On the Stability of Context Prediction

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Abstract
Context prediction is a key technique for proactive environments adapting to user's needs. To prevent wrong predictions is one key factor to achieve a high user acceptance. A wrong prediction could be caused by faulty or disturbed sensor data. With the triumph of the Smartphone, a wide range of context sources has become ubiquitous. Often, context prediction approaches today do not utilize these multiple context sources to cope with faulty or disturbed sensor data. We propose and evaluate an approach that uses multiple context sources and exploits the correlations between context sources of one user to get a more fault tolerant prediction.

Author Keywords
Context; prediction; multi - source; stability; robustness; disturbance

ACM Classification Keywords
H.5.0. General, H.5.m Miscellaneous

General Terms
Algorithms, Measurement, Human Factors

Introduction
Mark Weiser's vision of ubiquitous computing [1] has become true in a way at least for ubiquitous computers, which have come in the form of Smartphones, but the part of his vision, where these devices become

proactive little helpers to ease our everyday life is still not fulfilled. Smartphones offer mobile processing power and are equipped with sensors like accelerometer, gyroscope, compass, GPS, barometer, light sensor, and proximity sensor, as well as lots of soft sensors, like the calendar, emails and messages, dialed numbers and WLAN hotspots plus other nearby devices detected using wireless technologies like Bluetooth or NFC.

In addition to Smartphones, smart spaces become more common these days, because they offer a wide range of applications, like ambient assisted living, leveraging user comfort, and energy saving [2]. Smart spaces are usually based on home automation systems, which are also able to collect information on user behavior. For example, a smart space can be equipped with motion detectors monitoring the area where the smart space user currently is located. In addition, the furniture of a smart space can be equipped with sensors detecting, for example, whether a chair or a sofa is occupied or not. Also, sensors can be used to monitor whether windows and doors are open or closed.

Context prediction is an important building block to enable smart spaces to become proactive environments, but we still do not make enough use off all the available sensors to enable a robust context prediction. To achieve the needed user acceptance the prediction has to be correct to make a useful and acceptable adaptation of the proactive environment. Many different available sensors can be used to derive several contexts [9]. These contexts can enable services to react on user behavior and adapt the proactive environment and the user's devices to the user's needs.

However, in a real world environment the sensors used for context prediction are exposed to disturbances. For example, a system can utilize the accelerometer in a modern Smartphone to recognize user movements as a context. This movement context can then be used to predict, e.g. leaving or entering a room. However, a user may also shake his Smartphone for whatever reason. This would be a disturbance, which might lead to a faulty prediction. This could cause an annoying or at least useless adaptation of the proactive environment.

One way to tackle this problem is to try to verify each sensor value and to filter the errors and maybe correct them. But this would have to be done for each sensor type with a specialized algorithm. Another solution is to use a prediction algorithm able to treat contexts based on disturbed sensors. Such a prediction algorithm is the multicontext alignment algorithm. This algorithm was already described in [13] and a detailed description of the algorithm is also given in Section III. In [13], the multicontext algorithm was proposed for a more precise context prediction.

In this paper, we investigate on the stability of the multicontext alignment based prediction, facing sensor disturbances. We do this by using a simulation and performing a real world experiment.

The remainder of this paper is organized as follows: Section II gives an overview of different context prediction approaches. The multicontext alignment approach used in this paper is described in Section III.

In Section IV and V the effect of stability against disturbances is investigated in simulation and real world experiment results are presented, respectively. This supports the usefulness of the multicontext prediction approach. In Section VI the conclusion is given.

Related work

Different algorithms for context prediction have been proposed, like ARMA (Auto Regressive-Moving Average) [3], neural networks [4], HOSVD (Higher-Order Singular Value Decomposition) [15] or alignment [5]. Not only the used algorithms but also the used contexts vary, such as position, activity and, temperature, to name just a few. Although some authors propose the use of multiple sensors or multiple contexts in parallel for prediction, the research is concentrating mainly on methods based on a single context as an input for the context prediction algorithm. In the following approaches are described that utilize multiple sensors or multiple contexts.

Eagle and Pentland propose the use of Eigenvectors for context prediction [6]. They build these Eigenvectors from multiple sensors sources from a Smartphone.

Mayrhofer proposes the use of ARMA [3] for context prediction. ARMA was developed for other domains like finance predictions and adopted by Mayrhofer. The use of multiple sensors in parallel was proposed by him and included in his framework.

Woerndl et al. propose a proactive recommendation system [7]. The system is combining user context, temporal context, geographic context and social context. These contexts are used to give recommendations to the user based on rules.

The use of alignment [11] was proposed by Sigg et al. in [5]. The local and global alignment algorithms have their origin in bioinformatics, where they are used to get the match of two DNA sequences. The strength of these algorithms is to find a sequence in spite of mismatches and gaps. In addition, nominal values can be matched and used for prediction. Therefore, alignment is especially useful for context prediction as contexts are often represented by nominal values and sensors sometimes get disturbed and provoke mismatches. Sigg et al. also propose a method of combining several contexts [10] for a prediction. In [13], this approach was enhanced to the multicontext alignment and further elaborated. In [13], it was also shown that increased prediction accuracy can be reached by the multicontext alignment.

Some authors like Eagle and Pentland mention the capability of correcting disturbances due to data corruption or a switched off Smartphone. But none of the above mentioned authors investigate on the influence of sensor disturbances.

Alignment algorithm and multicontext enhancement

In this section, the algorithm and the basic assumptions are described.

A context is usually derived by processing sensor values. This process is illustrated in Figure 1. An accelerometer, for example, could be used to derive the activity of a user. The user's activity could be used as a context. The context "user's activity" could have values like "sitting", "standing" or "walking". By deriving this context from the accelerometer, we implicitly assume the accelerometer values to be dependent only on the user's behavior. But, of course there can be more influences on a sensor than the user's behavior, which then add disturbances to the sensor data and influence the prediction. As shown in the introduction multiple sensors related to one user are available today, either from his Smartphone or a surrounding smart space. Possibly only one of the sensors available is disturbed by phenomena not related to the user's behavior. Still some of the other sensors may also be influenced by the user's behavior and thus generally correlated. The correlation strength between two certain sensors can be stronger or weaker depending on the investigated sensors and the user's behavior. The accelerometer and the proximity sensor of a modern Smartphone, for example, will only show a small correlation while the user moves and carries the Smartphone in his pocket all the time. Two contexts processed from these two sensors will also show only a small correlation. On the other, hand the accelerometer and the compass sensor may show a large correlation when the user moves through an area. Two contexts processed from those two sensors may show a large correlation. This correlation of different sensors leads to a correlation of the processed contexts. The correlation can be found in the patterns generated by these contexts if they are recorded over a certain time.

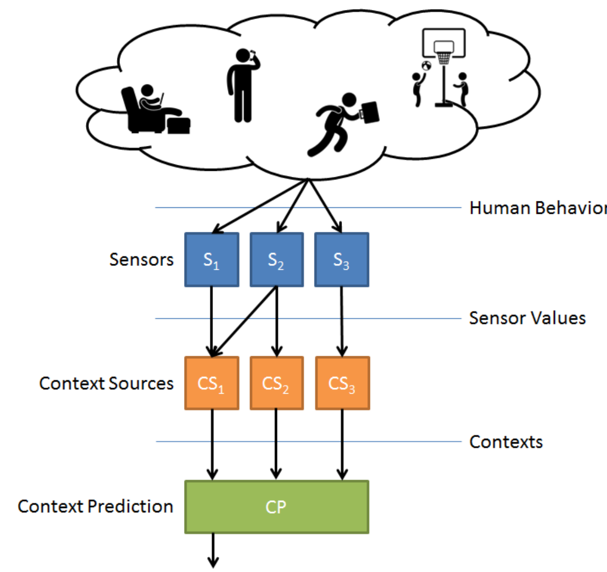

Figure 1. From Sensor value to context prediction.

Our multicontext prediction approach enhances the alignment based context prediction approach proposed by Sigg et al. in [5]. The alignment based approach utilizes a record of past context values. This record is called the context history and each entry has a timestamp representing the time it was recorded. In the first step, the alignment approach combines the last few values that have occurred from a context to a pattern. In the second step, this pattern is aligned with a local alignment over the respective history. This aligning process returns each match where similar patterns also occurred in the history. The quality of the match is returned as well. In the third step, the entry following on the pattern of the match in the history is taken as a prediction.

The multicontext enhancement to the described alignment based approach is to include the correlation of several contexts. A pattern from a first context, derived from one sensor, is correlated to a pattern from a second context, derived from a second sensor, as we have seen in the considerations in the beginnings of this section, as long as these contexts are correlated. Therefore, our multicontext alignment needs one history for each of the included contexts. A pseudo code of the multicontext alignment algorithm is shown in Figure 2. In the first step, not only the last few values that have occurred form a context that we want to predict are needed, but also the last few values that have occurred from all the other contexts are needed. The second step is repeated for each included context. An alignment is performed for each context in its corresponding history. As a result of the performed alignments we have several matches spread across all included histories. Now the main step of the multicontext alignment is to be taken. Each match is used to make a prediction but not based on the history it has been found in. The prediction is always made from the history corresponding to the context that should be predicted. This is done by using each resulting match and its timestamp and lookup this timestamp in the history of the context that should be predicted. By using the history of one context for the prediction of another context, we utilize the correlations of the contexts when the histories were recorded. In the last step, a merging of the different predictions needs to be done. In our approach we use a majority voting weighted by the match quality.

Task: Context prediction for context **A**

```
for (context i in all_available_contexts)
{
    timestamp = align(
        history_of_context(i),
last_values_context(i))

    prediction_i = get_from_history(
        history_of_context(A), timestamp + 1)
}

predicted_value = build_majority(
        prediction_1 … prediction_i)
```

Figure 2. Pseudo code of multicontext alignment. Please note that A is constant over the whole Task.

This multicontext enhancement is based on an approach used in communication techniques. Sometimes multiple paths can be used to transmit a message. A message is then usually split up and the information is enriched with redundancy. Afterwards one part of the message is transmitted over one path and the other part over another path. If one path gets disturbed, the message can be reconstructed at the receiver by combining the message part from the other path and the redundancy. In the area of context prediction we can regard the user behavior as a message, which has to be transmitted. We usually do not have any influence on the division and the redundancy of the message as the sensors are influenced by the user behavior and by the given physics, which we cannot change by software. But it is possible and likely that only some part of the user behavior is represented by various sensors. The described multiple paths technique is used in communication techniques to get a stable connection between the transmitter and the receiver, even if there are disturbances. In our multicontext alignment approach this leads also to a more stable context prediction, even if there are disturbances. This is verified in the next section.

Simulation

To prove the stability against wrong sensor data we decided to test our approach on data from both a simulation and a real world experiment. A simulation of several contexts related to one user is more useful for verifying the approach than the real world experiment because there are no disturbances in the simulation and we can control how much disturbance is introduced to the context history. In a real world experiment we always have these influences and we cannot tell how much of the data has been disturbed.

For the simulation we used SIAFU, an open source context simulator [12]. We used the office scenario included in SIAFU where a person moves through several rooms in an office building. While the person moves, four contexts related to the person are recorded. These 4 contexts are: activity, noise level, office area and Wi-Fi reception.

After finishing the simulation we manually added disturbances to the simulation data. We did this by interchanging two randomly selected entries in the history. We repeated this disturbing process until a certain amount of disturbance had been reached. Afterwards we saved each version of the disturbed simulation data.

To investigate how stable our context prediction approach is, we did 100 context predictions with each version of the simulation data. Therefore, we split the simulation data into a history (≈2/3 of the simulation data) and a test set. The test set was used to generate patterns that had to be found in the history. Also the prediction accuracy was determined by comparing the test set values to the predictions. By disturbing both, the history set and a test set we stick to the scenario from the introduction where sensor data may be disturbed, regardless if they are recoded as a history or if they are part of the current recorded time series. We also did this with an alignment based context prediction without our multicontext enhancement.

	history disturbance [%]					
	0	10	20	30	40	50
only one context	84	71	53	35	24	11
multicontext	88	88	82	77	73	71

Table 1. Simulation results of the prediction accuracy [%].

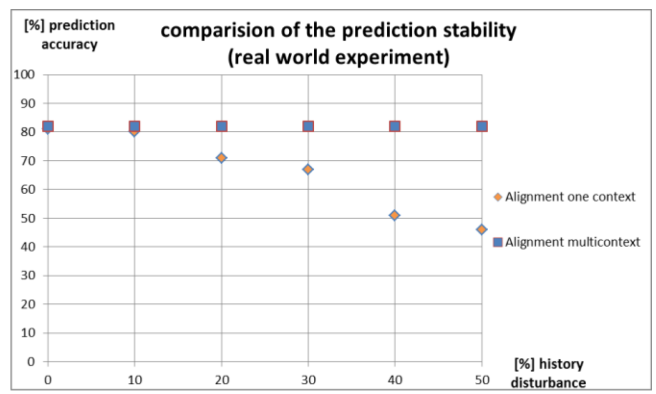

Figure 3. Comparison of prediction stability based on simulation data.

The simulation results can be seen in Table 1 and Figure 3. Without any disturbance the multicontext alignment approach has a 4% point better prediction accuracy than the original approach. This was already described in [13]. But if we add more disturbances the prediction accuracy of the original approach quickly decreases. The multicontext alignment approach only slightly decreases and even with a disturbance of 50% of all context histories we only lose 17% points of prediction accuracy. As the histories of the contexts are correlated the information that gets lost in one context history, still can be found in one of the other context histories.

Experiment

To verify the results of the simulation described above we decided to do a real world experiment. We used a similar setup as in the simulation. We recorded the sensor data from a person carrying a Samsung Galaxy III Smartphone and who is moving through several rooms. These rooms were located both in the first and in the second floor. All in all, four contexts were recorded during the experiment. Three of them based on Smartphone sensors: The activity, the floor the user is on and the loudness. The fourth context is the location, given by the room the user is in and measured by a motion detector in the room.

For the activity context we used the algorithm described in [11]. The activity algorithm was set up to compute three activity values: "sitting", "standing" and "walking". For this context the accelerometer sensor of the Smartphone was used.

The floor context was calculated from the barometer values of the Smartphone. The air pressure was changing on average 0.5hPa per floor. With an initialization according to the air pressure at the beginning of the measurement we could use a two level quantization to compute the floor the user is on.

For the loudness context we used the microphone of the Smartphone and an algorithm computing five acoustic noise levels from "low", "medlow", "med", "medhigh" to "high".

With this set up we used three sensors of the Smartphone: the accelerometer, the barometer, and the microphone. In addition to the Smartphone sensors we also recorded values from sensors mounted in the building. Each of the eight rooms in the experiment was equipped with motion detectors. This enabled us to derive a fourth context: the room a user is located in.

To investigate the stability of the algorithm described in this paper we added random disturbances to the data recorded in the experiment. Therefore, the same process as described in the simulation section was used. Afterwards we did a series of context predictions based on the original alignment approach and the enhancement given in this paper.

The results of the real world experiment are shown in Table 2 and Figure 3.

	history disturbance [%]					
	0	**10**	**20**	**30**	**40**	**50**
only one context	81	80	71	67	51	46
multicontext	82	82	82	82	82	82

Table 2. Real world experimental results of the prediction accuracy [%].

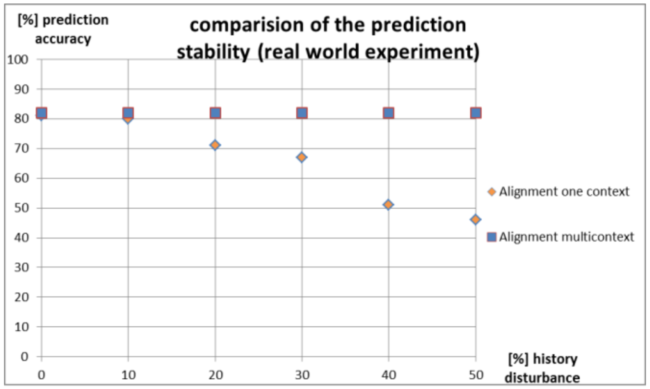

Figure 4. Comparison of prediction stability based on real world experiment data.

The proposed algorithm showed similar results in both, the real world experiment as well as in the simulation. Without any disturbances the multicontext alignment approach performs 1% point better. By adding 50 % disturbances the prediction accuracy decreases by 35 % points for the approach utilizing only one context. The multicontext alignment approach stays stable up to a high degree of disturbances.

Conclusion

In this paper we proposed the use of multiple contexts in parallel to make a context prediction more stable against disturbances of sensor data. We described a multicontext enhancement to the original alignment based approach by Sigg et al. [5]. We showed in a simulation that a more stable context prediction can be achieved by utilizing different contexts. In the simulation single context alignment had a loss of 73% points, which has to be compared with 17% points for the multicontext alignment when facing 50% disturbances in the context histories.

We also verified this result in a real world experiment. Here the prediction accuracy stayed stable for the multicontext alignment approach while the original alignment approach decreases prediction accuracy by 31% points when facing 50% disturbances.

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