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Title:Indoor Location IoT Analytics “in the wild”: Active and Healthy Ageing cases.

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Abstract

Recently much research has been conducted on early detection of cognitive and physical status deterioration in elderly adults. Primarily the focus is on gait analysis methodologies exploiting average speed, however this presents an issue when used for context aware applications. Additionally data capture tends to be in short bursts over a long period, allowing for localized temporal factors, such as short term injury, to potentially skew measurements. As such this work collects gait and trajectory IoT data from elderly adults in senior homes ("in the wild") over a sustained period of time (1 year). Density based clustering algorithms are then applied to the data to provide long-term insights into how the high density regions change over time. The data is collected, analyzed and made available by the indoor analytics client utilizing available processing resources and delivers the analytics outcome even when it is hosted in hardware with constrained resources. Promising results are obtained from the long-term study, suggesting that this form of evaluation has strong potential in the analysis of cognitive and physical status deterioration.

Keywords— indoor location, IoT analytics, active and healthy ageing, gait analysis

1. INTRODUCTION

Gait pattern analysis in elderly adults can be used as early predictors for cognitive decline [1], functional limitation and even mortality [2]. Additionally movement properties such as walking speed has been utilized as a means of predicting adverse events among elderly, such as falls [3][4]. Several other gait features have been extracted and explored as information of important diagnostic value, such as limb motion, body transfer, step length, step height and number of steps [1]. Due to increasing interest by the geriatric research and clinical community attempts of creating normative databases [5] and inclusion of several tasks in geriatric assessment batteries have been made lately so as to measure gait velocity [6].

In order for a system to analyze movement automatically the position of the subject must be tracked over a defined period of time. This provides the core data from which relevant features concerning a walking activity can be extracted. The field of indoor positioning systems and services [7] by which this core data is captured has received much research in recent times. Some such Indoor 3D Location Sensing Technologies [8] include: RF signal strength [9], WiFi apps [9], active RFID [10], Ultra Wide Band (UWB) or Li-Fi. Another popular approach includes the processing of depth image information extracted by contemporary commercial devices such as Microsoft Kinect sensor [11].

Recently research has been done in indoor location classification techniques, intelligent monitoring approaches, and moving object tracking in real-life contexts [12]. Additionally machine learning methods have been utilized to estimate indoor location and movement speed [13], while time-series analysis has been used to identify abnormalities in continuous assessment of video trajectories [14].

Context aware trajectory analysis is another relevant area of research. Using clustering algorithms which automatically recognize low and high density regions [15], it may provides more detailed information about behavioral patterns relating to activities of daily living and habit variation.. In that context, the Density-Based Spatial Clustering of Applications with Noise (DBScan) is an effective algorithm which has proven to be fairly robust when applied to noisy environments [16].

With the constant development of more intelligent sensors and devices, as well as data stemming from applications such as interventions for elderly people [17], the data produced by the Internet of Things (IoT) increases in volume and variety. However, this data is far from perfect, more often the streams provided by these devices are heterogeneous, imperfect, unstructured, unprocessed and in real time. This presents the need for specific analytics to extract the meaningful information [18]. To this end, ANGELS for distributed analytics in IoT have been suggested towards reducing the analysis load of cloud-based large data centers which form the basis of the “big-data” problem [19]. Utilizing this concept, IoT data analysis in the field by distributed IoT analyzers forms the basis for the practicality of long-term observations of this nature.

The work presented in this paper extends and introduces the authors’ previous work on density based clustering on indoor (location) transitions [20][21] in real seniors’ homes. Within this work, the CAC framework and Indoor Analytics Client are implemented over a long-term data capture period of about 12 months. The results of the high density region analysis are presented in the form of both a short and long term analysis, demonstrating the insights that can be gained through evaluations of this type. Utilizing this method has two main advantages. Firstly the system requires no direct input by the subject under observation, for example no tracking or monitoring hardware to be worn and maintained. Additionally the passive nature of the monitoring method helps to ensure that the data collected is as ecologically valid as possible.

The aim of this paper is to present the realization of IoT analytics on indoor body localization. The main parts of the implementation constitute the scheduled on site data analysis on extracting high density regions, communication of analysis results to other IoT objects (any hardware and software) through a Rest API and processing of long term observations. Results of the indoor localization algorithm are presented in the form of identified regions and processing time. In this work, the Microsoft Kinect was selected as the indoor location sensor. However, any other sensor producing indoor location information could be utilized within the framework. The remainder of this paper is structured as follows. The Methodology section outlines the architecture of the Indoor Analytics, outlining each individual component, information of the experiments carried out and the data collection methodology. The Results section presents an evaluation of the methodology, reviewing the efficiency of the algorithm's performance with respect to volume of the data input, as well as the outcome of the analysis of the long-term study of seniors' home installations. A discussion on the current research work in the field, along with research limitations and further envisaged work follows at the end of the paper.

2. METHODS

The work presented in this paper relies on the indoor density based clustering analysis of location tracking using Kinect methods presented in [20]. The realization of this work is in the context of the Internet of Things (IoT) analysis domain (c.f. Fig. 1). More specifically, streamed Kinect-captured body trajectories are received and recorded by a client as a set of (x,y) locations of the body’s center of mass [12]. The client then periodically applies a density based clustering algorithm [20] to the generated datasets, resulting in High Density Regions (HDR) of human activity. This information, as well as previous analyses', is then made available by the client through the Rest API interface, for consumption by any hardware or software as required.

2.1. CAC-framework Kinect connectivity and IoT

Following the publish/subscribe messaging pattern, widely adopted by many IoT implementations, the Controller Application Communication (CAC) [22] is a cross device/platform communication framework. Built on top of WebSockets, communication between controllers and applications is achieved using JSON messages. Given that the CAC focuses on gaming controllers such as Kinect, Wii Balance Board and Remote Control as well as wearable devices such as Emotiv amongst others, the framework’s real time communication streaming and data exchanging is adapted for high throughput. Each controller attached to the CAC framework publishes their respective data, which are then delivered to any service/application which has subscribed to that specific data client in the same session [23]. In this work, the client application utilizes the Microsoft Kinect SDK, communicating with a Kinect and streams the skeleton and RGB information to a CAC framework server. The indoor Analytics Client then receives the corresponding data packets ready for further evaluation.

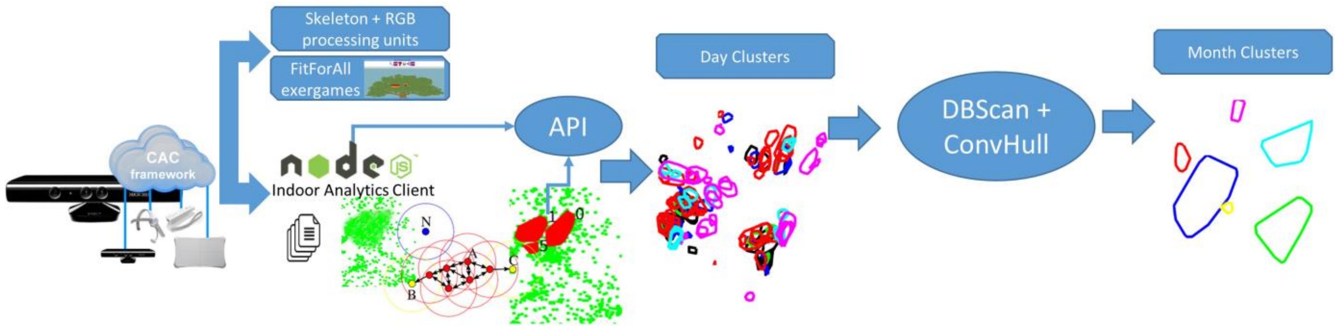

Fig. 1 Architectural design of the Indoor Analytics approach in the IoT domain

2.2. Indoor Analytics Client

The Indoor Analytics Client is implemented in NodeJS and is based partially on the Node.js CAC-framework client described in [20]. Realizing a CAC client API [23] (more information at http://www.cac-framework.com), the Indoor Analytics Client subscribes to the skeleton streaming channel made available via the CAC framework. The position of the skeleton’s center of mass along with a timestamp, skeleton id and the corresponding position of some of the body joints such as ankles, knees, hips, hip center, spine, shoulders and shoulder center [24] are saved into csv files.

The Indoor Analytics Client can initiate an analysis execution at a specific time of the day or at specific intervals. The RAM constraints refer to the total number of points that can be analysed each time, and facilitates the removal of intermediate points allowing the analysis process to be more efficient in terms of computational power. This has proven to be very effective when the Indoor Analytics Client is deployed on the Raspberry PI 2 (equipped with 1GB of RAM).

Each execution produces a number of High Density Regions(HDR's) which are saved in JSON format along with the size of each region (the number of points included in this region with respect to the total number of points) as well as the timestamp of the execution. Additionally a figure illustrating the points and the extracted HDRs is also created. Given that node.js can be executed on any hardware and software, the Indoor Analytics Client can be hosted on most of the IoT supported hardware and software, including Raspberry.

2.3. Processing Algorithms

The HDR are calculated and an optimal convex polygon that surrounds the points of each calculated HDR. HDR's are computed using the Density-Based Spatial Clustering (DBScan) which has the advantages of being data insensitive and suitable for applications with large, even noisy, datasets [16]. The algorithm groups the neighborhood points according to the minimum distance between two neighboring points (eps parameter) and the minimum neighborhood points that are sufficient to constitute a cluster (minPts parameter). The output of the algorithm gives a number of High Density Regions (clusters) [16]. For this work the minPts parameter is proportional to the total number of points [20]. The smallest convex polygon that surrounds the points of each calculated HDR is based on a convex hull [25]. This algorithm is applied to all DBScan clusters producing an equal number of convex polygons to defined HDRs.

Additionally, utilizing previously clustered HDR's and their associated convex hulls as points, the process can be repeated. Given that the initial analysis of the positional data is calculated once per day, a secondary analysis allows trends in long-term observations to be assessed. For example on a per month basis IoT Analytics API. The Indoor Analytics Client exposes a set of Rest API functions providing access to the calculated HDRs. Given that the outcome of every execution of the algorithms is stored to a file, the API exposes a history of the last calculated HDRs. Table 1 presents an example output of the Indoor Analytics Client API along with information about two extracted clusters. The hull polygon is defined by a number of points forming a polygon surrounding the HDR points.

Table 1 Indoor analytics client API output (IP:8085/getclusters/0)


```
{"ms":1446737356000,
"datetime":"20151105-152916",
"AllClusterInfo":[
    {"ID":0,
    "Size":940,
    "ProportionString":"94.15%",
    "HullPolygon":[
        ["1.28","2.58"],
        ["1.24","2.60"],
        ..........},
    {"ID":2,
    "Size":36,
    "ProportionString":"3.62%",
    "HullPolygon":[
        ["-1.24","3.23"],
        ["-1.27","3.24"],
        ..........}
    ]}
```


2.4. Experiment

The Indoor Analytics Client was deployed to seniors' homes as part of the USEFIL project [26]. The CAC-framework server and Microsoft Kinect, integral components of the USEFIL system, had already been deployed to seniors' homes [26]. Kinect was used to monitor the senior's daily activity while the CAC-framework supported the simultaneous communication of the extracted skeleton features, the Clothes Change Detection component [27] and the FitForAll exergaming platform [28].

The experiment run across five seniors' homes for a period of ~12 months capturing their daily transitions in their living room. In each case, the above setup was utilized. The data for each day run through the framework and the resultant HDR's and respective convex hulls calculated. These computed HDR's are then analyzed again using the Indoor Analytics Client to provide clustering on a monthly basis, allowing the inference of trends that change over longer periods.

3. RESULTS

The analysis was conducted on two levels. The daily and the monthly (aggregated) analysis. The analysis results of 6 days for 2 homes are presented as an indicative example of the daily analysis. In addition, the analysis for a specific day for one senior's home was carried out with respect to the points involved in the calculation, juxtaposing the involved points, the required processing time and the respective results.

Table 2 presents the datasets containing information about the number of the HDRs calculated, the number of total daily points, and the proportion of points out of the total points for the three predominant regions. Technical issues at home I in day 4 prohibited the client to collect data and generated the corresponding datasets.

In addition, the analysis for a specific day for one senior's home was carried out with respect to the points involved in the calculation, juxtaposing the involved points, the required processing time and the respective results.

Table 2: Experimental datasets presenting the number of total daily points, the number of the HDRs and the proportion of points for the three more predominant regions.

	Day	# points	# HDR	1st % HDR	2nd % HDR	3rd % HDR
Home 1	1	101288	6	50.13	28.69	7.67
	2	229936	3	59.86	35.72	1.31
	3	371415	4	61.02	21.91	12.18
	4	-	-	-	-	-
	5	555945	6	74.53	15.58	2.93
	6	301023	5	36.30	21.30	19.19
Home 2	1	370492	9	16.60	15.00	7.23
	2	604353	5	39.70	34.69	7.14
	3	531090	4	40.64	29.98	22.00
	4	361404	5	62.03	8.67	7.06
	5	223661	4	60.57	21.16	3.42
	6	272196	3	48.87	20.18	15.69

Fig. 2 illustrates the outcome of the CAC frameworks analysis for 6 individual days across two sites. Each green dot represents the seniors' position captured using the Kinect, each red area represents a high density region calculated by the Indoor Analysis Client. These visualizations present an intuitive view of single days' activity. Depiction I-4 corresponds to the day with the technical issues.

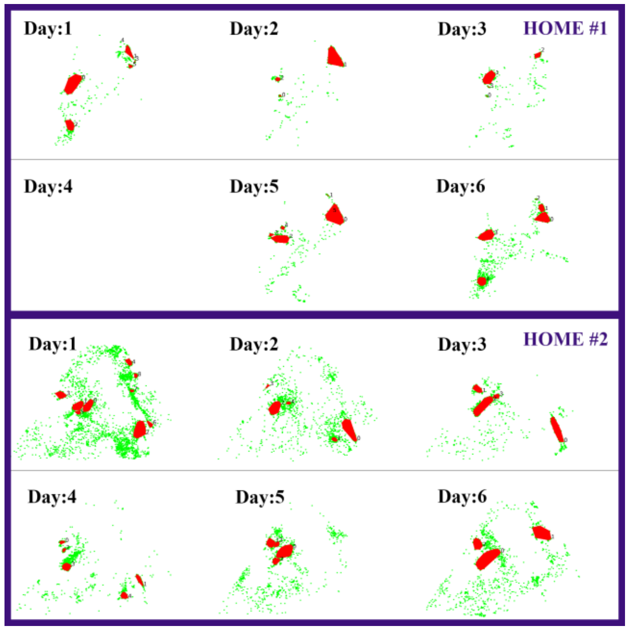

Fig. 2 Illustrative depiction of the daily trajectories and HDRs extracted for senior's home I and II daily (1-6).

Table 3 shows time required for the DBScan analysis computation. Analysis is given for the three predominant regions, with respect to the number of the involved points, for the second senior's home for the first day. Fig. 3 illustrates those same HDRs. The analysis refers to the second senior's home for the first day (c.f. In addition, the analysis for a specific day for one senior's home was carried out with respect to the points involved in the calculation, juxtaposing the involved points, the required processing time and the respective results.

Table 2 II-1) where the total recorded points were 370492. The analysis of a dataset (II-1) with respect to the points involved in the calculation (c.f. Table 3 and Fig. 3) shows that the accuracy of the results and the extracted information is slightly affected by the number of the involved points. Contrary, the calculation time is parabolically increasing, reaching about 2h for 50000 points.

Table 3: Time required for the DBScan analysis alongside the outcome of the three more predominant regions with respect to the number of the involved points.

#points	Time (ms)	1^{st} % HDR	2^{nd} % HDR	3^{rd} % HDR
991	5947	16.15	14.53	7.77
4812	82267	16.67	15.23	7.09
8420	232808	17.09	15.33	7.51
16839	900465	17.10	15.38	15.18
28505	2733849	16.78	15.43	15.08
46320	7015289	16.51	15.65	15.45

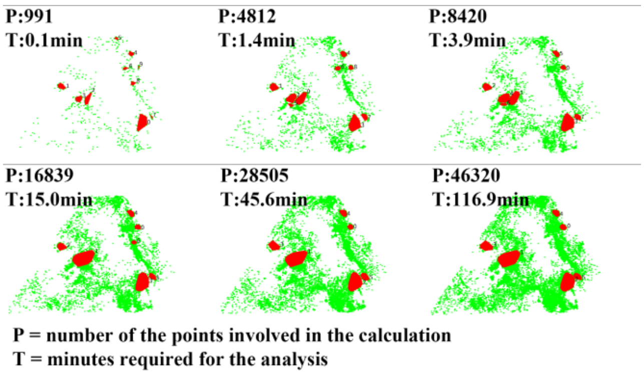

Fig. 3 Illustrative depiction of HDRs with number of points used and computation time in minutes required for the analysis to finish.

In addition to the above analysis of a single day's data, a review is given of data captured over a ~12 month period. In this case, the outputted daily HDR's are used as points in a secondary pass of the Density-Based Spatial Clustering (DBScan) algorithm to produce HDR's on a monthly basis. Again, convex hulls are produced for each HDR highlighting points of interest in the environment for that month. Fig. 4 demonstrates a month-by-month review of observations made in a single residence.

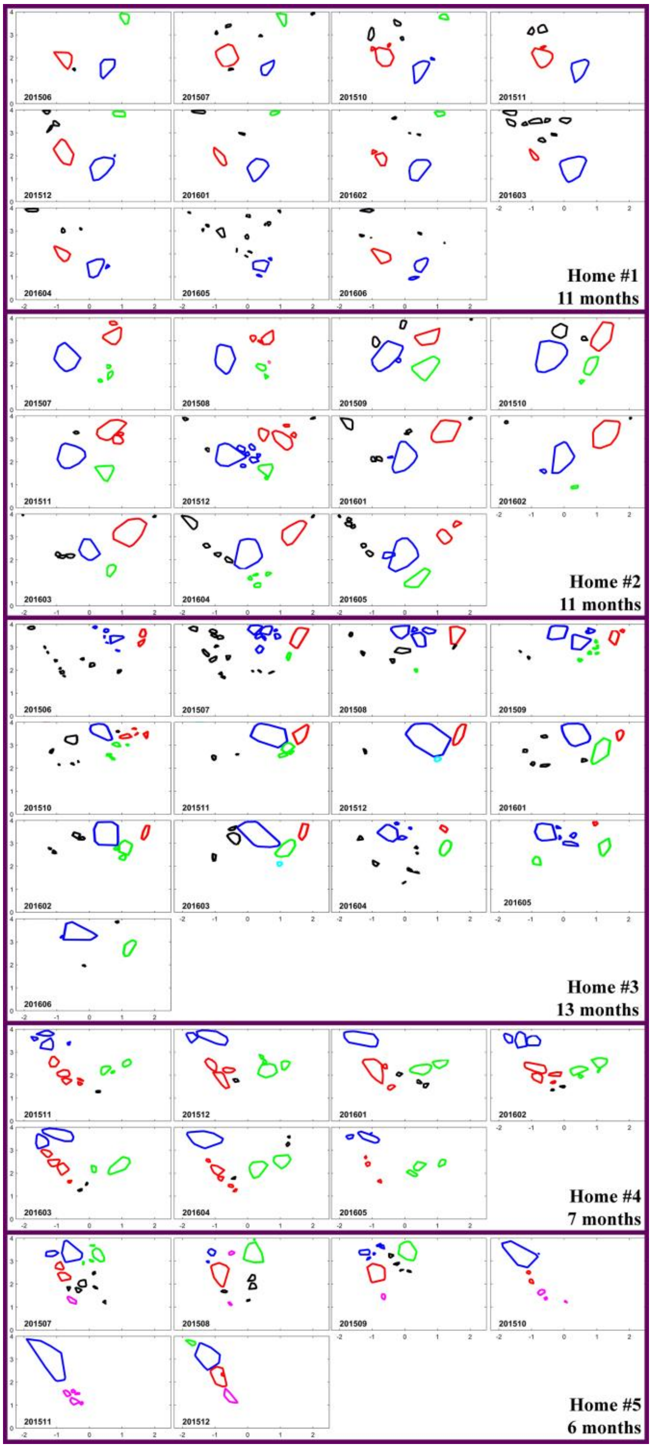

Fig. 4 Month by month presentation of the monthly aggregated clusters.

4. DISCUSSION

This long-term study applied a density based clustering algorithm on indoor body transitions in real seniors' homes over a period of ~12 months. The importance in terms of value and accuracy of the algorithm application on such data has been presented in a previous author's work where: data collected through trials carried out both in the Thessaloniki Active And Healthy Ageing Living Lab (Thess-AHALL), an adherent member of the European Network of Living Labs located in the Lab of Medical Physics in the Aristotle University of Thessaloniki in Greece [20], as well as in real seniors homes [21]. A software client subscribes, listens, collects and applies a density clustering algorithm on real IoT indoor position data, streamed at the time of occurrence, analyzes the data and exposes the so called IoT analytics results through a Rest API feeding back the environment with meaningful information. The high density regions, constituting the outcome of the IoT analytics, are then available to any IoT hardware and software. A secondary pass of the high density region analysis is then applied to give a less granular evaluation of the data.

Given the unavoidable trade-off of the real life settings, the authors investigated the correlation between processing time and algorithm performance. As such, the implementation skips some intermediate points to reduce the processing time of the algorithm, whilst still taking into account a representative portion of the points. It is worth mentioning that, according the results, although the processing time increases parabolically with the number of points involved in the calculation, the result is slightly differentiated. This could be attributed to the robustness of the DBScan algorithm along with the percentage value of the minPts parameter which is proportional to the total number of the points [16]. Similarly, the eps parameter could be also configured according to the dataset. This can be justified by the facts that body gait and posture are possessed by known and predictable conditions.

As the CAC framework [22] is built upon high throughput and pub/sub architecture, the facility is provided whereby events are made available to the IoT streaming channel, from the IoT data streams, at the time they occur. This provides the opportunity for other IoT objects to analyze in real-time concurrently. In addition, any location data source able to cooperate with such a framework, apart from Kinect which was utilized in the USEFIL project [26], could be the source of the work presented in this paper since the analysis is applied on the location of the senior. The indoor analytics client collects, integrates and processes all the activities as the data is being produced, without disrupting the activity of existing sources, communication channels or storage systems. The extracted HDRs and the percentage of points per region, formed as JSON, can be consumed by any hardware and software that has access to the Indoor Analytics Client through the Rest API. Such an approach enables big data analytics on the field at meaningful time intervals rather than subsequent analysis of the entire dataset.

To the best of the authors' knowledge [20], was the first study applying the DBScan algorithm [29], on real seniors' homes indoor location datasets. This, in conjunction with the application of the approach to real senior's homes for about a year make the outcome of this work even more important for consideration of future studies. As a step further, such analysis could become the base for further insights into context aware indoor gait analysis providing more fine-grained information to Decision Support Systems on the field [30]. This is clearly beyond current literature which merely focuses on average in-home gait speed [31][32]. Moreover, context aware gait velocity will be calculated for the seniors and will be compared against average speed.

Additionally with the extension to long term data, collected from real seniors' homes, long-term insights about the high density regions and their changes over time can be extracted. This ability to collect data over longer uninterrupted periods presents many advantages over long-term intermittent observations, such as minimizing the effect that temporary changes in subjects' health might have on the overall study. The privacy concerns of having a Kinect camera sensor present in the seniors homes are a documented issue [31][33], however these concerns are alleviated due to the Kinects introduction as a gaming sensor [34] for the FitForAll exergaming platform [28] given the beneficial role of the serious games that the seniors are informed about [35].

Similarly, in the context of the UNCAP project [36], the intension is to collect a large dataset of both outdoor and indoor positions that will be studied following the approach outlined in this work. The piloting phase involves 11 different structures across Europe including nursing homes, care centers as well as in residence deployments for the elderly living at their homes. Here position monitoring is used in real time, to trigger alarms and to interact with home automation systems. Outdoor localization data is acquired using GPS while indoor localization is achieved by leveraging on various different technologies: UWB, Zigbee, Kinect and capacitive floors to name a few. The variety of different positioning systems adopted, together with the collection of both indoor and outdoor data, represents a very interesting scenario for the work presented in this paper.

4.1. Limitations and further steps

This study does have several limitations. The position of the Kinect may have slightly changed over time. The results do not correspond to exactly the same months among the seniors that deters further correlation analysis among the seniors' patterns. In addition, although the minPts parameter of the DBScan algorithm is configured with respect to the total number of involved points, eps is set as a constant number that should be addressed in future work. Finally, the authors consider compliance and contribution to the IndoorGML which is an Open Geospatial Consortium (OGC) standard for an open data model and XML schema for indoor spatial information [37].

5. CONCLUSIONS

The work presented in this paper is an innovative step forward in the analysis of "wild" data. Providing an effective means of capturing long term localization data facilitated by IoT analytics and creating unfiltered high density regions. The increase in accessibility to robust data of this type provides an interesting and very promising new area of research, which might prove to be very useful for identifying early decline symptoms from simple daily living sensor recordings.

6. REFERENCES

1. Gillain S, Warzee E, Lekeu F, Wojtasik V, Maquet D, Croisier J-L, Salmon E, Petermans J (2009) The value of instrumental gait analysis in elderly healthy, MCI or Alzheimer's disease subjects and a comparison with other clinical tests used in single and dual-task conditions. Ann Phys Rehabil Med 52:453–74. doi: 10.1016/j.rehab.2008.10.004
2. Studenski S, Perera S, Patel K, Rosano C, Faulkner K, Inzitari M, Brach J, Chandler J, Cawthon P, Connor EB, Nevitt M, Visser M, Kritchevsky S, Badinelli S, Harris T, Newman AB, Cauley J, Ferrucci L, Guralnik J (2011) Gait speed and survival in older adults. JAMA 305:50–8. doi: 10.1001/jama.2010.1923
3. Montero-Odasso M, Schapira M, Soriano ER, Varela M, Kaplan R, Camera LA, Mayorga LM (2005) Gait Velocity as a Single Predictor of Adverse Events in Healthy Seniors Aged 75 Years and Older. Journals Gerontol Ser A Biol Sci Med Sci 60:1304–1309. doi: 10.1093/gerona/60.10.1304
4. van Schooten KS, Pijnappels M, Rispens SM, Elders PJM, Lips P, van Dieën JH (2015) Ambulatory fall-risk assessment: amount and quality of daily-life gait predict falls in older adults. J Gerontol A Biol Sci Med Sci 70:608–15. doi: 10.1093/gerona/glu225
5. Bohannon RW, Williams Andrews A (2011) Normal walking speed: a descriptive meta-analysis. Physiotherapy 97:182–9. doi: 10.1016/j.physio.2010.12.004
6. Peel NM, Kuys SS, Klein K (2013) Gait speed as a measure in geriatric assessment in clinical settings: a systematic review. J Gerontol A Biol Sci Med Sci 68:39–46. doi: 10.1093/gerona/gls174
7. Zou H, Lu X, Jiang H, Xie L (2015) A fast and precise indoor localization algorithm based on an online sequential extreme learning machine. Sensors (Basel) 15:1804–24. doi: 10.3390/s150101804
8. Liu H, Darabi H, Banerjee P, Liu J (2007) Survey of Wireless Indoor Positioning Techniques and Systems. IEEE Trans Syst Man Cybern Part C (Applications Rev 37:1067–1080. doi: 10.1109/TSMCC.2007.905750
9. Chintalapudi K, Padmanabha Iyer A, Padmanabhan VN (2010) Indoor localization without the pain. In: Proc. Sixt. Annu. Int. Conf. Mob. Comput. Netw. - MobiCom '10. ACM Press, New York, New York, USA, p 173
10. Ni LM, Liu Y, Lau YC, Patil AP (2004) LANDMARC: Indoor Location Sensing Using Active RFID. Wirel Networks 10:701–710. doi: 10.1023/B:WINE.0000044029.06344.dd
11. Saputra MRU, Widyawan W, Putra GD, Santosa PI Indoor human tracking application using multiple depth-cameras. 307–312.
12. Appiah K, Hunter A, Lotfi A, Waltham C, Dickinson P (2014) Human behavioural analysis with self-organizing map for ambient assisted living. In: Fuzzy Syst. (FUZZ-IEEE), 2014 IEEE Int. Conf. pp 2430–2437
13. Zhou Z, Chen X, Chung Y-C, He Z, Han TX, Keller JM (2008) Activity Analysis, Summarization, and Visualization for Indoor Human Activity Monitoring. IEEE Trans Circuits Syst Video Technol 18:1489–1498.
14. Jung C, Jacques J, Soldera J, Musse S (2006) Detection of Unusual Motion Using Computer Vision. In: XIX Brazilian Symp. Comput. Graph. Image Process. pp 349–356
15. Ordonez C, Omiecinski ER, Navathe SB, Ezquerra NF (1999) A Clustering Algorithm to Discover Low and High Density Hyper-Rectangles in Subspaces of Multidimensional Data.
16. Ester M, Kriegel H-P, Sander J, Xu X (1996) A density-based algorithm for discovering clusters in large spatial databases with noise. In: Kdd. pp 226–231
17. Bamidis PD, Vivas AB, Styliadis C, Frantzidis C, Klados M, Schlee W, Siountas A, Papageorgiou SG (2014) A review of physical and cognitive interventions in aging. Neurosci Biobehav Rev. doi: 10.1016/j.neubiorev.2014.03.019
18. Tönjes R, Barnaghi P, Ali MI, Mileo A, Hauswirth M, Ganz F, Ganea S, Kjærgaard B, Kuemper D, Nechifor S, others (2014) Real time iot stream processing and large-scale data analytics for smart city applications. Eur. Conf. Networks Commun.
19. Mukherjee A, Paul HS, Dey S, Banerjee A (2014) Angels for distributed analytics in iot. In: Internet Things (WF-IoT), 2014 IEEE World Forum. pp 565–570
20. Konstantinidis EI, Bamidis PD (2015) Density based clustering on indoor kinect location tracking: A new way to exploit active and healthy aging living lab datasets. In: 2015 IEEE 15th Int. Conf. Bioinforma. Bioeng. IEEE, Belgrade, Serbia, pp 1–6
21. Konstantinidis EI, Billis AS, Plotegher L, Conti G, Bamidis PD (2016) Indoor Location IoT Analytics "in the wild": Active and Healthy Ageing

Cases. In: XIV Mediterr. Conf. Med. Biol. Eng. Comput. MEDICON. Paphos, pp 1225–1230

22. Konstantinidis EI, Antoniou PE, Bamparopoulos G, Bamidis PD (2014) A lightweight framework for transparent cross platform communication of controller data in ambient assisted living environments. Inform Sciences 300:124–139. doi: 10.1016/j.ins.2014.10.070
23. Konstantinidis EI, Antoniou PE, Billis A, Bamparopoulos G, Pappas C, Bamidis PD (2014) Leveraging Web Technologies to Expose Multiple Contemporary Controller Input in Smart TV Rich Internet Applications Utilized in Elderly Assisted Living Environments. In: Univers. Access Human-Computer Interact. Aging Assist. Environ. Springer, pp 118–128
24. Microsoft Microsoft Kinect SDK JointType Enumeration. http://msdn.microsoft.com/en-us/library/microsoft.Kinect.jointtype.aspx. Accessed 16 Dec 2013
25. Jarvis RA (1973) On the identification of the convex hull of a finite set of points in the plane. Inf Process Lett 2:18–21.
26. Billis AS, Kartsidis P, Garyfallos D-KG, Tsatali MS, Karagianni M, Bamidis PD (2015) Ecologically valid trials of elderly unobtrusive monitoring: analysis and first results. In: 4th Int. Work. Artif. Intell. Assist. Med. Pavia, Italy, pp 32–41
27. Sgouropoulos D, Giannakopoulos TD, Petridis S, Perantonis S (2014) Clothes change detection using the Kinect sensor. 12th Int. Conf. Signal Process. Multimed. Appl.
28. Konstantinidis EI, Billis AS, Mouzakidis CA, Zilidou VI, Antoniou PE, Bamidis PD (2016) Design, Implementation, and Wide Pilot Deployment of FitForAll: An Easy to use Exergaming Platform Improving Physical Fitness and Life Quality of Senior Citizens. IEEE J Biomed Health Inform 20:189–200. doi: 10.1109/JBHI.2014.2378814
29. DBSCAN, Wikipedia the free encyclopedia. https://en.wikipedia.org/wiki/DBSCAN#cite_note-2. Accessed 5 Aug 2015
30. Billis AS, Papageorgiou EI, Frantzidis CA, Tsatali MS, Tsolaki AC, Bamidis PD (2015) A Decision-Support Framework for Promoting Independent Living and Ageing Well. IEEE J Biomed Health Inform 19:199–209. doi: 10.1109/JBHI.2014.2336757
31. Stone EE, Skubic M Passive, in-home gait measurement using an inexpensive depth camera: Initial results. 183–186.
32. Stone E, Skubic M, Rantz M, Abbott C, Miller S (2015) Average in-home gait speed: investigation of a new metric for mobility and fall risk assessment of elders. Gait Posture 41:57–62. doi: 10.1016/j.gaitpost.2014.08.019
33. Kepski M, Kwolek B (2014) Fall detection using ceiling-mounted 3d depth camera. In: Int. Conf. VISAPP, pages II. pp 640–647
34. Konstantinidis EI, Bamparopoulos G, Bamidis PD (2015) Moving Real Exergaming Platforms on the Web: The webFitForAll case study. IEEE J. Biomed. Health Inform Accepted:
35. Bamidis PD, Fissler P, Papageorgiou SG, Zilidou V, Konstantinidis EI, Billis AS, Romanopoulou E, Karagianni M, Beratis I, Tsapanou A, Tsilikopoulou G, Grigoriadou E, Ladas A, Kyrillidou A, Tsolaki A, Frantzidis C, Sidiropoulos E, Siountas A, Matsi S, Papatriantafyllou J, Margioti E, Nika A, Schlee W, Elbert T, Tsolaki M, Vivas AB, Kolassa I-T (2015) Gains in cognition through combined cognitive and physical training: the role of training dosage and severity of neurocognitive disorder. Front Aging Neurosci. doi: 10.3389/fnagi.2015.00152
36. Ubiquitous iNteroperable Care for Ageing People (UNCAP) web page. http://www.uncap.eu. Accessed 12 Jan 2016
37. Open Geospatial Consortium Official Web Page. http://www.opengeospatial.org.