

Ellipse Fitting Model for Improving the Effectiveness of Lifelogging Physical Activity Measures in an Internet of Things Environment

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Abstract: The popular use of wearable devices and mobile phones makes the effective capture of lifelogging physical activity data in an Internet of Things (IoT) environment possible. The effective collection of measures of physical activity in the long term is beneficial to interdisciplinary healthcare research and collaboration from clinicians, researchers and patients. However, due to heterogeneity of connected devices and rapid change of diverse life patterns in an IoT environment, lifelogging physical activity information captured by mobile devices usually contains much uncertainty. In this paper, we project the distribution of irregular uncertainty by defining a walking speed related score named as Daily Activity in Physical Space (DAPS) and present an ellipse-fitting model-based validity improvement method for reducing uncertainties of life-logging physical activity measures in an IoT environment. The experimental results reflect that the proposed method remarkably improves the validity of physical activity measures in a healthcare platform.

Keywords: physical activity, ellipse fitting, life-logging, internet of things

1. Introduction

As a key indicator in a number of obesity, diabetes and other chronic diseases, effective measurement and monitoring of physical activity is critical in order to design programs for preventing/treating metabolic syndrome and chronic diseases (i.e., obesity, diabetes or arthritis) [1], [2]. Measuring physical activity and the associated estimates of instantaneous and cumulative energy expenditure (EE) in the long term enable clinical decision making and provides important feedback to caregivers in order to assess a patient's symptoms and thus achieve a healthy lifestyle. In the last few decades, Radio Frequency Identification (RFID) technology [3], [4] has been proposed as a solution to resolve many healthcare challenges. In recent years, the concept of an "Internet of Things" (IoT) [5]–[7] has emerged as new tools have promoted renewed interests in healthcare areas where a number of physical activity sensors and monitors have been developed for capturing lifelogging physical activity information and providing continuous, real-time feedback to users.

However, due to inherent commercial drivers, nearly all of the popular wearable devices and mobile phones in the market focus more on personal fitness and exhibit a lack of compatibility and extensibility. In addition, as a result of the heterogeneity of connected devices and rapid change of diverse life patterns in an IoT environment, lifelogging physical activity information captured by mobile devices usually

contains much uncertainty. Effective and efficient validation of big volume, highly dynamic and multi-dimensional personal lifelogging physical activity data becomes an extremely challenging task. Traditional methods use either dedicated wearable sensors [8]–[11] or advanced machine learning algorithms [10]–[17] to accurately monitor lifelong physical activity and access activity patterns and intensity level. Most of these methods, however, process and analyse human behaviours through raw sensor data of a single sensor or a combination of GPS and accelerometer. In contrast, in IoT-based personalized healthcare systems, physical activity data is generated on a daily basis from globally heterogeneous third party devices. As such, physical activity validation is harder to handle by virtue of scattered and heterogeneous data sets. Almost no literature to date reports successful validation of heterogeneous physical activity from different resources in an IoT healthcare environment.

This paper is organized as follows: section 2 reviews existing mobile and wearable devices for lifelogging physical activity measurement. Section 3 represents a brief analysis of uncertainties of lifelogging physical activity measures in an IoT environment. Section 4 proposes an ellipse-fitting uncertainty removal approach for improving the validity of lifelogging physical activity measures. Section 5 addresses a set of experimental evaluations of our proposed approach over real lifelogging physical activity datasets from a mobile personalized healthcare platform MHA [18] [19]. Further discussion, limitation and conclusion are presented in section 6 and 7, respectively.

2. Related work

The concept of IoT based personalized healthcare systems [5] uses a set of interconnected devices to create an IoT network devoted to healthcare assessment, patient monitoring and automatic detection of defined situations. It provides personalized health information from different wearable sensing devices through middleware that provides interoperability and security needed in the context of IoT for healthcare. These wearable devices are capable of recording multiple types of health data, including physical activity, sleep patterns, heart rate and blood pressure. Within this data, due to the technical and functional maturity of MEMS accelerometer technology and GPS, physical activity is mostly well-observed.

Recently, many commercial wearable products and mobile applications have been released that support long-term recording and collection of personal health information, particularly on physical activity. Popular mobile apps, such as Moves [20], are based on smartphone 3D accelerometer data and GPS information which allows tracking user movement activities including location, distance and speed. The wearable products, such as *Fitbit Flex* [21], *Nike+ Fuelband* [22], *Withings* [23] and *Endomondo* [24], are all wristband devices that record steps count, distance, and calories burnt. A brief comparison of above

Table 1 Pros and Cons of existing life-logging physical activity measure devices

	Product	Data	Pros	Cons
Mobile Apps	Endomondo	Route, distance, speed	Community sharing, Android and iOS	Short battery longevity, not work indoor
	Moves	Route, distance, speed	View data live, application program interface (API) support	Short battery longevity, not work indoor, step counter not precise. Android only.
	Google Fit	Duration, distance, steps, calorie	Connected to the android wear, manually choose different types of activity in the list	Heart beat value not correct
	Cyclemeter	Duration, distance, calorie	Accurately records bike related data as well as steps	No supported API
Device	Fitbit Flex	Steps, calories, food	Low cost, Android and iOS, long battery life	Limited application program interface (API)
	Nike+	Steps, calories, food	Reasonable cost, Android and iOS Reasonable cost, Android and iOS	Variations on accuracy
	Jawbone Up	Steps, distance, calorie		No application program interface (API)
	Misfit	Steps, calories, distance, sleep	Low cost, Android and iOS	Variations on accuracy

products is listed in Table1 and explained in detail below:

- *Endomondo* is a popular GPS based mobile application for tracking route, distance, duration, split times and calorie consumption. It offers a full history with previous workouts, statistics and a localized route map for each workout.
- *Moves* is also based on the use of GPS to record the user's path, speed, distance and elevation while they walk, run, and cycle (or do any activities) outside.
- *Google Fit* can automatically detect walking, running and cycling. It also works with Android wear, and supports third-party devices and apps. Visual graphs are available to observe the user's physical activity changes.
- *Cyclemeter* can accurately assess cyclists' activities and record bike related data, e.g. bike speed, bike cadence and power. It also tracks the user's steps while walking and running. There is no valid API that can be accessed by third-parties.
- *Fitbit Flex* records steps taken, distance travelled, and calories expended. These devices communicate with a host computer using Bluetooth that in turn sends data directly to a user's account on the Fitbit website.

- *Nike+ Fuelband* is worn on the wrist and records calories, steps, distance, and Nike's own unit of activity terms "Nike Fuel". The device connects via USB to a host machine which synchronises the data to a user's account on the Nike+ website.
- *Jawbone Up* calculates steps, distance and calories. Currently the Jawbone up can only be used with a mobile device, drivers for laptop and PCs are not provided.
- *Misfit* is a low cost and light wearable band. It records basic steps, sleep and calories that can be synchronised to a mobile app on the user's phone.

These wearable devices communicate with a mobile phone via Bluetooth running the relevant mobile application. While the above products have proven their popularity among general users, their usage is limited in the fitness field. This is due to a diversity of life patterns and environmental impact since personal physical activity data from an individual wearable device exhibits remarkable uncertainty. The validity of physical activity data in lifelong healthcare cases is very challenging. Also, with the rapid growth in the mobile healthcare market, numerous similar wearable products have been developed, which significantly increases the heterogeneity and diversity of devices connected in IoT-based personalized healthcare systems.

3. Classification of data uncertainty in IoT healthcare systems

In an IoT-enabled healthcare system, lifelogging healthcare data is ultra-diverse, dynamic and multi-dimensional. Regarding physical activities, accuracy of lifelogging data is widely impacted by a variety of issues, including devices, ages, gender, activity subjects, etc. Thus, uncertainties of lifelogging PA data are distributed differently, and occur persistently according to these issues. Also, considering the dimension of time, the increment of lifelogging physical activity data over a given timeline results in an expansion of the entire data, further leading to more complex uncertainties. In this paper, we attempt to classify data uncertainty in IoT healthcare systems by three important factors: person, time and devices, as shown in Fig.1. In terms of the concept of IoT, personal health data is accumulated and measured as a cube in three dimensions (3D): Persons, Devices and TimeLine. The increment in any dimension results in an expansion of the health data grid. The products like Fitbit Flex [21] or Moves [25] occur on a 2D plane (Persons \times TimeLine), which refer to scenarios in which a single device is used by an increasing population over time. Similarly, physical activity recognition with sensor fusion [26]–[28] appears on a 2D plane (Devices \times TimeLine) for classifying an individual person's activities with historical health data.

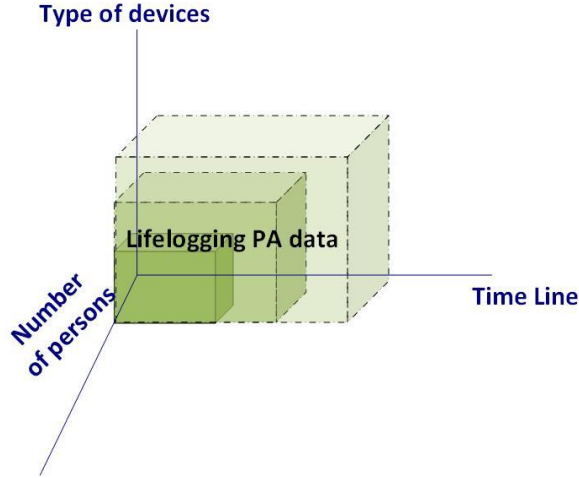


Fig. 1. Concept of IoT personalized healthcare systems

The uncertainty of physical activity here can be categorized into two types:

Irregular uncertainty: Irregular Uncertainty (IU) in physical activity data occurs randomly and accidentally. The causes of these uncertainties may include device malfunctions or faults, breakdown of a third-party server, misuse of mobile apps, or sudden change in personal circumstance for example. The occurrence of irregular uncertainty in physical activity data will significantly impact the efficiency and accuracy of assessing personal health.

Regular uncertainty: Regular Uncertainty (RU) in physical activity data occurs frequently and persistently. The causes resulting in these uncertainties are mainly from some regular influencing issues in a completely uncontrolled environment, i.e., divergent activity pattern due to different age, health condition, etc.; intrinsic sensors' errors; transmission failure; differentiation of personal physical fitness and changes of environment. Thus the occurrence of regular uncertainty in physical activity data is inevitable.

4. Ellipse fitting model for removing irregular uncertainty

After classifying the above two types of uncertainties, it is important to clearly understand the distribution of IU and RU. Typically in an IoT environment, the level of physical activity is assessed and represented by the number of steps walking per day, named as Daily Steps S_d , or the distance walking per day, named as Daily Walking Distance: D_{dw} . Current wearable devices or smartphones also enable measuring walking speed related information, like Daily Walking Speed V_{daw} . Therefore, our inspiration for managing the above two types of uncertainties is to build a 2D distribution of physical activity regarding two benchmarks: Daily Walking Steps (Steps) and Daily Walking Speed (Speed). In terms of

the characteristic of two uncertainties, the distribution of daily physical activities with normal life pattern and wearable devices can be conducted to follow a condition that: a centroid point P marks by an average DWS_s and an average DWS . Although there are some points might fall in to normal range (e.g., 4000 steps/ hour), here it is only taken into account estimation of the best fit of samples for individuals, and thus the distance from the centre to the perimeter along the x and y axis are distributed a certain range close to the mean. Accordingly, the daily physical activities with regular uncertainties will be regularly all around point P ; the daily physical activities with IU will be some distance away from point P . As shown in Fig.3, the x axis represents walking speed and the y axis represents daily walking steps. The light points represent daily physical activities with regular uncertainties; and the dark point represents daily physical activities with IU. Regarding this assumed distribution of physical activity, we are able to use an ellipse shape to separate RU and IU. In Fig.3, the dark dots that fall outside of the ellipse represents the IU. The light dots are the regular physical activity data with RU covered by the ellipse modelling algorithm.

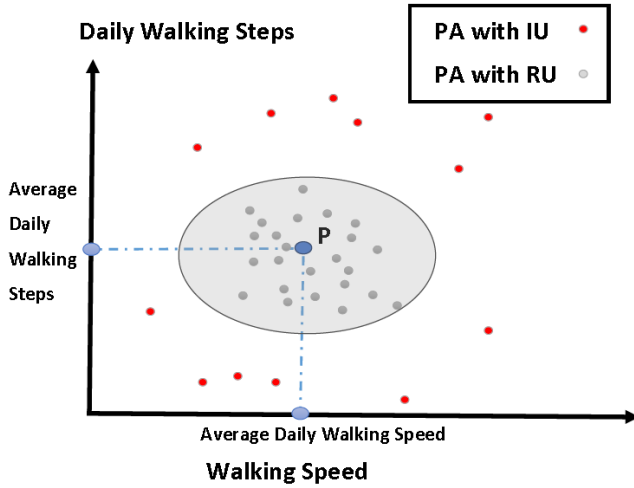


Fig.2. Distribution of PA with IU and RU

Fig.2 presents the physical activity samples distribution. In order to enclose points $P: \{P_1, P_2, \dots, P_n\}$ in the 2D plane, we use an ellipse ε to cover all the points with RU: P_n . The ellipse with central point (i, j) and semiaxes m and n can be defined in equation (1):

$$\frac{(x-i)^2}{m^2} + \frac{(y-j)^2}{n^2} = 1 \quad (1)$$

Where:

i : Average daily walking speed

j : Average daily walking steps

m : Error range of average daily walking speed

n : Error range of average daily walking steps

Additionally, the benchmark of DWS can be extended to represent a person's physical fitness from completed physical activity data sources. Here a walking speed related score is defined to represent a person's physical fitness, named Daily Activity in Physical Space (DAPS). This score is inspired from earlier work [6] that proposed a Movement and Activity in Physical Space score as a functional outcome measurement for encompassing both physical activity and environmental interaction. Currently, most third party APIs of wearable devices or mobile apps provide functions to assess the intensity of physical activity regarding walking speed. For instance, *Fitbit* [21] classifies the intensity of daily activities into Very Active, Moderately Active, Lightly Active and Sedentary; *Moves* [25] records a series of walking segments containing duration, distance and speed. Here, we classify the intensity of daily physical activity into N levels in terms of the ranges of walking speeds (V_1, V_2, \dots, V_n). The DAPS formula is created by summing these different level walking speeds:

$$DAPS = \sum_{i=1}^N V_i \quad (2)$$

Using the data of DAPS and Daily Steps, we can calculate V_{daw} , and plot S_d and V_{daw} in 2D diagram as in Fig.3. A noticeable issue here is that we only consider the lower limits of walking steps and the upper limits of walking speeds as threshold parameters. On some days users might walk distinctly more steps than normal, while other days might be more sedentary. The threshold parameters are represented in equation (3):

$$\begin{aligned} T_y &= i + m; \\ T_s &= j - n \end{aligned} \quad (3)$$

Thus, the strategy for removing irregular uncertainty will follow the steps below:

- To configure the information related to the IoT environment and collect certain types of raw physical activity (PA) data.
- To calculate the parameters S_d , D_{dw} , V_{daw} with raw data.
- To plot the data of S_d , D_{dw} , V_{daw} and calculate the value of T_s and T_y with an ellipse filtering equation to cover data with a confidence interval of 95%-99%. The confidence defines that 95%-99% of all samples can be drawn from the underlying Gaussian distribution. The value of confidence depends on the different sample distribution. For instance, when the data is scattered and disordered, the value can

be set to be 99% so that it covers a wider range. In contrast, when the data is insensitively aggregative, the value can be set to be 95% to enclose the best fit.

- To use T_s and T_y for removal of irregular uncertainty physical activity data.
- To iterate the above process in another time period with updated raw data.

The following rules are also applied:

- Following the ellipse filtering equation, we can get the value of T_s and T_y .
- For daily physical activity data, if daily walking steps is lower than T_s , or average daily walking speed is lower than T_y , we will abandon this data.

5. Performance Evaluation of our Ellipse Fitting model

In order to evaluate the performance of our proposed ellipse fitting model, we use the life-logging PA data collected from a research platform MHA [20]. This platform is an IoT enabled personal healthcare experiment platform connecting Moves, Fitbit Flex and Withings. This platform enables a user to transfer their physical activity data from these third party providers into the MHA server, and then to be able to visualize and analyse this information to gain a better understanding. The evaluation of irregular uncertainty distribution is based on the MHA platform. We initially collected daily physical activity (Steps, Distance and Calories) of seven users over one year using three types of wearable device (Withings, Fitbit Flex and Moves). All these users (one female and six male) are researchers in a university, and their ages are in the range of 30-50 years old. The methodology for evaluating the performance of our ellipse fitting model includes four steps: A) Evaluation of the overall physical activity distribution; B) Evaluation of an individual PA distribution; C) Evaluation of the group PA distribution; and D) Effect of the changed confidence interval.

5.1. Evaluation of the overall PA distribution

Firstly, we calculate V_{daw} , and plot S_d and V_{daw} in a 2D diagram with the overall set of “Moves” and “Withings” data from randomly selected individuals.

The features of this physical activity data are:

- All seven people use Moves. Two of them additionally use “Withings”, and another three people use Flex.
- Missing data occurs frequently in Withings and Flex because users easily forget they are wearing them.

- Some data in Flex shows lower steps, which is because users take off their wearable devices sometime during the day, or the devices run out of battery power.
- Moves data are more complete than Flex or Withings, but with relatively high errors.

Based on these PA data, the ellipse fitting method is used to cover the distribution of all data. Some facts are concluded:

- Daily steps of an individual recorded by Moves are about 4000 – 7000,
- Flex or Withings give daily steps about 6000 – 13000.
- Moves gave a lower measurement of daily steps than Flex or Withings with the same conditions.
- Healthy people should have daily steps in the range 1000– 20000.
- Flex and Withings sometimes show daily steps below 1000.
- Following equation (3), we can get $T_s = 68$, and $T_y = 0.56$ for Moves, and $T_s = 1329$, and $T_y = 1.67$ for Flex.

For dealing with overall PA uncertainty, the proposed ellipse-fitting model allows us to obtain two parameters T_s and T_y to effectively filter IU.

5.2. Evaluation of an individual PA distribution

While our ellipse-fitting model works with overall physical activity data, it is also necessary to know its performance on an individual activity distribution. We randomly selected four individual persons' PA data and see if their distributions still work with the proposed ellipse-fitting model. Fig.3 shows four individuals daily steps and speed acquired from the mobile personalized healthcare platform MHA connecting the mobile app “Moves”. The confidence value of ellipse fitting is 0.95 for each individual, which means that 95% of samples fall inside the defined region based on a Gaussian distribution. The features of this PA data are:

- Four persons have a different PA distribution pattern.
- Two persons' PA data have a dense distribution, which reflects that their life patterns and mobile devices are relatively stable.
- Two persons' PA data have a sparse distribution, which indicates that their life patterns are irregular; or their mobile devices have some larger intrinsic errors.
- Subject A's regular daily steps are significantly less than subject B and D.

- Subject C and D have fairly sparse physical activities during the test period. On the contrary, their speed is relatively similar, ranging from 0.5 up to 2.2 m/s.

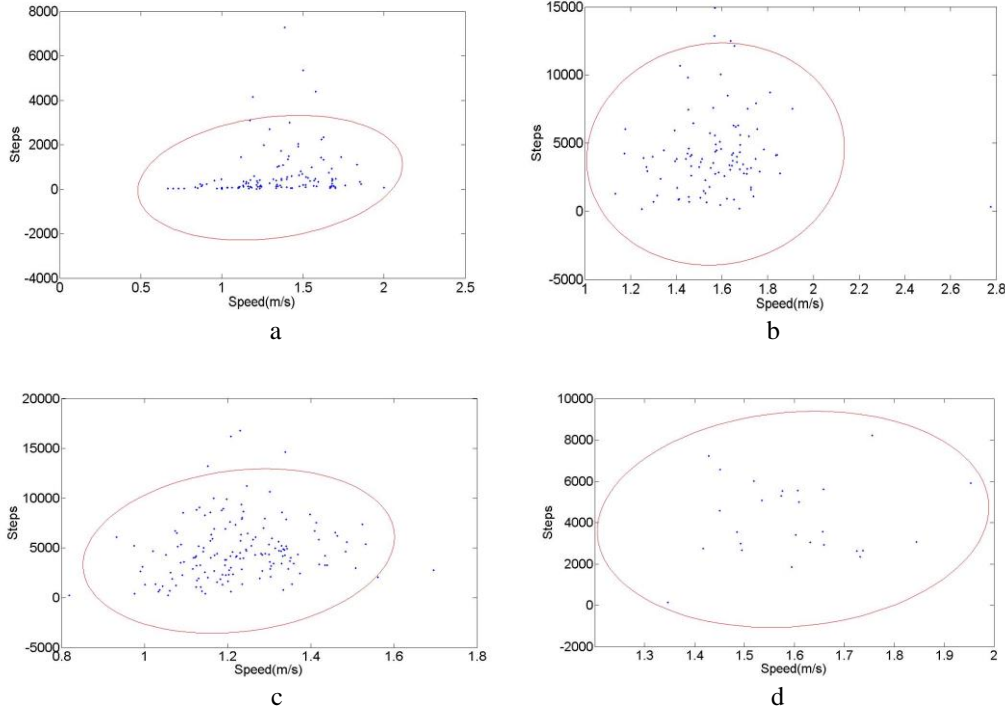


Fig.3. Ellipse fitting distribution of daily steps and speed of four subjects, respectively ($c=0.95$)

a Subject no.1
b Subject no. 2
c Subject no.5
d Subject no.12

Table 2 m, n, T_y, T_s values of four individuals

	m	n	T_y	T_s
P1	2451.2	0.6979	2967.4	0.5997
P2	7135.2	0.4924	11333	1.0796
P3	7225.9	0.3233	11921	0.9034
P4	8476.8	0.4639	13676	1.0265

Table 2 shows m, n, T_y, T_s values of four individuals in terms of equation (1) and (3). The results of the first subject (P1) are relatively different from others. Most of individuals, however, have closed parameters from their activity patterns. In other words, diverse physical characteristics (i.e. height, weight, age, etc.) do not lead to a significant difference in physical behaviour measurement.

In summary, different subjects have different physical activity distribution patterns. The ellipse-fitting model is still able to work with these data, but the shape and axes angle of ellipse are different for

each person. The key parameters of the ellipse will be varied in terms of an individual's circumstance. Further, the parameters T_s and T_y for filtering IU will be also varied in terms of individuals.

5.3. Evaluation of the Group PA distribution

We further consider evaluating the performance of our ellipse fitting model on certain groups of personal PA distribution. We randomly selected three groups of personal physical activity data:

- Group_1 (Subject 1, 2, 3)
- Group_2 (Subject 4, 5, 6)
- Group_3 (All subjects)

Figures 4.a, 4.b and 4.c respectively shows the physical activity distribution for the above three groups. The confidence value of ellipse fitting is also 0.95 for each group, which means that 95% of samples fall inside the defined region based on a Gaussian distribution. The features of this data are:

- The three groups have a similar physical activity distribution pattern.
- The physical activity data on walking speed of each group is within a very close interval (0.5~2.5).
- The physical activity data on daily steps of each group differs within intervals, which are (0~500), (0~1000) and (0~2000).
- The physical activity data on daily steps of each group is similar within intervals, which is in the range of (0~20000).

Table 3 a , b , T_y , T_s values of the three groups

	a	b	T_y	T_s
G1	7547.4	0.6295	10551	0.7068
G2	7083.7	0.5378	11635	0.9416
All	7602.4	0.6246	10900	0.7309

Fig.4 shows that different groups of subjects have different physical activity distribution patterns. Our ellipse fitting model is still able to work with this data, but the shape and axes angle of ellipse are different by groups. Further, the parameters T_s and T_y for filtering IU will be also varied in terms of groups.

From table 3, we can see that data in group 2 (G2) are quite scattered and most of them are distributed in the range of (2500-10000), compared with the range (0-8000) in group 1 (G1), leading to a bigger average value of daily steps (a), which is the k value defined in equation (1). And thus, although its a and

b value are smaller than group 2's, T_y and T_s are outnumbered. This also implies that some subjects in group 2 keep irregular uncertainties that are far more than in normal situations. Nevertheless, there is no great influence on the overall measurement with only a few irregular samples, which strongly demonstrated that our ellipse fitting model is adaptive for different occasions.

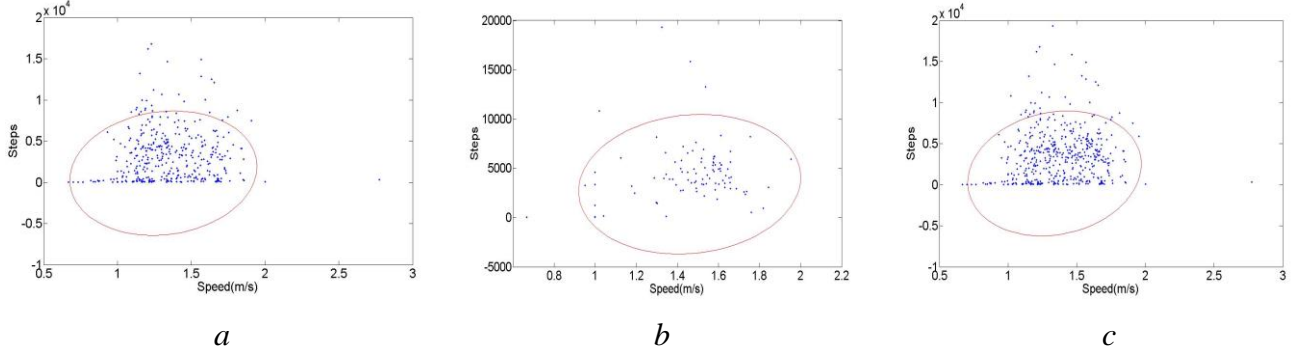


Fig.4. Ellipse fitting distribution of daily steps and speed of selected subjects ($c=0.95$)
a Group 1 (subjects no.1 & no.2 & no.3)
b Group 2 (subjects no.4 & no.5 & no.6)
c All Subjects

5.4. Impact of Central Point

Another key parameter for the proposed ellipse fitting model need to be considered: the central point of ellipse (i, j). Regarding the definition in equation 1, the central point represents the value of average daily walking steps and the value of average daily walking speed. But a number of ways are available to calculate the average mean in literature. Here, we choose two typical methods to measure the mean of distribution: geometric mean and arithmetic mean.

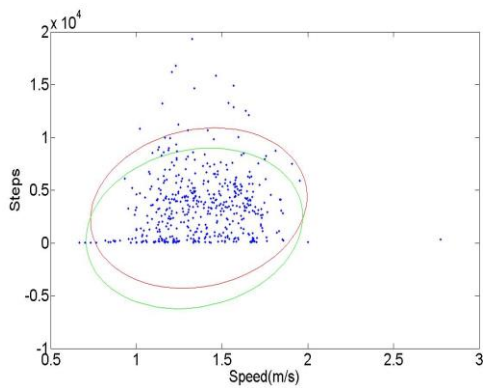


Fig.5. different central coordinate of ellipse fitting (green: geometric mean; red: arithmetic mean)

A comparison of the geometric mean and arithmetic mean set for the central points of the data distribution is presented in Fig.5. The red ellipse is modelling with arithmetic mean: the range of steps is 0-10000, and the speed is between 0.7m/s-1.9m/s on average. The green ellipse is modelling with

geometric mean: the range of steps is 0-8000, and the speed is 0.4m/s-1.8m/s. It appears that the green ellipse covers less samples than the red ellipse but the gap between them is not large. This means that both samples are distributed in balance and regular on average daily walking speed. But, daily walking steps differs by individual, leading to an apparent gap between geometric mean and arithmetic mean. Although there is only a slight difference between the two central points, the arithmetic mean covers more samples than the geometric one, and thus achieved a better result.

5.5. Comparison with other fitting methods

Two curve fitting methods (Smoothing Spine fitting and Gaussian fitting) are carried out in order to compare with our ellipse fitting model, shown as equations (3) and (4).

$$y = p \sum_i w_i (y_i - s(x_i))^2 + (1 - p) \int \left(\frac{d^2 s}{dx^2} \right)^2 dx; \quad (3)$$

$$y = \sum_{i=1}^n a_i e^{\left[-\left(\frac{x-b_i}{c_i} \right)^2 \right]}; \quad (4)$$

In equation (3), p defined in the range 0 to 1, from a least-square straight-line fitting to cubic spline interpolant. Equation (4) is based on the Gaussian distribution presenting the numbers of Gaussian peaks. In Fig.6(a), the smoothing parameter $p = 0.95$ is selected to produce a relatively smooth curve. Nevertheless, as the raw samples are abundant but aggregated, we can see an amount of data in a normal step and speed range are above outside of the curve. In comparison with our ellipse model presented earlier, the 1D fitting functions shown in Fig.6 hardly fit in our data samples. Therefore, the ellipse fitting model is the most suitable fitting method applying in this situation.

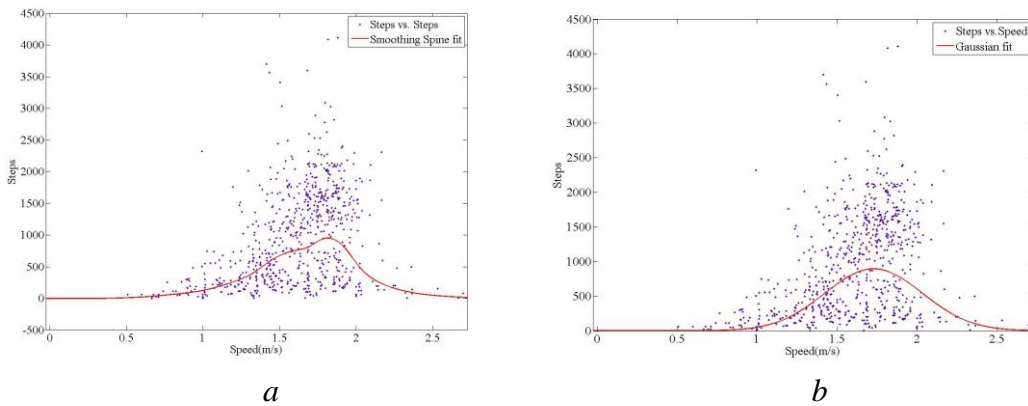


Fig.6. results of other fitting methods

a Smoothing Spine fitting

b Gaussian fitting

5.6. Evaluation among devices

In this section, we discuss the performance evaluation of our proposed method in a case study on the MHA platform [18]. The criteria for verifying our validation model will concentrate on the efficiency and adaptability of the method.

Table 4 Removing irregular uncertainties (IU)

	Moves	Fitbit Flex	Withings
T_s Daily Steps	4303	6872	5267
T_y DAPS Speed (m/s)	2.0	4.0	NA
Total number of people	14	5	3
Percentage of people with IU	43%	100%	100%
Number of IU occurrence	40	17	8
IU confirmed by user	40	15	5
Average number of IU occurrence per person (User Feedback)	6.6	5.4	2.7
Accuracy of identifying IU (95%)	100%	88.2%	62.5%
Accuracy of identifying IU (98%)	100%	100%	100%

The dataset from the MHA platform includes year-long daily physical activity information of 14 subjects acquired with three devices: Moves was used by 14 users for nine months; Flex was used by five users for 12 months; Withings was used by three users for three months. These people are healthy in the age range of 30-50 years. The evaluation methodology for verifying the efficiency of proposed model involved interviews with the participants, collection of feedback reflecting on users' experiences on their physical activity uncertainties through different devices. The feedback is used as a standard benchmark to compare the correctness of model.

In order to validate the accuracy of identifying IU, we follow equation (2) and (3) with a confidence interval of 95% to filter data from three different devices. We use the values (130, 1784, 884) of threshold parameter T_s respectively in Moves, Flex and Withings, for filtering incorrect daily steps data. The results are shown in Table 4.

Moves has much lower threshold parameters of Daily Steps and DAPS speed than Flex and Withings which are 130 and 0.5 m/s respectively (Table 4). This is because Moves has larger device uncertainties than Withings and Flex as we observed in section 4. Thus the GPS and smartphone internal sensors-based App is not as accurate as an accelerometer-only based wrist wearable device. In terms of percentage of people having IU, Moves is much lower than Withings and Flex. It is because most of uncertainties from

Moves have been classified into regular uncertainties, so its irregular uncertainties became less than for other two devices. However, for average IU occurrence per subject, Moves has higher performance than other two devices (Table 4). The accuracy of identifying IU appears that on the condition with a confidence interval of 95%, the related value of threshold parameter T_s can successfully filter IU in Moves. So Moves has the best IU identification accuracy up to 100%, which means that the incorrect daily steps detected by equation (3) in Moves have been all approved by users. Flex and Withings have accuracy up to 88.2% and 62.5% respectively, which implies that some correct daily steps are eliminated by our method. The increase of confidence interval will have an affect on filtering accuracy of IU. If we increase the confidence interval up to 98%, and recalculate threshold parameters, the accuracy of identifying IU of three devices would increase to 100%. However, a noticeable issue here is that if we increase the confidence interval, some IU might be ignored and put into the procedure of dealing with RU. Similarly, in Moves, a high accuracy of identifying IU does not mean all the IU have been removed but more likely that some of the IUs are considered as regular uncertainties.

For validating the adaptivity of the proposed ellipse fitting model, we consider the whole group of 14 subjects as one group due to the similar professions and backgrounds. We estimate the change of daily steps T_s and DAPS with different periods (from one to 12 months) with a confidence interval of 95%. The results are shown in Fig.7.

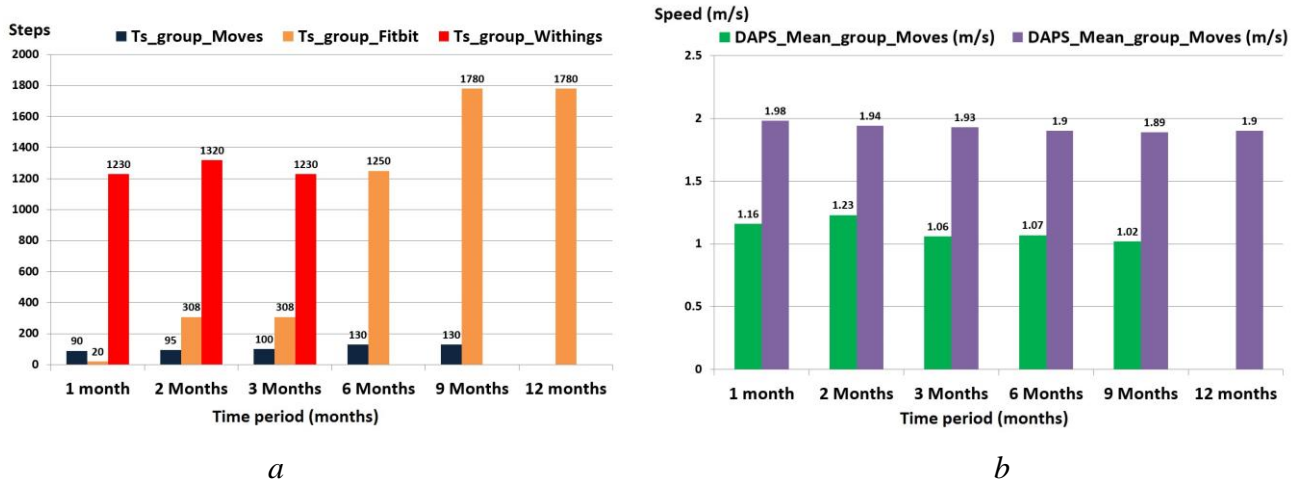


Fig.7. The function of time period duration
a Average of daily steps as the function of time period duration
b DAPS as the function of time period duration

Fig.7 (a) shows the parameter Daily Steps as the function of time period duration. The value of this parameter is lower for shorter time periods than for longer time periods. The value of this parameter also varies with different devices. For Moves and Withings, the value of this parameter over different periods

is slightly growing, but for Fitbit Flex, this parameter dramatically increases after six months. This effect may be influenced by the setting of the confidence interval.

Fig.7 (b) shows little variation of DAPS parameter in the proposed method when the time period duration is changed. There are some minor fluctuations of DAPS on both Moves and Fitbit Flex but in the long term, the value of DAPS is quite stable, which indicates that personal physical fitness does not have significant differences within this group of 14 people.

6. Discussion and Limitation

There are several obvious concerns of the method proposed in this paper. First, the scalability of our proposed ellipse-fitting model-based validity improvement method for dealing with increased volume and types of health data has not been considered in this paper. In a practical IoT-enabled healthcare environment, personal health information will be a life-long collection. The practical efficiency on multi-type health data in a long-term collection needs further evaluation. Second, the evaluation of data validation efficiency and regular uncertainty indicator for our proposed method is subject to a small number of users' feedback. The standardized criteria of judging correctness and efficiency of the ellipse-fitting model-based validity improvement method on removing and estimating uncertainties requires more user feedback. Also, for different targeted groups, the adaptability of the proposed method needs to be verified by more users. While this work has the above further improvements to make in this study, we believe that the benefit of this method outweighs its current limitations. The proposed ellipse-fitting model-based validity improvement method has provided a new approach to validate physical activity data in an IoT environment and has been verified by a rich set of personal health data in real experiments, including other medical data, such as ECG and blood pressure for example. The research outcome is extremely valuable and beneficial for effective and efficient management, analysis, visualization and exploration of large-scale health data in order to bring useful knowledge and intelligence for more solid clinical decision-making and policy formulation.

7. Conclusion

This paper presents an ellipse-fitting model-based validity improvement method for reducing uncertainties of life-logging physical activity measures in an IoT environment. The experimental result on an IoT enabled healthcare platform MHA [18] shows that this method can effectively improve the validity of physical activity measures in a small populations. While efficiency and accuracy of our method require further investigation by more populations and connected devices, our method demonstrates a development

in the improvement of the validity of life-logging physical activity data in an IoT environment. Future work in this study will focus on extending the proposed method in a large-scale IoT environment, which will include more wearable devices and more subjects. It will also attempt to analyse and process the life-logging data with machine learning techniques for improving the accuracy of the proposed validation method.

8. References

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