Towards Proximity Tracking and Sensemaking for Supporting Teamwork and Learning

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***Abstract*— A large number of learning tools offering some sort of personalisation features rely mainly on the analysis of logged interactions between students and particular user interfaces. Much less attention has been given to the analysis of physical aspects so often present in 'traditional' intellectual tasks, although these are both important in the full development of a life-long learner. This paper (1) discusses existing literature focused on supporting learning using proximity and location analytics and sensors; and, based on this, (2) illustrates the feasibility and potential of these analytics for teaching and learning through an study in the context of proximity and location analytics in a team-based health simulation classroom.**

Keywords-physical spaces; mobility tracking; teamwork; classroom; computer vision; indoor positioning

I. Introduction

Traditionally, learning tools that offer adaptation features or personalised feedback often rely on behavioural data consisting of the logged students' interactions with particular learning systems [1]. This can generate at least two situations. First, those learning tasks that are aimed at promoting the development of kinaesthetic skills are often neglected (e.g. learning to play a musical instrument, dance, use clinical equipment, improve the technique in sports, etc.). Second, the physicality aspects of 'traditional' intellectual tasks (e.g. face-to-face collaboration dynamics, classroom processes, teacher's activity), which are also crucial for the full development of a life-long learner, may also be easily overlooked. These interactions between students and user interfaces have been feeding both Data Mining and Learning Analytics approaches to data-driven educational innovations (e.g. see [2]). Exceptions gone beyond this centre of interest can be found within multimodal analytics efforts [3] and approaches to understand affective states of learning [4].

With the recent and rapid progress in mobile and emerging pervasive technologies, many devices have extended capabilities to sense physical aspects of the learning context, such as *proximity* (e.g. the relative distance to a particular section of the classroom or to peers), and *location* (e.g. the position of students or teachers in the classroom, field, or public spaces). This means that student models can now include these physicality aspects, leading to a broader, richer understanding of learning behaviours.

This paper has two parts. The first part discusses literature (Section 2) and identifies key areas (Section 3) where the physicality of learning can be supported by leveraging analytics and sensors of these two aspects (proximity and location). The second part illustrates the feasibility and potential of these analytics for supporting teaching and learning. We present one study that illustrates ways in which proximity and location tracked data can help us make sense of physical aspects of teamwork (Section 4).

II. Related Work

In this section, we briefly discuss multimodal analytics approaches that have looked at other dimensions of student's data, beyond interaction data, and the emerging interest in generating analytics support for physical aspects of learning.

A. Multimodal learning analytics

Multimodal learning analytics (MMLA) approaches have focused on integrating data from multiple dimensions of student activity beyond clickstreams and keystrokes. E.g., some studies have looked at analysing speech, handwriting, sketch, gesture, physical movements, facial expressions, gaze, and neurophysiological signals [3]. In the last few years, there has been an emerging interest and numerous advances in the area of MMLA. For example, multimodal data (digital pen, speech, images) have been analysed to understand how maths students work and collaborate [5]; and computer vision techniques have been used to identify gestures that differentiate experts from novices [6]. However, most MMLA studies have been conducted under controlled laboratory conditions [7]. Thus, still much work is needed to find ways in which these approaches can solve challenges in realistic, mainstream learning scenarios.

B. Analytics Support for Psychomotor Learning

The acquisition of kinaesthetic skills is crucial for many kinds of learning tasks [8] such as learning a sign language, improving handwriting, drawing, practicing sports or martial arts, etc. Generating personalised support in this area would involve monitoring the physical movement of the student, comparing this against the movement as it is carried out by

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an expert and, if needed, delivering the feedback to the student to correct their movements [9]. The monitoring can be done either with optical motion capture systems [10] and/or wearable inertial sensors [11] (e.g. accelerometers and gyroscopes). The latter have the advantage of not requiring an infrastructure setup as they are already embedded in most wearable and mobile devices. To compare the expert's and learner's performance, a modelling process is required. Although 3D skeletal models are sometimes provided by the capture system, usually customised algorithms need to be generated for the particular subject being measured [12]. Typically, the system feedback is visual, showing the movement carried out by the student. There is recent interest in providing automated vibrotactile feedback which shows promise in helping students correct their motion errors [9].

III. Applications of Proximity Analytics for Learning

A number of learning tasks, modalities and/or educational activities can be identified where physicality of interactions or learning processes can be supported by applications of proximity and location analytics.

1) F-formations. When working f2f, people do not only communicate verbally but also through gestures, postures, and other non-verbal cues [13] and may use the space or multiple objects. A key spatial aspect in f2f team work are the F-formations [14]. These refer to the **proximity**, **location** and **body orientation** of collaborators. A recent example of this applied surveillance algorithms to track collaborators working in a Design Studio suggesting the importance of patterns of usage of the collaboration space [15].

2) Physical social interaction. Data mining techniques were used to look for patterns within social networks in physical environments in [16, 17]. For tracking face-to-face interactions at a wider scale (e.g. within an organisation, at a conference or in public events), they developed sociometric badges. These can track basic aspects of social interaction such as whether two people were talking to each other, levels of voice, and movement. These kinds of social **proximity** data, can be exploited through social network analysis for finding patterns in settings where collaboration happens not only in small groups, but also through small and heterogeneous interactions within the community.

3) Analytics in the classroom. Besides the diversity in architectural formats, the classroom still basically allows educators to interact with students [18]. Tracking the **location** of the teacher or students in the classroom may provide new insights about key events such as the provision of feedback, communication patterns, or the identification of inactive students. For example, Prieto et al. [19] presented an elaborated approach to collect teaching analytics using accelerometer data, EEG, audio, video and eye trackers' data, to create 'orchestration graphs'.

4) Learning in and from physical spaces. Certain learning tasks may require field work that is more commonly supported with mobile or augmented reality (e.g. [20]) technologies. These scenarios may not only require students to access content online but also make sense of it and associate it with the physical context where the task unfolds. Data obtained from **location** and usage logs could unveil patterns of the processes that students follow or generate while learning in the physical space.

IV. Illustrative Study

In this section we present an educational case study that illustrates the feasibility and potential of proximity analytics.

A. Proximity Analytics for Healthcare Simulation

Healthcare simulations are integrated into the Bachelors of Nursing and Midwifery at the University of Technology Sydney. Simulation classrooms are equipped with 5-6 manikins that produce indicators of a patients' health, respond to actions and can be pre-set to deteriorate over time. Each manikin is on a clinical bed which, in this case, was equipped with a depth sensor to track students around it. Students have to apply their health care knowledge and skills to oversee a patient manikin in a hypothetical clinical scenario. The challenge here is that, although students are

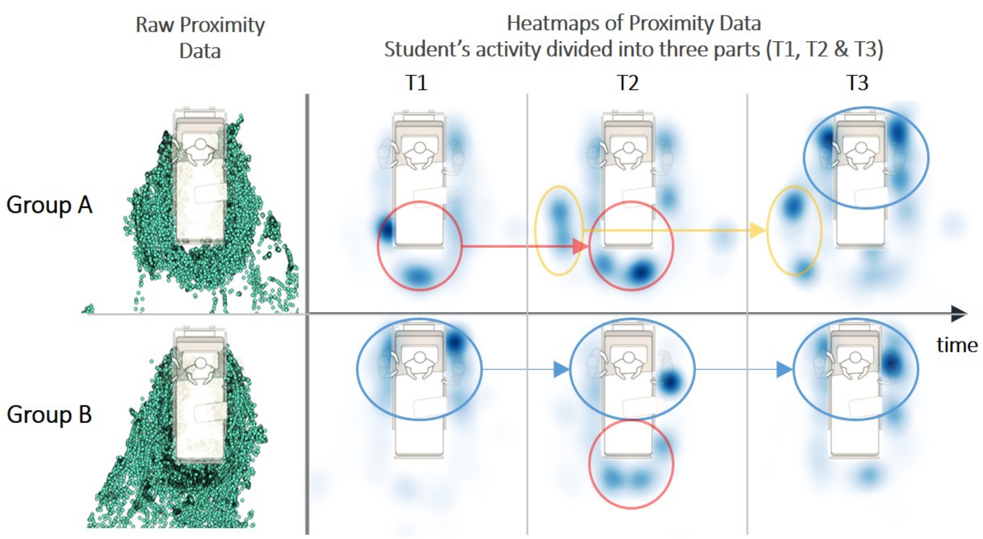

Figure 1. Raw proximity data (Column 1) and Heatmaps of student's activity (1 hour) divided in three parts (T1, T2, T3) of 20 min. each for two groups in the same classroom: A and B. Coloured ovals mark clusters of activity near (blue), far (red) and further (orange) from the

required to reflect about the task, they do not have access to any evidence about how they performed. Teachers commonly have to divide their attention among multiple small teams working simultaneously and only rely on what they can partially observe in each bed to provide feedback.

One potential that proximity analytics can bring to this learning scenario is that a feasible source of student's behavioural evidence is the tracked position of the students around the manikin, which can help to describe how group members approach the tasks, the processes they follow before performing actions on the manikin and behaviour according to learners' roles. E.g., Figure 1 shows the data of two groups of 4-5 students each. The first column in Figure 1 shows the raw data captured in a whole classroom session where each data point corresponds to the distance and position of each student around the manikin. Up to 30 proximity data points per second are captured for each student standing around the manikin. The sense making of these data starts to unfold when adding spatiotemporal dimensions. E.g., Figure 1 (columns 2-4) shows heatmaps of proximity data with the activity divided in three parts. This unveils that Group A stayed mostly away from the patient during the first two thirds of the task (see red and orange ovals in thirds T1 and T2) to then work near the patient only during the last part of the activity (see blue ovals in T3). By contrast, Group B followed a very different approach by engaging with the patient from the beginning of the task and maintaining proximity throughout (see blue ovals in T1-3). This preliminary example shows how proximity and mobility data, when visualised in intuitive ways, could provoke productive reflection on the different student's strategies.

V. CONCLUSIONS

To conclude, we are seeing the increasing availability of affordable, mobile, multimodal sensors, coupled with data science techniques for the rapid analysis of large datasets. This opens the possibility that contexts in which learners' proximity, location and motion are important need not be 'digitally cloaked', that is, invisible to computational tracking. While these exciting technologies can certainly enable new forms of educational research, academics have always had access to advanced forms of sensors, computational tools for the study of co-located activity, and the expertise to generate representations for academic purposes. Arguably, the more profound implications are for practice: for the first time, educators and students could have access to timely, even real-time, feedback on embodied learning activity. For this potential to be realised, however, requires not merely the deployment of sensors in learning spaces, and the visualisation of the vast amounts of data they generate. What is required is a sound understanding of how to design data analysis frameworks and corresponding techniques that would enable discovery of pedagogically significant patterns, which can then be visualised in ways that make sense to educators and learners, enabling adjustments to their behaviour.

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