Towards Context Detection in the Ambient Classroom using Wearable Sensors

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Abstract. This paper presents first experiments and results on analyzing different contextualizations in the ambient classroom learning environment using smart sensors. We present an approach of identifying these using active RFID technology for face-to-face contact detection. Based on the results of our experiments, we outline next steps and interesting directions for future research.

1 Introduction

In the university world of today, many students and professors change the studying models from individual to collaborative, by forming research groups among PhD students and project groups among undergraduates. Then, one problem of such forms of modern learning and teaching lies in a huge amount of information that needs to be processed. Then, detecting the individual as well as the collective *context* of learning environments is essential, e. g., [23, 24]. In [5], we argued, that this process can be stimulated by an intelligent pervasive system that improves the overall efficiency of learning and teaching, and presented the *ambient classroom*: it utilizes sensor information as well as various online data sources, for providing ambient intelligence and context-aware solutions. Social interaction patterns [1], for example, can then be leveraged for enhancing social learning environments using ubiquitous social systems such as MyGroup [3, 4], This paper considers different contextualizations and situations in the proposed ambient classroom framework. We apply RFID proximity technology [17] for detecting face-to-face contacts and discuss first results, implications, and directions for future work.

This paper presents ongoing experiments and results on analyzing different contextualizations in the ambient classroom learning environment. We present an approach of detecting these using active RFID technology for face-to-face contact detection. Based on our first results, we outline next steps and interesting directions for future research.

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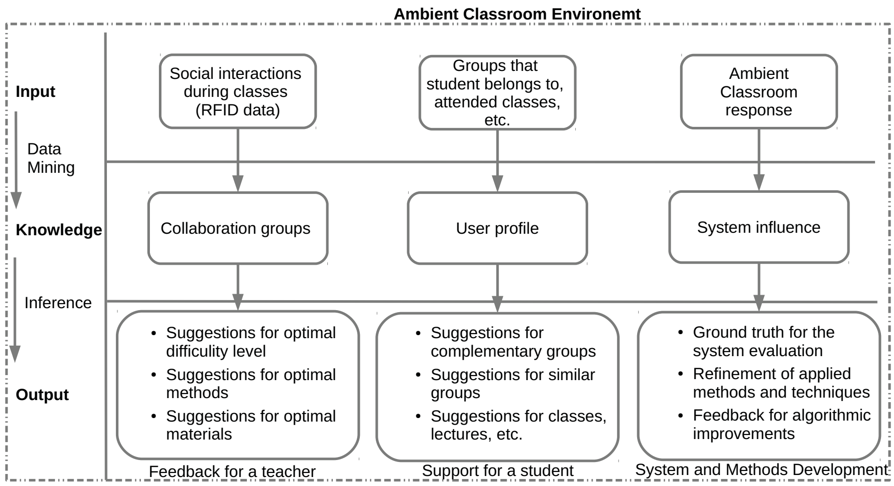

Fig. 1. Data flow of the proposed ambient classroom environment, cf. [5]. The figure shows the input data sources, the intermediate knowledge that can be derived using data mining techniques, and the actionable output that can be obtained.

2 Contextualization: First Results

The ambient classroom architecture is based on the assumption that it is possible to efficiently distinguish different types of collaboration groups among students, cf. [5] for a detailed discussion. Examples include students working alone, dyadic groups, groups of at most three persons, etc, for which different situations may occur. Figure 1 shows the data flow diagram of the ambient classroom environment presented in [5]. Below we focus on specific situations in certain learning contexts. Before describing these, we briefly introduce the applied technology.

For detecting face-to-face contacts, we apply RFID proximity technology [17]. A proximity tag sends out two types of radio packets: Proximity-sensing signals and tracking signals. Proximity radio packets are emitted at very low power and their exchange between two devices is used as a proxy for the close-range proximity of the individuals wearing them. Packet exchange is only possible when the devices are in close enough contact to each other (1-1.5 meters). The human body acts as an RF shield at the carrier frequency used for communication [17]. As in [17], we record a face-to-face contact when the length of a contact is at least 20 seconds. A contact ends when the proximity tags do not detect each other for more than 60 seconds. For analyzing the situations described above using wearable sensors we performed an experiment that involved five students wearing RFID proximity tags developed by SocioPatterns[3]. For more details, we refer to cf. [17].

[3] http://www.sociopatterns.org

Within contextual learning groups different situations may occur. Exemplary situations are shown in the Figure 2 and explained below.

1. Teacher helping a set of students. This can be described by any of the configurations shown in Figures 2(a)- 2(c), when one of the persons is the teacher.
2. Teacher supervising a set of students without paying special attention to any of them. This situation is best represented by the Figure 2(c).
3. Collaborative student discussion. This situation can be described by any of the configuration of the persons in Figures 2(a)-2(c), when none of the persons is the teacher.

Essentially, the student participants had to perform a couple of tasks to mirror the situations from Figure 2. The duration of every situation was limited to be between 30 to 60 seconds.

(a) (b) (c)

Fig. 2. Different situations that can be distinguish in ambient classroom.

First results indicate, that face-to-face contact detection works well in typical conversational situations, e. g., considering the participants 1, 2 and 5 in Figures 2(a) and 2(c), confirming our previous experiences, e. g., [6]. Also, contacts between people not facing each other, e. g., participant 1 vs. participants 3 and 5 in Figure 2(b) are not detected, as expected [17]. Challenging situations involve participants passing by, as shown in Figure 2(c): Here, contacts between participant 5 can be observed based on the time for the threshold for detecting face-to-face contacts. Furthermore, RFID proximity contacts can be well complemented using localization and/or co-location information provided using RFID technology; the proximity tags also send out tracking signals at different power levels, that are received by antennas of RFID readers installed at fixed positions, we can provide approximate positioning of the participants using RFID. Depending on the number of available readers, different accuracy levels can be achieved, cf. [35, 36]. This allows us to monitor encounters, e.g., the number of times a pair of participants is assigned to the same set of nearest readers.

3 Conclusions and Future Work

This paper discussed the contextualization setting in the ambient classroom and presented first results using RFID proximity technology. The contextualization is one of the fundamental parts in building an ambient classroom presented in previous work. We considered different types of collaboration and situations that may occur within such collaboration. Our first results indicate that the tested RFID proximity technology works well in typical situations but challenging situations (e. g., persons passing by) need further investigation. Additional information complementing the proximity contacts, e. g., localization information [35, 36] or sensor information obtained using smart phones, e. g., [8] seem promising in that respect.

For future work, we therefore aim to complement the analysis using localization and encounter information, as well as including further sensor information like Bluetooth low energy data. Further interesting directions include learning models for mobility and context prediction. Promising directions in that respect are given by extending and adapting methods for community detection and evolution (e. g., [7, 12, 19, 20]), and link prediction (e. g., [33, 34]).

Furthermore, we aim to investigate subgroup discovery (e. g., [2, 10, 11, 14]) for characterization of user groups, targeting continuous evolving groups. Then, using subgroups or communities that are "linked" concerning their learning environments we can, e. g., utilize predictions concerning further interesting resources or contacts for recommendation. This can also be applied for personalization, e. g., for *gamification* of the learning process [26] or in the context of *classroom response systems* [18,25] also complemented by rule-based approaches, e. g., [27,28]. Also, findings obtained by educational data mining approaches [29, 31] based on subgroup discovery techniques, e. g., [22] can be integrated into adaptive context detection approaches. Then, for example, context and profiled data, e. g., [15,30] can be exploited for further improving the contextualization in order to enhance the ambient classroom environment. Depending on the employed actions in the specific contextualizations, also adequate explanation facilities, e. g., [13,16] provide further interesting options for future research. For that, we also aim to tap into further heterogenous information sources, e. g., in classroom response or course management systems, e. g., [32]. Then, extending and integrating information extraction techniques, e. g., [9, 21], provide for important options to consider.

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