A new approach for distributed and collaborative context prediction

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***Abstract*—The processing capabilities of current smartphones have increased significantly. We propose a distributed and collaborative context prediction approach that exclusively uses current smartphones to automatically collect, process and predict contexts of users. To predict a user's next context, not only her context history is utilised but also context histories of other users are used. The communication between the smartphones of the users is realised using peer-2-peer. Therefore, no centralised server unit is needed to process the context information of the users externally. We provide a proof-of-concept implementation and present experimental results that demonstrate the practicality of the proposed architecture.**

***Index Terms*—collaborative; context prediction; p2p**

I. Introduction

With the evolution of today's smartphones into powerful and ubiquitous computing devices, it is possible to predict future contexts in a distributed and collaborative way. Up-to-date smartphones offer additional sensors like an accelerometer, a gyroscope or even near field communication that can be used to collect additional contexts of a user. Due to improved battery and processing power, collected context data can directly be processed on smartphones. Moreover, the increased available mobile bandwidth enables the user to send and receive data almost continuously.

The extension of the context prediction process by the additional usage of distributed and collaborative mechanisms increases the benefit for the user and for services that proactively adapt to the user's needs equally. Thus, for example, shopping places a user is going to visit next, could be automatically predicted using her context history and the context histories of other users whose shopping interests show sufficient similarities. If the user makes her predicted shopping interest visible to her environment, personalised advertising can be displayed on her smartphone.

In addition, the proposed distributed and collaborative context prediction approach combines all tasks required to make existing applications in context prediction, like Car-2-Pedestrian scenarios [1] or users' next place prediction [2], [3] more suitable for daily live usage. From a technical perspective, gathered contexts must not be transferred and pre-processed on a server anymore, which is in most cases complex, time consuming and typically prevents just-in-time prediction. From the user's perspective the prevention of external data processing hinders unauthorized third parties to gain access to personal data to create profiles.

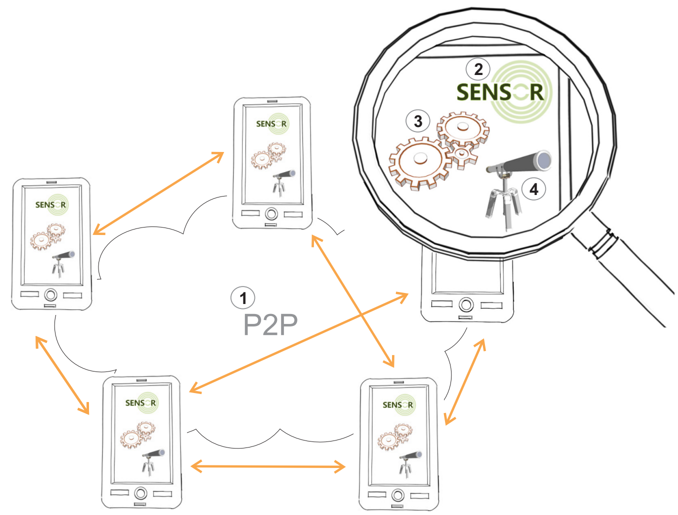

Fig. 1. Collaborated and distributed context prediction process.

Figure 1 shows the proposed distributed and collaborative context prediction approach. Distribution and collaboration in the context prediction process can be achieved by using peer-to-peer (P2P) communication (1) for the exchange of context data between different users, collected (2) and pre-processed (3) by their smartphones. Consequently, these contexts are utilised by prediction algorithms (4) that are directly executed on the smartphone to forecast a user's next context.

A first solution that uses a hybrid server and P2P approach for context monitoring, reasoning and prediction is proposed in [4]. The limitations of present mobile devices prevented a standalone P2P solution. Another approach that built up a P2P-based context-aware information system using data gathered by mobiles is introduced in [5]. Mobile data is collected directly and shared by mobile phones of users. Due to limited battery and processing power of the mobile phones the devices cannot be used for the processing part of the context data.

An approach that proposes a P2P infrastructure to derive high-level context data from low-level context data is outlined in [6]. The main focus presented in this research work is the evaluation of the proposed P2P infrastructure with regard to memory consumption and query processing. In contrast to the above-mentioned research we are going to use current smartphones to directly perform context prediction tasks. Further,

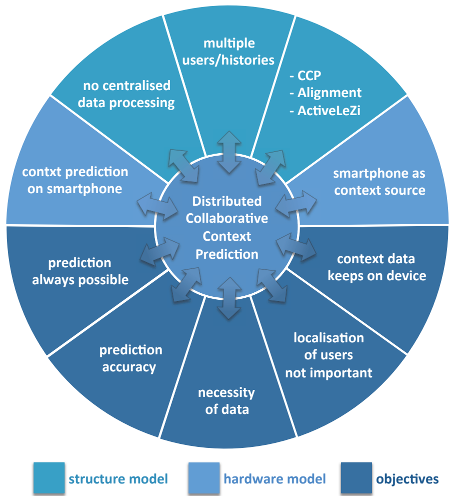

Fig. 2. System model for distributed and collaborative context prediction.

no centralised server is used to handle communication between devices but P2P is used to enable direct communication.

In this paper, we first outline in Section II our system model that characterises the underlying environment of the distributed and collaborative context prediction approach. In Section III we derive the general and technical requirements based on the introduced system model. Section IV presents our new approach considering the derived requirements. An experimental evaluation of our approach is outlined in Section V. Finally, we conclude this paper in Section VI with a brief summary and considerations for future work.

II. System Model

To determine the requirements for the distributed and collaborative context prediction approach we first define our system model comprised of the underlying environment with its characteristics and our objectives.

Our system model comprises three different dimensions, as shown in Figure 2 and detailed below. In our *structure model* we specify the components the environment consists of. We assume that the algorithms used to predict a user's next context in a distributed and collaborative manner are Alignment [7], ActiveLeZi [8], and the Collaborative Context Predictor (CCP) [9]. Furthermore, we assume that the knowledge base is not restricted to the user's own context history but also uses additional knowledge in context histories of other users. Additionally, we assume that no centralised server unit is used to perform the prediction of a user's next context. Hence, the users do not have to trust one central processing unit. The *hardware model* describes our assumptions about the hardware components used in the distributed and collaborative context prediction approach. We assume that in our environment only smartphones are utilised and therefore a user's smartphone is used to determine her next context. Hence, we assume that smartphones serve as processing units. *Objectives* of the distributed and collaborative context prediction approach are that the prediction of a user's next context always has to be possible, even if a user's own context history does not provide sufficient context information. Therefore, it should also use context information of other users whose context histories show sufficient similarities. Further objectives are that current whereabouts of the users whose context histories are used for the prediction process are not important for the distributed and collaborative context prediction approach. For this reason, a geographical proximity of users is not necessary. Context data of a user is only stored on the user's smartphone. If context information has to be transmitted it has to be pseudonymised. Additionally, only context information that is necessary for the prediction process is stored. Any contexts that are not relevant have to be deleted. Finally, the achieved prediction accuracy of a used algorithm has to be sufficiently accurate.

III. Requirements

Based on the system model outlined in Section II technical and general requirements are derived in this section. These requirements provide the basis for a realistic implementation of the distributed and collaborative context prediction approach.

In the system model a user's smartphone is proposed as a computational device for the distributed and collaborative context prediction scenario. In the proposed approach smartphones utilise built-in soft- and hardware sensors e.g., accelerometer, magnetometer, gyroscope, etc. to automatically collect context information of a user. Collected context information is only stored on the user's smartphone. Further, smartphones serve as processing units. Hence, context prediction algorithms run directly on the smartphone to predict a user's next context.

In order to use smartphones for these tasks, the devices have to be up-to-date with respect to their processor unit and internal memory size. Otherwise the time needed to predict a user's next context directly on the device using the prediction algorithms might take too long to provide just-in-time context prediction. Collaboration, respectively the combined usage of context information of different users is used to achieve high prediction accuracy and to provide context prediction even if the context history of the user does not contain suitable information. This implies that contexts located in histories belonging to other users that are stored on their own smartphones must also be utilised by the prediction process if necessary. Therefore smartphones require a stable internet connection. If a context predictor does need context information from other users to make a reliable prediction, required context data must be transmitted pseudonymised. A centralised server unit must not handle the communication between the smartphones of the users during a prediction process. A prerequisite is the usage of P2P communication between the smartphones of the users. Thus, context information is not concentrated on a processing unit of a single service provider. As context prediction approaches, Alignment, ActivLeZi and the Collaborative Context Predictor (CCP) have to be supported. All approaches are state of the art context prediction algorithms. Regarding to their different working methods the following requirements have to be considered: To use Alignment or ActiveLeZi in a collaborative manner the context sequence which is used

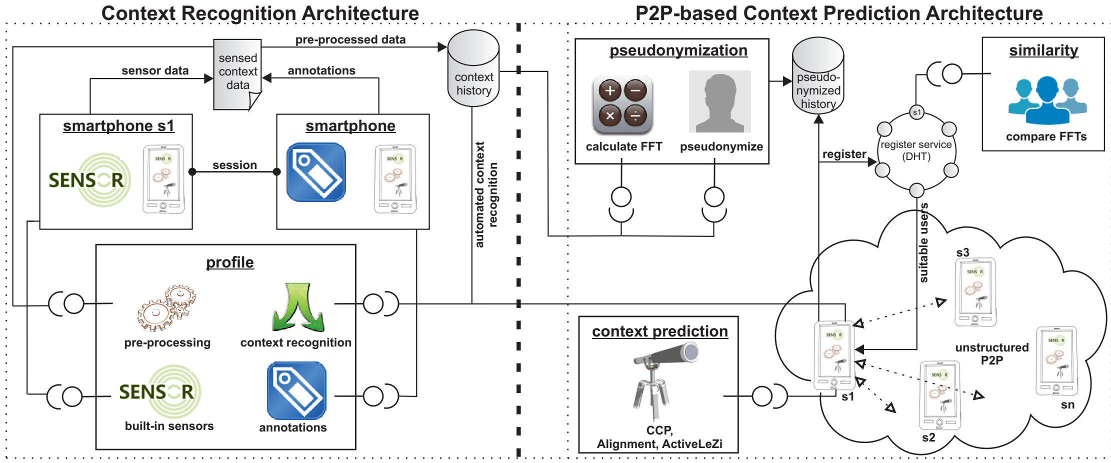

Fig. 3. Proposed architecture for the distributed and collaborative context prediction approach.

to predict a user's next context is sent to the smartphones of appropriate users using P2P communication. Subsequently the user who sends the context sequence and the users who also receive her context sequence use Alignment or ActiveLeZi to make a prediction on their own devices using their own context histories. Afterwards, each user returns the predicted context to the user the context sequence originally came from. Finally, voting is used to determine the context that follows up the given context sequence. In contrast to the other algorithms, CCP needs at least one additional context history of another user on the same smartphone of the user whose next context has to be predicted to work properly. For this reason, the context histories of the users, which will also be used, have to be completely transmitted to the smartphone of the user. Consequently, CCP is executed on the user's smartphone to make the prediction. To limit the number of additional context histories used to make reliable predictions, those who are most appropriate have to be identified first. Hence, it is necessary to compare the history of the user whose context has to be predicted with those histories available in the P2P network of the other users. Thereby, context histories do not need to be compared directly to each other to avoid additional communication traffic and to avoid that context histories are processed in plain text centrally.

IV. Our Approach

In this section we present our new approach for the distributed and collaborative context prediction. The underlying architecture is outlined in Figure 3. The proposed architecture is divided into two parts: The *Context Recognition Architecture* describes how high-level context information of a user can be automatically received and processed using the built-in sensors of a user's smartphone. The *P2P-based Context Prediction Architecture* describes the P2P-based context prediction process which is executed on users' smartphones.

A. Context Recognition Architecture

To provide an easy to use possibility for a user to collect context information, a web application is provided. By using this web application the user is able to create profiles, respectively templates, to automatically gather high-level context data. Defined profiles can be simultaneously accessed and used by arbitrary smartphones. After a profile has been chosen on smartphone s1, it automatically starts the tasks specified in the profile. A profile determines which built-in sensors of a smartphone are utilised to collect context information of a user. All available hard- and software sensors are supported. It is also possible to specify the pre-processing of collected sensor data. For example the deletion of redundant sensor information or the clustering of sensor information to meaningful high-level context information using e.g. k-Means or other appropriate algorithms. In addition, low-level sensor data can also be mapped to high-level sensor data using annotations predefined in the profile. Annotations can e.g. be *walking, sitting, standing* if built-in sensors are used to recognise the movement behaviours of a user. These annotations can be used by another smartphone, which accesses the same profile to label the sensor information currently collected by the smartphone s1. Annotations and collected sensor information are automatically merged after s1 has stopped its data collection process. The merging result represents the context history of the user. The history can be used by context recognition approaches also defined in the profile to automatically derive high-level sensor data from low-level sensor data gathered by built-in sensors using supervised approaches. Then, no manual annotation of the gathered sensor data is needed.

B. P2P-based Context Prediction Architecture

The second part of the architecture performs the prediction process to forecast a user's next context based on her most recently recognised sensor data. The user's most recently context data is automatically derived from the sensor data using her context history located on s1 and a supervised learning approach specified in the profile. Before the prediction process starts the context history of the user is pseudonymised. In addition, the Fast Fourier Transformation (FFT) of the user's context history is calculated on s1. Subsequently, the FFT representation is transferred in a vector of quantifiers where each FFT floating-point value is transferred into a value of discrete range between 0 and 4. This vector of quantifiers represents the context history of a user and is used to identify similar context histories of other users without comparing the histories directly but by comparing the vectors.

The usage of a server-based register would be the simplest way to perform the similarity check of the vectors. However, this would violate our requirement of a pure decentralized architecture with no single-point-of-failure. Thus we propose to distribute the register service among all users by using a distributed hash table (DHT) as the underlying architecture for a P2P network. Each device that is available in the P2P network can be used to predict a user's next context. Therefore, it registers with the register service its current IP-address, with its vector of quantifiers and with the profile ID the context history of the user has been generated with. Thereby, the used key for storing this information in the DHT-based register service must be derived from its vector of quantifiers while preserving order to enable other devices to search for similar histories. A device can also be registered with several vectors that belong to different context histories that have been generated using different profiles. As soon as the preferred context prediction approach is selected by the user on device s1, the smartphone sends a prediction request to the register service, i.e. the P2P network. The prediction request includes the profile ID, the IP address of s1 and the quantifier as the key. The responsible device in the DHT for the requested vectors returns the IP addresses of the devices to s1 whose quantifiers are most similar to the quantifiers sent from s1, i.e. all values found in the keyspace around the requested key ($k \pm c$, with k being the requested key and c a constant). After that s1 initialises connections to the devices of the users whose context histories show the most sufficient similarities using socket communication. If the user chooses Alignment or ActiveLeZi to perform the prediction task, s1 sends the pseudonymised context pattern whose next context has to be predicted, the chosen prediction approach and the profile ID of the current context history to the devices a connection has been established with. Subsequently, all devices connected to s1 and s1 itself perform the prediction task for the current context pattern using their own pseudonymised context history.

After the prediction task has been finished all devices return their prediction to s1. The final prediction results from a majority vote of all incoming prediction results. If the user chooses the CCP approach the pseudonymised context histories of the connected users have to be sent to s1 first. Afterwards the prediction task is performed directly on s1. If the prediction task is finished the received context histories are deleted. The proposed *P2P-based Context Prediction Architecture* complies to the requirements described in Section III for the distributed and collaborative context prediction approach: mobile devices instead of PCs are used for the calculation tasks; context prediction approaches are directly executed on the mobile devices; recognised context data are solely stored on a user's mobile device; context histories do not have to be transferred to other user's devices except if CCP is used for prediction; transferred context data e.g., the current context pattern or context histories for CCP are pseudonymised; only devices of users whose context histories show sufficient similarities to the user whose next context has to be predicted are used; communication between devices is handled using P2P-based communication, no centralised server unit is needed.

V. Experimental Evaluation

In this section, the experimental evaluation of the *P2P-based Context Prediction Architecture* is discussed. A full evaluation of the *Context Recognition Architecture* is currently underway and will be part of future work.

We describe experiments to determine the prediction time needed by the distributed and collaborative context prediction approach using Wi-Fi and UMTS connectivity. In the scenario four users are involved. Each user has its own smartphone. On each smartphone training data belonging to two different context datasets are stored. One dataset consists of movement behaviours (sitting, standing, walking, etc.) of four persons, derived from an acceleration sensor of a smartphone [10] called *mov*. The second dataset contains outdoor movement paths of four pedestrians derived from various sensors built-in a smartphone the pedestrians carried in their trouser pockets [1] called *ped*. Each dataset consists of training- and test data. The training data is used to build the prediction model for a chosen context predictor. The test data is used to evaluate the results of the predictors using their trained model for a certain dataset. The training data belonging to a certain context dataset is unique on all smartphones. Hence, each user provides different context information for a certain context dataset. During the experiments the prediction tasks in the P2P environment are performed on Motorola DROID RAZR MAXX smartphones. Each smartphone has a dual-core 1.2 GHz Cortex-A9 processor and 1 GB RAM. In the experiments the required time to make various forecasts with a user's smartphone s1 is proposed.

First, a baseline is given by measuring the needed prediction times of the predictors for the two datasets on a server unit (*PC*). The server unit has an Intel Core i7 with 2 GHz and 8 GB RAM. In addition, the needed prediction times are also measured using only the smartphone of one user (*s1 local*) that holds the test data of the two datasets. In both cases the training data of all four users are previously merged to one big training data for each dataset. This is because no P2P communication has been used for this experiment to derive additional context information of other users. Moreover, the prediction time, needed to predict the contexts for all instances of a given test data belonging to a certain dataset using P2P communication, was measured. The measurements have been performed while the four smartphones have been connected using Wi-Fi (*P2P Wi-Fi*) respectively UMTS (*P2P UMTS*). If all devices are located in the same Wi-Fi network a direct connection between devices can be established. Otherwise, if the devices use the UMTS network they have to share the same VPN connection. A direct connection between mobile devices using UMTS is not possible because the telecommunication provider blocks it. Furthermore, the accuracy (*acc*) gained by the prediction approaches and the number of test instances (*ins*) included in a test dataset are outlined.

CCP						
data	*PC*	*s1 local*	*P2P Wi-Fi*	*P2P UMTS*	acc	ins
mov	0.74	13.9	13.5	49.1	90%	20
ped	0.30	1.39	3.9	41.2	87.5%	24
Alignment						
data	*PC*	*s1 local*	*P2P Wi-Fi*	*P2P UMTS*	acc	ins
mov	90 ms.	0.96	16.1	86.9	75%	20
ped	61 ms.	0.59	4.5	73.7	66.6%	24
ActiveLeZi						
data	*PC*	*s1 local*	*P2P Wi-Fi*	*P2P UMTS*	acc	ins
mov	160 ms.	5.43	19.6	62.45	80%	20
ped	94 ms.	1.13	7.8	49.1	66.6%	24

TABLE I
MEASURED PREDICTION TIMES IN SECONDS USING THE P2P-BASED CONTEXT PREDICTION ARCHITECTURE.

The results of the experiments are shown in Table I. The baseline presented by (*PC*) shows that the server always needs the shortest execution times for all prediction approaches and all datasets. The same experiments needed longer execution times when performed directly on the smartphone s1 (*local s1*). In both cases CCP required the longest execution time because of its complex mathematical computations. *P2P-Wi-Fi* and *P2P-UMTS* show the execution times of the algorithms on the two datasets using P2P for direct communication between the four devices. The measured execution times are significantly higher than the execution times measured without P2P communication. The reason is the additional cost of communication needed to send the context pattern to the other smartphones respectively to receive the prediction results and the context histories from the other smartphones. Nevertheless, the average prediction times per instance for the algorithms are quite promising. They range between 0.16 and 0.98 seconds in *P2P Wi-Fi* and between 1.72 and 4.34 seconds in *P2P UMTS* for a single prediction depending on the chosen algorithm and on the chosen dataset. The faster prediction times of CCP compared to Alignment and ActiveLeZi results from the less demand of communication needed between the smartphones. CCP needs a P2P communication to be established to the other three devices only once to get the context histories of the users. ActiveLeZi and Alignment establish a P2P communication to the other devices for every test instance. The highest prediction accuracy for both datasets is achieved by CCP.

VI. CONCLUSION

We have presented an approach for distributed and collaborative context prediction. Contexts of users are exclusively collected, processed and predicted using up-to-date smartphones. To provide collaboration the proposed approach not only uses the history of one user but also uses histories of additional users. Distribution is achieved using P2P that allows direct communication between smartphones used to predict a user's next context. Hence, no centralised processing unit is needed. To implement the approach a system model is outlined that describes the underlying environment and its characteristics. Subsequently technical requirements are derived from the system model, which are used to build a P2P-based context prediction architecture that fulfils the requirements. Experiments to measure prediction times needed to forecast a user's next context using different datasets, algorithms and smartphones in a P2P network with Wi-Fi and UMTS connection demonstrate real-world practicality.

Future work includes a mechanism to prevent "bad" users from requesting a context prediction only to collect context information of other users. Later, a full evaluation of the *Context Recognition Architecture* will be provided.

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