Indoor Navigation Ontology for Smartphone Semi-Automatic Self-Calibration Scenario

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Abstract—**The indoor navigation within public environments and location-based service development are very interesting and promising tasks. This paper describes an ontology-based technique for human movement recognition using the hybrid indoor localization technique based on received signal strength multilateration and pedestrian dead reckoning which relies on internal smartphone sensors. This technique takes into account the anchor node proximity zones and using internal sensors performs the semi-automatic online calibration procedure of log-distance path loss propagation model in accordance with a certain semi-automatic self-calibration scenario. The usage of indoor navigation ontology allows to decrease the influence of radio signal obstructions induced by user's body and moving people.**

I. Introduction

A number of indoor localization techniques and solutions was suggested and developed last ten years. Many people in science and business are involved in this process. The result of indoor localization solution development as a promising and complex task can provide an information to different context-aware and location-based services. Traditionally, as examples of such services, airport, museum [1] and shopping mall visitor localization services or personnel and equipment location detection services are considered. Development of some indoor localization solution requires map construction based on floor plans of indoor areas, the effective localization techniques and algorithms, deploying the appropriate facilities inside buildings [5], [6], [7] or other localization areas [8], [9].

The described in this paper indoor localization technique relies on wireless localization methods which are classified in common case into signal propagation model based techniques [10], [11], [12], [13], [14], [15], [16], [17], [18], scene analysis [21], [22], [23] and proximity detection [24], [25], [26]. These indoor localization techniques are thoroughly investigated and a lot of appropriate solutions are developed. However, it is not easy to deploy various implementations of existent techniques, because one need to allocate special equipment within indoors and take into account such difficulties like a missing line-of-sight channel between the transmitter and the receiver, multipath signal propagation, scattering, shadowing and fading are caused by moving people and reflecting surfaces. It implies that deploying process needs to be augmented by data acquisition and equipment calibration. In previous paper [27] the technique which alleviates these processes is proposed.

The presented in [27] technique facilitates the accurate localization and reduce the impact of the environment by means of online calibration phase, which consists of received signal strength (RSS) measurement and RSS values processing according to smartphone orientation angle. The proposed techniques belongs to a group of wireless multilateration indoor localization techniques which are used to localize a human with her/his smartphone within public environments. The multilateration technique uses log-distance path loss model [28] of Bluetooth Low Energy (BLE) signal. The model has several parameters that taking into account environment features and can be determined empirically during the offline calibration phase [29]. The proximity zone of a BLE beacon can be used to determine several initial values for the online calibration procedure. In addition, the usage of internal smartphone sensors for distance detection is proposed. Thus, online calibration phase allows to avoid the manual signal propagation model parameter adjustment.

The described in [27] steps of online calibration phase are considered as a common calibration scenario which is closely related to user's movement through a room. It doesn't mean that the user must control the corresponding movement pattern, but such pattern exists and if the user follows it then the online calibration performs. For this reason, the aforementioned procedure is named also as semi-automatic self-calibration procedure. The paper [27] describes cases when RSS measurement suffers from user's own turns and moving people. The special improvements for these cases are proposed and this paper continues these ideas.

The special indoor navigation ontology has been developed to process the cases mentioned before. This ontology is involved in processing a number of measurements which constitutes a measurement history. For this reason, the ontology includes the necessary concepts to measurement history support and a list of production rules needed to decision making if the case is met. The implementation is based on the language OWL 2 [30], the imported OWL Time Ontology [31] and production rules written on SWRL [32]. The indoor navigation ontology is based on SROIN(D) description logic, therefore it leads to NExpTime-hard complexity for concepts satisfiability and ABox consistency reasoning problems [33].

The rest of the paper is structured as follows. Section II presents works related to the subject of the paper. Section III describes the semi-automatic self-calibration procedure. Section IV introduces the indoor navigation ontology.

II. Related Work

The main goal of using ontology for indoor navigation task is to provide semantic description to the certain events occurring within indoor environment and to support decision making which corresponds to recognized case. There are also a number of developed semantic models and ontologies which focus on representation of indoor spaces like indoor navigation frameworks IndoorGML [34] and BIGML [35].

Published by OGC (Open Geospatial Consortium) IndoorGML provides a spatial data model and exchange encoding rule for interfacing different components in an ecosystem of indoor spatial services. IndoorGML uses XML-based schema of OGC GML (Geography Markup Language) to expressing geographical features in accordance with cellular space model. The model supports two- and three-dimensional spatial objects and their geometry. IndoorGML describes also topology of indoor spaces, i.e. the relationships between cells which are derived from topographic layout of indoor space by Poincaré duality [36]. Moreover, the cell semantic is presented including the classification of spaces and boundaries.

Geometric and semantic information hybrid modeling is proposed in OntoNav [37]. OntoNav consists of navigation, geometric path computation and semantic path selection services which are using navigation ontology, users' profiles and spatial database data. The special algorithm for path computation is developed. The ontology OntoNav provides the multi-floor localization, determination of the navigation starting point and ending point, semantic-driven selection of the best path and determination of all the possible paths from user's current location to the target location.

A color Petri net model (CPN) used as an RDF ontology representation has been developed for an indoor location-based system [38]. The paper describes how RDF ontology can be transformed into CPN. The CPN representation of ontology is used to obtain RDF query answers. This model is able to identify the properties of core classes (such as subject, predicate, and object onto places), and map these properties onto CPN places. The CPN model is used for querying spatio-temporal information about moving users. In addition forward and backward inference algorithms are proposed.

In [39] an ontology to support autonomous indoor navigation in the production environment is presented. In this research RFID and ultrasound technology are used to support autonomous indoor navigation and develop a tracking system called LotTrack. The fusion of such approaches like a Genetic Algorithm (GA) and a neural network [40] to collect positional data using RFID tags, RSS information, and four reader devices is proposed. This research was limited in scope, because it covers only one level.

In [41] Multi-Level Indoor Navigation Ontology is described. The ontology provides indoor positioning, geofencing, and way-finding features. The several node and route types are presented corresponding to their roles which are activated depending on current situation in the building like regular or emergency situations.

III. Semi-automatic Self-Calibration Scenario

The essence of online semi-automatic self-calibration scenario is that in the case when the human with a mobile device is walking through the indoor area in accordance with a certain movement pattern, the special mobile application is performing the calibration of signal propagation model. The calibration is performed parallel with multilateration and improves the quality of multilateration. There are several signal propagation models [42], [43]. However, the log-distance path loss model for estimation of distance between receiver and transmitter is more accurate. The model equation is presented as follows:

$$PL = P_{Tx} - P_{Rx} = PL(d_0) + 10n \times log_{10}\frac{d}{d_0} + X_{\sigma RSS} \quad (1)$$

where PL – is total path loss (dB), P_{Tx} – transmitted power (dBm), P_{Rx} – received power, also RSS (dBm), d – true distance between transmitter and receiver, n – path-loss exponent, $PL(d_0)$ – power loss (dBm) at a reference distance d_0. The quantity $X\sigma_{RSS}$ in dBm is a random variable representing the noise and is often assumed to be a zero-mean Gaussian random variable with RSS variance σ. The path loss exponent indicates the rate of path loss according to the distance and takes into account multipath effects. $X\sigma_{RSS}$ represents fading effects and without them is set to zero.

The mentioned idea is shown on Fig. 1. The RSS measurements starts to be collected at the known point corresponding to the nearest zone of proximity to some anchor node like a Wi-Fi access point or BLE beacon. The user's location is defined in this case as a location near the anchor node each time the user enters the appropriate zone of proximity. Thus, map-aided information and user's proximity are involved to fix the moment of calibration start. The user doesn't need to control neither the moment she/he meets this zone of proximity nor the movement pattern.

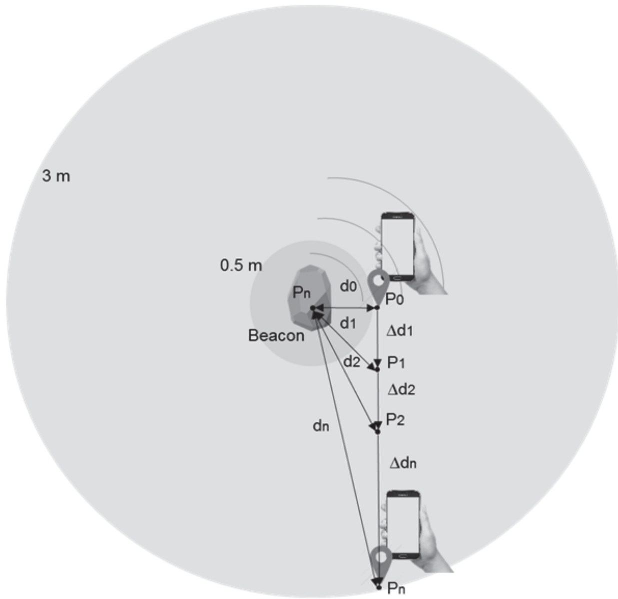

Fig. 1. RSS measurements for BLE beacon semi-automatic calibration

While moving after calibration start RSS measurements are collected to calculate and calibrate path-loss exponent value.

For this purpose, the internal built-in smartphone sensors like accelerometer and gyroscope are involved in localization process. The sensors are used to step detection and real distance estimation.

The measurements at several distances are necessary, because it is needed to calibrate path loss exponent using linear least square approximation. For this purpose the distance values are calculated. Thus, the equation of the path loss exponent is:

$$n = \frac{P_{Rx}(d_0)\times m - RSS}{10\times log_{10} d} \quad (2)$$

Thus the proposed technique can be considered as a combination of RSS multilateration, pedestrian dead reckoning method and map-aided technique. However, the acceptable quality of calibration is achieved in the case when the user follows the pattern.

The semi-automatic self-calibration scenario assumes that the user moves in straight direction regarding the beacon (Fig. 2). Thus, during the RSS measurement corresponding to near proximity zone, the online calibration starts if the user moves on the tangent to the border of the zone are considered. However, this scenario has several drawbacks like impossibility to move arbitrarily and the signal affection by user's body. Despite this, a new value of distance can be obtained by internal smartphone sensors. Thus, defined in the nearest proximity zone values of distance, RSS defined after several steps, new values of distance and RSS are used to calibrate the path loss exponent. To define the new distance value the user's velocity calculation is performed. Unfortunately, the aforementioned procedure doesn't take into account several exceptional situations like non-straight movement, other moving people and smartphone orientation.

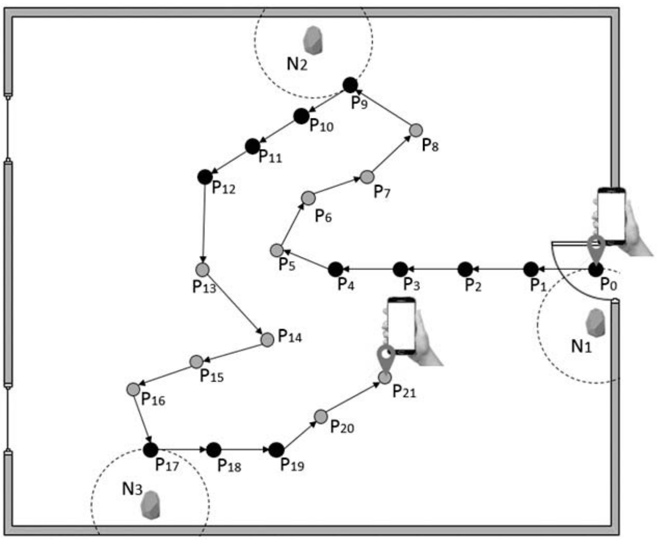

Fig. 2. The containing semi-automatic self-calibration scenario schema of user's movements

The Fig. 2 shows the example of user's movements within a room including the tracks where the semi-automatic self-calibration scenario is followed by the user. As it's shown the calibration process is performed parallel with multilateration using BLE beacons. The phases of log-distance path loss model online calibration accomplished within the semi-automatic self-calibration scenario correspond to user tracks (P0-P4, P9-P12, P17-P19) marked by black color points (P5-P8, P13-P16, P20-P21). The arbitrary user's movements are marked by grey colored points. As it was mentioned before, the mobile application recognizes user's movement pattern and if user's track is direct, i.e. it corresponds to predetermined by semi-automatic self-calibration scenario, the online calibration is performed. If the user stops to move directly then the online calibration stops. However, user's rotations are acceptable during the scenario if the user keeps going directly.

The BLE beacon is considered as anchor nodes because of their mobility that allows to allocate beacon freely to achieve line-of-sight propagation channel. In common case such approach to relying on nearest proximity zone with highest level of signal power can be applied to other types of anchor nodes like Wi-Fi access point. Since the line-of-sight propagation suffers from smartphone antenna orientation change, a number of obstacles and moving human bodies, the localization accuracy depends on line-of-sight hardly. Unfortunately, moving people damage the received signal strength measurement process. The case when a user stands back to the BLE beacon and blocks the line-of-sight by her/his body leads to decreasing the RSS.

To overcome this drawback the special indoor navigation ontology is developed. The concepts of the ontology are the basis of measurement history which can be processed by rules to find the described above exceptional cases. To construct measurement history concepts of OWL Time ontology are involved into original concepts description.

IV. INDOOR NAVIGATION ONTOLOGY

A. *Measurement representation*

The semi-automatic self-calibration scenario described above does not take into account issues related to the dependency of the path loss exponent on smartphone orientation regarding the anchor node. The issue is that the angle after several steps in straight direction has another value.

If the user turns in this new point then the path loss exponent, obviously, will change. This issue is shown in Fig. 3 and Fig. 4. The Fig. 4 shows the user changes the orientation in the new point P1. To overcome this drawback path loss exponent needs to be calibrated depending on user's orientation regarding the anchor node. For this reason, one need to detect steps and measure several values at the same moment, namely an relative angle of user's orientation regarding the anchor node, an absolute angle of user's orientation, received signal power and time of measurement to incorporate all these values in a one tuple.

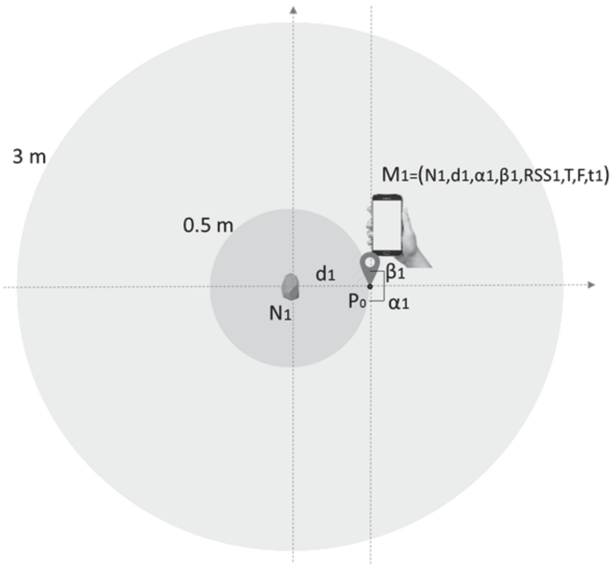

Fig. 3. User orientation regarding the anchor node at calibration start

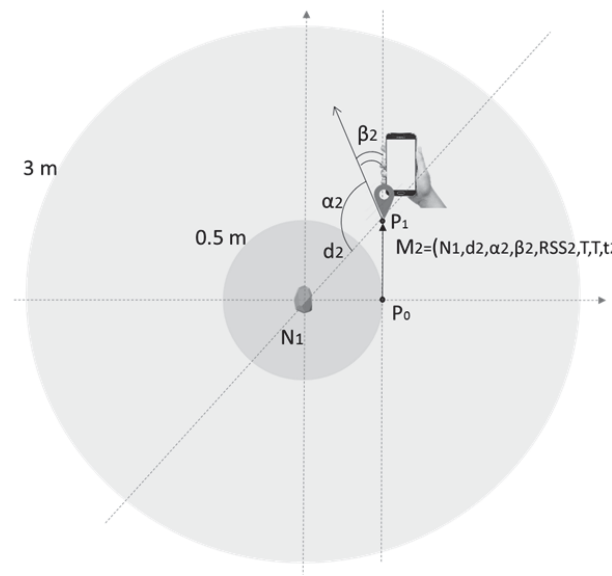

Fig. 4. New user's orientation regarding the anchor node and general coordinate system after several steps in straight direction

Thus, one need to represent the calibration measurement in more complex way. Let the calibration measurement is a tuple M, which can be defined as:

$$M = (B, d, \alpha, \beta, P_r, s, r, t) \quad (3)$$

where B – is a beacon id, d – is a distance between the user and the anchor node, α – is an angle of user orientation regarding the anchor node, β – is an angle of user's direction regarding general coordinate system, P_r – received signal power, s – step detection flag, r – rotation detection flag, t – time of measurement performing.

The measurements with the same values of B, α, β only can be taken to path loss exponent calibration process. Thus, there is the possibility to develop the first fragment of indoor navigation ontology which will operate the concept Measurement and related to it properties and concepts. The fragment schema is shown on Fig. 5.

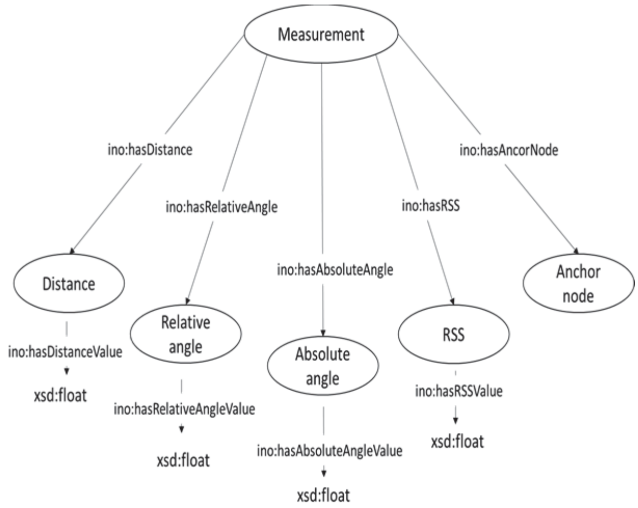

Fig. 5. Indoor Navigation Ontology fragment related to Measurement concept

The relation between the measurement and time concepts is presented in the Fig. 6.

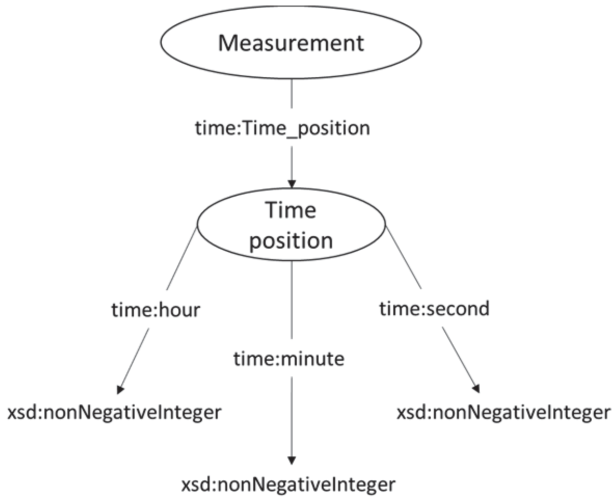

Fig. 6. Indoor Navigation Ontology fragment related to Measurement concept

The prefix "time:" corresponds to OWL Time Ontology property. Time position concept represents the time at which the measurement is taken.

B. *Event types representation*

The case when the user turns her/his back to the beacon leads to significant received signal power decreasing. In this case, the given measurements should not be used for online calibration of path loss exponent. For this purpose, the mechanism which can determine how to distinguish the cause of RSS decreasing related to user's rotations from the other one related to moving people. It can be performed, if we detect a rotation without step detection and the RSS is decreased then there is signal obstruction by user's body. In opposite, if no movement is detected then somebody stands between the user and the beacon. In accordance with constructed fragment of indoor navigation ontology one can write the SWRL-rule which can detect this case.

But previously the other fragment should be developed. This fragment comprises of different types of events which can be recognized. The presented on the Fig. 6 following types of events are:

- Calibration – the event which has duration and corresponds to semi-automatic self-calibration procedure;
- NavigationInTheRoom – the related to an appropriate room event which also has duration and corresponds to multilateration-based localization process;
- AnchorNodeMet – the event which is time instant in opposite to duration entity; corresponds to entering nearest anchor node proximity zone;
- DynamicObstacleMet – the event which has indefinite duration; corresponds to moving people in the case when user doesn't move and RSS decreases and increases significantly;
- UserTurnsBackToAnchorNode – the event which has duration; corresponds to the case when user turns his/her back to anchor node;
- RotationPerformed – the event which corresponds to user's rotation and has fixed time value;
- StepPerformed – the event which corresponds to user's rotation and has fixed time value;

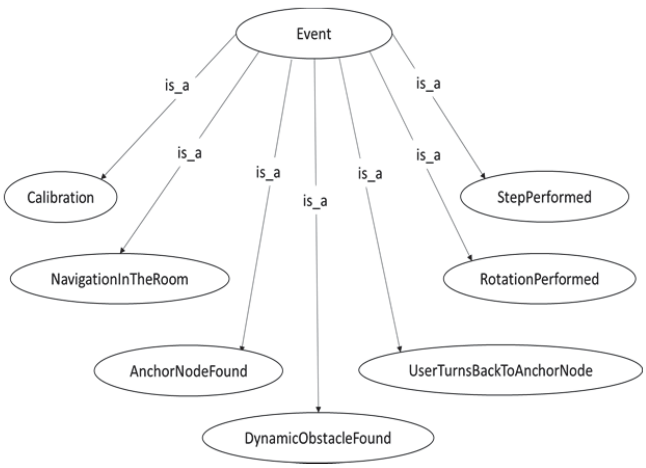

Fig. 7. Indoor Navigation Ontology fragment related to Event concept

Previously is determined that the obstruction by user's body occurs, if no step is detected, the user's heading angle is within the range: [180° - θ ; 180° + θ], where θ – limit angle, and received signal power is less than a liminal value P_{rb} which depends on beacon transmitting power and the distance.

Thus, SWRL-rule for signal obstruction by user's body case can be written as follows:

$$Measurment(?\,m)\,^\wedge hasNotDetectedStep(?\,m,?\,s)$$

$$^\wedge\, Time\_position(?\,m,?\,t)\,^\wedge hasDetectedRotation(?\,m,?\,r)$$

$$^\wedge hasRSS(?\,m,?\,rss)\,^\wedge swrlino{:}\,lowerThan(?\,rss,<P_{rb}>)$$

$$^\wedge Event(?\,e) \rightarrow\; UserTurnsBackToAnchorNode(?\,e)$$

where m is an instance variable of concept Measurement, s is a Step_Detection_Flag instance variable, t – Time_position instance variable, r – Rotation_Flag instance variable, rss – RSS instance variable, P_{rb} – RSS liminal value constant, e – Event instance variable, $swrlino$ – custom SWRL built-in prefix.

Note that instead of compare relative angle to its boundary values hasDetectedRotation range value check is implemented. Moreover, the custom SWRL built-ins should be developed to correct comparison operations performing. SWRL-rule for the case of moving people can be written as follows:

$$Measurment(?\,m)\,^\wedge hasNotDetectedStep(?\,m,?\,s)$$

$$^\wedge\, Time\_position(?\,m,?\,t)\,^\wedge hasNotDetectedRotation(?\,m,?\,r)$$

$$^\wedge hasRSS(?\,m,?\,rss)\,^\wedge swrlino{:}\,lowerThan(?\,rss,<P_{rmp}>)$$

$$^\wedge Event(?\,e) \rightarrow\; DynamicObstacleMet(?\,e)$$

where P_{rmp} – a liminal RSS value constant for the moving people case. The rules don't consider the history of measurements, but despite of that are efficient for event detection.

The actions which should be made after recognition of such cases could be different. It means that after occurring the aforementioned case should be invoked the technique of localization which can provide high accuracy. In the case when user rotates itself back to anchor node a path loss exponent calibrated for this orientation angle can be used for distance calculation. If moving people are detected dead reckoning technique can be used instead of multilateration. If these cases are not recognized then the user can enter the zone with certainly low value of RSS.

It is difficult to maintain such situations like presented on Fig. 8 using rules. The user enters the zone in the room where RSS is low and one need to process the measurement history to detect user's position, predefine the zones with certainly low value of RSS and choose the nearest of them in accordance with last known location.

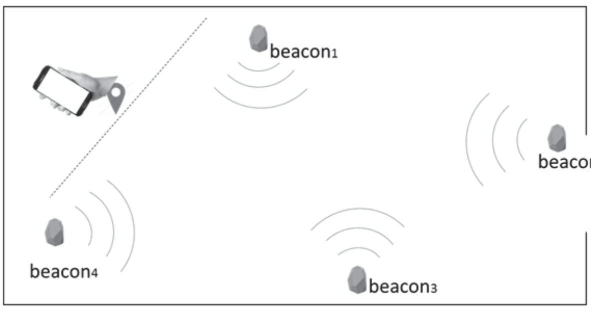

Fig. 8. User heading regarding the beacon after several steps in straight direction

The usage of ontologies and rules for this case looks like a challenging task due to the need to maintain ordered structures like lists. The implementation of lists by using OWL is trivial, but leads to increasing computational complexity.

The algorithm of user's localization which includes rule processing and self-calibration are presented as follows:

Algorithm 1 Semi-automatic calibration

// Online semi-automatic calibration of the path loss exponent
$n \leftarrow 2.6$ // path loss exponent
if user enters a room then
  while user moves in a room **do**
    for each anchor node **do**
      $M := (B, d, \alpha, \beta, P_r, s, r, t)$
      if user turns back to anchor node **then**
        choose a calibrated for this angles *n*
        determine location
      endif
      if dynamic obstacle met **do**
        determine location using steps and rotates detection
      else determine location using multilateration
      endif
    endfor
    if user is in near proximity zone an anchor node **then**
      while user follows semi-automatic self-calibration scenario **do**
        $n \leftarrow$ calibrate path loss exponent
      endwhile
    endif
  end while
endif

Thus the presented algorithm is aimed to perform different user's localization techniques by using rules to determine user's activities and to define the suitable localization technique.

V. Conclusion

The presented ontology-based semi-automatic self-calibration scenario includes multilateration technique based onlog-distance path loss model in combination with semi-automatic self-calibration procedure. This technique can be applied to Bluetooth Low Energy beacon and Wi-Fi access points. The procedure is performed parallel with multilateration to improve the values of path loss exponents corresponding to a number of distances between user's smartphone and appropriate anchor node. The technique also can be performed parallel in combination with pedestrian dead reckoning and multilateration to improve the user's localization accuracy. Despite the user's application implements multilateration and proposed procedure detects user's proximity and automatically starts the calibration, it requires to follow straight direction of movement by the user.

The advantages of indoor navigation ontology usage are providing the possibility for online calibration to processing obstacle influences and smartphone orientation changes. The ontology opens possibility to calculate user's location depending on his/her movement history. Thus, the indoor navigation ontology is flexible to new scenario updates and can cover additional exception cases related to user's movement. Moreover, the developed ontology can be used as a basis of more complex information model and can provide semantic interoperability between components of systems which potentially can utilize this information model.

The disadvantages are the facts that the presented technique doesn't take into account complex trajectories of user's movements, the user still should control her/his movement pattern and big errors at small distances. The ontology model doesn't solve these problems.

To overcome these drawbacks the hybrid method comprising pedestrian dead reckoning technique and multilateration should be realized. The method should process smartphone orientation change more precisely. The free trajectory processing will allow to fully automate self-calibration scenario.

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