute to study the dynamic of urban system. In [14] the study show the individual speed of 100,000 mobile phone users based on tracked location data, providing new insight into understanding the basic law of human movement. As a general research framework discuss five key task in geographic data mining and knowledge discovery, spatial classification and capturing spatial dependency, spatial segmentation and clustering, spatial trend, spatial generalization and spatial association. The discovery of geographical knowledge is primarily focused on acquisition of new knowledge from big dataset, such as the extraction of movement pattern based on triggers. However, many spatio-temporal dataset provide incomplete data about low resolution and attributes such as georeferenced mobile phone data [15]. It is important for us to determine to what extent we extract information from sparse dataset and also deal with uncertainties in incomplete dataset. In this article, we provide a framework for extracting spatio-temporal information in georeferenced mobile dataset [16]. This will help us updating the work of discovering geographical knowledge. We use information that published on social media and mobile phone user data both served as a proxy for human activity and mobilization. The result shows the hotspots of human behaviours and mobility in selected European environment and provide additional information such as how collective social activity shape the urban environment [17].

Table-1. Brief overview on related work.

Author	Domain	Methodology	Conclusion & Result
Yihong Yuan, Martin Raubal [6]	Extracting spatio temporal extraction	Using different Communication modes such as synchronous presence etc.	Framework Provide us 1. Individual Oriented Research 2. Urban Oriented Research
Günther SAGL, Bernd RESCH, Bartosz HAWELKA, and Euro BEINAT [7]	Using sensor data to collect human pattern	Geo Spatial method from social sensor data.	It show the network activity of when and where peoples actively using mobile phone.
Muhammad Shoaib, Stephan Bosch, Ozlem Durmaz Incel and Paul J.M. Havinga [10]	Online Activity Recognition Using Mobile Phones	Decision Tree, SVM, KNN and Naive Bayes.	Real time assistive, Adaptive Sensor Sampling and Selection, Resource Consumption Analysis
Yihong Yuana, Martin Raubal and Yu Liu [11]	Correlating mobile phone usage and travel behavior	Methodology applied to the dataset from Harbin, China	It shows the relationship of activity behavior and mobile phone usage.
R. Ahas, A. Aasa, S. Silm, R. Aunap, H. Kalle and Ü. Mark [13]	Mobile Positioning in Space time Behaviour Studies	Social Positioning Method (SPM)	Mobile positioning tracing is applicable for pattern movement and activity spaces.
Rein Ahas, Ülar Mark [12]	Location based services	Social Positioning Method (SPM)	Research shows that the SPM will became more useful in future.
Paul Lukowicz, Jamie A Ward, Holger Junker and Thad Starner [18]	Recognizing Workshop Activity with Accelerometers	Applying accelerometer in different activities of wood shop.	Successfully segment wood shop activities with 84.4% accuracy and no error.
D.M. Karantonis, M.R. Narayanan, M. Mathie, N.H. Lovell, and B.G. Celler [19]	Implementation of a real-time human movement classifier	Using Embedded intelligence to identify rest and activity (Walking and falls)	System implemented with 90.8% accuracy. Rest and Activity implemented with no error. Walking accuracy is 83.3% and falls accuracy is 95.6%.
Nishkam Ravi, Nikhil Dandeka ,Preetham Mysore and Michael L. Littman [20]	Activity Recognition from Accelerometer Data	Using Triaxial Accelerometers to identify the activity near to hand and mouth.	Research described that Plurality Voting is one of best classifier for activity recognition and energy is not a important attribute.
Ling BaoStephen, S. Intille [21]	Activity Recognition from User-Annotated Acceleration Data	Mean, Energy, Frequency Domain Entropy and acceleration data was collected and several classifier are tested.	Decision Tree implemented with best accuracy 84%.

Identification can be obtained from various resources such as environmental and body worm sensor. Some approaches adopted sensor in different part of body such as wrist, chest to achieve high classification performance. These sensors are not capable of monitoring activity for long term. Moreover, a variety of work carried out in [22-27] for transportation and travel behavior with big data perspective as well.

3. METHODOLOGY

A set of experiment was performed to obtain human activity recognition dataset. Thirty volunteers between the age of 19 to 29 were selected for a job. Everyone was instructed to follow the activity protocol while using a smartphone. The eighteen selected activities were sleeping, eating & drinking, sports, leisure, Pro care service, Shopping, Religion, work, household care, Non household care, education, personal care, Misc., Phone call, Volunteering. The purpose of human activity recognition is to identify a set of user observation and action performed by a given person and using Force Directed Graph and Scatter plot to visualize the daily activity of user.

At First, we develop a mobile application where user enter his/her phone number for authentication as we see in Figure-4. OTP will send to user and application automatically logged into the system.

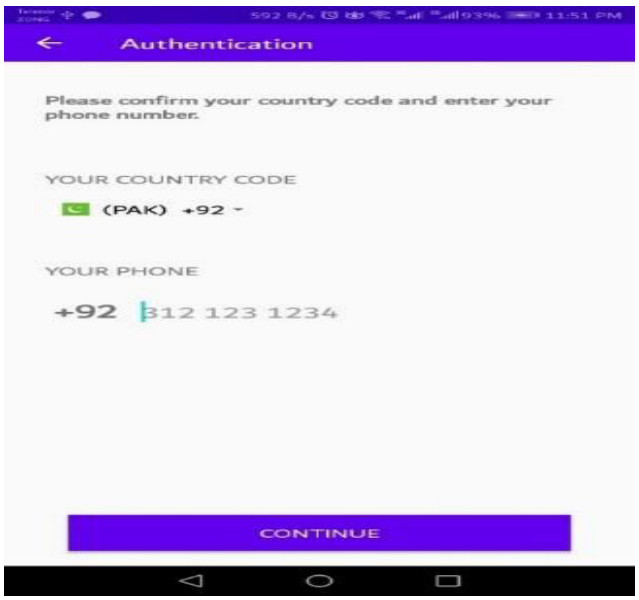

Figure-4. Authentication process.

After login, user registers him/herself by providing information such as name, email, job, age, gender etc. That information is stored in database and that can be used for further classification like gender base classification.

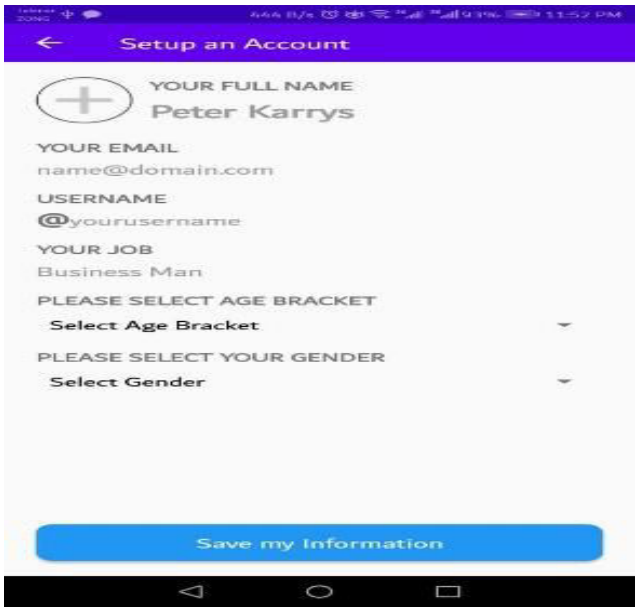

Figure-5. Registration process.

After user registers himself/herself, see Figure-5. The activity page shown to user as Figure-6 depicts. Where total 18 activities user select his/her activity and that activity is stored in database with time.

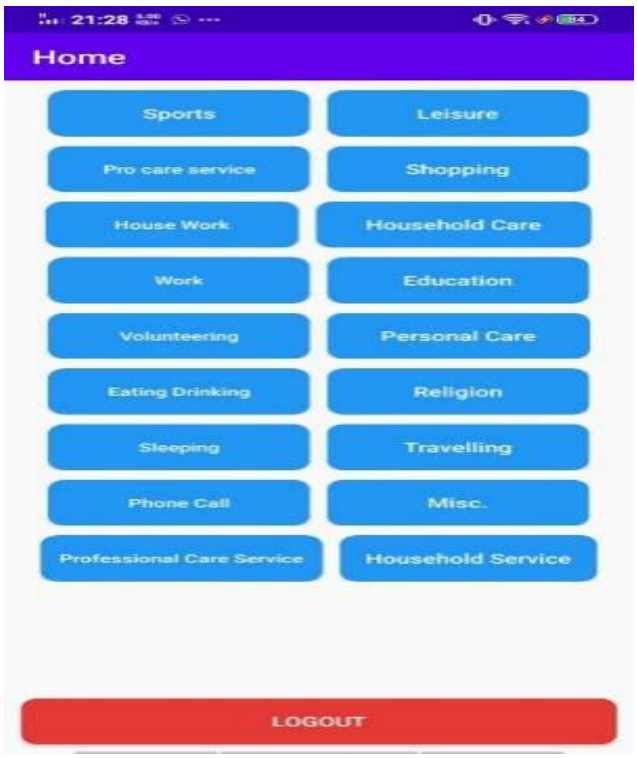

Figure-6. List of activities used.

When user enters his/her activity next page shown to user where user change his/her activity whenever user wants using change activity button and user back to activities page as we see in Figure-7.

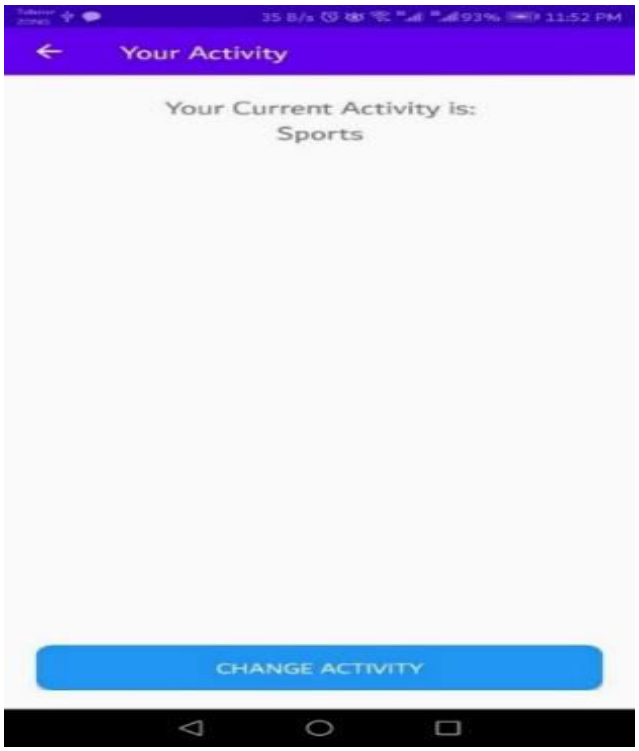

Figure-7. Change activity workflow.

We used 30 user data who use mobile application. Dataset have 5-features ID, start minute, stop minute, activity code and number of activities. When user logged into the system a specific id is assign to user. When user enter his 1st activity that activity is stored in database with time. This time is the start minute of activity. When user enter his 2nd activity the time of this activity is stop minute of previous activity and start minute of this activity. Activity code is fourth feature where we assign all 18 activities a specific code start from 0 to 17. And last feature is number of activities that how many activity users perform in 24 hours.

For visualization the data of mobile application we use Force Directed Graph. In Force Directed Graph we assign each user data a specific bubble. These bubbles move with respect to time. We also used Scatter plot to represent the data of user at specific time like how many users have same activity at 5pm or 10pm.

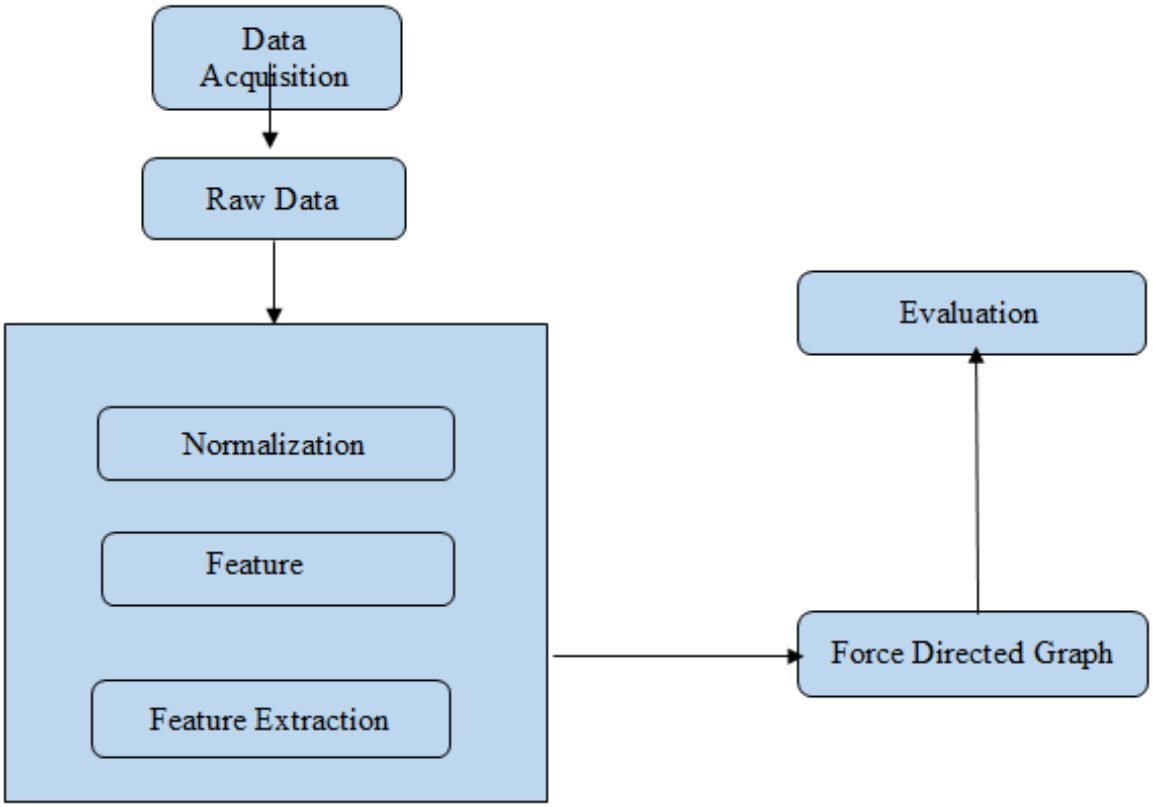

Figure-8. Data acquisition and pre-processing.

Figure-8 shows the phases from data acquisition through analysis, raw data has been collected using mobile application where user input his/her activity and that activity is stored in Firebase database with start time of that activity. In this work, eighteen activities were targeted (travelling, housework, household care, non-household care, work, education, shopping, professional care service, household service, misc., eating and drinking, leisure, sport, religion, volunteering, phone call, shopping) to be recognized. The experiment was performed on a group of 30 volunteer between the age of 19 and 29. Volunteer performed these activities when they had smart phone. Any activity can be performed in any order for any period of time such as eating & drinking for 1 minute, leisure for 5-minute, religion for 10 minutes etc. Preprocessing raw data is one of the most important steps. This involve normalizing raw data, selecting feature and extracting feature. 6 features were used illustrate in Table-2.

Table-2. One user's activities all around a day.

Activity ID	USER ID	Start Minute	Stop Minute	ACTIVITY CODE	ACTIVITY NO
151	20170101170520	240	300	18	1
152	20170101170520	300	315	14	2
153	20170101170520	315	345	11	3
154	20170101170520	345	450	18	4
155	20170101170520	450	480	1	5
156	20170101170520	480	747	5	6
157	20170101170520	747	800	11	7
158	20170101170520	800	820	14	8
159	20170101170520	820	840	12	9
160	20170101170520	840	960	5	10
161	20170101170520	960	990	1	11
162	20170101170520	990	1020	12	12
163	20170101170520	1020	1180	2	13
164	20170101170520	1180	1140	13	14
165	20170101170520	1140	1150	14	15
166	20170101170520	1150	1200	2	16
167	20170101170520	1200	1230	3	17
168	20170101170520	1230	1245	11	18
169	20170101170520	1245	1260	14	19
170	20170101170520	1260	1280	10	20
171	20170101170520	1280	1327	16	21
172	20170101170520	1327	240	18	22

1st feature is "total activity no" shows overall number of activities of one volunteer having ID '20170101170520' who use the application. 2nd feature is "user id" whenever a user registered himself/herself in android application a unique id is assigned to user. 3rd feature is "start time" when user enter his activity the time of that activity is stored in firebase in database that's the start time of that activity. We convert these times into numeric form by multiplying hours to 60 and minute add in it. Like 4:00 am multiplying hour "4" to 60. 4*60 = 240 and minute "00" add in 240. Similarly, we convert each user activities start time. 4th feature is "stop minute" when user enter his activity the start minute of that activity will be the stop minute of previous activity. Fifth feature is "activity code" we assigned each activity a unique code starting from 1 to 18. The last feature is "activity no" it shows the number of activities that a single user performs in a day.

4. RESULTS ANDDISCUSSIONS

We have applied two different modes for visualizing the data of 30 volunteers who use the mobile application. As mentioned below in Figure-9 these are the results that we obtained using Force Directed Graph. The bubble in the graph represent a volunteer. Bubble move toward one activity to another according to time. This cycle starts from 4am to so on. As mentioned, these are the results that we obtained using Force Directed Graph.

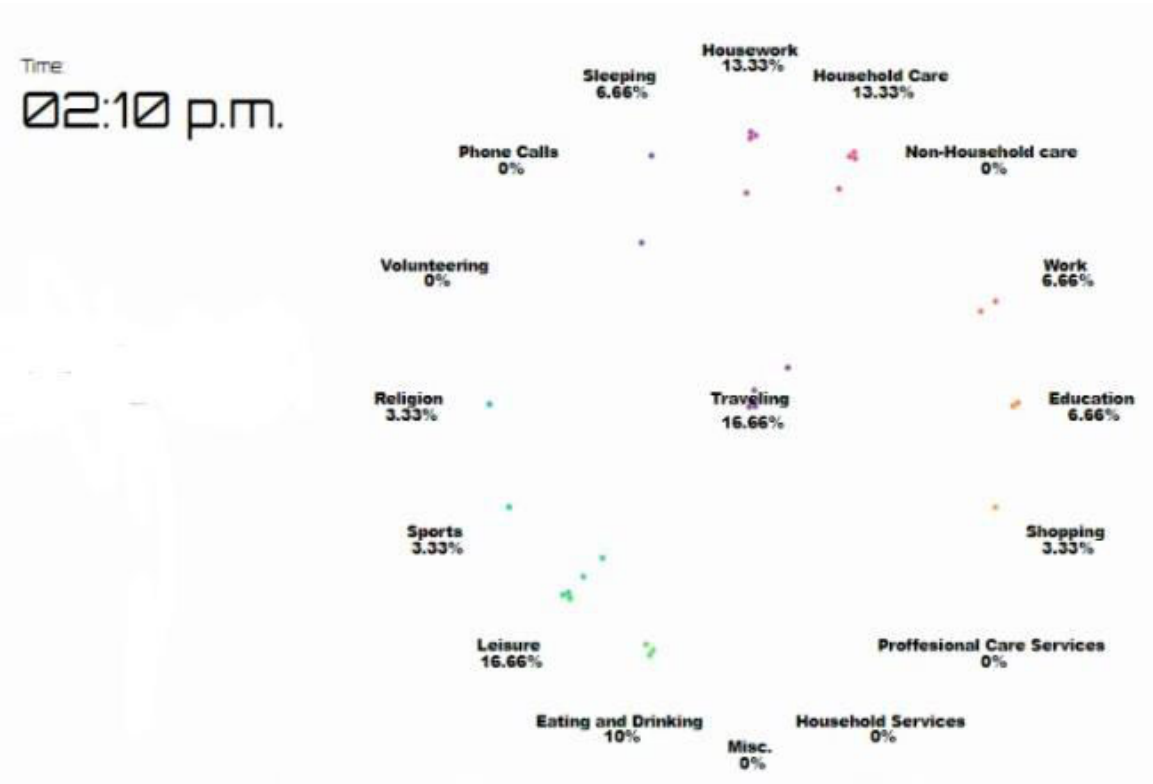

Figure-9. Bubble moving chart.

The bubble in the graph represent a volunteer. Bubble move toward one activity to another according to time. This cycle starts from 4am to so on.

Scatter Plot:

At scatter plot we represent each activity as a number starting from 1 to 18.

1. Traveling
2. Housework
3. Household Care
4. Non-Household care
5. Work
6. Education
7. Shopping
8. Professional Care Services
9. Household Services
10. Misc.
11. Eating and Drinking
12. Leisure
13. Sports
14. Religion
15. Personal care
16. Volunteering
17. Phone Calls
18. Sleeping

Waking Up:

Between 8:00am and 9:00am, most of the people wake up (See Figure-10), go to personal care such as showering and brushing their teeth and then to work, eat breakfast, get some rest and do some housework.. As we see in graph 25% of the people's activity is housework and household care. Some of the people are going to work as their activity is traveling. While 30% of the people are still at home to have some rest and eating breakfast and 10% of people are studying.

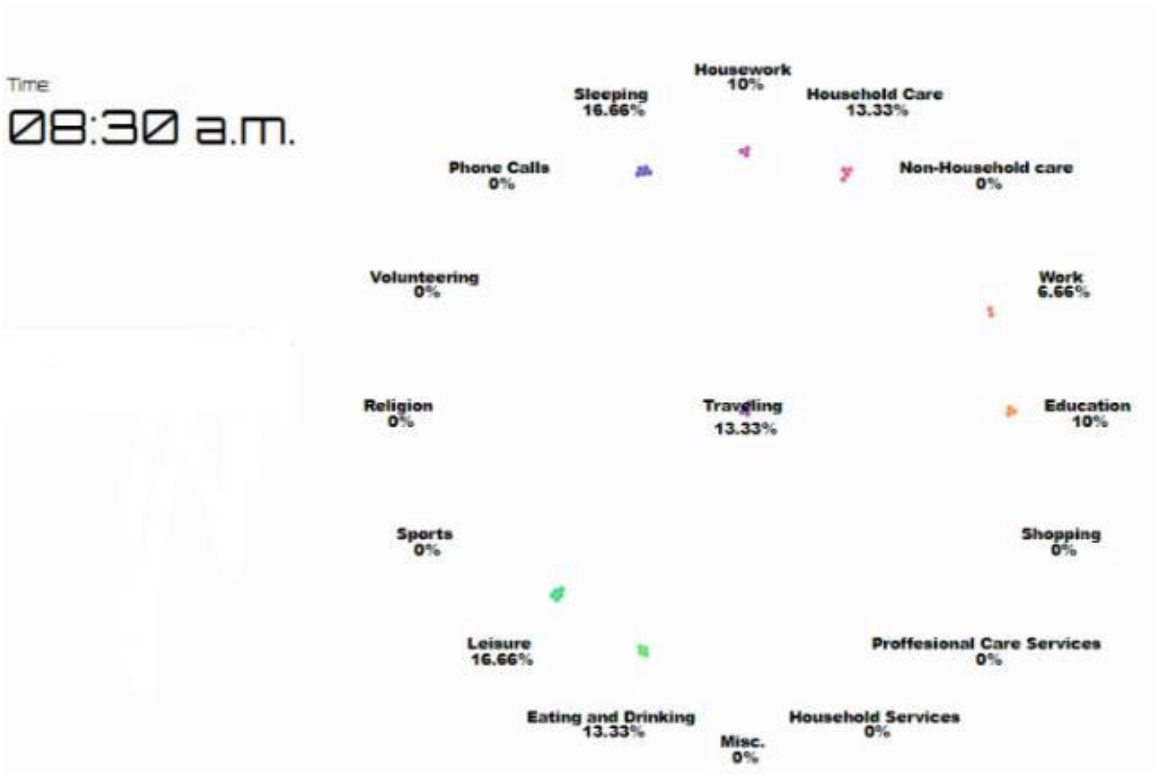

Figure-10. Waking Up.

Lunch Hour:

From 1:00pm to 2pm, most of the people activity is work, housework and eating & drinking and then back again. Some people take time for rest. As we see in graph 25% of people activity is housework and household care. While 35% of them take time for rest and eating lunch (See Figure-11). And some people are studying.

Figure-11. Lunch Hour.

Getting Off Work:

As you might expect, when the clock strikes 5:00pm, Almost 50% of people activity is household care, leisure and housework. Many people going to home to prepare dinner and having some rest. Some of them go to Masjid for prayer. 10% people went to play different game and some of them are still at work.

Figure-12. Getting off work.

Winding Down:

Figure-13 shows that people usually rest between 11:00 pm and midnight; from leisure to personal care and finally fall asleep. As we see in graph after the 11:00 pm 80% of the people activity is sleeping some of them taking some rest.

Figure-13. Winding down.

5. CONCLUSIONS

The system has been implemented with the data of Pakistani peoples. We exploited ICT to use a mobile based application to collect data. We constructed similar system to analyze daily life activities for Pakistani people. We can also categorize different Force Directed Moving Bubble Graph for Women and Men (i.e., gender based analysis), age based analysis and more specific activity based analysis in future. We can also add different new method of visualization the activity of people in future.

ACKNOWLEDGEMENT

The authors wish to acknowledge the assistance and work carried out by our students Mr. Hamza Ashfaq and Mr. Sabahat Hussain in application development and data collection as part of their undergraduate final year project at Federal Urdu University of Arts, science and Technology, Islamabad, Pakistan.

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