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Physical Activity Calculation by Transport Modes Detection Using Fuzzy Logic

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Abstract: This research presents a methodology, to calculate the amount of physical activity during the transportation. It contains the following steps: (1) trip and activity detection (2) speed calculation (3) splitting trips into trip-leg (4) transportation mode detection and (5) physical activity calculation. The Global Positioning System is used to record the transport activities, either single mode or multimode. During the trip execution, the travel behaviour and the travel mode are also observed to obtain the physical activity levels. The physical activity levels are calculated by taking the ratio of the Total Energy Expenditure and the Basal Metabolic Rate. To obtain the results, an automated system is presented which calculates the speed and also detects the mode of each trip-leg. It also calculates the amount of physical activity. The obtained physical activity levels for the recorded 1750 trips are unit less and range from 1.10 to 2.00. By using the motorized transportation mode, the physical activity levels stay low and the subject failed to achieve the recommended health guideline. The minimum value for the moderate level of physical activity is 1.6. The requirement can be fully achieved when the transportation mode is active i.e. walking, cycling, and performed at moderate intensity level for at least 30 min a day.

Key words: Mobility behaviour, physical activity, active transport, mode detection, fuzzy logic, GPS.

1. Introduction

The movement of body muscles that consumes energy is known as physical activity. Some good examples of physical activities are: cycling, gardening, ladder climbing, sports. The physically active people are considered healthier than the inactive people and they can gain long term health benefits. Health guidelines suggest, the person who performs physical activity of moderate level intensity for 30[min] a day, (s)he will not get over weight, remains fit, physically active and have less chance of heart diseases, blood pressure and stroke [1-5]. While performing the physical activity of moderate or vigorous level intensity, the person's heart beats faster and feels hard to breathe. With the passage of time, the body parts grow stronger and work better. Without performing any physical activity, the body parts become weak [6-10]. People often ignore transport as an activity (i.e. travelling via bicycle and walking to/from bus-stop) but it also requires energy and can be categorized as physical activity [11].

New paragraph: Physical activity levels can be expressed in term of energy consumption that can be recorded by travel diaries, accelerometers and Global Positioning System (GPS). Travel diary is used to collect information about an individual, household, and a diary of journeys on a given day. The accelerometer records the movement of the body along X, Y and Z-axis [12-15], records the activity counts and estimates the number of steps within the specified time period [16, 17]. The GPS is mostly used to detect the mobility behaviour in transportation [18, 19]. It also can be used to record the movements of an object, to navigate route and to store object's speed and location over time. In some researches, the GPS is used with the accelerometer and the geo-data, to calculate the physical activity. In this research the GPS device is used to collect the data, because the speed is calculated from the longitude and latitude

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coordinates.

The main objective of this research is to estimate the transport physical activity recorded by the GPS device. During this research a methodology is proposed, which contains following steps: (1) extract trips from GPS traces, consider trips only and ignore all the activities (2) calculate the travelling speed (3) the trips are categorized into single and multimodal trips, the multimodal trips consists of legs (each leg consists of single mode of transportation) (4) by applying fuzzy logic, the transportation mode is detected and (5) by using the speed and transportation mode, the appropriate Metabolic Equivalent Tasks (MET) value is selected from the compendium develop by Ainsworth et *al.* [20]. By using MET value the physical activity through mathematical expressions is calculated from individuals' personal attributes. The MET is a term used to express the energy cost of the physical activity. It is the ratio of work metabolic rate to the standard resting metabolic rate [21]. The fuzzy logic threshold values (membership functions: average speed, time travel, acceleration, and distance) are taken from the data of 100 respondents comprised of 1110 trips, collected with the GPS and the travel diaries. Whereas, the proposed methodology is evaluated by using the data of 120 persons (collected by using GPS) having 1750 trips. To obtain the transport physical activity, an automated tool is developed by using java. It reads the GPS logger as an input, having information about the date, time, longitude and latitude of the subject. The tool gives us the information about the speed, expected travel mode and the amount of physical activity.

This paper is organized as follows: section 2 summarizes the related work on physical activities and mode detection. Section 3 presents the methodology of the work and the calculations. Section 4 explains the experimental results and discussion. Finally, conclusion and recommendations are presented in Section 5.

2. Related Work

Researchers have been examined people in the controlled environment to calculate their physical activity in the sports medicines field. Researchers used accelerometers and the travel diaries to calculate the physical activity levels. The travel modes are determined by using the Geographical information systems (GIS) and GPS. A few studies categorized into the determination of the physical activity levels and the applications of GPS in the mode detection are as follows:

2.1 Physical Activity Levels

Thompson & Kayak [22] presented a methodology to estimate the personal physical activity by using the accelerometer. It provides the experimental evidences by using the collected data of a single subject. The proposed procedure provided the practical means by evaluating (1) the health guidelines for an individual; being achieved or not (2) allowing the health benefits of active transport; to be explored. Authors also suggested that the presented research has potential to do the further investigation. The similar approach used by Chaix et *al.* [23] to assess the physical activity at the trip level, gains from the transportation modes (walking or public transport). Authors quantify accurately (1) the differences in the physical activity (2) different steps counted by the accelerometer (3) the energy expenditure and (4) the sedentary time between different transport modes i.e. walking to public transport. Authors associate the counted number of steps with different transportation modes and use an algorithm to calculate the physical activity from the data collected by Actigraph.

A survey based approach is used by Norwood et *al.,* [24] to evaluate the active travel initiatives, the smarter choices and the smarter places program of the study area (Scotland). It intended to encourage the use of active transport modes to travel i.e. walking and cycling. Authors analyzed the physical activity by focusing on, what can be inferred from the initiative with regards to the adult uptake of physical activity participation. Rissel et *al.,* [25] investigated the impact on the physical activity level; how staff and students travel to the University of Sydney. Authors did an online survey to inform about the planning of the physical activity and the active travel promotion programs.

Shetty et *al.,* [26] discussed several issues related to the physical activity levels and the influence in the estimation of the adult energy requirements. Authors concluded discussion by factorial approach which assesses the total energy expenditure by using the Physical Activity Levels (PALs). In Fjørtoft et *al.,* [27] the level of physical activity monitored by the heart rate (HR) using a Polar pulse watch. The data (collected by using the GPS device and by considering the heart rate) is transferred to GIS for further analysis and for visualization.

2.2 Travel Mode Detection

The Particle Swarm Optimization Neural Networks (PSO-NNs) introduced in the Xiao et *al.,* [28] which distinguish among the travel modes (walk, bike, bus, and car). The GPS data collected through the smart phone-based travel survey. The Das et *al.,* [29] simulated nearly the real-time mode detection classification framework by using a neural network based classifier. Authors evaluated performance of the neural network in various modes detection. The neural networks adjusted different input and output parameters easily. Zong et *al.,* [30] identified different travel modes by using the collected GPS data. Authors recognized the travel modes (walking, bicycle, subway, bus, and car) by providing crucial trip information. The results contributed in the modelling and analyzing of the travel behaviour and also applicable to a wide range of the transportation practices.

In the Xu et *al.,* [31], authors proposed a fuzzy approach to recognize the travel modes from the GPS travel data. Four speeds related fuzzy variables were selected to characterize five movement patterns in the urban daily traffic. The fuzzy sets and the membership functions were constructed by using the sample data. Xiao et *al.,* [32] identified the travel modes by using a Bayesian network approach, whose structure based on a K2 algorithm. The corresponding conditional probability tables can be estimated by using the maximum likelihood methods. Five representative travel modes i.e. walk, bike, e-bike, bus and car, also distinguished by the resulting Bayesian network.

Stenneth et *al.,* [33] presented an approach inferring a user's mode of the transportation, based on the GPS sensor on the mobile device and the knowledge of the underlying transportation network. The network information included the real time bus locations, spatial rail and the spatial bus stop information. Authors also classified the user transportation modes based on the motion and the location by using the smart phones. In Ref. [34], authors proposed new depth analysis method which classified the transportation modes by considering the stationary state. The sub-modes (stay and wait) presented different semantics for the data mining applications.

Fan et *al.,* [35] developed an android based smart-phone application "UbiActive". The proposed application used the smart phone's built-in sensors to compute and communicate with the server. The application's is capable to detect the trip, physical activity and report the trip characteristics. It consists of features: (1) trip detection (2) self-reported after trip survey and (3) summary of the activity.

None of the reported research estimates the physical activity in transportation using GPS traces only. In this research, we proposed a methodology that uses GPS traces to detect the travel modes and also measure the performed physical activity levels.

3. Research Methodology

In this research, a methodology is proposed to estimate the physical activity from the mobility behaviour by using the GPS traces. It directs to suggestions in the area of transport: how to associate specific health behaviours with particular transport activity. The purpose is to highlight the importance of the transport as a physical activity. It also associates the physical activity with different travel modes (i.e. walking and cycling) based on the speed and the duration of the trip. The data used to evaluate this research is recorded by the GPS device and for the time period of one week.

The proposed methodology consists of different steps which are as follows (see Fig. 1): (1) trip and activity detection (2) speed calculation (3) trip-leg detection (4) transportation mode detection and (5) physical activity calculation. To validate the proposed methodology, an automated system is implemented by using 'Java'. It takes the date, time, longitude and latitude of the trip as input. The distance is calculated by using change in two consecutive GPS points. Each GPS point contains information about the position (the longitude and the latitude) of the subject. The distance is divided by duration between the successive GPS points to calculate the speed. The speed is further divided to find the acceleration by using the same time-duration.

Furthermore, the speed, acceleration, travel time and travel distance are used as input to the fuzzy logic module of the automated system. The fuzzy logic detects the expected transport mode. The mode and speed are used to pick the appropriate MET value. The MET is the intensity of the physical activity and is the multiple of resting energy expenditure (REE). Based on the duration and intensity of physical activity, the physical activity is calculated by using the mathematical expressions.

3.1 Data Collection

Data from 220 respondents living in Karachi (Sindh, Pakistan) is collected. The data is randomly divided in two sets. To estimate the physical activity, the sample data of 120 respondents contains 1750 travel records, collected during the specified period of one week. The record of each respondent in the dataset represents a GPS signal which was captured consecutively at the

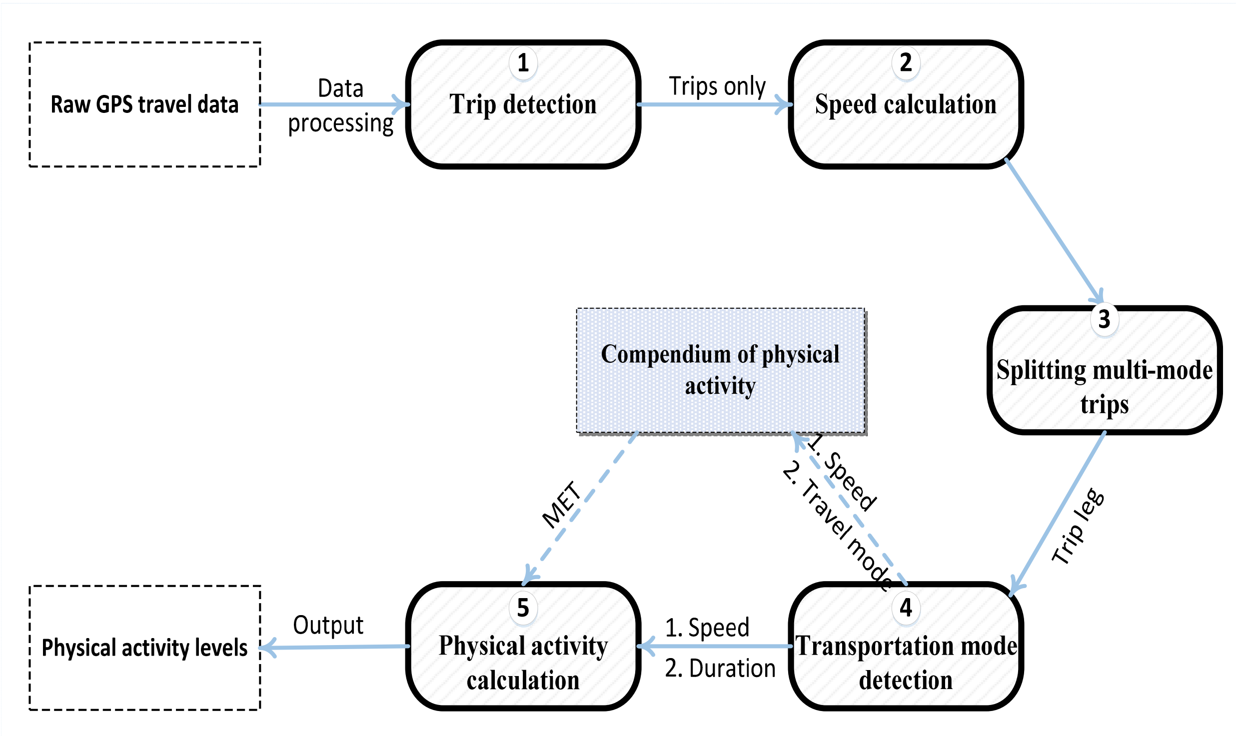

Fig. 1 The overall framework of the conceptual model to estimate the physical activity in transportation.

5-[sec] interval by using the GPS device. It contains information on different parameters: index, date and the time (universal coordinated time, UTC), latitude, longitude and the altitude. Unfortunately, the high recording frequency may cause issues with the battery consumption. It provides a higher accuracy for the travel mode detection. Respondents are requested to start the positioning application to automate the GPS recording before commencing the trip and keep it open until they reach at the destination. Since this study used only the recorded trips therefore any unrecorded trip by GPS is not included, whereas, partially recorded trips are included.

To identify fuzzy logic membership function values, the data collected with the GPS and the travel diaries from 100 respondents is used. The respondents are not the same whose data is considered for the experiments. This data is used because we don't have any information about the average speed, acceleration, travel distance and travel time associated with walking, cycling and the motorized transport for the specific region.

Each of the steps of the proposed methodology is discussed in more details, are as follows.

3.2 Trip and Activity Detection

In this step, the trip and activity are identified and separated from the GPS points. Initially, the data is divided into different data segments. Each data segment acquires one of the two parts: a moving part and a stopping part. The moving part considered the physical activity while the stopping shows the stationary state of the subject. While the main task is to identify the physical activity performed during transportation; therefore, it is necessary to distinguish between the trips and the activities. While performing an activity, the clusters of the GPS points are located closer to each other. According to existing studies, the cluster of the GPS points lies roughly within the diameter of 30 meter, when the subject stays at the same place (either at home or at office) during the execution of the activity [36, 37]. The 30 meter diameter is thrice of the standard deviation (10m) of the GPS measurement inaccuracy and the GPS points density will be at least of 15 points [38-40]. This technique is used if the GIS environment is not considered.

As our focus is on the outdoor travelling activities, the indoor logged points (performed activity at home or at work location) are removed by using Global Mapper i.e. Person travelling to airport; in this case, airport is the destination of the person, once the person reaches the destination the trip ends and the walking within the airport is not included because it is considered as an indoor activity. In the transition trip, it is not clear whether the subject is found at indoor or at outdoor. The transition trips (from the indoors to outdoors) are also removed due to the uncertainty [41] and the removal has no effect on the physical activity calculation. For each transition trip, there is a short interval of about 10 sec is found. The short interval is only a small amount (less than 1%) of all the logged points. By using the Global Mapper, the trips are extracted from the activity travel data. The Global Mapper is used to crop the trace so that every trip can be visualized individually.

Based on the GPS point densities, it is easy to differentiate between transport and non-transport activities. The combination of speed and dwell time can be used to detect the end trip locations. Ref. [41] suggested that the value of speed close to zero for time period lower than 120 seconds leads to the suspicious delays. When the speed value appears closer to zero for more than 120 seconds of the trip, it will be considered as the possible trip end. Note that the stopping speed is 0.01 m/s which is closer to zero.

In figure 2, the under observation subject has travelled to a place "B" from any other place "A". To detect the activity and the trip, first the map is loaded

Fig. 2 GPS point of a subject for a trip & activity.

in the Global Mapper with the GPS trace. The activity within a building and the transition trips are eliminated so that the data contains only the travelling trips. Trip purpose (e.g. educational, home based, work, shopping pick-drop etc.) can also be detected by visualizing the GPS traces on the map. For example, if the cluster of GPS points lies around the shopping-mall, the purpose of the trip can be identified as shopping. If there is no place identification on the map and the GPS-points lies close to each other, it can be assumed that an activity is performed at the specific place. As shown in the Figure 2, the red circled area where the GPS point are very close to each other which showed the high density, is considered as an activity. The green circle showed the transition of the trip from indoor to outdoor. The points from position A to point B, is the trip performed by the subject.

3.3 Speed Calculation

The speed of the trip is calculated in this step from the travelling trips' which is extracted from the step 1. According to the researchers [38, 39, 41], the GPS device records the data from the satisfied number of satellites. But the problem arises with the receiver device due to the bad weather conditions. It can cause errors in the recorded data. Due to the errors, the speed calculated from the collected data will be unrealistic [41]. The remedy is to apply filtration on the speed and acceleration. So the knowledge of advance filtration and their threshold values are required.

Although, the data used in this research is cleaned; therefore the data has no unrealistic values. The distance is calculated by taking the difference between two successive (latitude and longitude) points by using the "Haversine formula".

$$a = sin^2\left(\frac{\Delta\varphi}{2}\right) + cos\,\varphi 1 * cos\,\varphi 2 * sin^2\left(\frac{\Delta\lambda}{2}\right) \quad (1)$$

$$c = 2 * atan2\left(\sqrt{a}, \sqrt{(1-a)}\right) \quad (2)$$

$$d = R * c \quad (3)$$

Where φ is latitude, λ is longitude, R is radius of earth and d is the distance between the points. The calculated distance is then divided by the time difference of the two straight GPS points to give the speed (see Eq. (4)).

$$s = \Delta d/\Delta t \quad (4)$$

Where s is speed, d is distance between the points and t is the time. The speed s is again divided by the time t to give the acceleration a (see Eq. (5)).

$$a = \Delta s / \Delta t \quad (5)$$

3.4 Splitting Trips into Trip-legs

A trip can be a single mode (only one mode of transportation) or multimodal (more than one transportation modes). The calculation of physical activity in single mode of transportation is easy. Therefore the multimodal trip must be divided into legs (each leg has only one mode of transportation) [31]. Since, there is lake of information to split the multimodal trips into legs; therefore every trip (single or multimode) is split into trip-leg. To split the trips into trip-legs, each time interval associates with the single travel mode is taken. The time interval is the travel time between two consecutive stops or pauses. By grouping consecutive legs performed by the same travel mode are considered as a single leg only.

In this step the trip is split into legs where the speed is close to zero or less than 0.01 m/s. If the speed of the subject is continuously less than or equals to 0.01m/sec, for more than 10 seconds, the suspicious delay can cause by the mode switch. The suspicious delay can also occur due to the wait at the bus-stop, which is an activity. The start of the activity is usually the end of the trip e.g. walking to the bus-stop and vice versa. The end of the waiting activity is considered as the potential starting point of another trip; that can be travelled by the bus. The suspicious delay (stopping at a signal or waiting at bus-stop) can also be investigated by the GIS.

In Figure 3, graph shows the speed of the subject. When the speed of the person touches zero it is considered as the endpoint of one leg and also the start point of the next leg.

After getting the trip leg the average of the speed is calculated for each leg. The sum of all the speed values is divided by the total number of speed values obtained from GPS points.

$$\text{average speed} = \frac{\sum S}{n} \quad (6)$$

3.5 Transportation Mode Detection

The graph in Figure 4 shows the distribution of the speed and the acceleration by using different travel behaviours. Since there is lack of the cluster visibility for the specific travel mode, therefore, the transportation mode based on average speed, time travel, acceleration, and distance of the trip-leg is detected by using the fuzzy logic.

Fuzzy logic is a rule-based (multivalve logic) system that can rely on the practical experience of the user. It can be applied to almost any type of system that has inputs and outputs. It is a continuum of values between 0 and 1. This may also be thought of as 0% to 100%. Fuzzy logic process consists of three steps (1) Fuzzify all input values into fuzzy membership functions (2) execute all applicable rules to compute the fuzzy output functions (3) de-fuzzify the fuzzy

Fig. 3 Speed pattern of a trip.

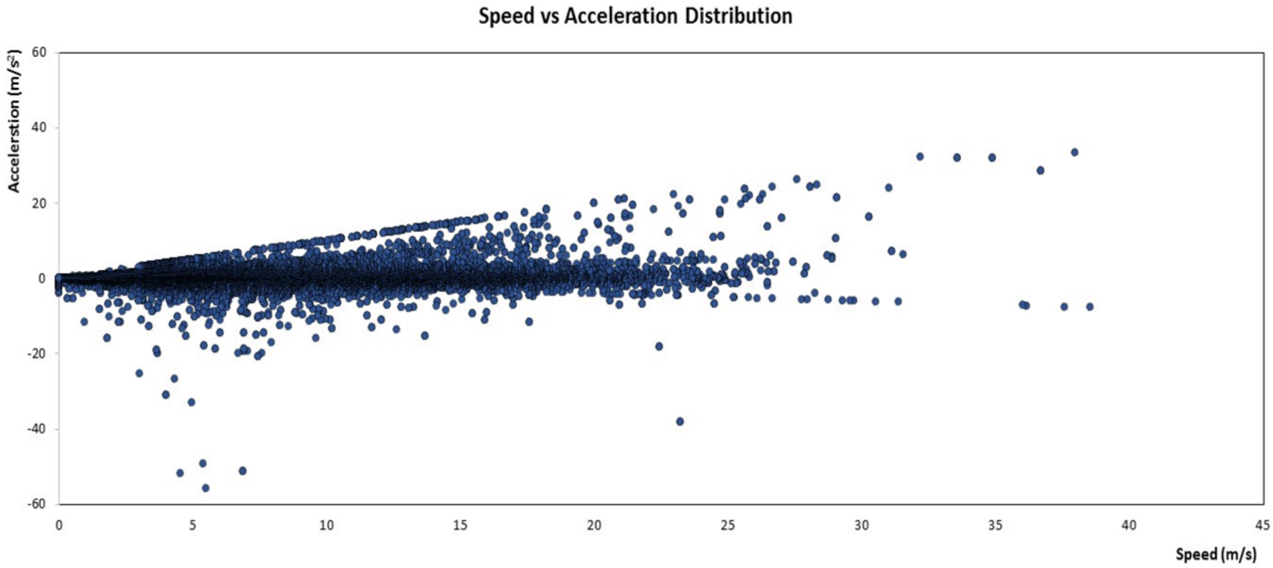

Fig. 4 **Speed and acceleration distribution of a subject for all trips (for the recorded period).**

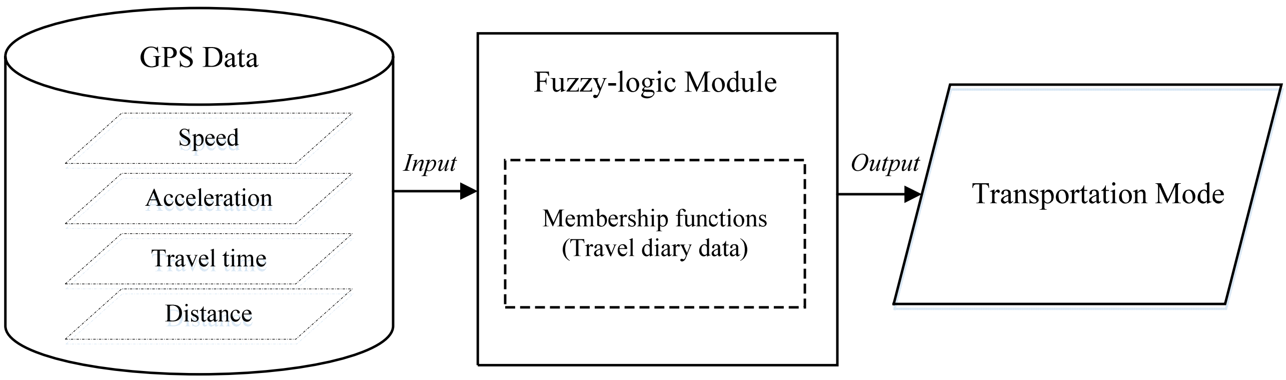

Fig. 5 **Use of Fuzzy logic Module.**

output functions to get "crisp" output values. The fuzzy system output is a consensus of all of the inputs, the rules and the weight of each rule. The output decision dependents upon the rule-based essential components, which are stored by using the human expertise [17].

The fuzzy logic module (java-based application programming interface) is embedded in the automated tool (the automated tool is implemented to validate the proposed technique which incorporates from step 2 to 5) to detect the travel mode. Since transport mode detection is a complex task, the fuzzy logic technique makes decision based on the fixed and the approximate logics. In this step, the design of the fuzzy logic system starts by creating the set of membership functions (average speed, time travel, acceleration, and distance) for each travel mode (see Fig. 5). For the values of membership functions, the data of 100 persons (having 1110 trips) is used. This data is collected by using the GPS and the travel diaries. The value for the trip duration (membership function) for the specific mode (walking, cycle and the motorized transport) is taken from the data collected by the travel diaries. Whereas, the values for the speed, acceleration and the distance membership functions are calculated from the GPS collected data. The value of distance membership function is calculated from the latitude and the longitude coordinates of the trip (see Section 3.3). The speed is calculated by dividing the distance with the trip duration. The acceleration is obtained by dividing the speed with the trip duration. Different percentile

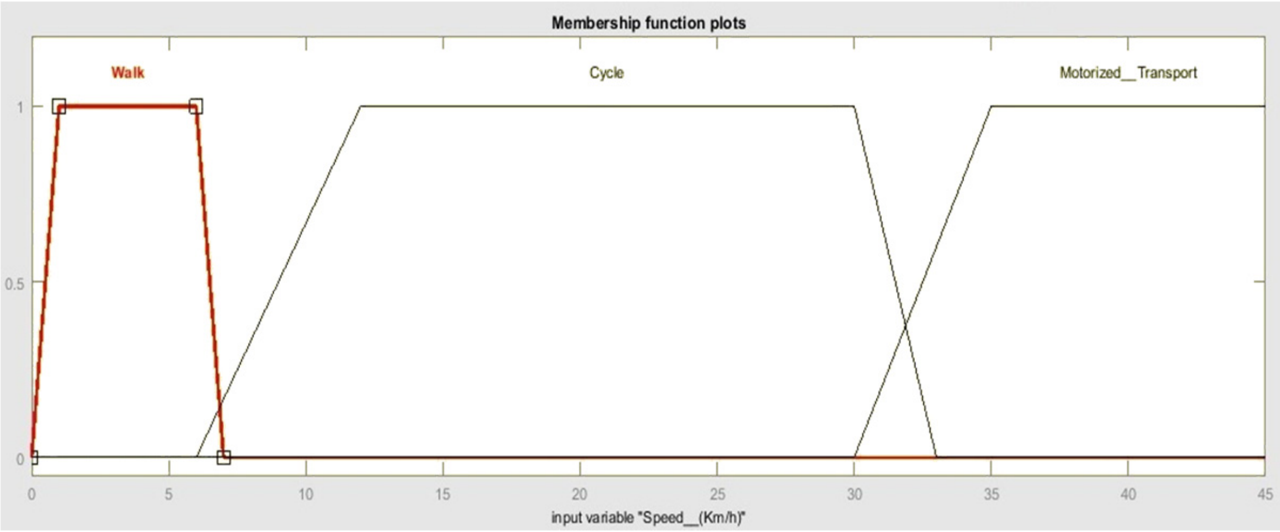

Fig. 6 The speed range of fuzzy membership function for the desired transportation mode.

values of each fuzzy membership function for each transportation mode are used. As an example Figure 6 shows the membership function of speed for walking, cycling, motorized transport (Bus and Car) are used for the fuzzy inputs: i.e. the minimum speed of walking will be 1 km/h and the maximum will be 7 km/h whereas the average lies between the 3.5 to 5 km/h. The motorized transportation mode have similar attributes i.e. the distance travelled by car is identical to the distance travelled by the bus between two GPS points [29]. The values of the average speed, acceleration, time travel and distance of trip-leg is fed into fuzzy as input. Fuzzy logic module detects the travel mode by using the membership functions values and the applicable rules.

3.6 Physical Activity Calculation

To estimate the physical activity by using the existing [22] mathematical expressions, the personal attributes i.e. age, weight, height and gender have similar importance like number, speed and duration of trip, and travel mode. The speed of travelling can be associated with the age and the gender of the subject. As we know the body movement requires energy which develops a relationship between the physical activity and the body composition i.e. weight, age, height, and gender. It is irrelevant to ask question from the subject regarding his/her weight and height in the transportation survey. So, the standard values for the height and weight are taken from the existing study presented by the National Center for Health Statistics (U.S.), National Health Examination Survey (U.S.), National Health and Nutrition Examination Survey (U.S.), & Hispanic Health and Nutrition Examination Survey (U.S.), (2012), which defines the average height and weight of a person by using the presented generic charts.

3.7 Mathematical Equations Used

The values of different variables i.e. the transportation mode, the duration, speed and the personal attributes (age, weight, height and gender) are calculated up to step 4. To estimate the physical activity, we used the equations presented by Refs. [25, 32].

Calculating the Basal Energy Expenditure (BEE) for male:

$$\mathrm{BEE_{male}} = 293 - 3.8 \times \text{age (years)} + 456.4 \times \text{height (meters)} + 10.12 \times \text{weight (kg)} \quad (7)$$

Calculating the BEE for female:

$$\mathrm{BEE_{female}} = 247\ 2.67 \times \text{age (years)} + 401.5 \times \text{height (meters)} + 8.6 \times \text{weight (kg)} \quad (8)$$

Calculating the physical activity impact on Energy Expenditure (ΔPAL):

$$\Delta \mathrm{PAL} = \frac{(\mathrm{METs} - 1) \times [(1.15/0.9) \times \mathrm{Duration\ (minutes)}]/1440)}{\mathrm{BEE}/[0.0175 \times 1440 \times \mathrm{weight\ (kg)}]} \quad (9)$$

Calculating the Physical Activity Levels (PAL):

$$\mathrm{PAL} = 1.1 + \Sigma \Delta \mathrm{PALi} \quad (10)$$

Estimating the Physical Activity Coefficient (PA) for male:

PA = 1.0, when 1.0 < PAL <1.4 – Extremely inactive

PA = 1.12, when 1.4 < PAL <1.6 – Sedentary

PA = 1.27, when 1.6 < PAL <1.9 – Moderate active

PA = 1.54, when 1.9 < PAL <2.4 – Vigorously active

Estimating the PA for female:

PA = 1.0, when 1.0 < PAL <1.4 – Extremely inactive

PA = 1.14, when 1.4 < PAL <1.6 – Sedentary

PA = 1.27, when 1.6 < PAL <1.9 – Moderate active

PA = 1.45, when 1.9 < PAL <2.4 – Vigorously active

Calculating the Total Energy Expenditure (TEE) for Male:

$$\mathrm{TEE}_{\mathrm{male}} = 864 - 9.72 \times \mathrm{age\ (years)} 90 + \mathrm{PA} \times [(14.2 \times \mathrm{weight\ (kg)} + 503 \times \mathrm{height\ (meters)}] \quad (11)$$

Calculating the TEE for female:

$$\mathrm{TEE}_{\mathrm{female}} = 387 - 7.31 \times \mathrm{age\ (years)} + \mathrm{PA} \times [(10.9 \times \mathrm{weight\ (kg)} + 660.7 \times \mathrm{height\ (meters)}] \quad (12)$$

4. Experimental Results

To estimate and analyze the physical activity from the mobility behaviour, an automated tool is implemented by using java. After separating activities in the step 1, the GPS traces of 120 subjects containing 1750 trips (transport activities), are used as input. The moving speed of the subject for each trip is calculated by using step 2. On the bases of speed, the obtained 1750 trips were further divided into trip-legs in the step 3. By applying fuzzy logic described in step 4, the transport mode was detected for each trip-leg. According to the first experiment, the overall accuracy of the mode detection is found to be 83% which is quite handy. The existing literature studies show the accuracy in between 70% and 95% (70% by Bohte et *al.,* (2008), 74% by Reddy et *al.,* (2010), 75% by Zheng, et *al.,* (2010), 82% by Byon et *al.,* (2009); Dodge et *al.,* (2009), 91% by Gonzalez et *al.,* (2010) and 95% by P. Stopher, et *al.,* (2008)). The accuracy of detected transportation modes individually is shown in the table 1.

The accuracy of the cycling mode is low as compared to the walking and the motorized transportation modes (see Table 1). The reason (observed) may be the membership function overlaps the walking mode, or the cycling membership sample is not quite good and it affects the results efficiency. The efficiency of the mode detection can be improved by considering the single mode only than the multimodal (multimodal trips are complex).

The graph in Figure 7 indicates the speed pattern of different transport modes. The speed pattern is different for the similar time periods of each mode. The x-axis shows the time period while the y-axis indicates the speed of the travel modes. Three curves used to show the different transportation modes: (1) red curve is used for walking (2) the blue for the bike

Table 1 Accuracy of mode detection.

Mode of transport	Number of trips	Number of trips identified	Detected trip accuracy
Walk	350	300	85%
Cycle	230	170	74%
Motorized Transport	1420	1290	91%

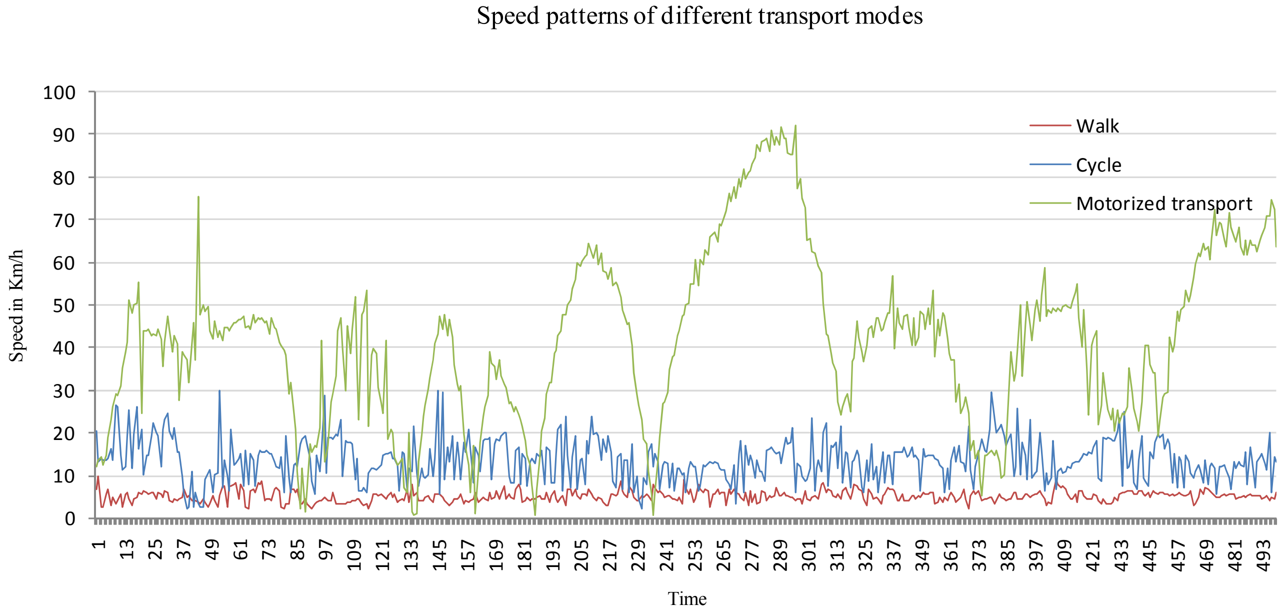

Fig. 7 Speed pattern of different transportation modes.

and (3) the green for the motorized transportation mode. The speed pattern of the transport modes (cycle and walk) remains constant with the minor ups and downs, up to the end of the time period. While the speed pattern for the motorized transport mode fluctuates with the random heights of the peaks, due to stopping at the bus stands or at the traffic signals. From the results shown in the Figure 7, the mean values can be visualized for each mode of the transportation i.e. below 10 Km/h for walking and above 10 Km/h for cycling. The average value for motorized transport lied above the 20 Km/h with the maximum value of more than 90 Km/h.

According to the transport mode (walking, bike and the motorized) and the speed of the trip, the appropriate MET value was selected from the compendium of physical activity. From the mathematical expressions discussed in section 3.6.1, the physical activity is calculated. As a case study, a male subject of 28 years old is assumed for all the considered trips. According to the National Center for Health Statistics (U.S.) et *al.,* (2012), the subject having normal weight and height of 83.4 Kg and 1.763m respectively considered. The results of PAL for all the trips (one thousand seven hundred and fifty (1750)) were calculated. The physical activity level for trips occurred in between 1.10 and 1.25 by using the motorized transport mode. Similarly, the physical levels for walking take place in between 1.12 and 1.50 and by bicycle are in between 1.15 and 1.63. For the multimodal trips, the physical activity happened in between 1.19 and 2.00 as shown in figure 8.

Based on the calculated PALs, the performed trips by car/bus and by walking are categorized as light intensity but by bicycle is moderate intensity. To meet the recommended health guidelines of moderate intensity, the PAL value should be more than 1.60. The calculated level of physical activities for walking and travelling by motorized transport found to be less than 1.60, which indicates that the activities performed by the subject did not meet the recommended health guidelines. Therefore, it be necessary perform aerobic activities along with transportation to meet the health guidelines.

The result findings can be concluded by considering two main reasons of failure which meet the health guidelines: (1) trip mode selection which requires less energy has low MET value and (2) performing of an activity for short time period. It is clearly visible that walking has high MET value but it still fails to meet

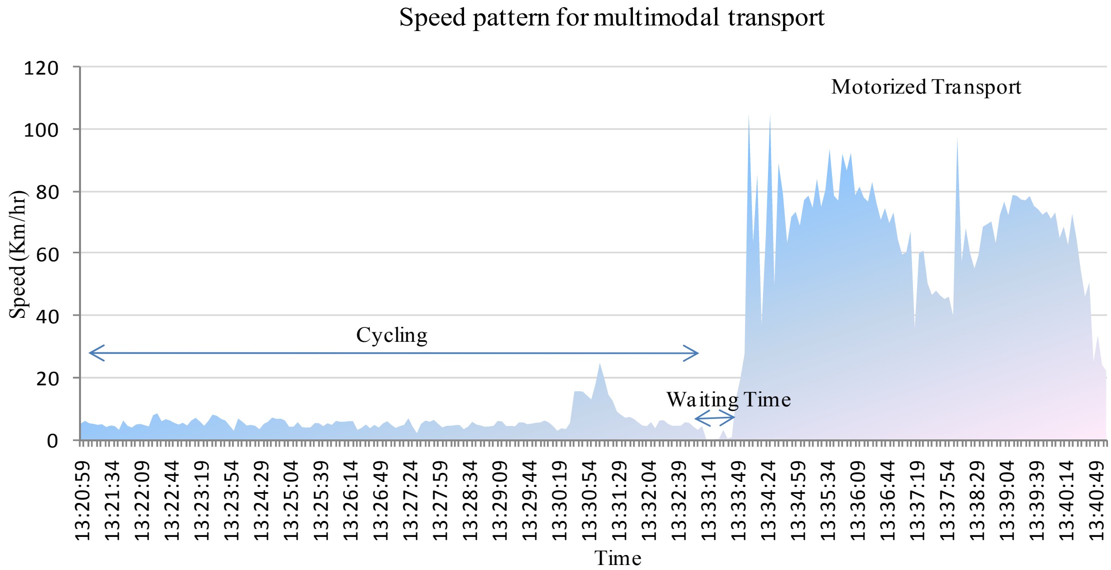

Fig. 8 different ranges of Physical activity for transportation mode.

the health guidelines due to the very low duration of the performed trip. Generally, walking is used as a transit to switch between transportation modes or going to/ from bus-stop. When walking, jogging and running activity performed for longer time duration, the recommended health guidelines can be achieved successfully.

5. Conclusion and Recommendations

The dataset of different subjects collected by GPS device is ideal to measure the outdoor transportation related physical activity (if the mode of transpiration for the activity is available). It contains the complete trip and the activities chain over the given multiple days which describe the travel behaviour in a broader sense. For the trip-leg, the easiest way is to search for the potential Mode transfer Points (MTP) on the route. Each trip-leg is separated by MTP. Using GPS traces in the GIS, the place where the speed reaches at the zero (i.e. at the Bus stop), considered as the MTP. Finally, the consecutive trip-legs are grouped with the same transportation mode, also consider as one trip-leg. During this research, the contribution of the physical activity to personal energy expenditure is also investigated. It provides a practical means to determine the health guidelines through which the health benefits can be achieved. The generalized fuzzy logic approach discussed in the section 3.4 is considered for the mode detection. However, different variables and the new rules have been applied. The achieved physical activity of few trips does not meet the recommended health guidelines due to the use of motorized transportation mode, e.g. car, bus, train, having low MET values. By using the active transportation mode (which have high MET values), the requirements can be fulfilled when the duration of the activity is sufficient.

In this study, the special speed pattern is found (approximately) in all the multi-modal trips (see Figure 9) by using fuzzy-logic. The pattern consists of multimodal transport mode (cycling and motorized transport). By analyzing this pattern behaviour carefully, we can also detect the trip type (single mode or multi-modal) and transport modes for each trip-leg by using pattern recognition, which can be considered in the future studies.

Although the subjects contain 1750 trips but still they are limited in numbers i.e. only 120 number of subjects. If the dataset collected from more than one subjects, performing the same trips, the variation in

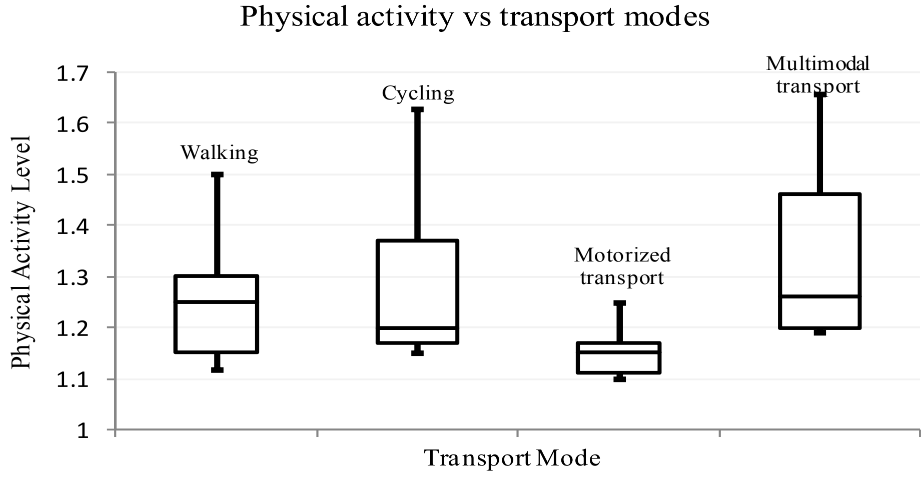

Fig. 9 Speed pattern for a multimodal trip.

the pattern will be minimum. The results can be accurate by using the exact values of height and weight of the subjects (in this research the approximate values are used). One of the main concerns is the similarity of the motorized transportation modes (i.e. bus and the car). The proximity of the routes has the potential of distinction between the public and the private transportation modes. The accuracy of the mode detection was found to be around 83%. The insufficiency of the fuzzy variables and the high level uncertainty were caused due to the travelled-dataset. All these limitations lead to cover in the future research studies. The other research directions can be: (1) incorporate auxiliary information as geo-spatial data layers from a GIS database (2) land use data and the socio-economic attributes may provide more evidential support in the decision making of mode pattern (3) map-matching and other spatial analysis methods can be utilized to reduce data uncertainty and ambiguity.

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Conflicts of Interest

There are no conflicts of interest. This research was conducted as a part of Master’s Thesis in the School of Transportation Sciences at Hasselt University, Belgium.

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