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Continuous Gait Velocity Analysis using Ambient Sensors in a Smart Home

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Abstract. We present a method for measuring gait velocity using data from an existing ambient sensor network. Gait velocity is an important predictor of fall risk and functional health. In contrast to other approaches that use specific sensors or sensor configurations our method imposes no constraints on the elderly. We studied different probabilistic models for the description of the sensor patterns. Experiments are carried out on 15 months of data and include repeated assessments from an occupational therapist. We showed that the measured gait velocities correlate with these assessments.

Keywords: Ambient Assisted Living (AAL), gait, Smart homes

1 Introduction

With the increasing number of older adults that live independently in their own homes, sensing systems that monitor someone's health are becoming popular. A wide range of sensor systems exists, often aimed at specific applications such as sleep monitoring or medicine intake monitoring. For more general lifestyle monitoring, ambient sensor networks consisting of motion and switch sensors mounted in the environment have been presented. In this paper, we focus on measuring gait velocity (walking speed) of elderly with such systems. Gait velocity is an important predictor of functional health; it is shown that it predicts the risk of falls [11,14], but also of hospitalization and survival [17]. For that reason, gait velocity is an important measure in comprehensive geriatric assessment in clinical settings.

The disadvantage of the clinical assessments is that the tests are usually carried out over a short period of time in an unnatural setting. In long term studies, regular measurements by a therapist are time consuming and therefore expensive. The measurements may also be subjective to the therapist taking the tests.

Continuous domestic monitoring may provide a clearer and more objective picture of a person's mobility. Systems have been presented that suggest specific sensors in the home such as RGB-D cameras, radar sensors [20], motion sensors placed in an array [10], or use wearable sensors such as accelerometers [13].

We developed a system for measuring gait velocity from an existing ambient sensor network. Because the elderly are not instructed to follow predefined paths, the variations in walking patterns will be large. The contributions of this paper are: (1) we propose a method for automatically identifying useful paths for speed estimation, (2) we show that unconstrained daily activities result in non-trivial distributions over path durations and propose a model to deal with those (3) we investigate whether long paths or short paths provide a more consistent measurement of walking speed. Finally, we compared the results with measurements from an occupational therapist over a period of 15 months.

2 Related Work

Approaches for continuous walking speed assessment for elderly use either *wearable* sensors or *ambient* sensors. A review of wearable sensors for gait analysis is given in [18]. Apart from velocity, other characteristics of the gait may be measured such as under-foot pressure (the GaitShoe [2], the Smart Insole [21] and the In-Shoe device [5]) and rotation of the foot, that can be measured with gyroscopes. Pedometers are suitable for a long-term measurement of the physical activity. However, the accuracy of these pedometers is dependent of the implemented algorithm to count the steps. Furthermore, pedometers significantly underestimate the gait velocity of older adults [4]. The disadvantage of using wearable sensors in general for gate analysis is that the subject must not forget to wear the device and has to recharge it regularly. The acceptance of wearable sensor applications for long term monitoring is therefore low. Ambient pressure sensors can be used to build large sensor mats for the analysis of gait. GAITRite® is a portable electronic walkway of $0.89m$ wide and between 5 and $8m$ long where pressure sensors are embedded in a grid. This system is frequently used for clinical and research purposes [3,19]. Imaging devices such as the Microsoft Kinect have been presented to evaluate the gait [16]. The advantage of using the depth RGB-D is the ability to capture different parameters of gait such as walking speed, stride time and stride length. The disadvantages are, however, privacy related although only a silhouette of the subject is captured. An unobtrusive way for the continuous measurement of gait velocity is using motion sensors. A specific lay-out of motion sensors was used in [8], who mounted four motion sensors with a restricted view to $\pm 4°$ in a line on the ceiling of a hallway with approximately $61cm$ distance between them. The assumption of this method is that a long and narrow hallway is available to enforce the subject to walk in a line. This is not always the case in elderly apartments.

[7] introduced a fully automated approach to calculate the Timed Up and Go (TUG), including the walking speed, using ambient sensors. These sensors consisting of force, light barriers and a Laser Range Scanner are incorporated in a chair to measure the walking direction and the speed. Both the GAITRite®

and the TUG-chair are suitable for periodic instrumented clinical tests, but the systems are expensive for continuous gait monitoring.

3 Sensor Data

We have continuously collected data, in several ambient assisted living apartments, for more than a year. The sensor networks used to collect data use the Z-Wave protocol and consist of off-the-shelf binary sensors that measure motion, pressure on the bed, toilet flush and the opening and closing of cabinets and doors. An overview of the location of the sensors in the apartment of one resident is shown in Figure 1. The elderly are living their routine life and are not told to modify their behaviour in any way. The location of the sensors is chosen so that all the important rooms in the apartment are covered and so that the network does not affect the elderly's daily life. For instance, the pressure sensor for the bed is installed under the mattress and sensors in the kitchen are installed above the stove, under the freezer, etc. A list of the all the sensors installed in the apartement of volunteer A is shown in Table 1.

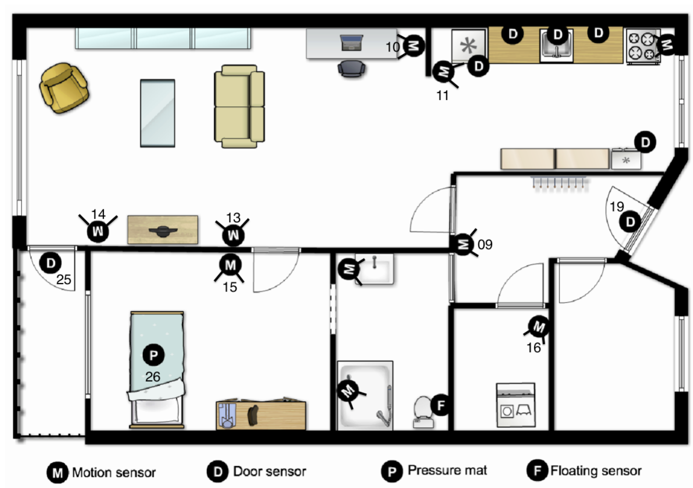


Fig. 1. A map of the apartment of volunteer A equipped with a wireless sensor network. Both apartments have the same basic size and layout. The number of used sensors, their types and their positions were kept as similar as possible between the two apartments.

4 Approach

To calculate the gait velocity, we collect the walking paths of the resident in his home during a period of time (*e.g.* week). We represent these walking paths by

Id	Sensor name	Sensor type	Room (number)
09	Hall	Motion	Hall (3)
10	Desk	Motion	Living room (6)
11	Kitchen	Motion	Kitchen (4)
12	Kitchen hob	Motion	Kitchen (4)
13	Living front	Motion	Living room (6)
14	Living back	Motion	Living room (6)
15	Bedroom	Motion	Bedroom (2)
16	Laundry	Motion	Laundry room (5)
17	Washbasin	Motion	Bathroom (1)
18	Shower	Motion	Bathroom (1)
19	Front Door	Door	Hall (3)
20	Freezer	Door	Kitchen (4)
21	Fridge	Door	Kitchen (4)
22	Cupboard1	Door	Kitchen (4)
23	Cupboard2	Door	Kitchen (4)
24	Cupboard3	Door	Kitchen (4)
25	Balcony	Door	Living room (6)
26	Bed	Pressure	Bedroom (2)
27	Toilet	Floating	Bathroom (1)

Table 1. A list of the sensors (id, name, type and room) installed in the apartment of Volunteer A, as shown in Figure 1. Cupboard1 contains coffee/tea items, cupboard2 contains spices and cupboard3 contains dinner dishes

trajectories in a graph where the nodes represent sensors and the edges represent the distances between them, and calculate the corresponding durations. For each collected trajectory, the gait velocity is then equal to the length of the trajectory divided by its mean duration. To deal with the non-Gaussian noise in the data, we fit a probabilistic model to the durations and obtain the mean duration as an estimated parameter of the model. Before describing our approach in detail, we next describe the challenges involved.

4.1 Challenges

In instrumental tests, both the walking path and its duration are known. As the subject is instructed to walk without stopping, the gait velocity is therefore easy to compute. The calculation of the walking speed from ambient sensor data used for continuous monitoring is more challenging:

- The walking path is neither fixed nor precisely known, as the resident is not instructed to follow a specific walking path.
- The walking paths of the resident do not necessary follow straight lines.
- It is unknown if the resident's walking paths are interwoven with some other activity or not.
- Motion sensors do not provide us with accurate locations, and to save their batteries the sensors do not transmit every detection they make. The start

time and location and the end time and location of the walking path are, therefore, not known precisely due to the nature of the sensors.

- There is more variation in the walking paths and speeds in natural conditions than during a controlled test.

4.2 Features

When the resident performs his activities of daily living during a period of time, the binary sensors generate a continuous stream of sensor-events. A sensor event $e_n = (t_n, s_n)$ is defined as a tuple consisting of the time stamp t_n of the sensor signal (ON or OFF) and the identity of the sensor that fired that signal, $s_n \in \{s_1, s_2, \ldots, s_{|S|}\}$. [3] The sequence of N sensor-events collected during some period of time can be represented as $e =< e_1, e_2, \ldots, e_N >$. The OFF-signals of the motion sensor correspond to the end of the sleep-time of the sensor. These OFF-signals are ignored as they do not necessarily correspond to the end of the movement of the resident. For the same reason, the OFF-signal of the float sensor is filtered out as this signal indicates the end of filling up the toilet water tank. Furthermore, if more than two consecutive sensor events come from the same sensor, only the first and last event are taken into account. The reason is that many consecutive events of a sensor usually do not correspond to a displacement of the resident, and we cannot associate any walking distance with them. For example, consecutive events of the bed sensor mean that the resident is changing his posture. Finally, the sensor events corresponding to visits to the resident are automatically detected and excluded from the data under consideration [12]. The method used, Markov Modulated Multidimensional non-homogeneous Poisson Process (M3P2), is an extension of the Markov Modulated Poisson Process (MMPP) to allow the incorporation of multiple feature streams. The periodic portion of these features is modeled using a non-homogeneous Poisson process, while the visits are modeled using a hidden state that varies according a Markov process.

To estimate gait velocity, we rely on sensor transitions $\tau_{ij}^{(n)}$ and their associated duration d_n. Let a transition between sensors i and j be a pair of consecutive sensor events e_n and e_{n+1}, where $s_n = i$ and $s_{n+1} = j$. The time stamp of the transition is chosen to be t_n and its duration is defined as $d_n = t_{n+1} - t_n$.

4.3 Model

We represent the walking paths of the resident in his home by trajectories in a graph. Figure 2 shows a graph of all possible walking paths of volunteer A. The node identities in this figure correspond to the sensors shown in Figure 1. The sensor ids, indicating the location of the resident, are used as nodes and the sensor-transitions, indicating the movement of the resident, are used as edges.

[3] The actual value of the event is not relevant to our purposes: we are interested in the knowledge that the resident is present at a certain location, not in their activity.

As example, a trajectory corresponding to sensor sequence $< 15, 27, 17 >$ consists of three nodes and two edges. This trajectory represents the walking path 'bedroom-toilet-washbasin' resulted from a toileting activity.

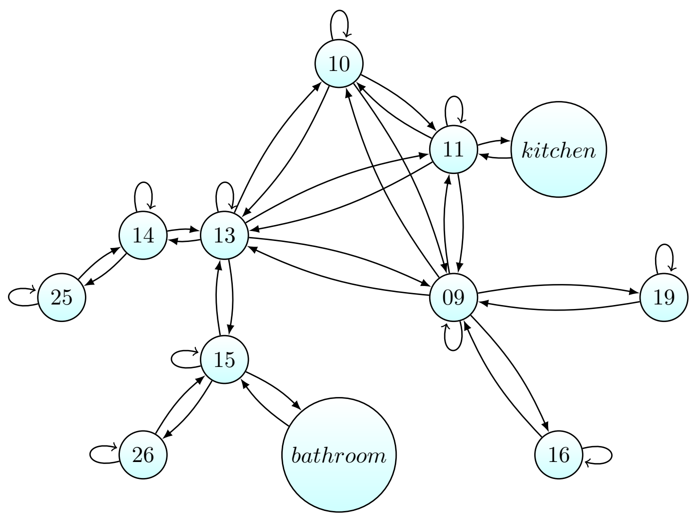


Fig. 2. A graph indicating the sensors that are topologically connected to each other. The node ids correspond to the sensor ids depicted in Figure 1. The node kitchen (resp. bathroom) consists of six (resp three) sensors that are topologically connected to each other. These sensors are omitted to keep the overview of the graph clear

The mathematical representation of the graph is $G = (V, E)$ where $V = \{s_1, s_2, \cdots, s_{|V|}\}$ and $E = \{(i, j)|\ i \text{ is topologically connected to } j\}$. To calculate the average gait velocity in a period of time, we assume that the average duration of typical paths in the house is representative of the person's gait velocity. For the calculation of the duration of the walking paths, we follow the approach:

1. We define a set of rules to create automatically extract valid walking paths (trajectories) from the sensor data and calculate the duration of the collected trajectories
2. Construct a model consisting of some (mixture of) probability distributions(s) to fit these durations (data points).
3. From this model, we extract the mean duration of each path and compute the corresponding walking speed.

Identification of valid trajectories: Given a sequence of sensor events $< e_1, e_2, \ldots, e_N >$ collected during a period of time T (*e.g.* a week), we need to identify subsequences that correspond to actual walking. We do this by cutting this sequence at edge $(n, n+1)$ if its duration $d_n = t_{n+1} - t_n$ is larger than some threshold τ. Cutting the sequence at $(n, n+1)$ means that one walking path ends with event e_n and a new path starts with event e_{n+1}. The variable τ correspond to a 'rest moment' of the resident. This cutting action results in K sensor sequence segments. Some segments correspond to the movement of the subject in the same room and are therefore not suitable for the calculation of the gait velocity. Other segments, on the other hand, correspond to long and complex activities. These activities may contain walking paths that are suitable for the calculation of the gait velocity. Therefore, two possibilities to extract valid potential walking trajectories from theses segments have been investigated:

1. Automatically detect all trajectories that involve at least two rooms to ensure that the collected trajectories correspond to a movement of the resident and not to some activity in a room. These trajectories are referred as *auto-detected* trajectories.
2. Search within the K segments for some predefined walking trajectories. These predefined walking trajectories are as long and straight as possible. The objective is to collect trajectories similar to the walking path used by the therapist to measure the gait velocity. They are selected by manually inspecting the map of the apartment of the older adult. These trajectories are referred as *predefined* trajectories.

For all the collected trajectories, both auto-detected and predefined, the corresponding duration is calculated.

Modelling the durations of the trajectories: The Poisson is a widely used distribution to model time durations and is the correct model to use if our collected sequences all correspond to the same physical walking path in the space. We therefore selected this distribution as a candidate model for the duration of the collected trajectories. Some trajectories may, however, sometimes be interwoven with another trajectory, in which case a mixture of Poisson distributions would be a more accurate model. Trajectories may also be interwoven with one or more activities, whose duration is not adequately modelled by a Poisson distribution. We therefore also selected a mixture of a Poisson and a Normal distribution as a candidate model.

In our experiments we evaluated the following set of three candidate models:

1. a Poisson distribution with parameter $\Theta_1 = \lambda$,
2. a mixture of two Poisson distributions with parameters $\Theta_2 = (\alpha, \lambda_1, \lambda_2)$,
3. a mixture of a Poisson and a Normal distribution $\Theta_3 = (\alpha, \lambda, \mu, \sigma)$.

The probability distribution function (PDF) of a Poisson and a Normal distribution are given in Equation 1 and Equation 2. The PDF of a mixture a Poisson and a Normal distribution is given in Equation 3. The PDF of the mixtures of two Poisson distributions can be obtained in the same way.

$$P(k) = \frac{\lambda^k}{k!} e^{-\lambda} \tag{1}$$

$$P(k) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(k-\mu)^2/2\sigma^2} \tag{2}$$

$$P(k) = \alpha \frac{\lambda^k}{k!} e^{-\lambda} + (1-\alpha) \frac{1}{\sigma\sqrt{2\pi}} e^{-(k-\mu)^2/2\sigma^2} \tag{3}$$

We estimated the parameters α, λ, λ_1, λ_2, μ, and σ maximizing the likelihood.

Calculate a goodness of fit function of the constructed distributions: After fitting the durations with different probability distributions, the goodness of fit is calculated using the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) metrics given by:

$$AIC = -2\log(\hat{L}) + 2\,K \tag{4}$$

$$BIC = -2\log(\hat{L}) + K\log(N) \tag{5}$$

In these equations, $\hat{L}$ represents the likelihood function of the model, K represents the number of parameters of the model and N is the number of observations. Both AIC [1] and BIC [15] metrics measure a penalised likelihood of the model. The penalty portion of AIC is only dependent of the number of the parameters of the model, while the penalty of the BIC is also dependent of the number of observations.

5 Experiments

5.1 Objectives

A set of three experiments is conducted to collect useful walking paths, to find the best model and to evaluate the resulting gait velocity. In the **first experiment**, we investigate the the effect of varying the duration of the rest time on the resulting trajectories, and find the optimal value of τ for our dataset. Our hypothesis is that small values of τ will result in the collection of few useful trajectories (*i.e.*, trajectories involving at least two rooms), while large values of τ result in long sensor trajectories corresponding to walking paths with too many interwoven activities. We seek for a value of τ that results in sufficient useful trajectories, so that we can estimate our model parameters accurately, and that does not result in too many trajectories with interwoven activities.

In the **second experiment**, we show that the duration of the collected trajectories cannot be modelled optimally with a simple, unimodal distribution. Our hypothesis consists of two parts: on one hand, we expect the most frequently *auto-detected* trajectories to be short (between rooms) and therefore should be fitted by one probability distribution as these trajectories correspond to walking paths without interwoven activities. On the other hand, the *predefined* trajectories are long and may correspond to walking paths with interwoven activities and therefore need to be fitted using a mixture of probability distributions.

In the **third experiment**, we compare the walking speed measured occasionally by the therapist with the gait velocity estimated from the sensor data. Our hypothesis is that the walking speed measured by the therapist is higher than the gait velocity estimated from the sensor data, because the residents tend to improve their behaviour as a response of being watched. We also expect the estimated gait velocity to correlate with the motor Assessment of Motor and Processing Skills (AMPS) measured by the therapist.

5.2 Sensor data and annotation

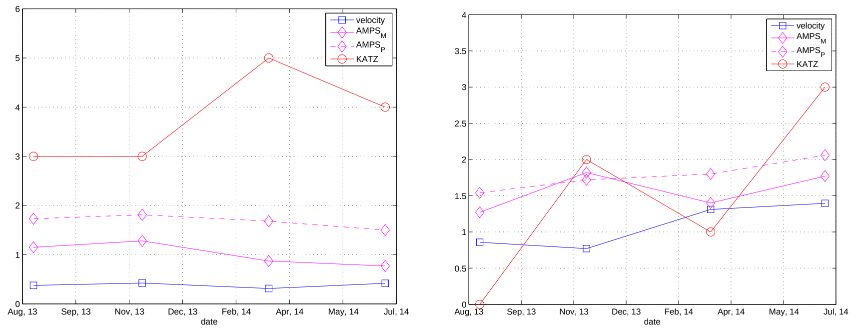
Two sensor datasets collected in our living labs are used to conduct the described experiments. The two sensor datasets are collected during 15 months between April 2013 and July 2014 in the apartment of two volunteers living alone. Volunteer A, a male of 84 years old, has difficulties with getting up from a chair and with walking. He occasionally walks in the apartment using a wheelchair as a support. Volunteer B, a female of 80 years old, has no difficulty with walking in her apartment. During this period, the two volunteers are visited by a therapist for the KATZ [9] and AMPS assessments [6]. The walking speed test taken over 3 meters is part of these assessments. The results of these assessments are given in Figure 3. The KATZ-score varies between a minimum value of 0, indicating the subject needs NO assistance, and a maximum value of 6 indicating the subject is dependent of assistance for performing the Activities of Daily Livings (ADLs). Two values of the AMPS, the motor part ($AMPS_M$) related to physical skills and the process part ($AMPS_P$) related to cognitive skills, are calculated from the assessment. A decrease of the AMPS indicate a decrease in the functional health of the subject.

The assessment scores show an approximately stable functional health of volunteer A during this period of 15 months. This may be concluded from the gait velocity and the AMPS scores, which show no significant increase or decrease. For volunteer B, however, the assessment scores show an increase of the gait velocity and of the process AMPS, indicating the subject's functional health is improving. On the other hand, the increasing of the KATZ score indicates the subject needs assistance for preforming her ADLs, which is conflicting with the improvement of her functional health. Her motor AMPS is stable during this period.

6 Results

6.1 Experiment 1: Effect of the rest time τ

For each subject, we collected sensor data around the dates the therapist conducted the KATZ and AMPS assessments. We ensured that the selected weeks do not lack any sensor data. This resulted in 9 weeks of sensor data around the 4 assessment dates given in Figure 3. From these 9 sequences of sensor readings, valid trajectories are extracted using the two proposed methods, *auto-detected* and *predefined* trajectories, as described in section 4.



(a) Volunteer A. (b) Volunteer B.

Fig. 3. Ground truth data consisting of the AMPS, KATZ and the gait velocity test over 3 m distance. The gait velocity (m/s) is repeated twice and the mean value is notated. An increase of the KATZ score $(\{0, 1, \ldots, 6\})$ indicates more need of assistance. A decrease of the AMPS $([-3, 4])$ indicates a decrease in the functional health. The exact assessment dates for both volunteers are '14-Aug-2013', '20-Nov-2013', '14-Mar-2014' and '27-Jun-2014'.

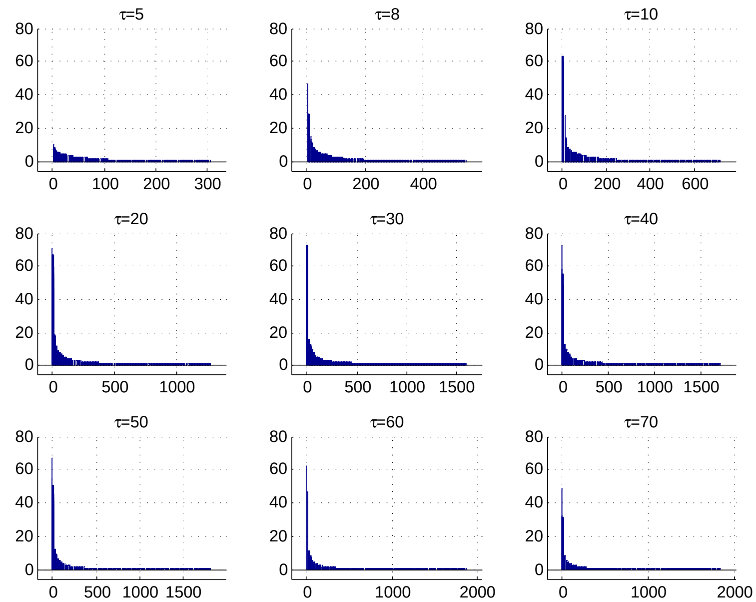
The frequency of the collected auto-detected trajectories as a function of the rest moment τ show that most auto-detected trajectories have a low frequency, which means that during a week, many unique trajectories are collected. For example, Figure 4(a) shows that for $\tau = 10$ more than 96% of the collected 713 trajectories have a frequency lower than 10. Comparable figures hold for the other values of $\tau \in \{5, 8, \ldots, 70\}$. The plot, given in 4(b), of the most frequently collected auto-detected trajectories (the peaks in the histograms) as a function of τ show that $\tau = 30$ gives us the largest number of auto-detected trajectories for which a good model fit can be expected.

Conducting the same experiment using the sensor data of volunteer A resulted in an 'optimal' value of $\tau = 60$ for collecting both auto-detected and predefined trajectories. Note that this higher values of τ for volunteer A compared to volunteer B correlates with the measured low walking speed of volunteer A compared to volunteer B.

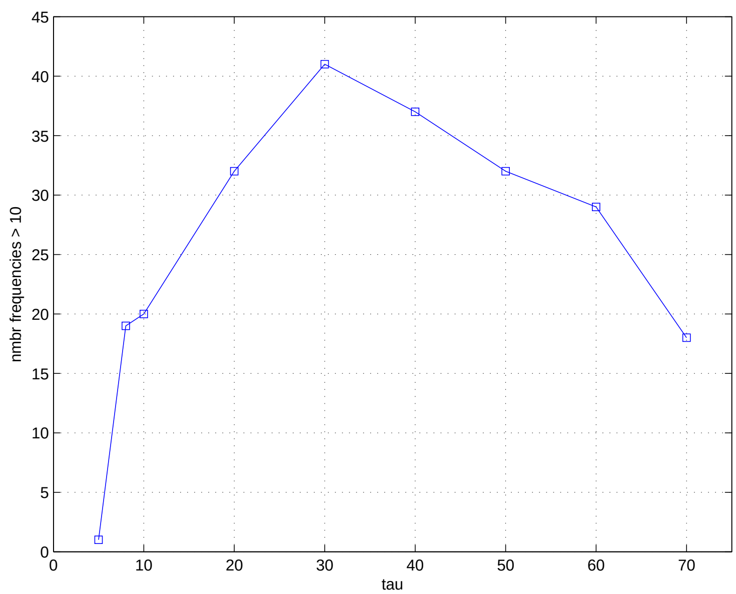
6.2 Experiment 2: Modelling trajectory length

In this experiment, we have selected 9 weeks of sensor data similar to the first experiment and we used the 'optimal' values of τ found in experiment 1. For the collected trajectories, the durations are calculated and fitted to the selected three models. For each trajectory we calculated the AIC and BIC values. Figure 5 gives an example of the observed durations in a histogram and the fitted mixture of a Poisson and a Normal distribution.

Table 2 shows the AIC and BIC average values for the two most frequently auto-detected trajectories. These results show that the Poisson distribution fits



(a) Histogram of the durations of auto-detected trajectories using different values of τ.



(b) Frequency of collected auto-detected trajectories, with at least 10 occurrences, versus τ.

Fig. 4. Visualisation of the collected auto-detected trajectories using different values of τ. Nine weeks of sensor data is used to collect these trajectories. The chosen weeks are around the assessment dates conducted by the occupational therapist.

the calculated duration less well than the two mixtures of probabilities. We may conclude that the most frequently walked paths during a week are almost always interwoven with some other activity. We therefore reject the first part of our hypothesis that these auto-detected trajectories are best fit using one distribution.

Table 3 shows the average AIC and BIC scores for the four collected predefined trajectories. Overall, we see that the mixture of a Poisson and a Normal distribution gives the best fit. This is conform the second part of our hypothesis.

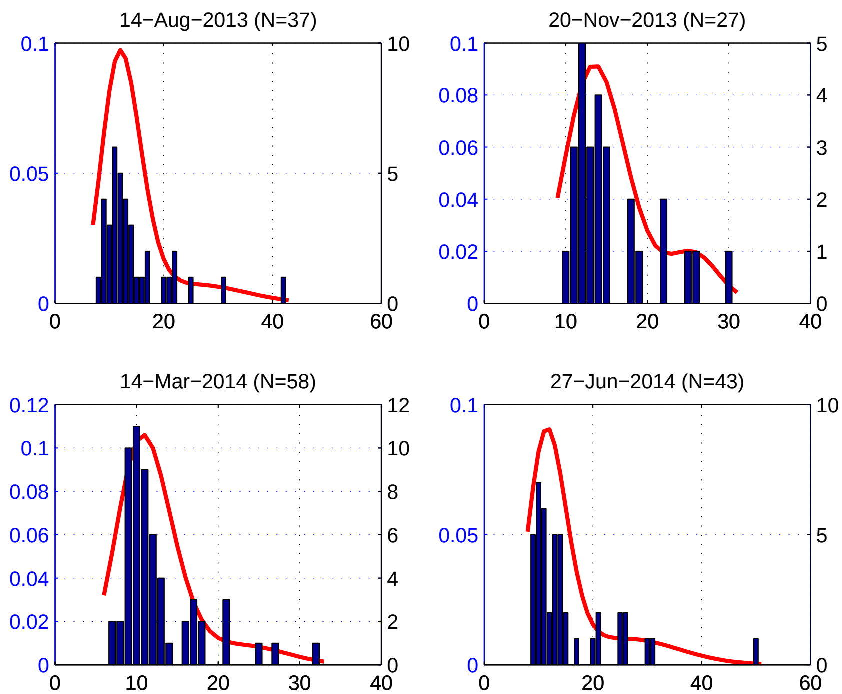


Fig. 5. A histogram of the duration of the collected *'living room back to kitchen'* trajectories. The data is fitted using a mixture of a Poisson and a Normal distribution. The X-axis denotes the durations, the Y-axis denotes the estimated probability and the Z-axis denotes the observed frequencies.

6.3 Experiment 3: Occasional versus continuous measurement of the gait velocity

To compare the gait velocity measured occasionally by the therapist with the gait velocity estimated from the sensor data, we used sensor data collected during three weeks around the AMPS and KATZ assessment day: the week the assessment is conducted, the week before and the week after the assessment.

	AIC and *BIC* of the model with parameter					
collected trajectories	$\Theta_1 = \lambda$		$\Theta_2 = (\alpha, \lambda_1, \lambda_2)$		$\Theta_3 = (\alpha, \lambda, \mu, \sigma)$	
Liv room front - kitchen	208.86	209.62	136.92	139.19	132.37	135.40
Toilet - bedroom	142.56	143.27	114.74	116.89	115.07	117.94
Kitchen - Liv room front	135.91	136.77	121.12	123.69	119.86	123.30

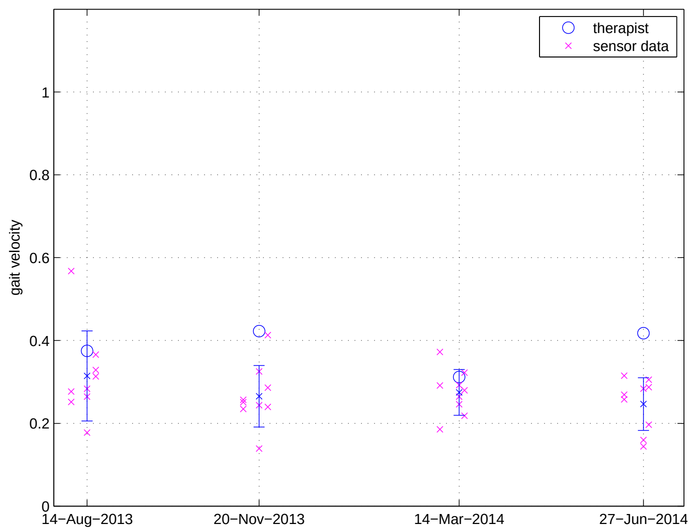
Table 2. Results of goodness of fit of the selected (mixture of) distributions applied to the collected top three *auto-detected* trajectories. The AIC and BIC values are calculated using 9 weeks of sensor data of volunteer A collected around the KATZ and AMPS assessment dates.

	AIC and *BIC* of the model with parameter					
collected trajectories	$\Theta_1 = \lambda$		$\Theta_2 = (\alpha, \lambda_1, \lambda_2)$		$\Theta_3 = (\alpha, \lambda, \mu, \sigma)$	
Front door - Liv room back	162.71	155.52	120.96	118.21	113.65	115.89
Hall - Liv room back	347.17	348.22	229.97	233.12	196.58	200.78
Liv room back - Front door	178.86	171.26	117.18	115.02	112.40	114.38
Liv room back -Hall	469.79	471.16	283.17	287.26	250.17	255.63

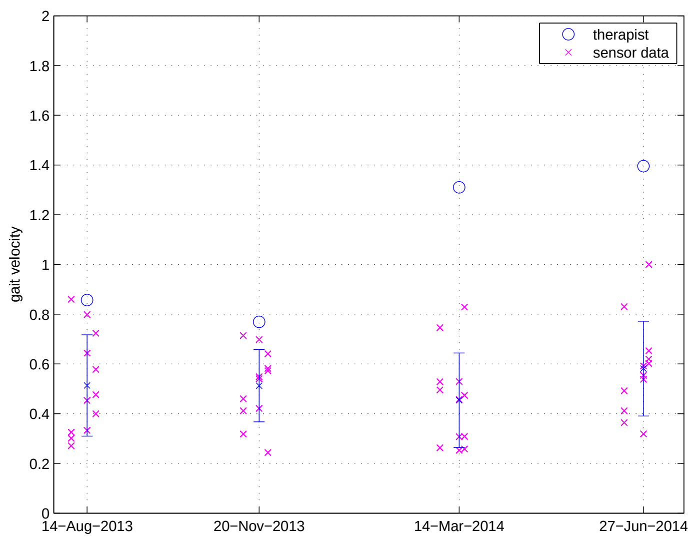
Table 3. Results of goodness of fit of the selected (mixture of) distributions applied to the collected *predefined* trajectories. The AIC and BIC values are calculated using 9 weeks of sensor data of volunteer B collected around the KATZ and AMPS assessment dates.

This resulted in 12 weeks of sensor data for the 4 assessments dates given in Figure 3. For this experiment, the value of τ and the probabilistic model found in the first two experiments are used, meaning that we fit a mixture of a Poisson distribution and a Normal distribution to the data. The value of λ, corresponding to the mean of the Poisson distribution, is used as the estimated duration. Using the distance of the collected trajectories obtained from the map of the apartment, we were able to estimate the average gait velocity from the sensor data.

Figure 6 gives the gait velocity estimated from twelve weeks of sensor data, its corresponding confidence interval and the walking speed measured by the therapist. The results show that, for volunteer A, the walking speed value measured by the therapist is higher that the average gait velocity estimated from sensor data. In two of the the four measurements is this value significantly higher. For volunteer B, all measurements of the therapist are significantly higher than the gait velocity estimated from sensor data. These results are conform to our hypothesis that the subjects tend to improve their behaviour as a response of being assessed. Using a sample t-test, we tested the null hypothesis that the estimated gait velocity values come from independent normal distributions with equal means. The results ($p > 0.4$) show no significant increase of decrease of the gait velocity for both subjects during the period of 15 months, which is conform their motor AMPS.



(a) Volunteer A.



(b) Volunteer B.

Fig. 6. Gait velocity measured by the therapist and estimated using a mixture of a Poisson and a Normal distribution with parameter $\Theta_3 = (\alpha, \lambda, \mu, \sigma)$. Each data point represents λ of one predefined trajectory collected during one week. The confidence interval of the estimated speed is also given. Four predefined trajectories and three weeks around the AMPS and KATZ assessment day are used.

7 Conclusion

This study shows the potential of continuously monitoring the indoor gait velocity of older adults living alone using a simple sensor network. We have shown that unconstrained behaviour leads to a multimodal distribution of path durations, as walking is interwoven with other activities. We have shown that we can nevertheless extract the gait velocity from unconstrained sensor data, by fitting a mixture model to the durations. In particular, the results show that the durations of the collected trajectories can be best fitted using a mixture of a Poisson and a Normal distribution as a model. Apart from the gait velocity, the method also allows us to detect the most recurrent indoor walking trajectories.

We applied this model to two sets of sensor data collected in a period of 15 months. Our results showed that the estimated gait velocity was conform the motor AMPS scores extracted from the assessments conducted by an occupational therapist. In accordance with the findings of [20], our results also show that the walking speed measured by the therapist is significantly higher than the average gait velocity. The subjects tend to improve their behaviour as a response of being assessed.

In a real-time situation, we could imagine a sliding window of one week needed to collect enough valid walking trajectories to be fitted by the model. In future work, we will extend the short period of 15 months during which data was collected, and during which the functional health of our volunteers did not change significantly. Moreover, the few assessments of the therapist do not provide a solid ground truth about the functional health of the resident. Currently, our group is involved in a monitoring older adults after having a hip surgery using comparable sensor networks. This project gives an opportunity to apply our findings to a new situation where we expect the walking speed to increase in a relative short period, as the functional health of these subjects gets better during the rehabilitation. It will be fascinating to have the same pattern from the gait velocity estimated from the sensor data. An interesting future challenge is the measurement of the gait velocity in a multi-person home setting.

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