Journal of Universal Computer Science, vol. 16, no. 12 (2010), 1556-1576
submitted: 29/12/09, accepted: 5/5/10, appeared: 28/6/10 © J.UCS

Context Awareness for Collaborative Learning with Uncertainty Management

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Abstract: In Collaborative Learning, groups of students work together using traditional and computer-based tools or applications. Participants are continuously moving and reorganizing in groups as tasks develop and the contextual information about the physical arrangement of people within groups determines the context of each sub-activity. The electronic environment needs to be in sync with the physical arrangement of the groups, but providing group context information to computer-based tools cannot effectively be done manually. This paper explores and addresses the problem of automating group awareness in CSCL applications by estimating group arrangements from location sensors and the history of interaction. We derive from case studies the requirements for context-awareness in collaborative learning, focusing on the Jigsaw technique supported by mobile devices. In our prototype system with real users, groups are detected from the location of the students within the classroom. However, this information needs filtering to avoid disturbing interruptions caused by uncertain location measures. A three-phase filtering strategy is proposed to manage uncertain contextual information by identifying sources of uncertainty, representing uncertain information, and determining how to proceed. Validation with experimental data shows the usefulness of introducing mobile devices with group-supporting applications that incorporate automatic group awareness. Results show that by managing uncertainty in the estimation of location, group membership information becomes reliable enough to satisfy the need for supporting collaborative learning with applications that are automatically group-aware, without introducing extra burdens or interruptions.

Keywords: Computer Supported Collaborative Learning (CSCL), Context Awareness, Ubiquitous Computing
Categories: L.6.2, L.7.0, K.3.1

1 Introduction

In traditional learning environments, students are generally regarded as passive learners. The assessment of student learning is generally based on a student's individual work such as quizzes, homework and tests. Each student competes with his or her peers to obtain the highest score. By using this learning method, educational content is teacher-directed and the learning process is highly individualistic: the teacher – the knowledge expert – delivers the content of the courses to the students and they rely mainly on the teacher as the only source of knowledge and information.

In contrast, [Stahl 06] collaborative learning occurs socially as the shared construction of knowledge. The learning is not based on individual activities; instead, it is based on group interactions that involve negotiation and/or sharing. Participants do not work individually, but rather remain engaged with a shared task that is constructed and maintained by and for the classroom group. This learning approach is student-centered and encourages students to cooperate and collaborate with each other in order to achieve their learning goals and outcomes. Among the many collaborative learning methods used in classroom-based environments, to evaluate the potential benefits that they can provide our proposal, we have focused on the Jigsaw technique [Aronson 78]. We strongly believe that these results can be easily extrapolated to other collaborative learning methods.

Collaborative learning, and the Jigsaw methodology in particular, entails a dynamic setting in which multiple parallel groups of people join and disband rapidly to form new groups. People move within the classroom from one location to another. Students experience much more mobility than in traditional learning settings. In addition, when students use mobile devices, such as laptops, smart phones, or PDAs, which are wirelessly connected and can be aware of the surroundings (context-aware), then we have what is called a context-aware ubiquitous learning scenario. In this scenario, there is the need of using physical devices that can serve as interfaces to facilitate the integration of real-world with computer-based objects – applications. This enables the users to benefit from services and resources that computers can provide, all in a transparent and natural manner, invisible to the user [Hwang 08]. However, when computer-supported collaborative learning (CSCL) applications that support group tasks are introduced in this scenario, there is also the need to automatically provide these applications with awareness of changes happening in the real-world environment, particularly regarding the spatial organization of the classroom – real-time location of the students groups.

The change in absolute or relative location of every significant element in the workplace – people or artifacts – is a rich source of information for understanding the structure and performance of the collaborative task. If the teacher or the students have to manually configure the groups in the computer application, then every time the groups' membership changes, the students have to wait until the manual setup is completed. As a result, this extra work may be of concern to the already overloaded teacher and introduces delays and an additional burden to the participants. Although there are many tools for providing some degree of automation and support for group activities, we have not found specific tools for automating and effectively linking the computer-based and physical environments in order to facilitate the process of creating the groups working environment.

These context-aware systems must have the capacity to perceive and capture the real-world surroundings of the user and to adapt its behavior to provide useful and relevant information and services [Abowd 02]. Low-level contextual data about location can be obtained directly from physical sensors, such as RFID or Wi-Fi. On the other hand, high-level context is more abstract and can be inferred from the low-level context [Prekop 03]. For example, the group membership, the participants' roles, and the type of activity can be inferred by using low-level contextual information.

The first contribution of this paper, described in [Section 3], presents a strategy which we developed to automatically detect the formation of groups of students using the location of participants within the classroom. The experimental evaluation aims to assess the effect of a group-aware collaborative application in a real-world learning activity. The experiments were carried out in a real-world setting with university students within a classroom and following the Jigsaw learning technique.

However, the results of our experiments show that low-level context information based on location data can be uncertain information due to diverse reasons such as flaws in the sensor devices and errors in the estimations or in the treatment of the results. Consequently, the low-level information is incomplete, incorrect, or ambiguous. If this uncertainty is not considered and appropriately managed, a context-aware application might become unusable as the derived contextual information can be confusing.

The second contribution of this paper, described in [Section 4], presents a strategy – based on filtering – for the management of uncertainty that follows three main stages: 1) identification and 2) measurement of the uncertainty and 3) the establishment of actions to be performed in the presence of uncertainty. This strategy was experimentally evaluated through simulations based on real-world traces and using as metric the undesired interruptions to the users caused by the system [Horvitz 03]. The purpose of these simulations was to assess the utility of the proposed uncertainty management strategy. By identifying and tagging uncertain data, we prove that the number of interruptions to users could be minimized.

In the next section, we describe the specific collaborative learning technique that has guided our research, the Jigsaw, the potential contribution of context-aware computer-support in collaborative learning, leading to a list of requirements based on of our ample experience in use cases.

2 The Need for Group Membership Estimation in CSCL

Collaborative learning is a method in which two or more people learn something together. It is based on the fact that knowledge can be created within a group where members actively interact with each other by sharing experiences and taking on different roles. In addition, collaborative learning helps individuals to get involved as group members. It includes individual learning, but not as the sole method for acquiring knowledge. Cooperative learning also entails some phenomena like negotiation and sharing, needed for the construction and maintenance of common learning tasks. Such tasks are accomplished as part of an interactive group process [Stahl 06].

A well-known collaborative learning technique used for classroom-based environments is the Jigsaw [Aronson 78]. Such a technique was successfully applied in several technical courses in the literature [Felder 94]. In addition, we also have obtained very good results by applying the Jigsaw method in our classes. Regarding realistic CSCL experiments, in [Collazos 07] the authors describe a model for designing environments that promote collaboration. They also present an experiment using a learning technique like the Jigsaw.

2.1 Context-aware CSCL

Computer-supported collaborative learning is a branch of research concerned with studying how people can learn together with the help of computers. In CSCL, learning is analyzed as a process – with both individual and group aspects – [Stahl 06].

A Context-Aware Ubiquitous Learning scenario is when students use mobile and wireless devices. Such devices are aware of the surroundings in order to provide resources and services for supporting the students' activities [Hwang 08]. In addition, resources delivery can be personalized and contextualized by compiling a profile that is built from keywords from the desktop or from the current task. As an example, the LIP system supports the situation-aware retrieval of resources adapted to the current context [Schmidt 06]. In [Bravo 05], the authors present an approach to the classroom context by using an identification process based on RFID technology. The main goal is to acquire natural interaction, identifying and obtaining contextual services. The only requirement for the user is to carry a small device – a smart label.

2.1.1 Related Work in Group Awareness

When CSCL applications that support group tasks are introduced, there is also the need to provide these computer-based applications with awareness of changes in the real-world environment, particularly on the organization of the groups.

In [Valdivia 09], the design and impact of a face-to-face CSCL activity named Collaborative Answer Negotiation Activity (CANA) is presented. They focus on the need to incorporate the notion of Joint Problem Space, a shared knowledge space that supports the collaborative work of the activity.

GroupNet [Chen 08] is an independent network where all members are located at the same place and all handheld devices involved are interconnected by peer-to-peer wireless technologies. They focus on how to design a mobile learning management system that can better support mobile learning for a small group of learners with effective social interaction within proximity.

Mobile Sensemaking [Zurita 07] is a context-aware collaborative tool developed to explore and understand information in highly mobile and dynamic situations, in which people engage in a multiple parallel, rapid, and ad-hoc fashion. Mobile Sensemaking is explored in the classroom context for collaborative activities. Interacting groups are created when two or more students are close to each other and wish to collaborate.

MCI-Supporter [Baloian 09] is an application supporting collaborative learning practices in the classroom. MCI-Supporter was conceived by first analyzing the best known collaborative learning practices, trying to find out which are the real needs for mobility and face-to-face interaction and then designing the application to support learning activities. In such work, mobile computing really does represent a benefit compared to the desktop computing scenario, because working groups have to be established manually by the teacher.

In [Ferscha 04], the authors discuss contextual information about groups (team learning context). They focus on workspace and social awareness and they even comment on team formation support: closed and open teams, teams joined and left manually, and dynamic teams formed automatically by the system based on profile and meta-information.

These works cover a wide variety of approaches to group-awareness, but none of them covers the problem of the automatic creation and management of the groups based on context-information.

2.2 Goals for Automatic Group Membership Estimation

The adoption of context-aware functionality in real-world products can be traced back to the fact that it has several linked challenges [Schmidt 05]. Some works have analyzed which contextual information was relevant and have developed many context models to support learning. In [Wang 04], contextual information is categorized into six dimensions that form a context space: identity, spatial-temporal, facility, activity, learner, and community. In [Zheng 05], a three-dimensional context awareness model for e-learning is proposed. This model involves: Awareness to Knowledge Context, Awareness to Social Context, and Awareness to Technical Context. In [Yang 06], two types of context ontologies for describing learners and services were developed. The interactive model is enacted by a semantic matchmaker, which can perform semantic reasoning for context-oriented service discovery and access based on both of the context ontologies. In [Derntl 05], a UML-based modeling extension is presented to explicitly include relationships between contextual information and learning activities in the design of the learning models.

The existing approaches –just discussed– show how to combine context-aware applications with collocated CSCL applications. All these works cover most of the requirements for face-to-face CSCL context-aware apps. In addition, they show in which ways context-aware CSCL applications could improve the learning process.

Most of the challenges have already been solved in other studies. Nevertheless, we believe that there are still some open challenges: “Context is difficult to acquire” and “Context is hard to make use of” [Schmidt 05]. For instance, from our experiences [Messeguer 07] we have noticed that in collaborative learning scenarios, group creation and management is a key concern.

The goals for this work can be summarized as follows:

Goal 1: A system/middleware should automatically form real and virtual groups of students – dynamic teams – using the current context.

Goal 2: A teacher should have a real-time view or snapshot of the classroom in order to have awareness of the activity progress and to obtain support for the evaluation of the students.

The next section describes experiments and the lessons learned in this direction.

3 Experimental Evaluation of Group Awareness

This section presents a real-world experiment conducted to assess the impact of introducing context awareness in a collaborative face-to-face learning scenario that is being supported by a CSCL application. First, the experimental setting of the case study is presented. In addition, the hypothesis about the expected results is described. Finally, we discuss the experimental results and present some lessons learned.

3.1 The Jigsaw Technique

The basic idea behind the Jigsaw technique is to divide a problem into sections. First, home groups are formed [Fig. 1] and each member takes responsibility for one part of the main task. In addition, each student receives resources to complete only his or her part and becomes an expert on this specific subject. Afterward, expert groups are formed. Students who are responsible for the same subject join and form a new, temporary group, whose purpose is to help each other to achieve the particular learning goals and outcomes of the assigned part. Moreover, the expert groups have to develop a strategy for teaching that which they have learned to the other members of their original home groups. After the expert groups have completed their work, the home groups are reassembled. The students then teach one another the subjects on which they have been working. Finally, in order to assure that each student has achieved the expected goals, each student can be individually tested on every part of the original task.

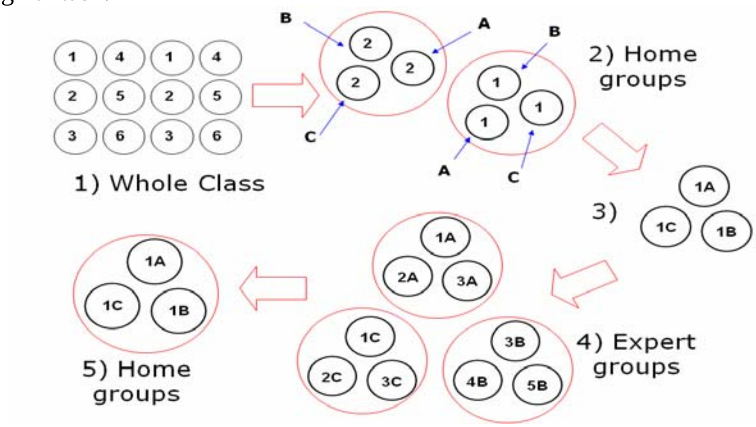

Figure 1: The Jigsaw methodology

The stages of the Jigsaw activity are [Fig. 1]: 1. introduction of the topic (whole class) 2. the teams go over the task and assign a part to each member (by group) 3. individual work of each part of the task (by student) 4. expert groups work to master the concepts of their assigned subject (by group) 5. home groups work to join all the parts and to complete the original task (by group) 6. evaluation of the task (by student and/or by group).

The Jigsaw method involves several reorganizations of groups during the whole activity. This is a critical and demanding task for the teacher, which may require detailed planning and note taking during the activity – to track deviations from the plan and to facilitate further evaluation. Therefore, relieving the teacher from most of this overhead is a goal for our work. Using computers instead of pencil and paper in this environment helps but also introduces an additional burden that we want to identify and minimize.

3.2 The Scenario of the Experiment

This experiment was done at the EPSC campus of UPC, an engineering school built and designed to be based on the collaborative learning and project-based learning models. Classrooms are equipped with tables and chairs enabled to facilitate the performance of collaborative learning tasks. Experiments were done in a course in which each student has a laptop connected via a Wi-Fi network, and they interact with one or more peers to perform a given task.

Figure 2: A classroom picture during the expert stage of the Jigsaw activity

The experiment was conducted in a course with 28 Telecommunications Engineering students. The students and teachers had previous experience in using the Jigsaw methodology but only with paper and pencil. They also are used to working with laptops but just for taking notes – not with additional support for communication and collaboration. Considering this scenario, we first determine the requirements for a successful learning activity.

3.3 Working Hypothesis

A collaborative application saves time when different groups have to share information and agree to a common outcome. As the time assigned for the activity is limited, the better the use of time is, the better the results the students can achieve. In the case of the context-aware application, the time saving is even greater because students do not have to spend time creating and configuring the application for the activity. The application itself creates groups, assigns members to them, etc. Moreover, this better use of time could allow for the students to obtain higher scores than those obtained when the same collaborative task is performed in the traditional way – with paper and pencil.

Therefore, the working hypothesis is the following: *Students working in groups and assisted by the context-aware application will have higher grades than those working in a traditional learning setting*.

We also want to investigate the student perception of the usefulness of technology – particularly to support group collaboration and context awareness – and the possible negative impact of such technology in supporting the learning activity – by distracting the users' attention from the current task to focus on the technology.

3.4 Experimental Conditions

In order to validate the hypothesis and to assess the impact of group-awareness in collocated CSCL applications (Goal 1, Goal 2), we performed experiments with groups of students. In order to distinguish the contribution of the three aspects that we want consider – computer support, mobility support, collaborative application to support the groups' activity and context awareness – we have defined four different scenarios:

a) Students use a desktop PC (not mobile), but no computer support for collaboration. This is the control scenario which will be compared with the other scenarios in order to assess the effect of changes on group work.

b) Students and groups use laptops (thus adding mobility support), but no collaborative application support.

c) This scenario is the same as b) but adding collaborative workspace software to provide a shared screen for groups (thus adding a collaborative application), but no automatic detection of groups (done manually by the teacher).

d) This scenario is the same as c) but adding automatic context awareness: groups with laptops, a shared folder application, and automatic group detection.

These scenarios were used to validate the hypothesis and to isolate the effect produced by adding the several kinds of supporting tools considered in this work.

3.5 Context Information and Processing

We analyzed which contextual information was relevant for group membership estimation and we discarded information that did not improve recognition accuracy.

To track the location of students we can use dedicated sensing devices (e.g. students bearing identification devices such as RFID tags) or we can use more familiar devices, such us the students' own computers (e.g. by radio signals from laptops or PDAs). The location information can be enriched by other contextual information (e.g. the location of tables, panels, or other elements in the classroom). This may describe in real time the evolution and membership of groups during the collaborative activity.

After testing several technologies (RFID, infrared, and Wi-Fi), we selected Wi-Fi as the best option. Initially we performed experiments using RFID tags and infrared technology. The results with RFID technology were discouraging due to the high rate of false readings, the difficulty of setting up some components – such as the antennas – or the problems in finding appropriate places to put the RFID tags. The results with infrared technology were also discouraging because of the lack of accuracy in the physical proximity and location measurements.

Each student has been provided with a laptop. Such laptops can be identified by their Wi-Fi MAC address – a unique identifier for each laptop. The system will detect which students belong to each of the classroom groups based on the location provided by the Wi-Fi signal of their laptops.

We finally selected the following items as relevant for predicting group creation:

- Time stamp: the time and the day of the week.
- User identifier: a unique id based on the identity of the user and his mobile device (e.g. username and Wi-Fi MAC address).

- Physical proximity: based on the information provided by a modified version of PlaceLab [Hightower 04] (e.g. proximity to access points) our system obtains information about the proximity of the users to a certain place (e.g. group table).

Our mechanism for determining group membership uses the relative location – physical proximity – between the user and the groups' tables to determine the group to which the user belongs. In order to measure this relative location, several access points were located in the tables where the students were performing the collaborative activity. In addition, we adapted the channel and transmission power of the access points to make the measurement process easier.

Moreover, our system collects several items of data about each student: physical proximity (calculated by means of the power level received from the fingerprinting of multiple Wi-Fi access points), identity (calculated from the MAC address of the student laptop), and the time (an event counter calculated from the timestamps of the centralized logging system).

The first step required for using and testing our service is to create a map of the classroom. This map is created by taking multiple measurements of power levels from multiple access points (fingerprinting) at many different places within the classroom. With that collection of measurements, we also statistically tested the reliability of the physical proximity estimations for each point within the classroom (a very similar or the same pattern of power can appear at two distant points of the room). For this purpose, we collected a considerable amount of traces.

The log data collected during the learning activity allow us to reproduce the whole group activity: tracking the location of every student and the groups (one person associated to each laptop, one group per table). Consequently, it was possible to identify the table on which every laptop was placed during the activity – this was interpreted as the student belonging to the group associated with such table. These physical proximity estimation logs can be seen in [Fig. 3].

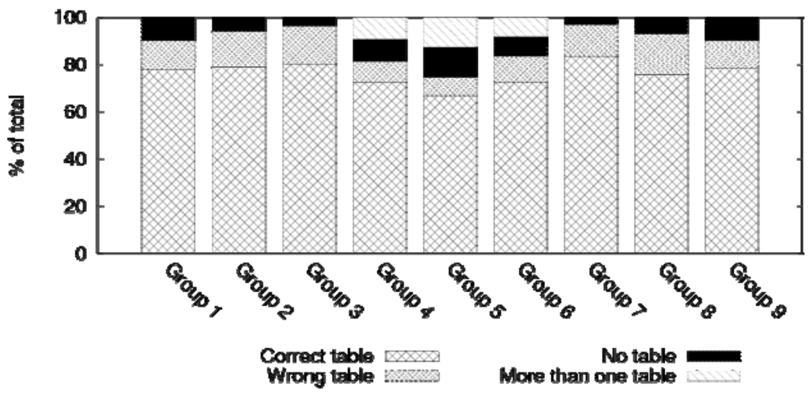

Figure 3: Estimation of physical proximity to group table, home group state, (27 students and 30 minutes)

We need to determine the criteria of how to decide the group's membership: the proximity to a certain object (e.g. a table), or to a person (to group leaders). This scenario is therefore very specific and it is linked with the physical room (but it could be reusable for any activity performed in that room). Our middleware collects the physical proximity information in order to detect when groups are created or disbanded following certain predefined rules. The formation of groups is affected by the resources that are nearby a specific student (e.g. close to a group's table) and in some cases, by the proximity to the students belonging to a certain group. [Fig. 4] presents the general structure of the mechanism for the assignment of group members.

The model consists of three types of rules:

1. Rules for creating groups (e.g. a temporary group is created whenever several people stay together in a place for more than a limited period of time).

2. Rules for destroying groups (e.g. whenever membership is less than 2 or 1 participants for more than a limited period of time).

3. Rules for belonging to a specific group (e.g. staying closer to a certain table).

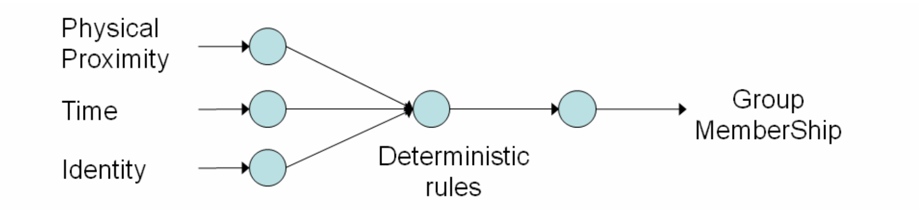

Figure 4: Group estimation

By defining these rules, it was observed that when a student moves with his laptop from his working table – the group to which he belongs – towards others groups' tables – e.g. to ask for some information from other classmates – our system detects the student's change in location and consequently creates a new temporary group.

It is very important to notice that this experiment could easily be applied to every collaborative application. In order to use the proposed context-aware software as support for a collaborative application, the only requirement is to integrate the context-sensing tools and the proposed system for membership estimation into the collaborative application. We developed an application to provide instant messaging and file sharing services to the group members. This application uses the proposed group estimation system. The application instances running on each laptop interact with each other using a peer-to-peer architecture based on Pastry [Rowstron 01].

Afterward, the learning activity can take place and takes full advantage of our service, which will be able to estimate the groups' membership.

3.6 The Observation and Evaluation Processes

Several strategies have been proposed to evaluate groupware systems: state of the product (prototyped, under development, or finished product), time span of each strategy (hours, weeks, months, or years), place of evaluation (laboratory, work context, etc.), type of people involved (domain experts, final users, or developers) and type of research (quantitative or qualitative) [Herskovic 07]. The scope of the evaluation process may also target different dimensions, ranging from the technical dimension (e.g., interoperability, connectivity, etc.) to the organizational dimension (e.g., effects on tasks performance, processes structure, etc.).

Our observation and evaluation processes are focused on the validation of the hypothesis, the assessment of the importance of our requirements, and the impact of the technology in the learning process. In the case study, we assessed a real-world learning activity, in which the students perform their work and then are evaluated.

The observation and evaluation of the experiments is based on four sources: two quantitative sources: 1) the score of the individual test and 2) the grade given by the teachers to the group's outcome, and two qualitative sources: 3) the opinions of students and 4) the observations of the teachers during the activity.

Firstly, the individual test is based on an individual quiz on the topics covered during the learning activity. Secondly, the score of the group's outcome is based on the evaluation of the final report done by each group during the activity. The grades obtained by the groups in such reports were used to validate the hypothesis. Thirdly, the opinions of students were obtained from a Critical Incident Technique (CIT) questionnaire [Flanagan 54] used for collecting direct observations of human behavior that have critical significance (a critical incident can be described as one that makes a significant contribution – either positively or negatively – to an activity or phenomenon). Finally, the observations of the teachers are a direct, first-hand observation of the daily behavior, a common method for collecting data in ethnographic studies [Herskovic 07].

3.7 Results and Findings

[Tab. 1] shows the average individual score (maximum of 10) per condition, from the quiz each student took on the topics covered during the activity. The difference in score is less than 10%. The highest score was obtained by the groups with context awareness and the lowest by the groups with technical support for mobility.

	Control group	**Mobility**	**Mobility + collaboration**	**Mobility + collaboration + context**
Average	8	7.4	7.9	8.2
Variance	2.5	2.3	2.6	2.5

Table 1: Individual assessment (scores from a quiz on the topics covered in the class)

	Control group	**Mobility**	**Mobility + collaboration**	**Mobility + collaboration + context**
Average	6.25	7.0	8.4	9.1
Variance	1.2	2.3	2.6	1.9

Table 2: Grades of the group's activity report

[Tab. 2] shows the results of evaluating the group report of the activity (average and variance), obtained from the different experiments. The groups with no technical support show worse performance in comparison with the ones which had context awareness.

The following is a brief validity analysis of the hypothesis (*Students working in groups and assisted by the context-aware application will have higher grades than those working in a traditional learning setting*).

Although the obtained results show that the score of the group's outcome increases when adding activity support, this does not happen in the individual assessment. However, [Tab. 1] shows that there is no significant statistical difference in the individual assessment between the control group and the mobility + collaboration group ($\rho = 0.918 > 0.05$) nor between the control group and the mobility + collaboration + context group ($\rho = 0.809 > 0.05$). In addition, the group assessment shows a statistically significant difference in the score of the group's outcome between the control group and the mobility + collaboration + context group ($\rho = 0.042 < 0.05$). Therefore, the experiments confirm the validity of the hypothesis.

The results from the CIT questionnaire also support these findings. The great majority of students affirm that either the use of laptops (21/28 75%), or the use of a collaborative system (17/28 60%) were useful for the activity performance. However, when more details are requested, some affirmations supporting that statement seem to be less reliable, as the main motivation seems to come from the technological novelty. Other responses to the questionnaire highlight that the technologically supported scenarios are more suitable for the activity. A few of them observed an improvement in the group work when a collaborative application was used, or an improvement in the group work and in the mobility capacity in the scenario with laptops. Among the negative opinions, the duration of the activity appears at the top of the list. Some students claim that both, the laptops and the collaborative software, only contributed to spending time on learning previously unknown programs. This was probably due to the lack of experience of the teacher and students in using these technologies. This problem did not appear in further activity sessions.

Among the observations from the teachers, several technical problems, unrelated to the planning of the activity, were reported: the loading of laptop batteries, the lack of experience in using the collaborative application, technical problems with the wireless network access, etc. All these problems were also addressed in further sessions.

Finally, both students and teachers reported that errors in physical proximity – proximity to group table – and group estimation were disruptive and involved interruptions in the activity of the students. For example, a teacher realized that some interruptions occurred when many students were standing up. He indicated that he believed this was due to errors in the location estimations by people temporarily obstructing the signal from the access points.

We have found that deriving group membership information from physical proximity information using the Wi-Fi network is technically viable, it can be successfully incorporated into CSCL applications and that it is beneficial for the participants. The effect can be perceived in terms of an improvement in the learning outcomes and consequently in the students' grades. Moreover, as we add further support to the scenarios, the outcomes of the groups' work improve, and therefore collaborative work becomes more and more efficient.

3.8 Lessons Learned and the Need for Context Awareness

Although we found that the proposed approach for group membership estimation was very useful for supporting group activity, we also realized that it has some problems that need to be addressed before introducing it in a real-world activity. The initial obstacles we faced were related to errors in the estimation of the physical proximity of the students to group tables. The estimation errors are disturbing when they involve a change in the group membership and then an interruption in the activity of the students involved.

These errors should be appropriately managed; otherwise, the context-aware application could become unusable. For example, when the system gives an incorrect estimation, the user is assigned to another group, interrupting his work, attracting his attention away from the current task to focus on the temporary interruption [Röcker 07] and requiring an action in order to return to the correct working group. Although there are many types of undesired interruptions, in this paper we focus on the interruptions generated by the system and their cost [Horvitz 03] as a metric to evaluate the system usability.

Comparing the relative location data collected during the experiments with what actually occurred and what was registered during the experiments, we learned the following: a) students were always part of a group, even when the location data incorrectly indicated that they were far from any group or outside the classroom; and b) there are not many frequent group membership changes around the classroom during the activities, even when the location data indicated that a student was rapidly moving between several groups – some students just stand up and ask their questions to colleagues who belong to other groups, the majority of them carrying their laptops. This is useful for the dynamic groups' management, but does not signal a formal group change.

The proposed approaches do not resolve the encountered problems. In addition, our work goals (Goal 1, Goal 2) have not yet been fully addressed. Consequently, there is a further need for improving the treatment of the contextual information, as described in the next section.

Finally, we would like to emphasise two additional facts.

First, our proposed group membership estimation strategy could be applied to almost every collaborative application (e.g. the presented existing approaches [Chen 08] [Zurita 07] [Baloian 09] [Ferscha 04] and [Valdivia 09]). For doing this, we should only embed a contextual module – to sense physical proximity – and a group estimation module in the collaborative application.

Second, our proposed approach could be applied to other collaborative learning methodologies – for example, Collaborative Answer Negotiation Activity (CANA) used in [Valdivia 09]. We should only change the rules for creating, destroying, and belonging to a specific group for their adaptation to each methodology.

In both cases, we must set up the classroom – group tables and their access points – and conduct the training process necessary for the calibration of the physical proximity measurements.

4 Uncertainty Management for Group Awareness

The results of our experiments show that estimations based on relative location data can be uncertain. If this uncertainty is not considered and appropriately managed, the context-aware application might become unusable as the derived contextual information can be confusing. Several approaches have been proposed to deal with uncertain contextual data. We propose an uncertainty management approach, which involves the tagging of the group membership estimations according to their degree of certainty. The proposed scheme was evaluated by means of simulations performed using data traces collected during the real-world experiment presented in [Section 3]. As a result of this additional management, interruptions to users can be reduced.

4.1 Related Work in Uncertainty Management

Several approaches have been proposed to deal with contextual uncertainty; some use quantitative methods to estimate uncertainty. For example, Bayesian networks are often used to deal with uncertainty quantitatively. [Gu 04] uses Bayesian networks to estimate user activity, given their ability to deal with uncertainty and the ontologies to define context using probability values and relationship links. [Truong 05] also uses Bayesian networks and ontologies, but their focus is on reusing context ontology definitions. They outline an ontology structure that may be used in different scenarios. [Ranganathan 04] proposes probabilistic reasoning and fuzzy logic to deal with uncertainty. They model uncertainty by attaching a confidence value between 0 and 1 to predicates. This value measures the probability (in probabilistic approaches) or the membership value (when using fuzzy logic) of the event corresponding to the context predicate being true. [Guan 06] also uses fuzzy logic to handle uncertainty when inferring higher-level context. Other proposals are based on the definition and assessment of context-conflict situations in which the solution is to select or eliminate any of the contextual information involved. For instance, [Bu 06] describes a raw context inconsistency resolution algorithm. The first step of inconsistency resolution is to detect conflicts. For example, if there are two raw contexts: “Tom, walk In, Room311” and “Tom, walk In, Aisle3,” a conflict will be detected because Tom cannot be at the same time in both places. When the conflict occurs, they calculate the relative frequency value of each raw context and discard the ones with smaller relative frequency values. A similar strategy is used by [Park 05], but they focus on high-level context, and propose a dynamic conflicts management schema for detecting and resolving conflicts between different kinds of context-aware applications which serve multiple users. The conflicts management process has three steps. The first is to manage action semantics. The second is to detect contextual conflicts by monitoring action semantics. The last is to resolve them based on user preferences. If the detector finds a conflict, the resolver generates a new action for its resolution. Action semantics that have been activated by stale actions are then invalidated and those derived by new ones are activated. The process is repeated until there are no more conflicts in the action semantic ontology. [Xu 05] defines uncertainty as inconsistencies in the contextual information. They present a proposal that allows users to define context patterns that can generate uncertainty. For example, when two contextual sources indicate that a person is in different places at the same time, their solution is to assess each of the contradictory context patterns, and modify or eliminate such patterns to solve the problem. Another set of proposals involve user intervention. These proposals are based on the direct intervention of the user for the management of uncertainty. For instance, [Dey 05] defines mediation as a dialogue between a human and a computer to resolve ambiguity. Mediation can conceptually be applied whenever misunderstandings arise between applications and users. In this sense, [Antifakos 05] proposes a strategy in which the users are notified of uncertainty in the application and which helps them to decide the appropriate course of action. In these proposals, there is no automatic uncertainty management; they always need user intervention to solve context inconsistency, which in a real scenario can be annoying for the users.

4.2 A Three-Phase Filtering Strategy for Uncertainty Management

We use a strategy for the uncertainty management that follows three main stages: 1. identification, 2. measurement of the uncertainty, and 3. establishment of actions to be performed in the presence of uncertainty.

In our scenario, we have found that uncertainty appears due to the inaccuracy of the contextual information; more precisely, on the relative location of every student.

To be able to handle uncertainty, first we must be able to identify its presence. For that purpose, we have to create a representation of the uncertainty, with the aim of creating rules that can signal its presence or absence.

Spatial uncertainty occurs when the location information of a laptop points to an incorrect place, called the "forbidden zone" (e.g. far away from every group) as in our activity, in which students were always belonging to a group. These cases are detected by a rule and then tagged as "uncertain".

Temporary uncertainty in group assignment is signaled by a rule that every time there is a change in relative location that leaves the participant in a new group. Because in our activity students do not change groups very often, this rule allows us to evaluate the presence or absence of uncertainty in membership estimations. The change in location, and consequently, the group membership assignment, is confirmed with repeated location samples – only then does this uncertainty disappear.

These two rules help us to know about the presence of uncertainty in the assignment of one student to a specific group. Therefore, we classify all the estimations as true or uncertain, following the schema shown in [Fig. 5].

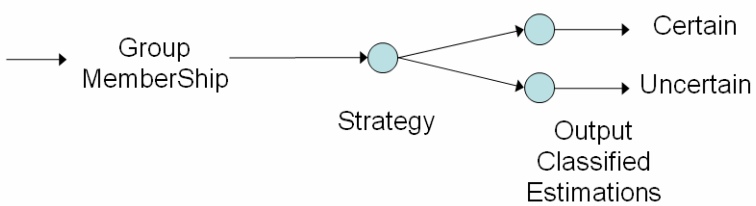

Figure 5: Management of uncertainty

The utility of this classification is twofold: it allows for the identification of unsafe and probably erroneous estimations and it processes and hides these uncertain estimations, improving the accuracy of the system.

For the case of uncertainty in the contextual information (in the relative location data – incorrect or multiple possible locations) [Fig. 6], a rule combines such information with other contextual elements. Therefore, if this kind of uncertainty is detected and the system is not able to definitely estimate the group to which a certain user belongs, the service looks for the students nearest to his current location and assigns him to their group. This mechanism of group assignment is based on the fact that a student – standing in an uncertain location – is most of the time relatively close to his group partners. Consequently, there is strong evidence that the closest students to the uncertain location are usually members of the same group.

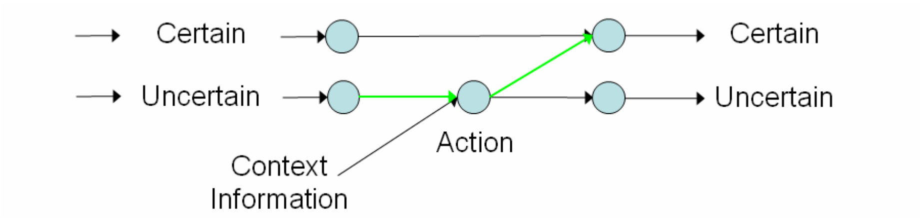

Figure 6: Action of combination with other contextual elements in original uncertainty

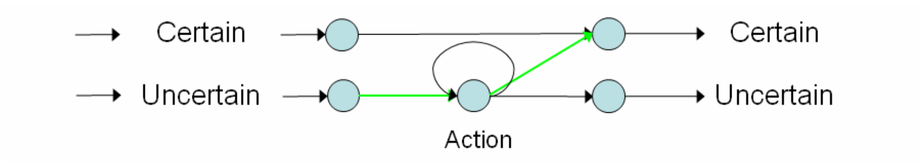

Figure 7: Action of re-estimation in derived uncertainty

In the case of temporary uncertainty [Fig. 7], the action to carry out is to wait or perform a re-estimation of location. That is, when the temporary uncertainty is detected, the application repeats the process based on a new location sample with the aim of confirming the change of group. It has been found that two consecutive assignments to the same group usually imply that the change of group is correct.

4.3 Simulation, Results, and Findings

Using the log data collected in the experiments with students in the mobility+collaboration+context scenario, we have evaluated our mechanism (the rules) comparing to what really happened (the ideal or "true logs").

[Tab. 3] shows the accuracy of this mechanism for detecting uncertainty (measured group membership estimations considered correct, considered uncertain with respect to those we knew were wrong). A pattern that we have observed in this application-specific scenario is that the great majority of the estimations marked as uncertain correspond to wrong estimations in reality, as can be observed in [Tab. 4].

Estimation	Correct	Uncertain	Wrong
Home	1546 (95%)	44	30 (1%)
Expert	1579 (97%)	27	14 (<1%)

Table 3: Estimations classified and improved with the strategy of management of uncertainty

Estimation	Wrong / Uncertain
Home	41 / 41
Expert	25 / 27

Table 4: Relationship of wrong estimations among those marked as uncertain

4.4 Effect on Users: Interruptions and Notifications

It has to be noted that not every erroneous or uncertain estimation implies an interruption in the attention of the student. For example, two consecutive erroneous or uncertain estimations that happen before the user recovers from the interruption are not two interruptions but just one. The first one interrupts the student and diverts the student's focus away from the main activity towards the change of context, tools, group, etc. decided by the system, but the second one does not interrupt since it is consistent with the new context, until the user can recover from the error.

We defined a burst as a sequence of erroneous and/or uncertain estimations. The end of the burst, or the return to normality, is identified with two consecutive correct estimations. From the log data, we identified the bursts with erroneous and/or uncertain estimations. In the case of an uncertain estimation burst, without erroneous estimations, the system would not carry out any action; it would just inform (via a notification) of this state of uncertainty, without interrupting the student activity.

	Without	With uncertainty management	
	Erroneous & uncertain	Erroneous & uncertain	Uncertain only
Home	211	34	20
Expert	200	18	11

Table 5: Total of bursts of erroneous estimations and in the case with uncertainty management also the bursts with uncertain estimations

In [Tab. 5] we present the total number of bursts with erroneous and uncertain estimations that can be observed during a concrete activity. We also show the total number of bursts composed by uncertain estimations. [Tab. 6] shows the impact on the activity of the student, measured in interruptions and notifications.

	Interruptions	**Information**
Home	1.1	1.6
Expert	0.5	1.0

Table 6: Average of interruptions for student and activity with the strategy of uncertainty management and the average of uncertain info for student and activity

4.5 Discussion

The results just presented relate to Goal 1, namely, “The system should automatically form real and virtual groups of students using the current context (dynamic teams).” In [Tab. 6], we can clearly see that with the original algorithm, the student had an average of seven to eight interruptions while performing an activity 30 minutes in duration. We found this value too high as it distracts the operation of groups and student activities. With uncertainty management, these interruptions are reduced to one, on average, for each student during the same activity. We believe this value is acceptable and has little impact in the operation of the group or the student.

Therefore, we find that a mechanism for the administration of uncertainty, precisely the labeling of the uncertain estimations, is very useful for the design of context-aware apps. that assist the user with automatic group membership detection.

This group membership information can be further exploited as pointed out by Goal 2: “A teacher should view a real-time classroom snapshot for activity log and evaluation support.” Although this application has not yet been built, the information required for it has been produced (it includes the history of location, identity, time, all estimations of groups, and their uncertainty tagging) and it will be very useful for the teacher as a record of the activity for evaluation, as proposed in [Juan 08].

Finally, a re-evaluation of the impact of technology on a learning activity with uncertainty management is presented based on the results shown by simulation. [Tab. 5] and [Tab. 6] show how interruptions in the students’ attention are reduced to acceptable values by including uncertainty management.

5 Conclusions

In this paper, we have explored effective mechanisms for computer-supported group-awareness in collaborative learning scenarios. We describe a ubiquitous learning scenario in a mobile and collocated collaborative learning environment.

Automatic derivation of contextual information on groups is required to support groups of students without increasing the burden on teachers and students to manually inform CSCL applications about group arrangements. To deal with this problem, we implemented a service that, based on relative location information of the students’ laptops used within a classroom and connected to multiple Wi-Fi access points, is able to automatically estimate the groups’ membership. Based on several experiments performed in real-world classrooms and lectures using group-aware collaborative applications, we report the lessons learned from such experience. We confirmed the usefulness of group-aware applications in supporting collaborative learning activities.

It was also noticeable that the groups' contextual information – derived from students' location – is inaccurate and causes disturbing interruptions to the participants' activity.

Therefore, this information has to be carefully filtered to evaluate the degree of uncertainty and protect the system from erroneous estimations, which otherwise can cause undesired interruptions to the students. For this purpose, we propose a strategy for uncertainty management consisting of three main stages: identification, measurement, and treatment of uncertainty. The utility of this strategy is twofold. First it allows for the identification of unsafe and probably erroneous estimations, and it allows for processing and correcting these uncertain estimations – improving the accuracy of the system. Finally, we evaluated the utility in terms of the rate of undesired interruptions to users' activity made by the system. The quality of the filtered location estimations has been found to be appropriate for the reliable detection of groups' formations. These results enable the construction of group-support applications that effectively track participants, assisting them with automatic sharing, communication, and coordination mechanisms as they move and reorganize by groups in synchronous and collocated collaborative learning activities.

Acknowledgements

This work was supported in part by the Spanish Ministry of Science and Innovation under grant TIN2007-68050-C03-01 and by CONACYT through a scholarship provided to Pedro Damian-Reyes. We also thank the anonymous reviewers for their constructive comments.

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