The Complex Indoor Localization Technique Based on Ontology and SLAM-Method

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Abstract— One of the problems associated with methods using to determine the location of users of mobile devices within indoors, based on Wi-Fi radio signals, is the time-consuming procedure for setting up and placing equipment, which includes building a map of the room, creating a map of radio signals, or calibrating the radio signal propagation model. In solving this problem, it is planned to use complex indoor localization technique based on the usage of ontology and the SLAM method, which includes the phase of forming a training sample, as well as the phase of simultaneous navigation and mapping. The SLAM method is based on The Gaussian Process Latent Variable Model (GP-LVM) and includes requirements for correlation of the signal level values of the nearest points of the user's localization, for which the parameters of the correlation function are configured based on the training sample. The proposed method is based on solving the regression problem using machine learning methods to form a training sample, as well as solving the problem of reducing the dimension for simultaneous navigation and map construction. As a training sample, the smartphone's internal sensor readings (steps and rotation angles) and Wi-Fi received signal strength values obtained using crowd calculations are used. The resulting training sample is used to determine the parameters of the correlation function that sets the correlation between the user's localization points. The proposed ontology is intended to determining the user's entrance to the room and searching for Wi-Fi access points.

I. INTRODUCTION

Creating indoor location services based on radio signal processing, despite considerable research, remains a difficult task. The main problems faced by developers of such systems are the multipath propagation of signals, reflection and refraction; the need to locate and calibrate the infrastructure for localization, namely Wi-Fi access points; dependence of localization accuracy on the number and location of access points, as well as signal propagation in the line-of-sight zone. The indoor location problem is defined as the process of locating a person using a mobile device inside buildings: airports, museums [1], shopping centers, or office space. Depending on the task, you can also consider a Wi-Fi access point [2], a reference node [3], a mobile device, a robot [4], a vehicle [8, 9], and so on as a localized object. In addition, the object is considered not only buildings, but also other forms of engineering structures, such as mines, etc. [5-7].

It is worth noting that to localize a user within indoors methods based on the fixation of the signal strength, time of arrival of radio signals from transmitters [10-12], time difference of arrival of radio signals [13], the transit time of the signal from the transmitter to the receiver [14, 15], angle of reception of the signal [16, 17] and the direction of reception [18] are used. The fingerprinting method and the method of multilateration are more widely used. The fingerprinting is based on the measurement of signal levels at pre-defined points, which is performed by a specialist in the setup phase or offline phase. In the online phase or navigation phase, the location of an object is estimated by comparing measurements taken in the online phase with pre-collected measurements in the offline phase [19, 20]. This method allows achieving localization accuracy about 2.5-3 m [21]. The method of multilateration of signal levels operates on a model of radio signal propagation in the room, on the basis of which the distance to the signal sources can be estimated. The complexity of implementing indoor navigation systems based on these methods is characterized by the need to measure signal levels in order to create a database of fingerprints or calibrate the parameters of the signal propagation model. Such steps significantly complicate the deployment of location systems and lead to a significant increase in the cost of their implementation. Using SLAM methods that allow to simultaneously build a map of the room and navigate, would allow to solve this problem much more effectively.

The method proposed in this article makes it possible to avoid the time-consuming procedure of measuring signal levels in the offline phase, since it is proposed to use collaborative measurement of received signal strength values within indoors. In addition, the method does not use a map of the room and any data about its geometry, since it is intended for building a map of the room. It is assumed that the localization object is a person with a mobile device, and the localization area is a building that is accessible to a wide range of people. The initial information for building maps of indoor rooms is used to estimate the location of Wi-Fi access points or Bluetooth Low Energy tags, determine the user's entry points into the rooms, determine the trajectory of movement using smartphone sensors, and collect measured signal strength values at various points in the user's trajectory to create a training sample. The obtained data are used to determine the user's trajectory using the dimension reduction method based on the Gaussian Process Latent Variable Model (GP-LVM) [22].

Thus, this method involves the formation of training samples for the rooms for which the map is being built, directly by users during their movements around the building. The generated samples are used to train the parameters of the core function, which is used to determine the location using GP-LVM. To determine the location in the phase of building a

training sample, the pedestrian dead reckoning (PDR) is used, which is based on the data from the built-in sensors of the smartphone. This process doesn't require direct control on the part of users, but as an additional way to clarify the actual values of the user's location and the angle of rotation of his smartphone can be used detection the user near the Wi-Fi access point, as well as a model of signal attenuation inside the room. If the user passes near the source of the radio signal, this signal is applied to the map under construction as a reference point that allows you to specify the user's location and thereby increase the accuracy of the data collected for the training sample.

The purpose of this article is to create a SLAM method that provides accurate localization in rooms without using room maps, radio signal maps, and preliminary information about the location of signal sources. During the navigation process, maps of radio signals, user paths, and landmarks are automatically generated using the PDR method. This process is performed by each user at least once for each room.

The rest of the paper is structured as follows. Section II presents works related to the subject of the paper. Section III describes the indoor navigation ontology. Section IV introduces the SLAM-based indoor navigation technique.

II.   RELATED WORK

Location systems based on SLAM algorithms, i.e. simultaneous navigation and mapping, allow to determine the distance to the walls of the room and thus build a map of the room during the navigation. However, for smartphone users, this approach is not applicable, since it is assumed that the user doesn't have to spend time on complex measurements, and the user's smartphone, of course, is not equipped with a laser rangefinder. In this regard, the creation of methods is limited to the use of existing smartphone sensors.

Various methods can be used to solve the problem of simultaneously determining the location inside indoors based on the use of wireless data networks and building a map of the rooms. For example, the method proposed in [23] uses a priori knowledge of signal propagation in a room and estimates stochastic perturbations using an EM algorithm to construct a map of signal propagation and a multi-frequency filter (sequential Monte Carlo method) to filter signal level measurements. The WiFi-SLAM method [24] uses the Gaussian hidden variable process to determine the user's location, and considers the localization process as a task of reducing the dimension of the original space of the measured signal level values to the coordinate space. To improve localization accuracy, a dynamic motion model and a Gaussian-trained model of Wi-Fi signal strengths are used. The SignalSLAM method [25] provides a solution to the problem of constructing a map of observations using collaborative data collection from several experimenters who freely pass through the building: WiFi radio prints, 4G LTE RSRP, magnetic field, GPS coordinates in the open air, NFC values on specific landmarks, and motion paths based on inertial data. This method uses a modified version of the GraphSLAM method that includes optimizations for user coordinates using sets of absolute locations and pairwise constraints that include multimodal similarity of signals.

The PiLoc system can be considered as an example of a system that uses crowd computing to solve an indoor location problem [26], [27]. PiLoc uses crowd computing to collect user movement paths using built-in smartphone sensors and fingerprints of Wi-Fi network signals. Clustering is used to combine Wi-Fi signal strength values and movement paths into disjoint sets. The generated disjoint sets are used to search for similar segments based on matching movement vectors and Wi-Fi access point signals. The obtained trajectories are combined to build floor plans of the rooms.

Currently, the direction of creating positioning methods based on visual methods, including those based on depth maps, is being actively investigated. Semantic methods of image analysis are increasingly used. In [28], a visual semantic LLN-SLAM method for portable devices is proposed. The method extracts the semantic information by matching the object discovery and segmentation of the projection of the point cloud. The MobileNet network is used to ensure the program's performance during object detecting and Euclidean distance clustering is used during the point cloud segmenting. Thus, semantic information is used to facilitate positioning. The described in [29] approach uses a modified ORB-SLAM method with semantic segmentation of scenes. The method belongs to a class called feature-based. ORB SLAM builds a sparse map of the area using the Bundle Adjustment algorithm and the Orb detector (Oriented FAST and Rotated BRIEF). In [30], the concept of a system of proactive localization of the user within the enterprise, in which the cyber-physical system is formed, is proposed. The system allows to coordinate the distribution of all available enterprise resources and predict user routes based on information about their current location and their movements in the past. Methods and algorithms for predicting sequences and time series are used for forecasting: Decision Trees, Random Forest, artificial neural networks with LSTM and GRU blocks.

The main goal of using ontology for indoor navigation task is to provide semantic description of the certain events occurring within indoor environment and 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 [31] and BIGML [32].

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) for expressing geographical features in accordance with cellular space model. The model supports two- and three-dimensional spatial objects and theirs' 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 [33]. Moreover, the cell semantic is presented including the classification of spaces and boundaries.

Geometric and semantic information hybrid modeling is proposed in OntoNav [34]. 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 [35]. 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 temporal information about moving users. In addition forward and backward inference algorithms are proposed.

In [36] 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 [37] 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 [38] 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.

In [39], an ontology was developed for the system of visual location determination inside premises. The ontology is intended for solving problems of determining obstacles, detecting objects, walls and passages, and determining the direction of movement. Ontology concepts are entities of 4 types: basic concepts, concepts that describe basic concepts, concepts of space dimensions, and concepts of object geometry. Rules are supposed to be used for inference. In [40], we propose a model for classifying rooms based on the ontology of indoor spaces, which takes into account both their semantic and geometric characteristics. The model is an extension to the IndoorGML data standard.

III. THE INDOOR NAVIGATION ONTOLOGY

The indoor navigation ontology allows to process several events occurring during navigation process using different types of contextual information obtained by the smartphone's built-in sensors. The examples of such contextual information are the signal levels of Wi-Fi access points or Bluetooth beacons, the user's rotation angles with the smartphone, information about whether the user has made steps and whether the RSS levels of Wi-Fi access points or Bluetooth beacons have changed in the absence of any user movements. In this way, the positioning and navigation ontology stores measurements of smartphone rotation angles and RSS levels, Boolean values for event occurrence facts for processing using rules, and the time at which measurements were made. The ontology has basic concepts for describing the types of information mentioned above: Measurement, Distance,

Relative angle, Absolute angle, RSS, Anchor node (access Point), Time position (time point), Event. These concepts are used to build rules for handling events that occur when the user moves indoors, in order to improve the accuracy of positioning and navigation.

Concepts that extend the Event concept include (Fig.1):

- Calibration – the event which has duration and corresponds to calibration procedure start;
- NavigationInTheRoom – an event associated with being in a particular room during the positioning and navigation processes;
- AnchorNodeMet – event that corresponds to the user's entry into the zone with the highest signal level;
- DynamicObstacleMet – an event that corresponds to the appearance of other people (the event is detected if the signal level of the access point or beacon has changed significantly in the absence of movement on the part of the user);
- UserTurnsBackToAnchorNode – an event that corresponds to the moment when the user turns his back to the access point or beacon, does not take steps, but changes the angle of rotation, which leads to a significant decrease in the signal level;
- RotationPerformed – event corresponding to the user-made rotation;
- StepPerformed – event corresponding to the step made by the user. To detect complex events when a user enters a zone where the signal strength of all access points or beacons is weak, the measurement history and the corresponding rule are used, which determines that the user has entered such a zone. The history consists of instances of the Measurement concept that contain the measurement time.
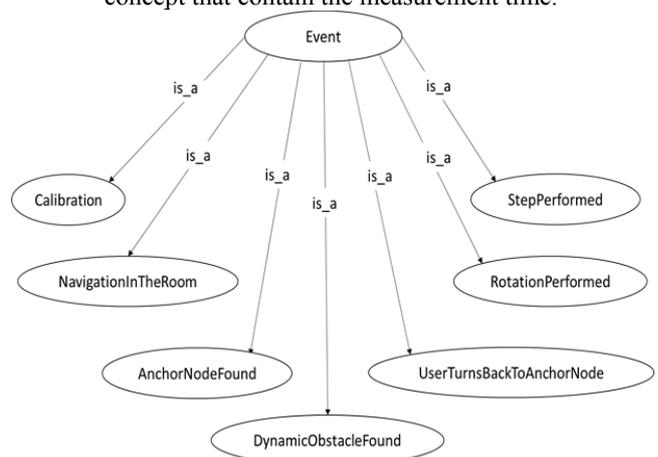
Fig. 1. Event concept

The measurement concept is a core concept of the ontology which aims to represent in the common case the measurements provided by indoor localization algorithms based on built-in smartphone sensor use. Let the calibration measurement is a tuple M, which can be defined as:

$$M = (d, \alpha, \beta, P_r, s, r, t) \qquad (1)$$

where 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.

Thus, the measurement concept can be described via ontology as a hierarchy based on "has-a" relationship, which encompasses the aforementioned concepts (Distance, Relative angle, Absolute angle, RSS, Step performed, Rotation performed, Time position).
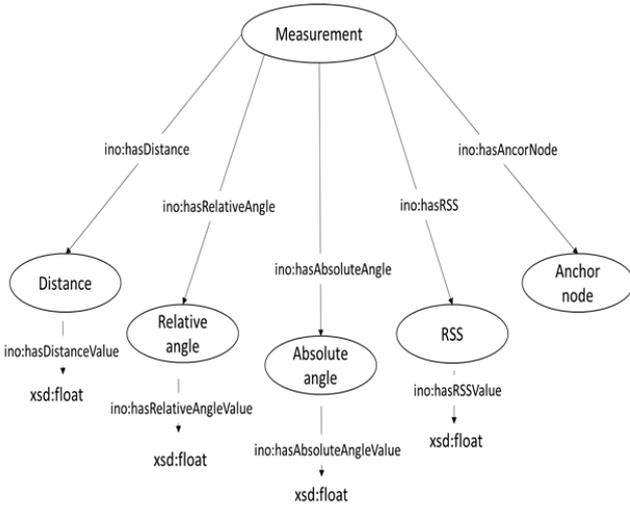
Fig. 2. Measurement concept

The relation between the measurement and time concepts is presented in the Fig. 3. The prefix "time:" corresponds to OWL Time Ontology property. Time position concept represents the time at which the measurement is taken.
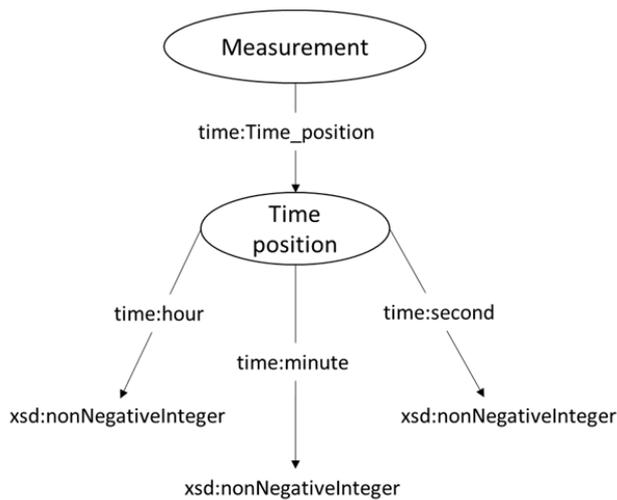
Fig. 3. Time position concept

The case when the user enters the room leads to significant received signal power increasing. For this purpose, the mechanism which can determine how to distinguish the cause of RSS increasing is proposed. It can be performed, if there is the possibility to detect RSS increasing with step detection. In accordance with constructed fragment of indoor navigation

ontology one can write the SWRL-rule which can detect this case.

The OWL ontology description language [41] and the SWRL rule language [42] were chosen to represent the positioning and navigation ontology. In addition, the ontology has the necessary concepts for representing time intervals imported from the existing "OWL Time Ontology" [43]. The developed ontology is described by the SROIN(D) discretionary logic [44] and has a NExpTime-hard complexity for problems of concept feasibility and consistency of multiple statements about ABox individuals.

IV. THE SLAM-BASED INDOOR LOCALIZATION TECHNIQUE

To determine the user's location, we suggest using the dimension reduction method based on the Gaussian Process Latent Variable Model (GP-LVM). This method is chosen, in particular, because Gaussian processes allow to find complex patterns in data and many models have already been built on their basis for solving various machine learning problems: regression, classification, and dimension reduction. In this case, we will consider the problem of reducing the dimension. The GP-LVM method allows you to map multidimensional data to a smaller space. In the case of determining the user's location using Wi-Fi signals, multidimensional data refers to the levels of signals from different access points, and smaller data refers to the user's two-dimensional coordinates or localization points. As already suggested in [24], it is proposed to impose the following restrictions on the data received:

- At localization points that are close to each other the values of the signal levels differ slightly from each other;

- Values of signal levels that differ slightly from each other correspond to localization points that are close to each other;

- Successive changes in signal level values in the data stream correspond to successive changes in the user's location.

We describe the formulation of the regression problem for the Gaussian process. An important condition will be that there is a sample of data that includes the coordinates of the localization points and the associated values of the signal levels from any access point. Let $\boldsymbol{X} = (x_1, x_2, \ldots, x_n)^T \in \mathbb{R}^{n \times q}$ – an indicative description of the sample of n objects as $\boldsymbol{y} = (y_1, y_2, \ldots, y_n)^T \in \mathbb{R}^n$ – values of the target variable. In this case, $\boldsymbol{y}$ is the noisy values of some Gaussian process $f: \mathbb{R}^n \longrightarrow \mathbb{R}$ with zero mathematical expectation and some covariance function k. The process equation can be represented as:

$$y_i = f(x_i) + \varepsilon \ , \tag{2}$$

where x_i is the coordinates of the localization point, y_i is the value of the signal level from one Wi-Fi access point at a given localization point, and noise ε is a random variable that has a normal distribution with zero expectation and variance σ^2. The Gaussian process evaluates the a posteriori distribution of functions f based on training data $<\boldsymbol{X}, \boldsymbol{y}>$. The key idea underlying the use of Gaussian processes is the requirement of

correlation function values at different points, where the covariance between two function values $f(x_i)$ and $f(x_j)$ depends on the covariance between the inputs x_i and x_j. This dependency can be specified via an arbitrary covariance function, or kernel function $k(x_i, x_j)$. The choice of the kernel function is usually left to the user, the most widely used is the exponent square:

$$cov\left(f(x_i), f(x_j)\right) =$$
$$= k(x_i, x_j) = \sigma_f^2 \exp(-\frac{1}{2l^2}|x_i - x_j|^2), \qquad (3)$$

where σ^2 is the dispersion of the signal, and l is the scale that determines the strength of the correlation between points. Both parameters control the smoothness of functions evaluated by the Gaussian process. As can be seen from (3), the covariance between function values decreases with the distance between their respective input values. Since the function values are unknown, and only noisy measurements of signal levels are known, it is necessary to present the corresponding covariance function for measuring signal levels:

$$cov\left(y_i, y_j\right) = k(x_i, x_j) + \sigma_n^2 \delta_{ij}, \qquad (4)$$

where σ_n^2 is Gaussian noise, and $\delta_{ij} = 1$ if $i = j$, $\delta_{ij} = 0$ if $i \neq j$. for the entire set of input values X, the covariance for the corresponding observations Y is expressed as:

$$cov\left(\mathbf{Y}\right) = K + \sigma_n^2 I, \qquad (5)$$

where K is the covariance matrix and I is the unit matrix.

Thus, based on the obtained covariance matrix, it is possible to select the corresponding values from **Y** to fulfill the set restrictions. In addition, the a posteriori distribution of function values on the training data **X**, **Y** is important. It follows from (3) that the a posteriori values of the function have a normal distribution with an average μ_{x*} and a variance σ_{x*}^2:

$$p(f(x_*)| x_*, X, Y) = \mathcal{N}(f(x_*), \mu_{x*}, \sigma_{x*}^2), \qquad (6)$$

where $\mu_{x*} = k_*^T(K + \sigma_n^2 I)^{-1}Y$, and $\sigma_{x*}^2 = k(x_*, x_*) - k_*^T(K + \sigma_n^2 I)^{-1}k_*$, k_*- n×1 vector of covariances between the x_* and values of the training sample **X**, K-covariance matrix of values of the training sample **X**. There is a need to predict function values at an arbitrary point x_* is due to the training data **X**, **Y**. For this one need to take into consideration the random variable specifying the noise. The resulting predictive distribution summarizes the key advantages of using Gaussian processes in the context of wireless signal level models. In addition to a regression model based on training data, the use of Gaussian processes also presents forecast uncertainty, taking into account both sensor noise and model uncertainty. So, the predictive distribution for observation y_* can be expressed as follows:

$$p(y_*| x_*, X, Y) =$$
$$= \int p(y_*|f(x_*))p(f(x_*)| x_*, X, Y)df(x_*), \qquad (7)$$

This forecast distribution takes into account the noise and uncertainty of the model, and allows to build a regression in the context of processing the signal levels of Wi-Fi access points. Thus, solving the regression problem will allow to configure the parameters of the model, namely the parameters of the kernel function, so that it becomes possible to use this model in GP-LVM. Data is collected to form a training sample and configure the model while users are moving indoors. With the help of built-in smartphone sensors, the method of calculating coordinates is used to determine the user's real location and measure the RSS. This creates a training sample,
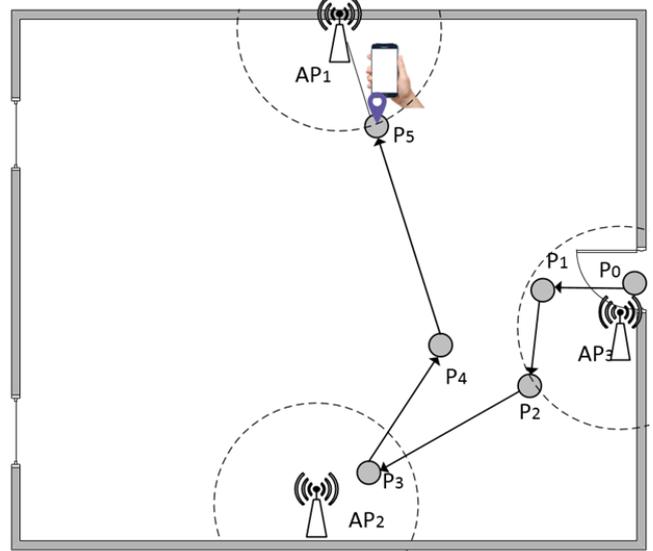
which is essentially a database of fingerprints. This process is sensitive to accumulated errors when turning and determining the distance traveled. In this regard, it is proposed to use knowledge of RSS near Wi-Fi access points or Bluetooth tags to refine user's location. Getting into the area of proximity of the signal source allows for semi-automatic calibration [45] of the signal propagation model and putting the signal source itself on the map of the room as a reference point. Finding at least three signal sources will allow for multilateration of signals to refine the coordinates of localization points obtained using the PDR method (Fig. 4).

Fig. 4. Phase of forming a training sample

Data is accumulated for creating a training sample after the user enters a new room. To detect this event, we suggest using the following rule: if the signal level of some access points becomes qualitatively higher, namely more than -80dBm and the signal level increase was more than 15dBm, then there was an entrance to a new room. This approach, however, has a drawback, due to the fact that in each room the signals propagate, refract and pass through the walls in different ways.

It is not possible in each case to rely on automatic detection of the user's entrance to the rooms and finding access points on the map to create a training sample. In this case it is proposed to use indoor navigation ontology concepts of such events like NavigationInTheRoom and AnchorNodeMet, and related to them SWRL-rules.

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

$$Measurment(?m)\char`^hasDetectedStep(?m, ?s)$$

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

$$\wedge Event(?e) \rightarrow NavigationInTheRoom\ (?e)$$

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

Thus, the overall structure of the method can be reduced to two phases: the training sample preparation phase (PDR phase) and the GP-LVM phase (Fig.5). During the preparation phase of the training sample, respectively, the user is detected entering the room, finding Wi-Fi access points, determining the location using the PDR method, forming a database of fingerprints, specifying the user's coordinates using the multilateration of Wi-Fi signals. In the GP-LVM phase, the radio signal map and user navigation are fully automatic.
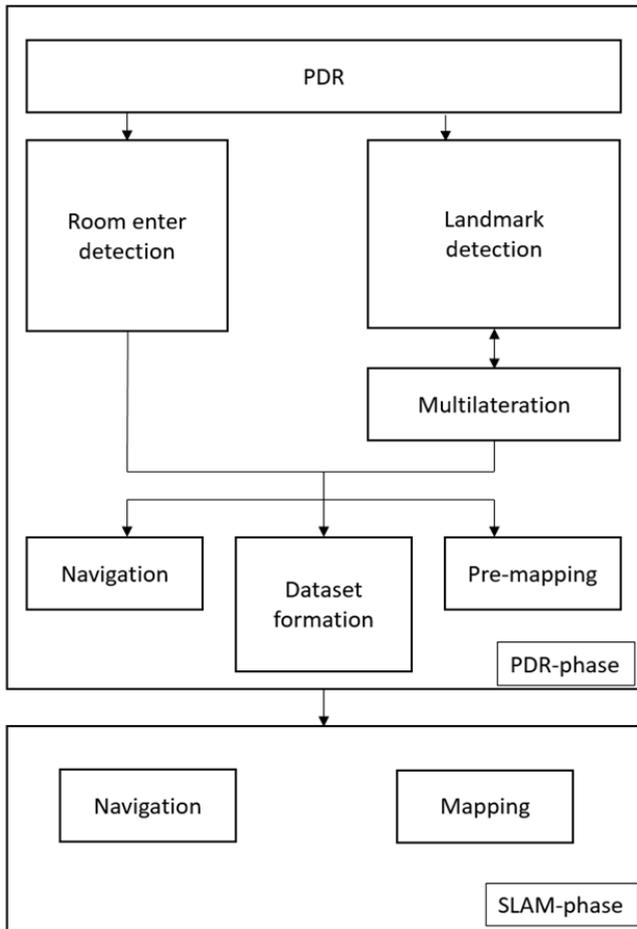
Fig. 5. Conceptual scheme of the combined SLAM method based on the Gaussian hidden variable process

The use of GP-LVM is intended for probabilistic modeling of the relationship between Wi-Fi signal strength readings **Y** and their localization points of user **X** in a two-dimensional coordinate space. The dependence of the signal level at each time point on the localization point and some hidden variable w can be written as follows:

$$y_{i,j} = f(x_i;\ w_j) + \varepsilon, \tag{8}$$

where $y_{i,j}$ is the i-th measurement of the signal level value for the j-th Wi-Fi access point, x_i is the coordinate vector of the localization points, w_j is the parameters of the $f(\cdot)$ function for the j-th access point, ε is the random value corresponding to the noise.

If we assume that the measurements of the level values of the signal levels from different access points are linearly independent, then:

$$p(Y|X, W) = \prod_{ij} p(y_{i,j}|x_i, w_j), \tag{9}$$

GP-LVM uses a Bayesian approach, and unlike the classical frequency approach, we do not need to use the maximum likelihood method, and the **X** matrix is treated as a matrix of hidden variables. This allows us to solve the problem of non-linearity of the function $f(\cdot)$, and find a marginal distribution only for the variables x_i:

$$p(Y|X) = \prod_j \mathcal{N}(y_j; 0, XX^T + \sigma_n^2 I\ ), \tag{10}$$

This distribution is a product of Gaussians with a linear covariance function. In the described method, instead of the linear covariance function, the kernel function (3) is used, whose parameters are configured in the PDR phase.

V. CONCLUSION

The proposed combined SLAM method of indoor navigation based on the Gaussian process latent variable model is partly based on the previously proposed methods that use the GP-LVM method for solving the problem of simultaneous navigation and mapping. The use of GP-LVM is possible due to the assumption that the values of signal levels are correlated at neighboring localization points. To establish such a relationship, the kernel correlation function is used, the parameters of which are pre-configured. This method combines the phase of learning the covariance function parameters and the phase of navigation and mapping without using data about the location of Wi-Fi access points and the room map. The phase of setting the covariance function parameters is performed by measuring the signal levels of many users using their smartphones and collecting the values of radio prints. Determining the location of users is based on the use of the PDR method. The method also uses additional approaches to clarify the location of users: detecting the entrance to a room and searching for Wi-Fi access points and using the multilateration of Wi-Fi signals. To search for access points and detect the entrance to a room OWL ontology and SWRL-rules are used.

REFERENCES

[1] A. Kuusik, S. Roche, F. Weis, "SMARTMUSEUM: Cultural Content Recommendation System for Mobile Users", *in Proc. ICCIT2009 (IEEE/ACM) International Conference on Computer Sciences and Convergence Information Technology*, Nov. 2009.

[2] Z. Tang, Y. Zhao, L. Yang, S. Qi, D. Fang, X. Chen, X. Gong, and Z. Wang, "Exploiting Wireless Received Signal Strength Indicators to Detect Evil-Twin Attacks in Smart Homes", *Mobile Information Systems*, vol. 4, 2017, pp. 1-14.

[3] F.Mekelleche, H.Haffaf, "Classification and Comparison of Range-Based Localization Techniques in Wireless Sensor Networks", *Journal of Communications*, vol. 12, No. 4, April 2017, pp. 221-227.

[4] H. Surmann , A. Nüchter, J. Hertzberg, "An autonomous mobile robot with a 3D laser range finder for 3D exploration and digitalization of indoor environments", *Robotics and Autonomous Systems*, 45(3-4), 2003, pp. 181-198.

[5] S. Dayekh, S. Affes, N. Kandil, C. Nerguizian, "Cooperative localization in mines using fingerprinting and neural networks", *in Proc. of IEEE Wireless Communications and Networking Conference*, Apr. 2010.

[6] G.-Z. Qiao, J.-C. Zeng, "Localization algorithm of beacon nodes chain deployment based on coal mine underground wireless sensor networks", *Meitan Xuebao/Journal of the China Coal Society*, 35(7), pp. 1229-1233, July 2010.

[7] V. Savic, H. Wymeersch, E.G. Larsson, "Simultaneous sensor localization and target tracking in mine tunnels", *in. Proc. of the 16th International Conference on Information Fusion*, Jul. 2013.

[8] G. de Blasio, A. Quesada-Arencibia, C.R. García, J.M. Molina-Gil, C. Caballero-Gil, "Study on an Indoor Positioning System for Harsh Environments Based on Wi-Fi and Bluetooth Low Energy". *Sensors*, vol. 17 (6), Jun. 2017.

[9] C. Röhrig, D. Heß, F. Künemund, "Constrained Kalman Filtering for Indoor Localization of Transport Vehicles Using Floor-Installed HF RFID Transponders*", in Proc. of the 9th IEEE International Conference on RFID (IEEE RFID 2015)*, Apr. 2015.

[10] M. Heidari, N. A. Alsindi, K. Pahlavan, "UDP Identification and Error Mitigation in ToA-Based Indoor Localization Systems using Neural Network Architecture", *IEEE Ttranslations on Wireless Communications*, vol. 8, no. 7, Jul. 2009.

[11] Md. H. Kabir, R. Kohno, "A Hybrid TOA-Fingerprinting Based Localization of Mobile Nodes Using UWB Signaling for Non Line-Of-Sight Conditions", *Sensors*, vol. 12(8), Aug. 2012.

[12] D. Liu, Y. Wang, P. He, Y. Zhai, H. Wang, "TOA localization for multipath and NLOS environment with virtual stations", *EURASIP Journal on Wireless Communications and Networking*, Dec. 2017.

[13] L Xinrong, K. Pahlavan ; M. Latva-aho ; M. Ylianttila "Comparison of indoor geolocation methods in DSSS and OFDM wireless LAN systems Sign In or Purchase", *Vehicular Technology Conference*, Sep. 2000.

[14] Z. Sun, R. Farley, T. Kaleas, J. Ellis, K. Chikkappa "Cortina: Collaborative context-aware indoor positioning employing RSS and RToF techniques", *2011 IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOM Workshops)*, Mar. 2011.

[15] M. Sivers, G. Fokin, P. Dmitriev, A. Kireev, D. Volgushev, A. A. H. Ali, "Indoor Positioning in WiFi and NanoLOC Networks", *in Proc.of International Conference on Next Generation Wired/Wireless Networking Conference on Internet of Things and Smart Spaces*, Sep. 2016.

[16] B. Hanssens, D. Plets, E. Tanghe, C. Oestges, D. P. Gaillot, M. Liénard, L. Martens, W. Joseph, "An indoor localization technique based on ultra-wideband AoD/AoA/ToA estimation", *2016 IEEE International Symposium on Antennas and Propagation (APSURSI)*, Jul. 2016.

[17] S.-H. Yang, H.-S. Kim, Y.-H. Son, S.-K. Han, "Three-Dimensional Visible Light Indoor Localization Using AOA and RSS With Multiple Optical Receivers", *Journal of Lightwave Technology*, vol. 32, issue 14, Jul. 2014.

[18] L. Deliang, L. Kaihua, M. Yongtao, Y. Jiexiao, "Joint TOA and DOA Localization in Indoor Environment Using Virtual Stations", *IEEE Communications Letters*, vol. 18, issue 8, Aug. 2014.

[19] X .Zhao, Z. Xiao, A. Markham, N. Trigoni, Y. Ren, "Does BTLE measure up againstWiFi? A comparison of indoor location performance", *in Proc. of the European Wireless 2014: 20th European Wireless Conference*, May 2014; pp. 1–6.

[20] J. Röbesaat, P. Zhang, M. Abdelaal, O. Theel, "An Improved BLE Indoor Localization with Kalman-Based Fusion: An Experimental Study", *Sensors*, vol. 17(5), Apr. 2017.

[21] F. Alsehly, R. Mohd Sabri, Z. Sevak, T. Arslan, "Improving Indoor Positioning Accuracy through a Wi-Fi Handover Algorithm", *in Proc.of International Technical Meeting of the Institute of Navigation*, Jan. 2010, pp. 822-829.

[22] D. Lawrence, Neil "Gaussian Process Latent Variable Models for Visualisation of High Dimensional Data", *Advances in neural information processing systems*, vol. 16, 2004.

[23] W. Liu, X. Fu, Z. Deng, "Coordinate-Based Clustering Method for Indoor Fingerprinting Localization in Dense Cluttered Environments", *Sensors*, vol 16, Dec. 2016.

[24] B. Ferris, D. Fox, N. D. Lawrence, "WiFi-SLAM using Gaussian process latent variable models", *in Proc. of IJCAI*, Jan. 2007.

[25] P. Mirowski, T. Ho, S. Yi, W. Macdonald, "SignalSLAM: Simultaneous localization and mapping with mixed WiFi, Bluetooth, LTE and magnetic signals", *in Proc. 2013 International Conference on Indoor Positioning and Indoor Navigation(IPIN)*, Oct. 2013.

[26] C.Luo, H. Hong, M. C. Chan, "PiLoc: a Self-Calibrating Participatory Indoor Localization System", *in Proc. of 13th International Symposium on Information Processing in Sensor Networks*, 2014, pp.143-153.

[27] C.Luo, H. Hong, M. C. Chan, J. Li, X. Zhang, Z. Ming, "MPiLoc: Self-Calibrating Multi-Floor Indoor Localization Exploiting Participatory Sensing", *IEEE Transactions on Mobile Computing*, 2018, vol. 17, issue 1, pp. 141 - 154.

[28] Q. Xichao, L. Weiqing. "LLN-SLAM: A Lightweight Learning Network Semantic SLAM", *Intelligence Science and Big Data Engineering. Big Data and Machine Learning*, Nov. 2019, pp. 253-265.

[29] A. N. Maksimov, M. A. Loktev, A. K. Volkov, "Modificirovannyj algoritm ORB-SLAM s semanticheskoj segmentaciej scen s podvizhnymi ob'ektami". *Nauchno-tekhnicheskij vestnik Povolzhya*, vol. 12, pp. 242-246.

[30] D. A. Malov, A.Y. Edemskij, A.I. Savel'ev, Razrabotka sistemy` proaktivnoj lokalizaczii kiberfizicheskogo prostranstva na osnove metodov mashinnogo obucheniya, *Informaczionnye tekhnologii i vychislitelnye sistemy*, vol. 4, 2018, pp. 72-83.

[31] J.-S. Kim, S.-J. Yoo, K.-J. Li, "Integrating IndoorGML and CityGML for indoor space", *in Proc. of International Symposium on Web and Wireless Geographical Information Systems*, 2014.

[32] M. Kessel, P. Ruppel, and F. Gschwandtner, "BIGML: A location model with individual waypoint graphs for indoor location-based services", *PIKPraxis der Informationsverarbeitung und Kommunikation*. vol. 33(4), 2010, p. 261-267.

[33] J. Lee, "A Spatial Access-Oriented Implementation of a 3-D GIS Topological Data Model for Urban Entities". *Geoinformatica*, vol. 8, 2004, pp. 237–264.

[34] V. Tsetsos, C. Anagnostopoulos, P. Kikiras, S. Hadjiefthymiades, "Semantically enriched navigation for indoor environments", *International Journal of Web and Grid Services*, vol. 2(4), 2006, p. 453-478.

[35] J. Yim, J. Joo, G. Lee, "Petri net-based ontology analysis method for indoor location-based service system", *International Journal of Advanced Science and Technology*, vol. 39, 2012, p. 75-92.

[36] J. Scholz, S. Schabus, "An indoor navigation ontology for production assets in a production environment", *in Proc. of International Conference on Geographic Information Science*, 2014.

[37] R. C. Chen, S.W. Huang, Y.C. Lin, Q.F. Zhao, "An indoor location system based on neural network and genetic algorithm", *International Journal of Sensor Networks*, vol. 19(3-4), 2015, pp. 204-216.

[38] S. Khruahong, X. Kong, K. Sandrasegaran, L. Liu, "Multi-Level Indoor Navigation Ontology for High Assurance Location-Based Services", in Proc. of IEEE 18th International Symposium on High Assurance Systems Engineering (HASE), 2017, pp. 128-131.

[39] N. Fernando, D. Mcmeekin, I. Murray, "Modelling indoor spaces to support vision impaired navigation using an ontology based approach", *in Proc. of Indoor Positioning and Indoor Navigation*, 2019.

[40] N. Maheshwari, S. Srivastava, K. Rajan, "Development of an Indoor Space Semantic Model and Its Implementation as an IndoorGML Extension", *ISPRS International Journal of Geo-Information*, vol. 8, 2019.

[41] W3C official website, OWL 2 Web Ontology Language Document Overview (Second Edition), Web: https://www.w3.org/TR/owl2-overview/6

[42] W3C official website, SWRL: A Semantic Web Rule Language Combining OWL and RuleML Web: https://www.w3.org/Submission/SWRL/

[43] W3C official website, Time Ontology in OWL, Web: https://www.w3.org/TR/owl-time/ 7

[44] I. Horrocks, O. Kutz, U. Sattler, "The even more irresistible SROIQ", *In Proc. of KR*, 2006, pp. 57-67.

[45] M. Shchekotov, M. Pashkin, A. Smirnov, "Indoor Navigation Ontology for Smartphone Semi-Automatic Self-Calibration Scenario", in Proc. of 24th Conference of Open Innovations Association (FRUCT), Apr. 2019, pp. 388-394.

[46] K. Kaemarungsi, P. Krishnamurthy, "Modeling of Indoor Positioning Systems Based on Location Fingerprinting", *in Proc.of INFOCOM Conference*, vol.2, Mar. 2004, pp. 1012-1022.

[47] R. Faragher, R. Harle, "Location Fingerprinting with Bluetooth Low Energy Beacons", *in Proc.of IEEE Journal on Selected Areas in Communications*, vol. 33, issue 11, Nov. 2015.

[48] D.-Y. Kim, S.-H. Kim, D. Choia, S.-H. Jin, "Accurate Indoor Proximity Zone Detection Based on Time Window and Frequency with Bluetooth Low Energy*", Procedia Computer Science*, vol. 56, 2015, pp. 88-95.

[49] C. N. Klokmose, M. Korn, H. Blunck, "WiFi proximity detection in mobile web applications", *in Proc of the 2014 ACM SIGCHI symposium on Engineering interactive computing systems. ACM*, Jun. 2014, pp. 123-128.

[50] S. Liu, Y. Jiang, A. Striegel, "Face-to-Face Proximity Estimation Using Bluetooth On Smartphones." *IEEE Transactions on Mobile Computing*, vol. 13, issue 4, Mar. 2013, pp. 811-823.

[51] M. Shchekotov, "Semi-Automatic Self-Calibrating Indoor Localization Using BLE Beacon Multilateration", *in Proc. of 23rd Conference of Open Innovations Association (FRUCT)*, Nov. 2018.

[52] M. Shchekotov, "Indoor Localization Methods Based on Wi-Fi Lateration and Signal Strength Data Collection", *in Proc 17th Conference of Open Innovations Association (FRUCT)*, Apr. 2015.