Modelling Embodied Mobility Teamwork Strategies in a Simulation-Based Healthcare Classroom

Roberto Martinez-Maldonado
Connected Intelligence Centre,
University of Technology Sydney,
Australia
Roberto.Martinez-Maldonado@uts.edu.au

Mykola Pechenizkiy
Department of Computer Science,
Eindhoven University of Technology,
the Netherlands
m.pechenizkiy@tue.nl

Simon Buckingham-Shum
Connected Intelligence Centre,
University of Technology Sydney,
Australia
Simon.BuckinghamShum@uts.edu.au

Tamara Power
Faculty of Health, University of
Technology Sydney, Australia
Tamara Power@uts.edu.au

Carolyn Hayes
Faculty of Health, University of
Technology Sydney, Australia
Carolyn.Hayes@uts.edu.au

Carmen Axisa
Faculty of Health, University of
Technology Sydney, Australia
Carolyn.Hayes@uts.edu.au

ABSTRACT

In many situations, it remains critical for team members to develop strategies to effectively use the space and tools available to complete demanding tasks. However, despite the availability of sensors and analytics for instrumenting physical space, relatively little progress has been made in modelling the embodied dimensions of co-located teamwork. This paper explores an in-the-wild pilot study through which we explore a methodology to model embodied mobility teamwork strategies in the context of healthcare education. We developed the means for tracking, clustering and processing student-nurses' mobility data around a patient manikin. We illustrate the feasibility of our approach by discussing ways to make sense of these data to uncover meaningful trends, and the inherent challenges of applying physical space analytics in authentic settings.

CCS CONCEPTS

•**Computing methodologies** → Modeling and simulation •**Human-centered computing** → Collaborative and social computing

KEYWORDS

Teamwork; Collaboration; Simulation-based Learning; Physical Analytics; Computer Vision; Proximity Data; Group Modelling

ACM Reference format:

Roberto Martinez-Maldonado, Mykola Pechenizkiy, Simon Buckingham-Shum, Tamara Power, Carolyn Hayes and Carmen Axisa. 2017. In *Proceedings of ACM User Modelling, Adaptation and Personalization conference, Bratislava, Slovakia, July 2017 (UMAP'17)*, 5 pages. DOI: 10.1145/3079628.3079697

1 INTRODUCTION AND RELATED WORK

Learning to collaborate, in general, and developing professional team practices, in particular, are skills that often require coaching [25]. Whether in education or professional contexts, teamwork has the potential to help people develop critical thinking, reduce workload, and generate creative solutions [8]. Although the internet has promoted spatially distributed teamwork, co-present teamwork remains entrenched in our society, particularly in practice-based professions. Face-to-face (f2f) teamwork enables levels of collaboration not easily achievable in online group work [22]. In short, learning to work effectively in teams f2f, is a critical skill for our times, but often requires practice, awareness of group dynamics, and reflection. Providing quality feedback for such team processes can be challenging [29]. Many team-based situations (such as the one illustrated in Fig. 1) require members to interact with an ecology of objects and devices [32]; to develop strategies to optimise the use of the physical space [7]; or even to learn in ways that cannot be mediated by traditional user interfaces as they involve psychomotor skills [27]. Some evidence suggests that the spatial arrangements and dynamics can strongly shape the interactive processes and the ways people tackle their tasks [14; 15; 16]. This is particularly important in classrooms because teachers and students perform embodied actions [9] and establish various proximity arrangements [12] that can influence students' engagement and learning. However, although understanding the mobility and proximity aspects of teamwork seems important, to date, little attention has been paid to conceiving ways to model and generate understanding of embodied mobility strategies.

A wide range of modelling and analytics efforts have explored how to generate understanding of *online* group processes to provide adapted team support (see reviews in [5; 11; 17; 28], with a few exceptions such as the ones outlined in [19]). Multimodal analytics solutions have partly focused on some

Figure 1. Four students tracked using a depth sensor while working at a healthcare simulation bed. Right: one minute of mobility data presented as an indoor map

ACM ISBN 978-1-4503-4635-1/17/07...$15.00
http://dx.doi.org/10.1145/3079628.3079697

physical aspects of student's learning by integrating data from multiple (often, but not always, physical) dimensions of student's activity [3]. For example, some studies have looked at analysing speech, gestures, handwriting, physical movements, facial expressions, gaze, and neuro-physiological signals which can all be critical aspects in co-present teamwork. Yet most of the advances in this area have been conducted under controlled laboratory conditions [4]. Thus, much work is still needed to find ways in which these approaches can solve challenges in realistic, mainstream scenarios.

Educational research literature has identified the importance of mobility and proximity primarily for teaching and classroom management (see a review in [21]). For instance, some authors have identified teaching proximity zones that can shape student's engagement [12] and embodied strategies that teachers can enact to orchestrate a classroom [9]. Similar embodied actions have been identified as important, but underexplored, for the case of patient engagement in healthcare education [6].

The body of work outlined above suggests both the need for and potential of developing modelling techniques to explore how physical aspects (such as mobility and proximity) can play a role in shaping epistemic elements of group work. The contribution of this paper is a pilot study through which we explore a methodology for modelling embodied mobility strategies of students practicing teamwork and professional skills in the classroom. We operationalise this in the context of nursing education where manikins are commonly used to represent patients in healthcare simulations (to be described in Section 2). We developed the means for tracking, clustering and processing students' mobility and proximity data around a patient manikin (Section 3) and demonstrate the feasibility of our methodology by suggesting ways in which these data may be associated with higher order mobility strategies enacted by teams in authentic classroom sessions (Section 4). Finally, we consider the potential and limitations of our approach for modelling teams' mobility, the inherent challenges of applying physical space analytics in-the-wild and avenues for future work (Section 5).

2 CONTEXT OF THE STUDY

Teamwork in simulation scenarios is a popular training technique in high risk industries such as aviation, energy and healthcare [2]. Healthcare simulations are commonly run as team-based learning experiences aimed at allowing healthcare students to engage in scenarios that mimic reality. The use of manikins as patients is increasingly common in nursing education worldwide [13]. This facilitates the practice of essential skills and avoids putting patients at risk [26]. Arguably, these simulations offer benefits for the development of teamwork, critical thinking, deterioration management and clinical skills [1]. The level of reality achieved during the simulations can result in students experiencing productive emotional and educational challenges [30].

This study was run in authentic laboratories where nursing classes are commonly conducted as scenarios involving simulated patients with acute or chronic conditions. The study focused on the 3-hour weekly classes conducted in Week 3 of a final-year subject in the Bachelor of Nursing at the University of Technology Sydney in 2016. In total, 580 students attended these classes with 20-27 students in each. The classrooms are equipped with 5 manikins in bed spaces (see Fig. 1). The manikins generate some physiological data and can be programmed to improve or deteriorate over time. In our pilot study, we focused on 5 randomly selected laboratory classes. Only the activity occurring in two of the available five beds was recorded in each class to allow students to opt out from the study. Thus, a total of 10 teams of varied sizes (56 students in teams, from 4 to 8 members each) and 4 teachers were involved in the study. The actual simulation task ran for 1-1.5 hours. In this time, students had to assess the condition of the patient, interact with him, assess chest pain symptoms, administrate medication, manage an adverse drug reaction and conduct an electrocardiogram analysis. Each student was asked to play one of 4 possible roles: a Team leader, the Patient, Nurses, and an Observer.

3 METHODOLOGY AND APPARATUS

In the following subsections we describe our methodology, which includes a mobility tracking solution, data modelling (with segmentation and visualisation examples) and means for making sense of the data in terms of emerging team strategies.

3.1 Mobility Data Tracking

Although some manikins have basic automated logging capabilities, often it is not possible to log the complete range of students' actions due to technology restraints and data accessibility limitations of the current equipment present in several universities. Moreover, these logs do not provide evidence about the ways nurses use the space around the patient and the proximity to the patient. To overcome this limitation, and achieve our goal of tracking student's mobility and proximity data, we positioned a depth sensor on the top of the bedhead. We used a modified version of a user skeletal tracking algorithm to record the raw coordinates of each team member. Depth cameras provide, for every pixel, a depth value that, along with the camera intrinsic features (image width w and height h in pixels, and focal angle f), can be processed to convert 3D depth positioning data points $p = (p_x, p_y, p_z)$ into 2D indoor mapping location points $l = (l_x, l_y)$ using the following formulas, assuming the camera is horizontally aligned: $l_x = p_x \sin\frac{f\left(\frac{w}{2}-p_x\right)}{w}$ *and* $l_y = p_x \cos\frac{f\left(\frac{w}{2}-p_x\right)}{w}$.

3.2 Mobility Data Clustering and Visualisation

Indoor localisation sensors are becoming increasingly available as they are a fundamental need in pervasive, context-aware settings [33]. Although other technologies can be used to capture mobility data (besides our depth-based solution), the ultimate goal is to be able to measure team members space usage and dynamics. Indoor analytics are readily available as adaptations of Geographical Information Systems (GIS) functions: heatmap visualisation, dynamic simulation, and clustering can be applied to understand space usage patterns [10; 20]. Recent work suggests a range of possible applications of such analytics in healthcare settings [31]. The result of mapping our teamwork mobility data is similar to an indoor localisation student map around the patient manikin (e.g. Fig. 1, top-right). These raw data can be further processed and visualised as heatmaps or clusters of activity (e.g. Fig. 2, right).

3.3 Mobility Data Segmentation

Temporality is a key dimension to understand progression and gaining insights into team processes, as opposed to just inspecting final outcomes. One technique for automatically analysing collaborative learning processes consists in segmenting chronological data into segments of equal or different sizes (e.g. [24]). This has proven promising in serving as a proxy to model group processes, even though some details of the collaboration are aggregated [18]. The goal is to enable pattern recognition in low level actions where the order and timing of events matter. In our case, we achieve this segmentation by dividing student's activity into n segments in order to allow the comparison of teams by stages in the simulation. Fig. 3 shows examples of series of heatmaps generated (using an open source GIS application[1]) by dividing the student's activity in equally-sized quintiles. The number of segments (n) can be arbitrarily defined (e.g. a small n would facilitate human's sensemaking while a larger n could serve for automatic analysis purposes). Similarly, the size of the segments can be fixed (as in our case) or variable (e.g. splitting the data according to meaningful sub-tasks or events).

3.4 Sensemaking for Modelling Team Strategies

In order to generate understanding from raw mobility data, additional steps, besides segmentation and data visualisation, should be performed to facilitate sensemaking. Although there are different ways to explain the data by using contextual information, in our case, we illustrate three possible ways to contextualise the data. Firstly, inspired by work on classroom proximity zones [12], we identified the potential meaning that the space around the clinical beds had during the simulations. Fig. 2 (left) shows three zones. Zone A corresponds to the area closest to the patient, from where the nurses can easily talk to the patient and perform clinical procedures. Zone B corresponds to the end of the bed, where nurses usually gather to perform a shift handover and/or real time note taking which commonly includes reading and taking notes about assessment, action, response and recommendations for the next shift. Zone C corresponds to the space around the clinical bed which is commonly used by nurses that are enacting the role of observers. Nurses also need to walk to other rooms adjacent to the classroom to collect clinical equipment and medications.

Secondly, we propose to identify the clusters of mobility data corresponding to the areas where more physical activity was recorded to highlight what spaces were used the most by nurses at a given time (see Fig. 2, right). To facilitate the interpretation, we have circled the clusters with a different coloured contour according to the Zones where these clusters appeared. Thirdly, we suggest a way to encode the mobility data divided into segments by using an alphabet. The alphabet used in this case consists of itemising the mobility data for each proximity zone and segment as p^z, where p is the proximity zone (A, B or C in our study) and z is the number of clusters found in that zone. In our pilot study, we chose to identify the number of clusters z as 1 (not shown), 2 or * (more than two). For instance, the three clusters in proximity zone A in Fig. 2 (right) would be translated into one item A^* and the ones in zone C as C^2. This type of coding has been useful to automatically identify sequences of events that may differentiate high from low performing groups [23]. Given the small number of observed teams in our study (10), we illustrate how this coding can facilitate association of raw data with embodied team strategies.

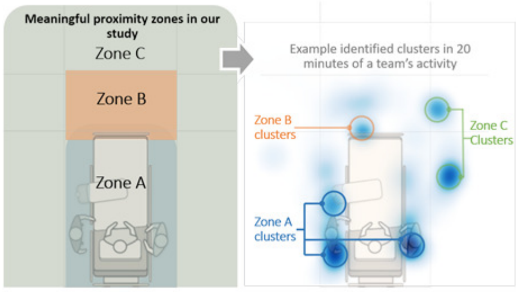

Figure 2. Left: proximity zones to a patient manikin. Right: heat- map of 20 min. of activity of a group with areas of intense activity

4 RESULTS

From Mobility Data to Embodied Strategies. We applied the methodology outlined in the previous section to the data we collected from the 10 beds of our study. We report on some of the brief comments that teachers gave about each group overall performance immediately after each class and those provided by two subject matter experts who looked at the series of heatmaps generated to facilitate the sensemaking of the mobility models.

Fig. 3 shows exemplars of three distinct types of strategies followed by the teams[3]. Two teams followed the Strategy 1 (example in Row 1), with teams commencing the simulation exclusively in zone B, (the space where nurses commonly work on the documentation about the patient and perform the shift handover, Row 1, Q1), to then approach the patient with the purpose of attending to him/her for the rest of the session while working across all the other zones (e.g. multiple clusters in zones A, B and C in Q2-4). A teacher referred to this strategy (of apparent initial inaction) as follows: "*some groups seemed to be slow before engaging with the patient*"; and added: "*this was good [if] they do a proper assessment of the patient before performing actions*". A second strategy was exposed by other two teams (example in Row 2) where most of the mobility data was recorded very close to the patient's area (a majority of clusters in zone A for Row 2, Q1-4). A possible explanation was hinted by

[1] Scripts for open-source QGIS (qgis.org), mobility tracking code, and raw mobility data for all the teams can be found in utscic.edu.au/healthsimlak-resources/

one of the teachers at the end if the class, as follow: "*sometimes it is nice that students [attend to the patient] from the beginning, but it [may also] indicate that they do not know the procedures [or] they [did] not read the information about the case*". A third strategy was observed in four of the teams that showed activity in zones A and B constantly and consistently through the whole simulation (e.g. see Q1-Q5 in Row 3). This may suggest that the team split in two, working close to the patient from the beginning to accomplish all the subtasks while also performing administrative tasks in zone B. The other two teams in our study showed a combination of the strategies identified above. In one of those cases, mobility data was missing for 1 quintile because of the teacher asked that group to do a special subtask elsewhere in the classroom. This got reflected in the mobility modelling. Additionally, some teams finished before other teams. This is reflected in the mobility models as it can be seen in Row 1 (Q5).

Encoding mobility data into discrete items: The last column of Fig. 3 shows how the clusters of mobility data can be encoded into discrete items. We can see that the resulting sequences of states can facilitate the interpretation of the data using a shorter format. For example, Strategy 1 can be characterised as a process that starts in the state with mobility data only in zone B of proximity (B^2 in Row 1). Strategy 2 can be characterised as a process mostly containing items *A*, near the patient zone, and Strategy 3 as a combination of items *A* and *B* in all the sequence.

In regards of reactions to the resulting mobility modelling, two teachers that commonly run healthcare simulations, said that they see potential in making visible this aspect of teamwork that would otherwise remain hidden. One explained that "*[the models] may help to actually see if students positioned themselves correctly [and] to find patterns of student's activity*". They also questioned the kind of claims that can be made based on these data. One teacher said that "*it would be interesting to know what people were saying or doing in specific places*". The other added that "*the models need to be complemented by the tutor to make sense of it*" and "*for some tasks people need to be in specific locations but for others they don't*".

5 CONCLUSIONS & DISCUSSION

We have presented a methodology to sense and model embodied mobility teamwork strategies in the context of healthcare simulation. We described the means for sensing, processing, visualising and processing student-nurses' mobility data that can be useful for modelling embodied strategies around a patient manikin. Our exemplars illustrate the methodology's potential by distilling at least three distinct, meaningful strategies (as judged by two subject matter experts) followed by the teams of our in-the-wild pilot study. Classroom settings can be messy and are intrinsically unpredictable. For example, in our studies the four teachers allowed different lengths of time for the actual simulations and provided varied support and guidance. Thus, students' strategies could be greatly shaped by the classroom conditions. Similarly, teams were integrated in quite different ways. Teams were commonly formed by 4-5 students (e.g. as the ones modelled in Figure 3) but in one class, groups had up to 8 team members. These and other physical conditions can impose limitations and challenges for mobility tracking. In summary, visualising mobility data as indoor maps may be useful for generating understanding about embodied strategies or to aid teachers and learners in post-hoc reflection. We also proposed an approach for encoding these data into discrete sequences of states. In a larger dataset and/or with a different segmentation approach, it would be possible to itemise the mobility dataset to then mine frequent sequential patterns associated with teams' performance or outcomes.

The long term vision is for personalised and group-customised feedback to teams Whilst we have made progress in modelling mobility data in a way that is meaningful to domain specialists, the full analytics workflow must be automated in order to provide *timely feedback* to students and teachers. We aim that the methodology presented in this paper could serve as a basis for more complex approaches to enhance sensemaking of students' embodied strategies by mapping *trajectories of particular people* in the learning space. Future work could, for instance, explore the use of alternative tracking techniques of indoor localisation. We also aim to *integrate other logged information* such as behavioural and physiological data. In order to develop *user and group competency models*, larger datasets are required to validate the robustness and significance of the patterns. Finally, we need to extend the students and teachers involvement in a more *participatory design process*, to elicit insights and feedback on the resulting models. Ultimately, this work is not about higher fidelity surveillance of students, but about *empowering them with timely, actionable feedback* that builds their metacognition for teamwork. In conclusion, we propose that this paper helps to characterise, and contribute to, a substantive new stream opening up in user modelling and adaptive interaction, which will extend the field into the modelling of physical space and embodied activity in order to support the many forms of authentic learning that go beyond personal computing, and online collaboration.

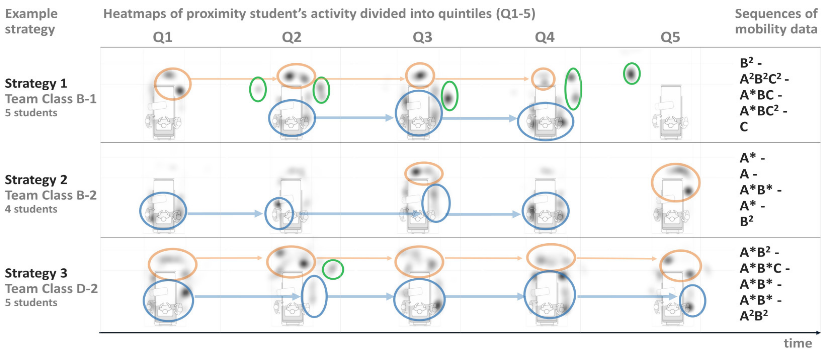

Figure 3. Heatmaps of nurses' activity divided in quintiles (Q1-5). Ovals indicate clusters of activity near (blue) far (orange) and further (green) from the manikin patient. Arrows indicate continuity of these clusters across time

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