The Ontology Driven Indoor Positioning System Based On BLE Beacon Localization

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***Abstract*—One of the problems associated with the implementation of indoor location detection systems is the time-consuming procedure of equipment adjustment, which includes indoor map construction, radio signal map creation and calibrating signal propagation model. Thus, the equipment adjustment is a time-consuming and expensive process to be perform every time when there are changes in equipment configuration and allocation. The developed indoor localization system provides navigation of the user inside a room and allows to building radio map and putting Bluetooth Low Energy (BLE) beacons on the map of a room by the efforts of a number of users walking indoors. The architecture of the system is developed so that the different indoor localization techniques can be used and different services can be requested by the user's mobile application. The user's navigation inside the room is a combination of PDR based on the built-in smartphone sensors, multilateration and fingerprinting. The indoor navigation ontology is implemented to make decision which of these methods should be used. The key feature of the system is determining the location of BLE beacon. For this purpose the Random Forest algorithm is used, which uses signal levels, user rotation angles and distance to Bluetooth beacon as a training dataset. The geometric parameters of a room are estimated by the radio map and Bluetooth beacon locations.**

I. INTRODUCTION

The modern information technologies affect more and more spheres of public life. This process leads to reformulation of the indoor localization task. The task is not only the problem of determining the location of a person using a mobile device inside buildings, but also access points [1], a robot [2-4], a vehicle [5], etc. airports, museums [6], shopping centers [7-9], office areas [10-12], as well as factories and other engineering structures [13], [14] are considered. In addition, the tasks under consideration include not only navigation, collecting statistics and providing users with contextual information, but also enterprise logistics [13], visitor security [15] and information security [16]. Currently, wireless data transmission technologies themselves are also developing, becoming more convenient for use in indoor location determination tasks [17], [18]. The creation of indoor location detection systems based on the processing of radio signals remains a difficult task in terms of implementation and implementation, despite significant research on the part of researchers. The main problems encountered by developers of such systems are the multipath propagation of the signal, its reflection and refraction; the need to place and calibrate the infrastructure for localization, namely Wi-Fi access points or Bluetooth beacons; the 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 localization methods are based also on fixing the level of the received signal, the time of arrival of radio signals from transmitters [19], [20], [21], the difference in the time of arrival of radio signals [22], the time of signal passage from the transmitter to the receiver [23], [24], the angle of signal reception [25], [26] and the direction of reception [27]. The fingerprinting and multilateration have become more widespread. The method of fingerprints is based on the measurement of signal levels at pre-determined points, which is performed by a specialist in the tuning phase (offline phase). In the online phase or the navigation phase, the location of the object is estimated by comparing the measurements taken in the online phase with the previously collected measurements in the offline phase [28, 29]. This method allows to achieving localization accuracy of the order of 2.5-3 m [30]. The method of multilateration of signal levels operates with a model of signal propagation in a room. Based on this model the distances to signal sources cane 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 compile a database of radio prints or calibrate the parameters of the signal propagation model. Such steps significantly complicate the procedure for deploying location detection systems and lead to a significant increase in the cost of their implementation. The use of SLAM methods allows to simultaneously building a map of the room.

The system proposed in this article allows to dispense with the time-consuming procedure for measuring signal levels in the offline phase, since it is proposed to use collaborative measurement of signal levels inside the indoor locations, building maps of radio signals and maps of the indoor locations themselves. The use of this system is assumed in rooms whose geometry and location of Bluetooth beacons are not known. The object of localization is a person with a mobile device, and the localization area is a building visited by a wide range of people. The initial information for building maps of indoor areas is used to estimate the location of Bluetooth Low Energy tags, determine the moment of the user's entry into the indoor areas, determine the trajectory of movement using smartphone sensors, collect measured signal levels at various points of the user's trajectory to create a training sample. Because of that the key the system is determining the location of BLE beacons. The obtained data is used for the user's navigation inside the room using the methods of multilateration and radio prints. The system architecture encompasses mobile application and core of the system, which includes a number of services processing user's data by machine learning models. The mobile application uses several indoor localization techniques to localize a user: Pedestrian Dead Reckoning (PDR), multilateration and fingerprinting. The indoor navigation ontology is used to choose the appropriate technique according to specified rules. The core of the system includes also the service of determining the location of BLE beacons.

II. Related Work

Location detection systems based on SLAM algorithms, i.e. simultaneous navigation and mapping, allow, for example, when using a laser rangefinder, to determine the distance to the walls of a room and thus build a map of the indoor areas, simultaneously allowing navigation. However, this approach is not applicable for smartphone users, since it is assumed that the user should not 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 by the use of existing smartphone sensors.

Various methods can be used to solve the problem of simultaneously determining the location inside the indoor areas based on the use of wireless data transmission networks and mapping the indoor areas. For example, the method proposed in [31] uses a priori knowledge of signal propagation in a room and evaluates stochastic disturbances using an EM algorithm to build a signal propagation map and a multi-frequency filter (sequential Monte Carlo method) to filter measurements of signal levels. The WiFi-SLAM method [32] uses a 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 values of signal levels into the coordinate space. To improve the localization accuracy, a dynamic motion model and a model of Wi-Fi signal levels trained on the basis of a Gaussian process are used. The SignalSLAM method [33] provides a solution to the problem of constructing an observation map using collaborative data collection from several experimenters freely passing through the building: WiFi radio prints, 4G LTE RSRP, magnetic field, GPS coordinates in the open air, NFC values at specific landmarks and motion trajectories based on inertial data. This method uses a modified version of the GraphSLAM method, which includes optimizations for user coordinates using sets of absolute locations and pairwise constraints that include multimodal similarity of signals. As an example of a system that uses crowd calculations to solve the problem of determining the location inside the indoor areas, the PiLoc system is considered [34], [35]. PiLoc uses crowd computing to collect user movement trajectories using built-in smartphone sensors and radio prints of Wi-Fi network signals. Clustering is used to combine the values of the Wi-Fi signal strength and movement trajectories into disjoint sets. The generated disjoint sets are used to search for similar segments, based on the coincidences of the movement vectors and signals of Wi-Fi access points. The obtained trajectories are combined to build floor plans of indoor areas.

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 [36] and BIGML [37]. 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 twoand 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 [38]. Moreover, the cell semantic is presented including the classification of spaces and boundaries. Geometric and semantic information hybrid modeling is proposed in OntoNav [39]. 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 [40]. 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 [41] 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 [42] 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 [43] 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 [44], an ontology was developed for the system of visual location determination inside indoor areas. 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 [45], a model for classifying rooms based on the ontology of indoor spaces is proposed, 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 processing 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):

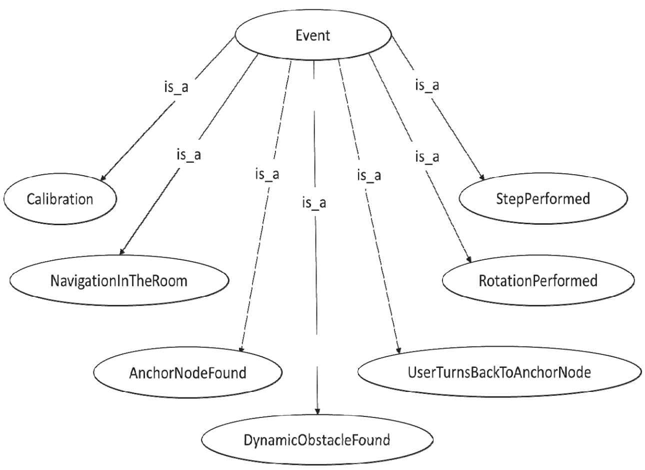

Fig. 1. Indoor Navigation Ontology fragment related to Event concept

- 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.

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.

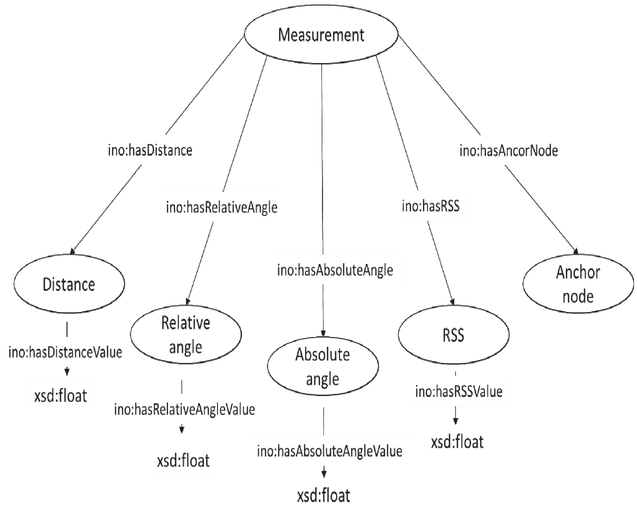

Fig. 2. Indoor Navigation Ontology fragment related to Measurement concept

Let the calibration measurement is a tuple M, which can be defined as:

$$M = (d, \alpha, \beta, Pr\ , s, r, t) \tag{1}$$

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, Pr – 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). 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. 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.

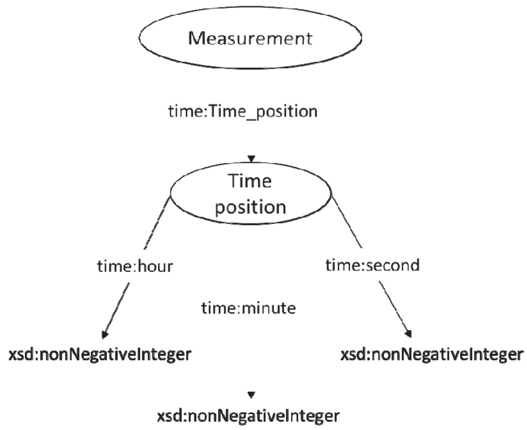

Fig. 3. Indoor Navigation Ontology fragment related to Measurement concept

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. Determining the location of anchor nodes

One of the problems of building indoor location detection systems is the time-consuming procedure for setting up equipment and calibrating it, which increases the cost of deploying such systems and complicates their operation. For example, the owners of shopping centers are not interested in buying indoor location detection systems because of the high overhead costs and low economic efficiency of such implementations. In addition, signs and information kiosks placed in the interior spaces can help solve the problem of determining the location of a visitor in a shopping center. The proposed method is the basis for a navigation system and collaborative mapping of indoor areas by a lot of people using smartphones and allows you to do without the procedure of setting up equipment before deploying the indoor positioning system.

The initial position for the developed navigation method is that the location of Bluetooth beacons, as well as the geometry of space, are not known in advance. Also, the key point when using this method is to determine the location of the Bluetooth beacons themselves by estimating the distance to the signal source and determining the signal reception angle. Let's assume that in the room where localization is performed, for example, in a store inside a shopping center, there is already the necessary infrastructure, i.e. Bluetooth beacons, but no configuration and calibration were performed. In order to determine the user's location in such a room, it is necessary to establish its approximate geometry and the location of access points, and perform calibration. As mentioned earlier, this procedure can be performed by the users themselves in automatic or semi-automatic mode with the involvement of the user in the gameplay to obtain data that, for objective reasons, cannot be established with reliable accuracy using smartphone sensors and software that implements navigation and location algorithms.

The signal from Bluetooth beacons is much stronger in the room in which they are located. This knowledge can be used to detect the moment of entry into the room, the map of which needs to be made. To detect this event, it is proposed to use the following rule: if the signal level of some access points becomes qualitatively higher, namely more than -90 dBm, then there was an entrance to a new room.

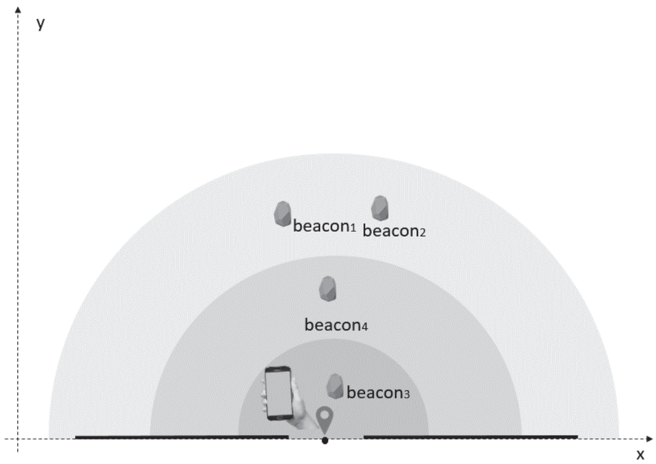

Fig. 4. Information available at the entrance to the room

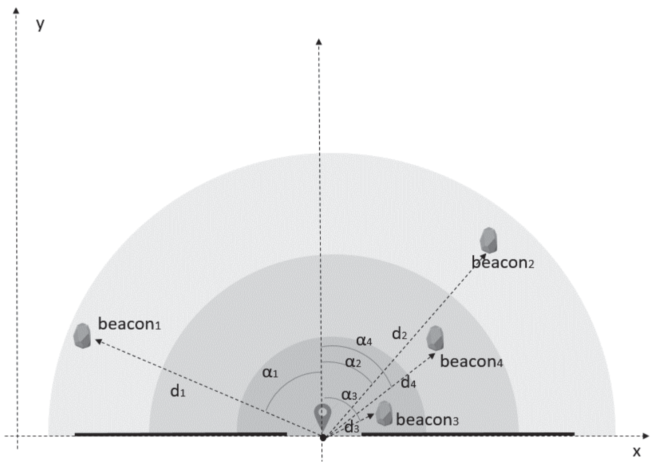

Fig. 5. Information available after the preliminary beacon location assessment

In particular for Bluetooth Low Energy beacons, there are several proximity zones in which the signal level value takes a certain range of values. Therefore, the only thing that can be set at the initial moment of time is the entrance point to the room, the conditional x and y axes, relative to which the coordinates will be counted, and the signal strength from the beacons that are located in the room (Fig. 4, Fig. 5).

It is necessary to find out the relative angles of the directions to the beacons (α1, α2, ... an) and estimate the distance to them (d1, d2, ... dn). To determine the distance for the signal source, existing methods can be used for estimating the distance in the indoor areas. The signal loss model, which depends on the logarithm of the distance (log-distance path loss), is used as a signal propagation model:

$$PL = P_{Tx} - P_{Rx} = PL(d_0) + 10n\lg\frac{d}{d_0} + X_{\sigma_{RSS}} \quad (2)$$

where PL is the indicator of signal power loss (dB), PTx is the transmitted power (dBm), PRx is the received power, signal strength (dBm), d is the real distance between the transmitter and receiver, n is the exponent of signal loss, Pt is the transmitter power (dBm), PL(d0) is the signal loss (dBm) at a distance of d0. The value of XσRSS (dBm) is a random error value.

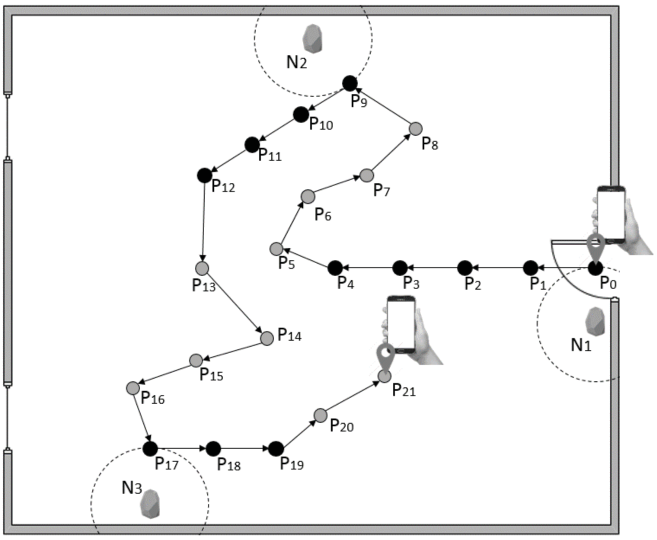

Fig. 6. The containing semi-automatic self-calibration scenario schema of user's movements

To determine the signal reception angle, it is proposed to use the Random Forest machine learning algorithm. 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 form a model for determining the signal reception angle of specific Bluetooth beacons. It is assumed that when training this model, the user will participate in the process of creating a training sample, indicating the angles of the directions to the beacons (α1, α2, ... an).

At the same time, getting into the zone of proximity of the signal source allows for semi-automatic calibration [37] 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 clarify the coordinates of localization points obtained using the coordinate counting method.

Semi-automatic calibration (Fig. 6) is necessary in order to further estimate the distance to the beacon next to which the user was located in the most accurate way. In addition, being in the proximity zone of the beacon allows to collect raw data for training a model for determining the direction to the beacon. This model can be used to subsequently determine the direction to the beacon of the same standard and manufacturer without the user's participation.

To determine the location in the phase of building a training sample, the method of calculating coordinates (Pedestrian Dead Reckoning — PDR) is used, using data from the built-in sensors of the smartphone. This process does not require direct control on the part of users, but serves as an additional way to clarify the actual values of the user's location and the rotation angles of his smartphone in order to navigate inside the room until its geometry and the location of all signal sources are clarified.

Thus, the sequence of actions when determining the location after entering the room is reduced to:

1) Detecting the entrance to the room.
2) Initial estimation of distances to signal sources and construction of relative coordinate axes.
3) Navigation using the coordinate calculation method.
4) When entering the proximity zone of the beacon, the user clarifies its position.
5) During further movement, automatic calibration of the signal propagation model for this beacon.
6) Clarification of the directions to the other beacons and the distances to them.

Since it is impossible in each hotel case to rely on the automatic determination of the direction to the signal source to create a training sample, in this case it is proposed to involve the user himself in the data collection process by giving him certain tasks as part of the gamification procedure of the data collection process. Such tasks will include the search for Bluetooth beacons and confirmation of entry into the room. For successful completion of tasks, it is proposed to award points in accordance with the reward model, in which one point is awarded for detecting the entrance to the room, and 5 points are awarded for finding Bluetooth beacons. It is based on the work [38], which suggests the use of an achievement system to facilitate the completion of homework in a mathematics course using a web application. In the developed method, it is proposed to use an achievement system, in which users receive points to move to a new level. At the same time, it is easier to raise the level at an early stage and make it more difficult to earn points throughout the game.

To motivate users, there are three types of achievements: those earned during the normal process, which all players will earn, additional achievements that can be earned by performing standard actions in the game, and, finally, an achievement that is rewarded based on a goal that is not related to the standard process. It is assumed that there are several simple tasks:

1) Determining the direction to the beacon.
2) Bypass all signal propagation zones near signal sources.
3) Involving other users in the process.

Thus, the general structure of the method can be reduced to two phases: the phase of preparing the training sample and the main phase (Fig. 7). During the preparation phase of the training sample, respectively, the entrance to the room is detected, Bluetooth beacons are found, the location is determined using the coordinate counting method, the base of radio prints (training sample) is formed, the user's coordinates are clarified using Bluetooth signal multiplateration. In the main phase, a fully automatic construction of a radio signal map and user navigation is performed.

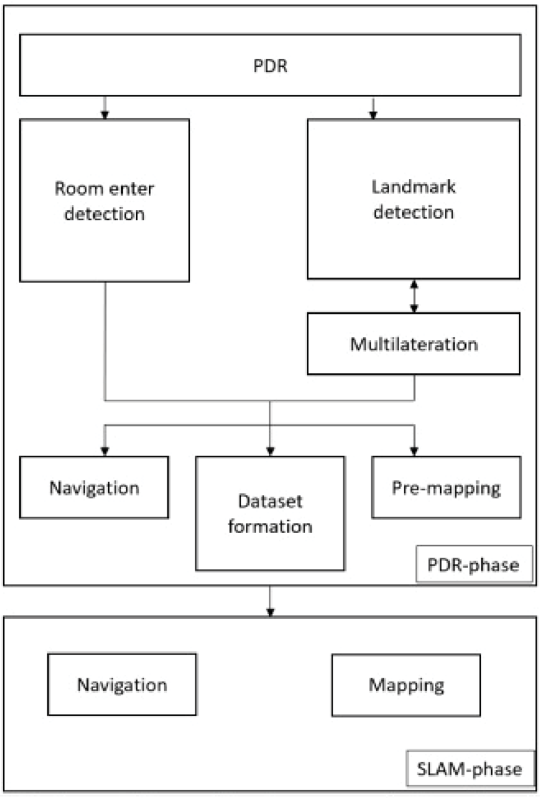

Fig. 7. Indoor localization system algorithm fusion concept schema

To determine the location of signal sources, it is proposed to use, for example, Bluetooth tags, the Random Forest machine learning algorithm used for classification and regression analysis. The algorithm uses a set of decision trees, which are separate instances of data classification. Random Forest takes into account the instances separately, taking the one that received the most votes as the resulting forecast. Random Forest was chosen because it can process large data with numerous variables, automatically balance data sets when a class is less common than other classes, and also allows to evaluate the importance of variables, which makes it suitable for complex classification tasks.

For the developed method, a limited set of measurements is used to form a training sample, which is generated by the user's device during the preliminary phase (Fig. 8).

$$D = (RSS, d, \alpha) \tag{3}$$

where – the training sample-the module of the signal level value, - the estimated distance to the access point, - the angle specified by the user.

RSS	angle	distance	result_angle
63	270	0.5	270
61	270	0.5	270
53	180	0.5	180
53	180	0.5	180
78	0	0.5	0
...	...	...	...
41	90	0.5	90
55	180	0.5	180
60	270	0.5	270
67	0	0.5	0
54	180	0.5	180

Fig. 8. Training set data

Then the sample was divided into sets of training and verification data. In the experiments conducted, the data is divided in the ratio of 20% to 80%, then the data is scaled, since they have different units of measurement. For the angle parameter specified by the user, four values are selected: 0, 90, 180, 270. The size of the training sample is 1200 dimensions. Such a small size of the training sample is explained by the small time that the user can spend on its formation. The verification was carried out using measurements taken for the same Bluetooth Low Energy beacon, the signal levels of which were collected for the training sample. The model was trained using the scikit-learn library [39] and the Jupiter Notebook toolkit.

After training the model, the hyperparameters of the model were optimized. Using the RandomizedSearchCV algorithm [40], the ranges of hyperparameter values were investigated and the best values for a set of hyperparameters were identified (Fig. 9). Hyperparameters that were analyzed:

- n_estimators is a number of trees.
- min_samples_split is aminimum number of objects required for a tree node to split.
- min_samples_leaf is a minimum number of objects in the leaves.
- max_features is a number of features to select splitting.
- max_depth is a maximum depth of trees.
- bootstrap is a parameter for building subsample trees.

Testing of the model showed that the accuracy of the model is 73%. In the course of the work, the accuracy of the model based on the Random Forest algorithm is compared with the model trained by the support vector machine (SVM). A comparative analysis showed that the model based on support vectors shows less accuracy (66%) on the same data set. The model based on the support vector method determines the angles of 180 and 270 degrees worse (Fig. 10).

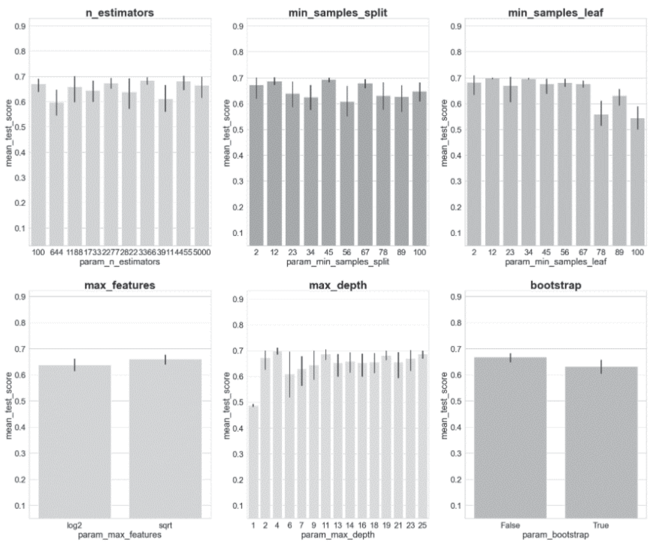

Fig. 9. Investigation of the values of the parameters of the model

	precision	recall	f1-score	support
0	0.72	0.76	0.74	63
90	0.78	0.59	0.67	64
180	0.52	0.68	0.59	63
270	0.59	0.52	0.55	69
accuracy			0.64	259
macro avg	0.65	0.64	0.64	259
weighted avg	0.65	0.64	0.64	259

Fig. 10. Analysis of the model accuracy based on the support vector machine method

V. The Indoor Localization system Architecture

The indoor localization system architecture is aimed to process a large number of raw data going from different users trying to localize themselves in different unknown locations. The system architecture should support different engines to process user's data by an appropriate way using machine learning model or neural network. The architecture consists of user's mobile application that supports three different indoor localization techniques and ontology-based engine that orchestrates their usage according to defined rules. The main advantage of ontology is the possibility to change business logic programmatically.

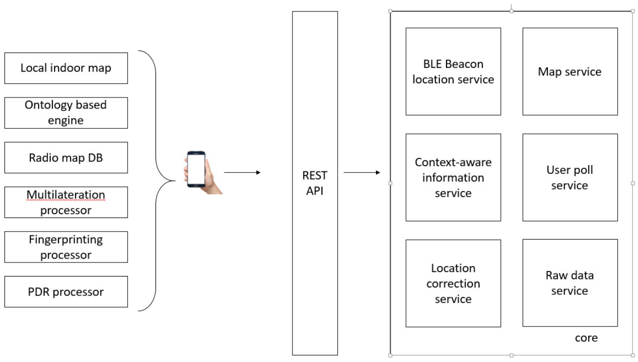

Fig. 11. Analysis of the model accuracy based on the SVM method

The mobile application constantly sends the raw measurements via common REST API to core of the system. These data are necessary to such processes like BLE Beacon localization, radio map and indoor map construction, filling ML datasets etc. The system services that can be achieved through REST API are:

- BLE Beacon location service – the service that uses the presented above model to localize BLE beacons.
- Map service – the service that provides indoor map information updates calculated by a number of user raw data.
- Context-aware information service – the service that provides some context information like a points of interest and their description.
- User poll service – the service that supports the gamification mechanism of user's localization.
- Location correction service – the service that corrects users location.
- Raw data service – the service that takes raw data from users.

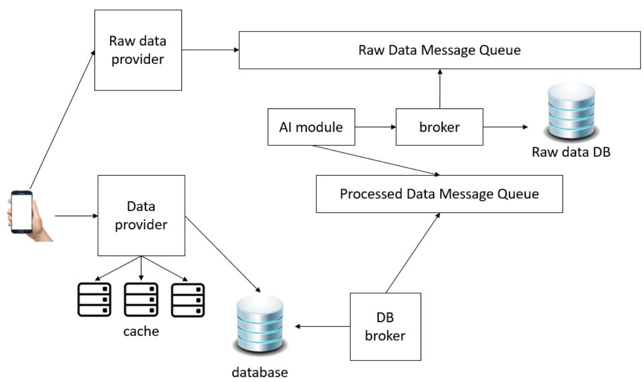

Fig. 12. Analysis of the model accuracy based on the support vector machine method

The system has two message queues to process the data. The first one has raw data that are necessary to AI model based services to predict new significant information. The second one transfers the processed data to specific data providers like a context-aware information services, map service etc.

The stack of technologies consist of different Java-based REST services, Python-based AI modules, NoSQL database MongoDB to store raw datasets, PostgreSQL instances for each data provider, Hazelcast instances to facilitate data access to the data by the users.

VII. Conclusion

The proposed indoor navigation system based on the determination of Bluetooth beacons is partly based on the previously proposed method of semi-automatic calibration of the signal propagation model in the room and the method of simultaneous navigation and mapping based on two phases. Determining the location of users is based on the use of the coordinate calculation method. The method also uses additional approaches to clarify the location of users: detecting the entrance to the room, searching for Wi-Fi access points or Bluetooth beacons, and using multilateration of Bluetooth signals. Its main difference from the known combined navigation methods is the procedure for determining the location of Bluetooth beacons using the Random Forest machine learning algorithm, which allows to determine the direction in which the beacon is located. The evaluation of the accuracy of the trained model showed that the error when using this method does not exceed 29%. To apply these approaches, the gamification of the Bluetooth beacon search process is used, based on the achievement system. The developed method allows to do without the time-consuming procedure of setting up and calibrating equipment and immediately start using the existing infrastructure for indoor navigation.

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