Geocontext extraction methods analysis for determining the new approach to automatic semantic places recognition

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***Abstract*—Goal of this paper is to determine actual trends in geocontext extraction methods and to understand which types of geocontext information are the most interesting for users. For this purposes comparison of recent researches about geocontext analysis was done. Researches were compared by the type of achieved result, used formalism, source data and limitations. As the main result of comparison new approach for automatic semantic places recognition was proposed. This approach is based on geotags markup with semantic user-defined tags. The solution allows extracting information (coordinates and a set of corresponding semantic tags on the natural language) about locations which are interesting for the location-based services users. The main advantage of the approach is its simplicity – the method does not rely on any syntax analysis algorithms during the semantic labeling stage. For illustrating the approach an example of the general purpose accidents monitoring service for the Geo2Tag platform was described.**

I. INTRODUCTION

Context-aware computing market is growing with promising pace - according to MarketsandMarkets's study [1] the market will grow more than four times by 2018 compared with the level of 2013. At the same time, the research field is continuously changing - context aware computing became socially-aware computing. Recent surveys [2-4] shows how this trend changed the understanding of the context. More attention is payed to contexts, calculated for the groups of people (social contexts) rather to individual users ones [2].

Location-related part of the context (geocontext) is also changed by this trend. Thats why it is important to understand what is meant to be by geocontext today and analyse new methods of its extraction.

II. TERMINOLOGY

Before the comparison and analysis itself key terms should be defined. The most important one is the "Context" term. In this paper will be used the most frequently used definition [5]: "Context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves". The "Geocontext" term does not have any settled definition and for the further usage in this paper the following definition based on "Context" term is proposed: "Geocontext is location information that can be used to characterize the situation of an entity". Also the term "Geocontext information" will be considered as a synonym of the "Geocontext" term.

III. COMPARED SOLUTIONS

For the comparison and analysis following recent works were selected:

- "SensLoc: sensing everyday places and paths using less energy" [6]. The work describe Android application which realizes extraction such geocontext features as paths and places from GPS data and robust algorithms developed for it.
- "Predicting future locations with hidden Markov models" [7]. In this paper algorithm for predicting human motion is proposed. The solution use clustered location dataset for teaching hidden Markov models (HMM) [14] which estimate probability of human existence in given locations by the given history of previous movements.
- "Inferring hybrid transportation modes from sparse GPS data using a moving window SVM classification" [8]. The proposed approach use movements history including speed to build a classifier which will answer to question on which type of transport does individual moving.
- "The places of our lives: Visiting patterns and automatic labeling from longitudinal smartphone data"[9]. The paper contains a survey about semantic places recognition using different criterions and data sources. Authors used special application which performed collecting detailed data about mobile phone usage. This dataset was analyzed and used for semantic places recognition and labeling task.

This four works were chosen because they match trends described in Introduction - moving from context-aware applications to the social-aware applications [6-9] and group contexts recognition [7-9]. The other reason was big variance of approaches and the fact that all of them allow extending geocontext with completely new information.

IV. Criteria for comparison

In this section several basic criterions for analyzing of introduced earlier solutions will are defined. The most important question which should be answered firstly is the following: "Which new geocontext information can be received by using proposed method?" It will allow to understand how the method can extend geocontext and in which geocontext applications it can be used.

The second question: "Which data is used for analysis?" Answer to this question will help to understand which real or virtual sensors should be used for this method and determine on which devices it can be applied.

The third question: "What approach is used?" Knowledge of the method basic formalism allows determining quality and volume of the needed raw data.

The fourth question "What limitations does the method have?" allows understanding additional requirements to the datasets, application and its use case.

V. Comparison

A. New geocontext information

In this section four methods and algorithms proposed in articles [6-9] are compared by the type of new context information, which they allow to receive without any complex interaction with user.

1) The SensLoc application proposed in the work [6] allows determining semantic places, travel paths between them and track user movements. The authors of [6] did not gave definition to "semantic place" term but according to [10-12] it can be defined as a geographical zone connected with a meaningful label e.g. at home, at work, in a restaurant. Paper [6] shows that process of receiving semantic places from the sensor data is not fully automatized - the name of the place are assigned by user.
2) The hybrid approach proposed in [7] allows building prediction model of the individual movements. The model can determine probabilities of the individual being in certain place. By the place term paper authors mean triangle regions of the same shape and square, in which the whole Earth surface is divided.
3) The approach proposed in [8] allows building the classificatory which can decide to which transportation mode given movement history belongs.
4) The method proposed in [9] allows performing semantic places recognition using various data from mobile phones. As in case with [6] the semantic meaning of place is assigned by user.

TABLE I. Types of geocontext information in each solution

Work	**Types of geocontext information**
"SensLoc: sensing everyday places and paths using less energy"	Semantic places, travel paths
"Predicting future locations with hidden Markov models"	Movements prediction model
"Inferring hybrid transportation modes from sparse GPS data using a moving window SVM classification"	Transportation modes classificatory
"The places of our lives: Visiting patterns and automatic labeling from longitudinal smartphone data"	Semantic places

The comparison showed that full automation of semantic places extraction still stays difficult for researches and it is solved by the interaction with user.

B. Source data used for building geocontext

This section describes needed datasets for the solutions proposed in [6-9].

1) The application, described in [6] requires access to the GPS and accelerometer data, WiFi network information. Application also performs direct polling of the user in cases when candidate to semantic place were found.
2) The solution, described at [7] use history of individual movements (time, coordinates), acquired using GPS sensor. Datasets from many individuals are merged and used together.
3) The solution proposed in [8] use history of individual movements (time, coordinates) and velocity history, acquired using GPS sensors. Each dataset also contain marks that define movement type in the logged moment of time. Datasets from many individuals are merged and used together.
4) The data collecting application proposed in [9] use all data available from mobile phone including GPS and SMS data, call and calendar history, WiFi network information. Also application performs direct polling of the user. Collected datasets from many users were merged and used together in further steps.

5) TABLE II. SOURCE DATA USED FOR BUILDING GEOCONTEXT

Work	Source data used for building geocontext
“SensLoc: sensing everyday places and paths using less energy”	GPS, accelerometer, WiFi network information
“Predicting future locations with hidden Markov models”	GPS (time, location) history
“Inferring hybrid transportation modes from sparse GPS data using a moving window SVM classification”	GPS (time, location, velocity) history
“The places of our lives: Visiting patterns and automatic labeling from longitudinal smartphone data“	All data available for measurement from mobile phone

The comparison between data sources showed that GPS data still stays the most common data source for geocontext applications, but usage of additional data sources (WiFi network information, call history, calendar data and etc.) allows to achieve new types of geocontext information, which was impossible using just GPS data. Also, aggregation of individual user geocontexts into group geocontext allows building complex models of the user behavior.

C. Approach used for geocontext building

The goal of this section is to answer on the question: “What formalisms and approaches were used in [6-9]?”

1) For places detection the application described in [6] WiFi data is used. The system calculates WiFi fingerprints for available beacons and use Tanimoto coefficient [13] for determining similarity between them. For the detecting entrance and departure slide window scan of fingerprints is used.
2) In the [7] complex approach of two steps is used. On the first step location histories are clustered using to the temporal periods (weekdays daytime/night time, weekends) when they were logged. On the second step HMM is trained for each cluster.
3) The work [8] use Support Vector Machines (SVM) [15] formalism for building a movement type classificatory based on user locations history.
4) The method of analysis proposed in [9] use hybrid approach. On the places recognition stage authors used simple statistical estimation - each round location where user stays for more than certain time and with certain frequency was treated as semantic place. After the statistical extracting of places, user gave their own labels to them and chooses type of the place. Collected preprocessed dataset with mapping “places-type” was used for training the classificatory.

TABLE III. APPROACH USED FOR GEOCONTEXT BUILDING

Work	Approach used for geocontext building
“SensLoc: sensing everyday places and paths using less energy”	WiFi fingerprints comparing, slide window scan
“Predicting future locations with hidden Markov models”	Statistical clusterization, HMM
“Inferring hybrid transportation modes from sparse GPS data using a moving window SVM classification”	SVM
“The places of our lives: Visiting patterns and automatic labeling from longitudinal smartphone data“	Statistical approach, supervised machine learning

Comparison revealed that straightforward approach for geodata analysis is not enough anymore. Instead most of authors [6-7, 9] use several different formalisms, applying statistical data preprocessing firstly.

D. Limitations

In this section main and the most important limitations of the [6-9] solution are described and compared.

1) The authors of SensLoc applications admit that the solution requires existence of the strong WiFi signal in the area which should be treated as a semantic place.
2) According to article [7] experimental part teaching of the HMM requires big datasets (17,621 trajectories) with small tracking interval (91% of trajectories were logged with 10 meters/ 15 seconds resolution).
3) According to article [8] training dataset should have big size (authors used 2-weeks long multi-modal tracks of 81 users).
4) In the survey [9] authors described that data-collecting application had full access to all mobile phone data and the collection of analyzed dataset lasted for 18 month.

TABLE IV. LIMITATIONS

Work	Limitations
“SensLoc: sensing everyday places and paths using less energy”	WiFi coverage
“Predicting future locations with hidden Markov models”	Big training datasets
“Inferring hybrid transportation modes from sparse GPS data using a moving window SVM classification”	Big training datasets
“The places of our lives: Visiting patterns and automatic labeling from longitudinal smartphone data“	Big training datasets, full access to mobile phone

Review of the main limitations showed that the most complex solutions require big volumes of well prepared data for building models of user behavior, which makes impossible use such solutions as standalone mobile application.

VI. Semantic places extraction using Geo2Tag

Comparison shows that automatic extraction of semantic places from user geodata is a challenging task because reviewed solutions relay from user input. This data source is used for retrieving missing semantic information – name [6] and category [6, 9] of a place. Without user interaction solution of this task requires semantic analysis of user social behavior related to his location. By the term "social behavior" we mean user posts in social media and blogs, calendar events, etc. Common approach for such analysis includes syntax and semantic processing of natural language. Despite the fact that this methodology allows to achieve big understanding of the domain field it also requires usage of complex algorithms. We propose much simpler approach based on social behavior automated tag markup with Geo2Tag platform. Term "tag" or "semantic tag" stands for a single word from a natural language.

Geo2Tag [16-19] is a software platform which provide base for creation of location-based services. Basic entity for the platform is the geotag – the composition of location information and annotated media content. Geo2Tag abstracts the developer from following tasks related to geodata:

- geo-tagging of annotated media content;
- storing of geotags;
- geo-search and spatial filtering;
- geotags markup with semantic tags.

For understanding the proposed approach of semantic place extraction the last type of functionality should be described.

The basic conception of the semantic tag markup functionality is the global semantic tag set. This set is defined by users according to their interests during the usage of services connected to the platform instance. The markup process for single geotag is a calculation of its personal semantic tag set. Word forms of each semantic tag at the global set are searched among content annotation as a substring.

The proposed approach of semantic place extraction in general can be described as a following algorithm:

1) Statistical determination of semantic places location using approach described at [9].
2) Semantic tag markup of geotags located at the position of semantic places.
3) Calculation of total statistic for each semantic tag at the current semantic place – total number of each semantic tag occurrences, total number of geotags with semantic tag occurrences, etc.
4) Decision making about the most important semantic tags at the current semantic place – using relative or absolute thresholds.
5) Result of the algorithm work – set of the most important semantic tags.

In the description several different statistical criterions were mentioned as an example. It was done because usage of a concrete criterion requires detailed accuracy analysis and depends from the domain field.

Proposed approach has following advantages:

- Algorithm does not require syntax analysis.
- Semantic places labeling part does not require training.

The main disadvantage of the approach is dependence from detailed word form dictionary.

Also there are opened questions about the approach:

- How to filter meaningless semantic tags from semantic place description?
- How to select optimal criterions for concrete task and use case?

VII. Possible use cases

In the chapter V reviewed papers were compared from the technical point of view. At the chapter VI the approach for automated semantic place discovery and labeling was described. In this chapter we will show use cases which are made possible by such functionality.

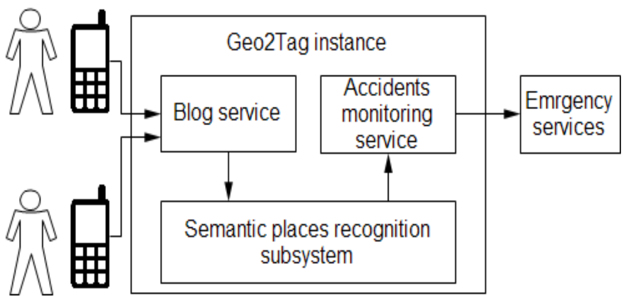

Fig. 1. Diagram of the basic use case for automatic semantic place recognition

We will describe basic use case as accidents monitoring service, but it is applicable to many different kinds of monitoring tasks. The described service and the blog service are considered as a part of Geo2Tag instance, but it also can be implemented as a standalone service, for example multi-blogging service on Smart-M3 platform [21]. Users post their messages with location data. Semantic places recognition subsystem analyzes geotags of the blog service. Accidents monitoring service use data provided by the subsystem to find semantic places which descriptions contain semantic tags from special subset, containing words related to accidents. When such place is found information about it is transferred to emergency service.

Despite the fact that described use case is very primitive and it ignores questions of data reliability, proposed accidents monitoring service still can be helpful as an additional source of information which will make localization of accidents faster.

VIII. Future work

The approach proposed for semantic labels localization and labeling is on initial stage. We are going to implement it as a part of Geo2Tag platform, test approach accuracy in case of different domain fields and try to analyze how statistical criterions can be selected to achieve the best accuracy.

We are also going to continue use cases analysis by applying the approach to different problems of Smart Spaces (concentrating on Smart-M3 model [20]) and Internet of Things domains.

IX. Conclusion

We have considered four papers contained researches about new methods of geocontext extraction and analysis. All of them were compared in aspects of needed data, received geocontext information, limitations and used approaches. As a result of this comparison next conclusions were made.

1) One of the biggest challenges of a geocontext building methods is an algorithm for semantic places recognition and labeling without user interaction.
2) For getting principally new types of geocontext information researchers should combine GPS sensor traces with other data sources (WiFi network statistics, call and text messages history etc.) or combine individual contexts into group contexts.
3) The most promising approach for extracting new types of geocontext information includes usage of several different formalisms. According to the comparison the most productive type of the hybrid approach is one with statistical preprocessing of raw data as a first step.
4) Complex models of user geo-related behavior require long training on big datasets. This makes almost impossible creation of mobile applications based on such models without strong cloud backend and put focus on questions of energy-efficiency.

We propose new approach to automatic semantic places recognition on the basis of these conclusions. This approach does not require syntax analysis and training on the stage of semantic places labeling. The approach use combination of Geo2Tag platform mechanism of semantic tags markup and semantic places localization algorithm from [9].

For the proposed semantic places extraction approach illustration we introduce an example of accidents monitoring service and describe its use case. This use case shows how to apply given methodology for services which are working under Geo2Tag platform instance. Also, example of accidents monitoring service demonstrates how the platform architecture can be changed to support given approach.

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