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# The iPhone Health App from a forensic perspective: can steps and distances registered during walking and running be used as digital evidence?

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ABSTRACT

The iPhone Health App automatically collects data on daily activities for health purposes. Detailed information on the number of steps taken and distances travelled is stored in a database together with timestamps with a time granularity of a couple of minutes. While such information can potentially be very valuable in a forensic investigation, one needs to have a good understanding of its reliability in order to make proper use of it.

In this study we investigate the accuracy of steps and distances registered by the Health App under a broad range of experimental conditions for an iPhone 6, iPhone 7 and iPhone 8. For five subjects, we varied carrying location of the telephone, walking distances, walking speed and compared steps and distances registered by the telephone to manually measured steps and the real distance.

The results of the experiments were similar for all three telephones. Steps registered by the iPhone Health App agree very closely to those measured manually with an averaged error of about 2%. The reliability of the registered distances, however, depends on a number of factors, including walking speed and walking style of the subject and can deviate up to 30–40% from the true value.

These results suggest that, if you take the properties of the iPhone Health App into account, digital traces from the Health App can be used for evidential purposes, for example to make a probability statement about different routes that may have been travelled in a case.



## Introduction

Besides traditional use such as communication, entertainment and banking, modern consumer electronics have in recent years increasingly proliferated into the field of health support (see e.g. Deep Knowledge Ventures (2018) for an overview). As a result, numerous applications are available on modern smartphones which monitor health related activities. For example, amount of daily activity can be monitored by keeping track of the number of steps taken during the day. These health related applications range between system apps, shipped with the phone by the manufacturer (e.g. Shealth on Samsung phones or Health App on iPhones) and third party apps (e.g. Runkeeper). Besides smartphone applications, dedicated wearable sensors such as Apple Watch or Fitbit are available for health support. Often, data collected by these wearables can be synchronized with smartphones or computers to get a more detailed picture of daily activities.

Although usually not specified in much detail, all these health related applications rely on data produced by sensors in the telephone or the wearable, such as accelerometers and gyroscopes to infer information on health related issues. Also, manufacturers are not very explicit about the way these sensor signals are processed, which makes it hard to independently judge the accuracy of health information derived from this sensor information.

Nevertheless, sizeable amount of processed data are stored in databases by health related apps. The information that is stored varies, but some apps are known to store detailed information with timestamps with a small time granularity. A good example of this is the Health App, which is shipped as a system App on iPhones since iOS 8. During the day, the Health App automatically collects data on number of steps taken, traveled distances and number of floors climbed which is stored in periods of a couple of minutes.

From a forensic perspective, such detailed information on

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(physical) user activity can, of course, be very valuable for investigative and evidential purposes. Numerous forensic applications of data from the iPhone Health App are imaginable, including the following examples:

*Probability statements about scenario's or routes*

If there are two or more scenarios in a case about what has happened, a probability statement can be made, for instance in the form of a likelihood ratio, about the support that traces found in the iPhone Health App give to either of the scenario's in question. Similarly, if there are several possible routes which might have been travelled in a case, a probability statement can be made about the likelihood of the traces found in the Health App under the assumption that either one of these routes was travelled.

*Analysis of (physical) user activity over time*

On the basis of timestamps in data stored by the Health App, one can try and make an estimate of relevant time periods in which physical activity was performed by the user, leading to information being stored by the Health App.

The fact that data from health related apps are a potential treasure trove of forensic information has not gone unnoticed in the law-enforcement community. In the Netherlands, data from the iPhone Health App has been used as evidence in a number of high profile cases. While these data is potentially a very valuable source of information in a criminal investigation, one needs, of course, to have a good understanding of its reliability in order to infer forensically correct information from it. Therefore, on a number of occasions the Netherlands Forensic Institute (NFI) has been asked to make an assessment of the accuracy of data collected by the iPhone Health App as part of its regular casework. As a spin-off of our casework, we present in this paper an in-depth analysis of the reliability of data registered by the iPhone Health App from a forensic perspective.

Our approach is to compare, under a wide range of experimental conditions, data from the iPhone Health App against independently collected data on number of steps and distances, which serve as the so-called ground truth. In the biomedical literature, a number of similar reliability studies on the accuracy of various activity trackers have appeared (e.g. Höchsmann et al., 2018; Duncan et al., 2018). The aim of these studies is to assess the applicability of activity trackers and the iPhone Health App for physical activity assessment and focus is therefore on accuracy of registered steps only.

## Methods

### *Subjects*

Three male and two female subjects participate in this study. From each subject, informed consent was obtained according to the policy statement of the American College of Sports Medicine. Characteristics of the group were (mean ± standard deviation): age: 33 ± 10 year, length: 1.76 ± 0.08 m, bodymass: 77 ± 10 kg.

### *Telephones*

Experiments are performed by all subjects carrying an iPhone 6 (iOS 10.2 or iOS 10.3.3) and an iPhone 7 (iOS 10.3.1). Besides this, two subjects performed additional experiments carrying an iPhone 8 (iOS 11.1.2). Before experimentation, it was verified that location services were enabled on the iPhones. The iPhone Health App offers the possibility to enter biometric data of the user. During the main series of experiments, biometric data was <u>not</u> set in the Health App user interface.

### *Experimental protocol*

In this study we focus on number of steps and distances registered by the telephones and we will not address information registered on the number of floors climbed. In order to assess accuracy of the former two, walking and running experiments are performed along a well-defined route on the site of NFI. The length of this route is measured with specialist equipment (Leica Viva CS15, Leica Geosystems, St. Gallen, Switzerland) with an accuracy of 1–2 cm. On the route there are a number of clear landmarks, which have been used to define three walking distances of 91.52 m, 247.12 m and 450.93 m. During experiments, the subjects carried telephones in the following locations (see Fig. 1): trouser pocket (male: front pocket, female: back pocket), jacket pockets (both at chest height and low side pockets), backpack and hand. During experimentation, the subject travels the three distances both in walking pace as well as in a freely chosen moderate running pace while carrying one or more telephones in one of the specified carrying locations.

Each subject performed a complete series of experiments, which means that for all five carrying locations of iPhone 6 and iPhone 7, each of the three distances were traveled at least two times in walking speed and at least two times in running speed. Additionally, a shortened protocol was carried out by all subjects in order to evaluate the influence of setting biometric parameters such as length and weight of the subject, in the Health App on registered distances. The biometric parameters were set through the Health App user interface for each subject individually. Next, a reduced set of walking and running experiments was performed, carrying the telephones on the specified carrying locations. Finally, as mentioned, two subjects performed a complete series of experiments carrying an iPhone 8 and a shortened series in which biometric parameters were set in the iPhone 8 Health App.

For each trial, which is one specific combination of walking distance, walking speed and carrying location of the telephone, the number of steps taken by the subject was manually recorded using a tally counter, both by the subject and the experimenter. To allow

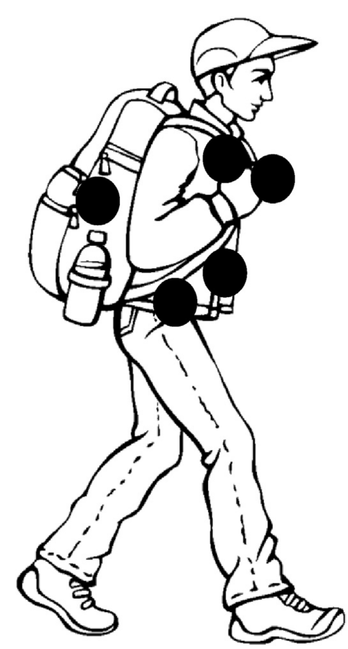

**Fig. 1.** Locations where iPhones are carried during experiments. Indicated positions are trouser pocket (male: front pocket, female: back pocket), jacket pockets (both at chest height and low side pockets), backpack and hand.

for subsequent identification of trials in data collected from the telephone, start and end time of each trial were recorded using a calibrated watch. Between trials, the subject took a pause to allow the telephone to store the data from the last trial. It was checked manually through the Health App user interface whether data was already written. For each subject data was collected during multiple sessions spread over several days.

### *Data collection and processing*

After each measurement session the telephones are imaged using commercial equipment (UFED PA, Cellebrite, Petach Tikwa, Israël) and the database healthdb_secure.sqlite, containing Health App data, is exported. Data containing the number of steps and distances is extracted from different tables in healthdb_secure.sqlite using standard SQL-commands. Next, the total number of registered steps and total registered distance is computed for each trial. In order to do so, all data registrations within the manually recorded start and end time for the trial are summed up together.

## Results

### *Structure of data in healthdb_secure.sqlite*

The format in which the iPhone Health App stores its data in the file healthdb_secure.sqlite has been described in detail by others (see e.g. Edwards, 2016). In short, data on number of steps taken, distances and floors are stored in two separate tables: samples and quantity_samples. The table samples contains the two timestamps start_date and end_date in Mac absolute time (number of seconds since 1 January 2001), as well as a code in the column data_type, indicating the type of value being stored (i.e. steps = 7, distances = 8, floors climbed = 12). The actual value corresponding to the time interval is stored in the column quantity in the table quantity_samples. Fig. 2 shows an example of data present in healthdb_secure.sqlite.

The time intervals in which data is stored in the database varies between different types of iPhones. During the experiments it was found that both the iPhone 6 (iOS 10.2 and 10.3.3) and the iPhone 7 (iOS 10.3.1) store data on number of steps and distances in relatively short time intervals. For the two iPhone 6 devices, the most frequent interval was 70 s while for iPhone 7 the most frequent interval was approximately 60 s. This implies that when a trial takes more time than the time interval for data storage, the data for that trial will be stored in multiple entries in the database. It appears to be the case for both iPhone 6 and iPhone 7 that the length of the time intervals used for data storage is adapted dynamically. In cases of prolonged activity, it has been observed that these intervals can increase. For both iPhone 6 and iPhone 7 the maximum time interval in which data is stored amounts to 600 s.

For the iPhone 8, equipped with iOS 11.1.2, no definite preferred short time interval for data storage was found in our experiments. In most cases, data on number of steps and distances for a trial are stored as a single entry in the database.

### *Experimental results*

During the experiments, approximately 600 trials were run by the five subjects together. During these trials, more than 144.000 steps were manually counted using a tally counter and a total distance in access of 130 km was traveled by the subjects.

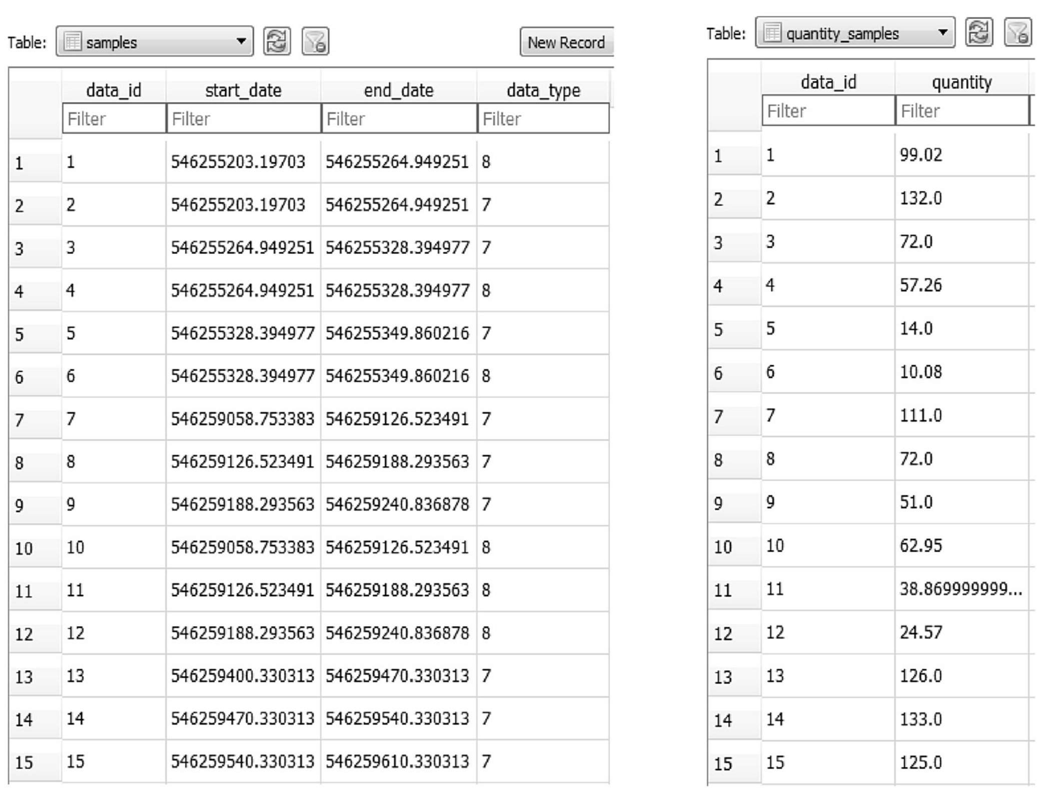

Table: samples New Record

| | data_id | start_date | end_date | data_type |
|---|---|---|---|---|
| | Filter | Filter | Filter | Filter |
| 1 | 1 | 546255203.19703 | 546255264.949251 | 8 |
| 2 | 2 | 546255203.19703 | 546255264.949251 | 7 |
| 3 | 3 | 546255264.949251 | 546255328.394977 | 7 |
| 4 | 4 | 546255264.949251 | 546255328.394977 | 8 |
| 5 | 5 | 546255328.394977 | 546255349.860216 | 7 |
| 6 | 6 | 546255328.394977 | 546255349.860216 | 8 |
| 7 | 7 | 546259058.753383 | 546259126.523491 | 7 |
| 8 | 8 | 546259126.523491 | 546259188.293563 | 7 |
| 9 | 9 | 546259188.293563 | 546259240.836878 | 7 |
| 10 | 10 | 546259058.753383 | 546259126.523491 | 8 |
| 11 | 11 | 546259126.523491 | 546259188.293563 | 8 |
| 12 | 12 | 546259188.293563 | 546259240.836878 | 8 |
| 13 | 13 | 546259400.330313 | 546259470.330313 | 7 |
| 14 | 14 | 546259470.330313 | 546259540.330313 | 7 |
| 15 | 15 | 546259540.330313 | 546259610.330313 | 7 |

Table: quantity_samples

| | data_id | quantity |
|---|---|---|
| | Filter | Filter |
| 1 | 1 | 99.02 |
| 2 | 2 | 132.0 |
| 3 | 3 | 72.0 |
| 4 | 4 | 57.26 |
| 5 | 5 | 14.0 |
| 6 | 6 | 10.08 |
| 7 | 7 | 111.0 |
| 8 | 8 | 72.0 |
| 9 | 9 | 51.0 |
| 10 | 10 | 62.95 |
| 11 | 11 | 38.869999999... |
| 12 | 12 | 24.57 |
| 13 | 13 | 126.0 |
| 14 | 14 | 133.0 |
| 15 | 15 | 125.0 |

**Fig. 2.** Example of the content of the database healthdb_secure.sqlite from an iPhone 6. Shown are the content of the table samples and quantity_samples. Note that for each time period, there are two registrations in the database: one for number of steps and one for distance travelled (see, for instance, rows 1 and 2, which have the same timestamps). For sample SQL queries to extract data from healthdb_secure.sqlite, see Edwards (2016). For explanation, see main text.

### Accuracy of number of steps registered by telephones

Fig. 3 shows data on number of steps pooled together for all subjects, distances travelled, walking speeds and carrying locations for the three iPhones investigated in this study. From Fig. 3, it is apparent that there is a close relationship between the number of manually measured steps and the number of steps registered by the telephones, apart from a few occasional outliers. We quantified the accuracy of the number of steps registered by the telephones by computing for each trial the Absolute Percentage Error (APE). APE is the deviation between measured and registered number of steps as a percentage of the measured number of steps. Then, the overall accuracy is calculated by averaging the APE over all trials, giving the Mean Absolute Percentage Error (MAPE). Table 1 shows results of statistical analysis of accuracy of registered steps. The MAPE found for the accuracy of steps registered by all iPhones in this study are similar to those reported by Höchsmann et al. (2018) for an iPhone SE and those by Duncan et al. (2018) for a broad collection of iPhones.

The data from Table 1 further confirm the results shown in Fig. 3, that all three iPhone are accurate devices in registering the number of steps over a wide range of number of steps, walking speeds and carrying locations.

### Accuracy of distances registered by the telephones

For distances registered by the telephones, the situation is somewhat more complicated than for registered number of steps. Registered distances are found to depend on carrying location of telephone, walking speed and (walking style of) the subjects. Therefore, in case of distances, results will be shown broken down by each of these categories. Fig. 4 gives an overview of averaged values of distances registered by iPhone 7 for each carrying location of the telephone. Similar results were obtained for the other two iPhones (see online supplementary material).

From Fig. 4, it can be seen that:

- There is significant variation in the distances registered by iPhone 7 with respect to the true distance.
- In the majority of walking trials, the averaged distance registered by iPhone 7 is lower than the real distance.
- There can be significant differences in registered distances between subjects for the same carrying location and walking speed. In some cases, the registered distance is larger in walking than in running, while for other subjects it is the other way round (see e.g. jacket pocket (chest)). We attribute this to differences in walking style between subjects.
- One subject shows much larger registered distances in running when holding the telephone in the hand. We attribute this also to the walking style of this subject, who strongly increased arm movements while running.
- When carried in trouser pockets, the telephone registers for all subjects a larger distance in running a given distance than during walking the same distance. We attribute this to increased forward-backward movement of the telephone (see next Section).

As in Section *Accuracy of number of steps registered by telephones*, the MAPE has been computed in order to quantitatively estimate the iPhone's accuracy in registering distances. Table 2 contains MAPEs of distances registered by iPhone 7 pertaining to the averaged data shown in Fig. 4. From Table 2, it can be observed that the MAPE can be as high as 30–40%. It is important to note that for a given subject, carrying location and walking speed, MAPE is almost the same for the three distances traveled. This result implies that the percentage error in registered distances does not depend on the

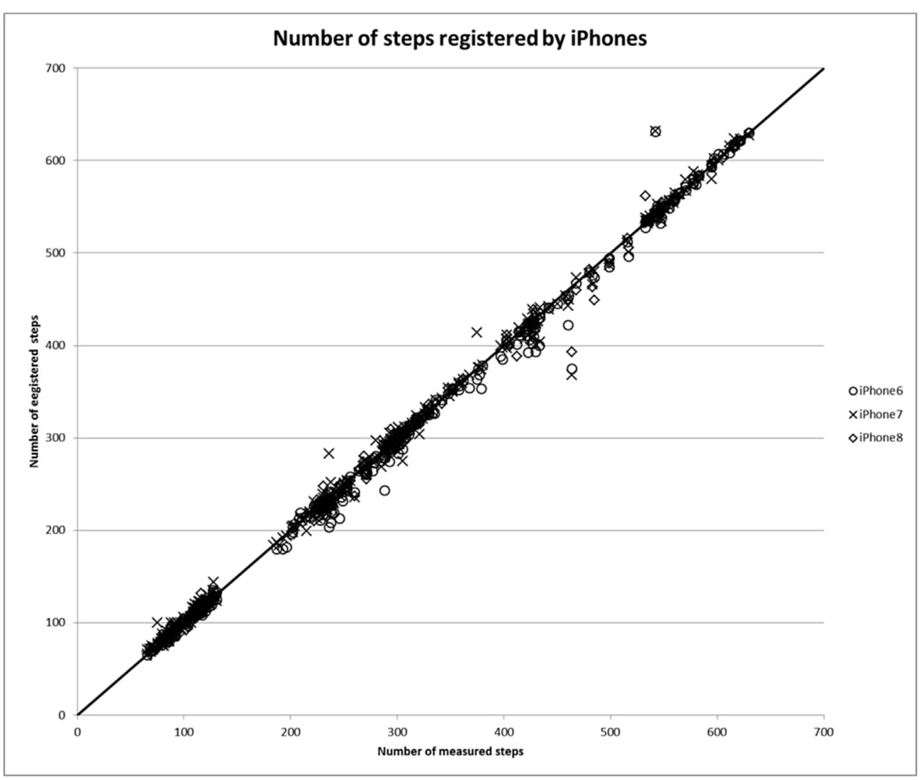


**Fig. 3.** Comparison of manually measured number of steps and number of steps registered by the telephone for all subjects, distances, walking speeds and carrying locations pooled together. The solid line indicates the situation that manually measured number of steps equals the number of steps registered by the telephone.

**Table 1**
Statistical analysis of accuracy of number of steps registered by the telephones. For each telephone, shown are the mean absolute percentage error (MAPE), obtained by averaging APEs over all trials, the percentage of trials having an APE < 10% and the largest value for APE encountered for that telephone.

| Telephone | Number of trials | MAPE | Percentage of trials having an APE <10% | Largest value for APE |
|---|---|---|---|---|
| iPhone 6 | 425 | 1.86% | 98.5% | 19% |
| iPhone 7 | 402 | 1.99% | 97.5% | 33% |
| iPhone 8 | 149 | 2.27% | 95.9% | 15% |

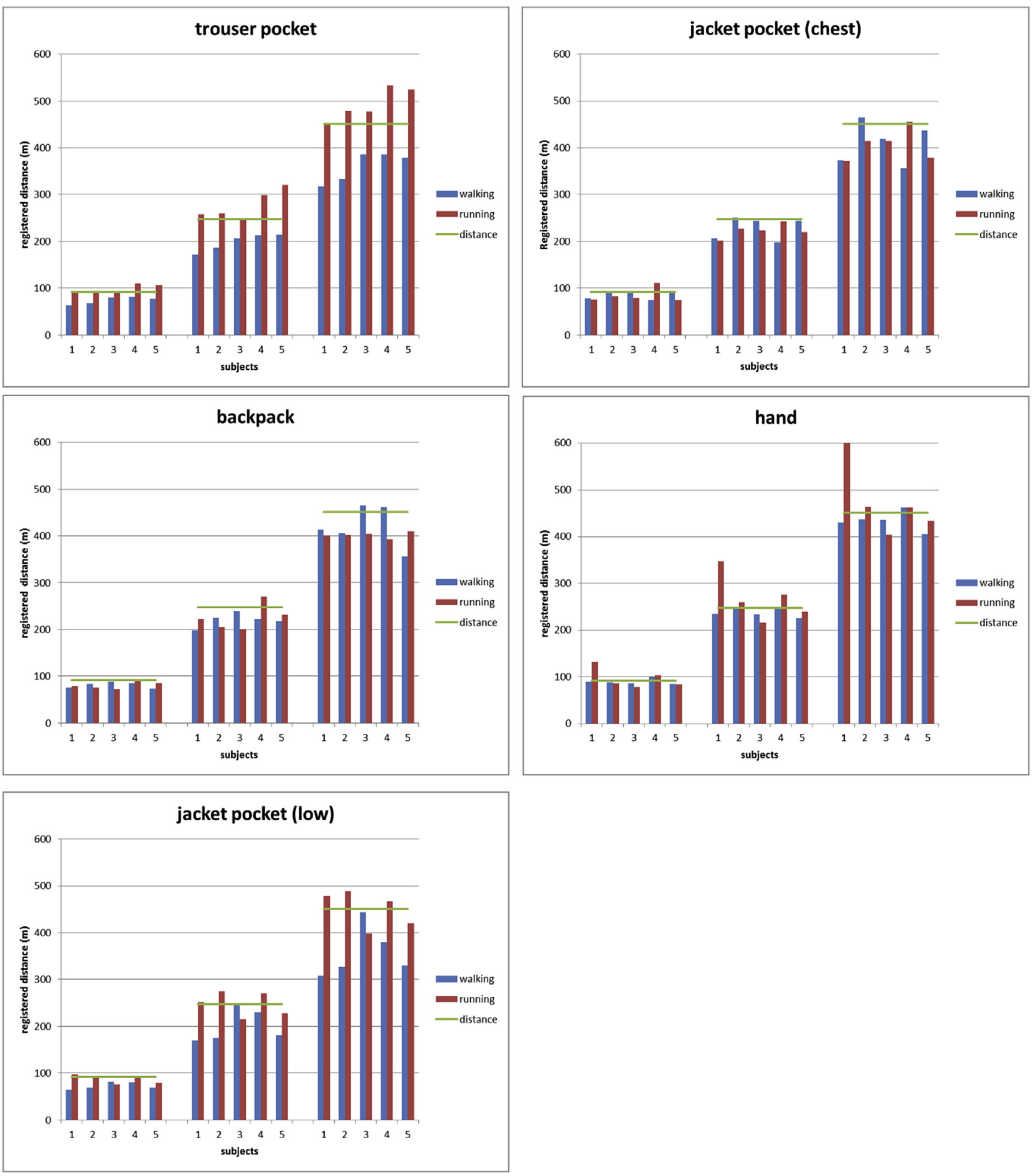


**Fig. 4.** Averaged values of distances registered by iPhone 7 during walking and running of three different distances for all five carrying locations specified in Fig. 1. In each graph, the real distance (i.e. 91.52 m, 247.12 m and 450.93 m) is indicated by the green line.

**Table 2**
Mean absolute percentage errors (MAPE) for distances registered by iPhone 7, broken down by subject, carrying location, walking speed and distance. MAPE is expressed as percentage of the true distance. Blue entries indicate that all registered distances are too low and their MAPE is >10%. Similarly, yellow entries indicate that all registered distances are too high and their MAPE is >10%.

| | | Walking | | | Running | | |
|---|---|---|---|---|---|---|---|
| Location | Subject | 91.52 m | 247.12 m | 450.93 m | 91.52 m | 247.12 m | 450.93 m |
| Trouser pocket | 1 | 30.92 | 30.33 | 29.80 | 10.86 | 6.13 | 6.08 |
| | 2 | 25.63 | 24.49 | 26.15 | 3.41 | 5.39 | 6.19 |
| | 3 | 11.71 | 16.70 | 14.53 | 1.96 | 2.94 | 5.93 |
| | 4 | 11.17 | 14.02 | 14.51 | 20.87 | 21.15 | 18.32 |
| | 5 | 15.40 | 13.17 | 16.02 | 16.22 | 29.55 | 16.12 |
| Jacket pocket (chest) | 1 | 14.64 | 16.70 | 17.27 | 17.42 | 18.18 | 17.59 |
| | 2 | 5.71 | 2.52 | 3.00 | 10.13 | 8.35 | 8.17 |
| | 3 | 1.82 | 2.36 | 7.06 | 13.18 | 9.70 | 8.03 |
| | 4 | 18.34 | 19.90 | 20.95 | 21.60 | 4.68 | 1.04 |
| | 5 | 2.06 | 1.52 | 3.05 | 18.80 | 11.12 | 16.05 |
| Backpack | 1 | 17.60 | 19.87 | 8.37 | 13.06 | 10.31 | 11.11 |
| | 2 | 10.13 | 9.09 | 10.15 | 17.20 | 17.16 | 10.99 |
| | 3 | 5.75 | 4.38 | 3.07 | 21.24 | 18.98 | 10.45 |
| | 4 | 15.29 | 12.76 | 2.68 | 5.32 | 14.22 | 13.00 |
| | 5 | 19.53 | 11.74 | 20.98 | 9.36 | 6.49 | 9.05 |
| Hand | 1 | 3.55 | 5.03 | 4.56 | 43.66 | 40.20 | 33.16 |
| | 2 | 3.70 | 1.71 | 3.16 | 6.32 | 5.28 | 2.74 |
| | 3 | 6.29 | 5.56 | 3.40 | 15.14 | 12.60 | 10.37 |
| | 4 | 8.53 | 9.31 | 2.46 | 13.38 | 11.77 | 2.47 |
| | 5 | 7.60 | 8.58 | 10.02 | 8.12 | 2.95 | 3.75 |
| Jacket pocket (low) | 1 | 29.72 | 31.45 | 31.81 | 5.97 | 1.83 | 6.02 |
| | 2 | 25.00 | 29.08 | 27.43 | 2.82 | 11.43 | 8.43 |
| | 3 | 10.65 | 0.36 | 3.44 | 17.15 | 12.88 | 11.61 |
| | 4 | 12.02 | 8.84 | 15.64 | 0.74 | 9.47 | 3.61 |
| | 5 | 25.07 | 26.72 | 26.85 | 13.63 | 7.94 | 6.73 |

distance travelled. Finally, as can be seen from Table 2 and Fig. 4, in the experiments iPhone 7 more often registered a distance which is too low than a distance which is too high. Similar results were obtained for the accuracy of the other two telephones in registering distances (see online supplementary material).

### *Influence of forward-backward movement of telephone on registered distances*

In order to understand the results shown in Fig. 4, a hypothesis was formulated that the telephones tend to register a larger distance when they perform a larger forward-backward movement during locomotion. This seems to be consistent with the data presented in Fig. 4, since it explains the increased distances registered during running when carrying the telephone in the trouser pocket and for subject 1 during running while carrying the telephone in the hand.

In order to verify this hypothesis, a series of additional experiments was performed by all subjects. In these experiments, the subjects held the telephone in the hand and performed walking and running trials. Whereas in the main experiments no instructions were given concerning arm movement, the subject was now asked to first perform a single walking and running trial while keeping arms as motionless as possible. Secondly, the subject was instructed to perform a single walking and running trial with exaggerated swinging arm movements, leading to a marching style movement. Fig. 5 shows for iPhone 7 distances registered during the single trials with these two types of special arm movements as compared to averaged distances registered during normal arm movements. For the other two telephones, similar results were obtained as for the iPhone 7. From Fig. 5 it is apparent that exaggerated arm swinging unequivocally leads to higher registered distances, whereas keeping the arms still leads to the same or, in case of running, to a lower registered distance. Therefore, based on the results of these experiments it seems to be the case that the forward-backward movement of the telephone is at least a significant factor contributing to the distances registered by the telephone.

### *Influence of setting biometric information in Health App on registered distances*

After setting length and weight of the subject in the iPhone Health App, subjects performed for each carrying location of the telephones two walking and running trials for the distance of 91.52 m and two walking trials for 247.12 m. Next, averaged values of the distances registered by the telephones were compared to averaged values from trials with no biometric data. For this, the average of the registered distance with biometry set is expressed as a percentage of the average registered distance with no biometry set. Table 3 shows values of these percentages, averaged over subjects and the two distances travelled.

From the admittedly limited data in Table 2, there appears to be a slight trend in which the setting of biometric data in the iPhone Health App leads to a small increase in registered distances of the order of 5–10%

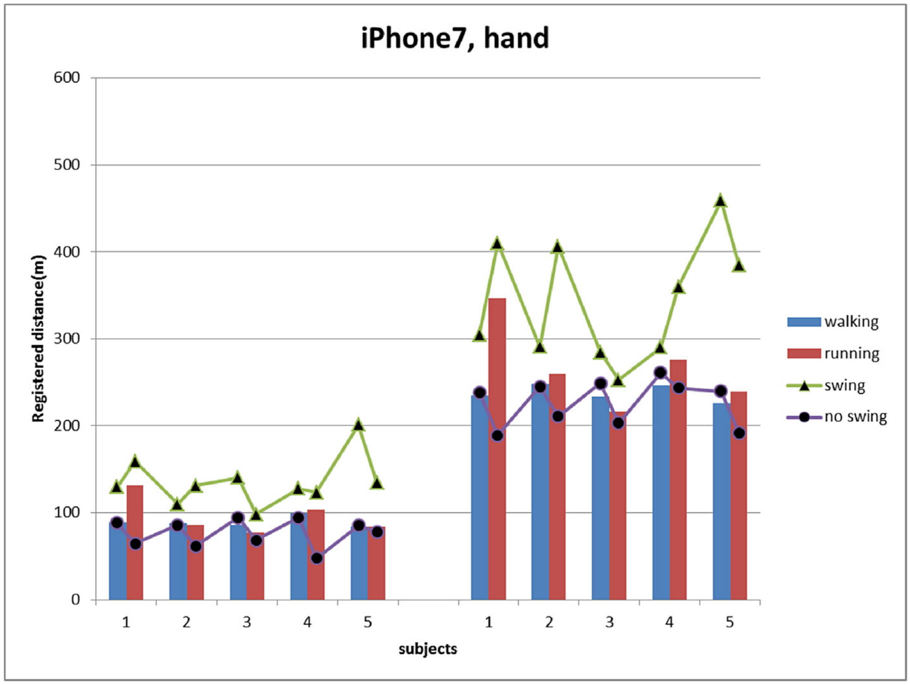


**Fig. 5.** Influence of forward-backward movement of the telephone on registered distances. Shown are averaged values of registered distances for trials with no instructions on arm movement (blue and red bars) for walking distances of 91.52 and 247.12 m (same data is in Fig. 4). Triangles and dots pertain for each subject to registered distances from a single trial with respectively exaggerated arm swinging and minimal arm swinging.

**Table 3**
Influence of setting biometric parameters on distances registered by the telephones. Shown are ratios of averaged distances registered with biometric data set as a percentage of those with no biometric data set. Data in the table are averaged over subjects and the two distances travelled (91.52 m and 247.12 m).

| Location | iPhone 6 | | iPhone 7 | | iPhone 8 | |
|---|---|---|---|---|---|---|
| | Walking | Running | Walking | Running | Walking | Running |
| Trouser pocket | 93% | 95% | 101% | 103% | 104% | 102% |
| Jacket pocket (chest) | 110% | 113% | 116% | 103% | 116% | 119% |
| Backpack | 109% | 101% | 109% | 102% | 97% | 107% |
| Hand | 105% | 96% | 105% | 104% | 105% | 102% |
| Jacket pocket (low) | 107% | 110% | 110% | 104% | 117% | 108% |

## Discussion and conclusions

In this study, we investigated the accuracy of number of steps and distances registered by Apple's Health App for an iPhone 6, iPhone 7 and iPhone 8 under various walking and running conditions. From the results presented in the Section *Experimental Results* we conclude that it is possible to use this data from the Health App for forensic purposes in cases where it is known (or assumed) that walking or running has taken place. It is important to note that the converse need not always be necessarily true: if steps or distances are registered by the Health App, this need not necessarily indicate that walking or running has taken place while carrying the telephone, since under specific conditions there might be false positive registrations in the Health App. For instance, initial research at NFI indicates that sometimes steps can be registered when driving in a car over speed bumps.

In using data from the Health App one has to be aware that the registered number of steps is much more accurate than the registered distances. This fact has, for instance, implications when making probability statements about different routes and scenario's, given the digital traces found in healthdb_secure.sqlite. Without prior knowledge of walking speed and carrying location, the likelihood of the digital traces might be the same if the lengths of the two routes under consideration are not too different. On the other hand, when the two distances differ considerably in length, meaningful probability statements can be formulated.

Furthermore, one needs to be aware of the fact that data in the Section *Experimental Results* is collected in a controlled experimental setting and that the accuracy of data collected by the iPhone Health App might be different during activities of daily living, where, for instance, walking speed is continuously changing. It is stated in Duncan et al. (2018) that accuracy of Health App step counts in free living condition is much less than in controlled lab situations. In that paper, iPhone step counts for the free living condition were compared against step counts produced by a commercial accelerometer, the accuracy of which during activities of daily living was not discussed. In the paper, decreased Health App step count accuracy is partially attributed to subject behaviour, such as not always carrying the iPhone during short walking breaks. Therefore, it remains to be seen to what extent activities of daily living affect the accuracy of number of steps and distances registered by the iPhone Health App. In cases where it is known that a significant amount of walking has taken place, however, it seems justified to use the results from this study.

As noted before, it remains an intriguing question how the number of steps and distances are determined by the Health App software. Research into the Health App itself at NFI indicates that geolocation APIs are not utilized by the Health App during locomotion, which would then most likely only leave accelerometer and gyroscope sensor data as the source for computing number of steps and distances. Data from the Section *Experimental Results* suggest that the Health App computes distances by multiplying number of steps by a (dynamic) estimate of stride length. Results from the Section *Accuracy of number of steps registered by telephones* indicate that the Health App software does an efficient job in determining number of steps. This is conceivable because every time the foot strikes the ground, a peak in the acceleration sensor signal will occur, which can easily be detected automatically. Computing stride length from acceleration data, however, seems a more difficult task. One obvious way to do this would be to estimate it from acceleration data in the line of movement (i.e. the forward-backward direction), for instance by double time integration. This in turn would imply that larger forward-backward accelerations lead to larger estimated stride lengths and, hence, larger registered distances, which would explain the findings from the Section *Accuracy of distances registered by the telephones*. Of course, it will require more research and more detailed analysis of the Health App software to further test this hypothesis.

The research presented in this paper can be seen as a first step of using health based applications for forensic purposes. We have shown that data from the iPhone Health App indeed can have evidential value, provided that one takes into account the peculiarities associated with registrations from this App. There are, of course, numerous possibilities for further research in this area. On one hand, the accuracy of other popular devices and applications, such as Fitbit and Samsung Shealth, can be investigated. On the other hand, it might be of value to investigate under which conditions, such as riding a bicycle or travelling by car, steps and distances are registered by health based applications.

## Acknowledgements

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.diin.2019.01.021.

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