Where is the Nurse? Towards Automatically Visualising Meaningful Team Movement in Healthcare Education

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Abstract. Providing immediate, effective feedback on team and individual performance in healthcare simulations is a challenging task for educators, such is their complexity. Focusing on emergency procedures on patient manikins, our prior work has demonstrated the feasibility of using multimodal data capture and analysis to generate visualisations of student movement, talk and treatment actions. The limitation to date has been the need for manual steps in the analytic workflow. This paper documents how we have automated several key steps, using new technologies, which were piloted during a nursing simulation. Combining role-based nurses' movement data with high fidelity manikin logs, we have implemented a zone-based classification model, and are able to automatically visualise movements within an emergency response team, providing the data needed to design near real-time feedback for both educators and students.

Keywords: teamwork, collaboration, analytics, movement, localisation

1 Introduction and Related Work

Healthcare simulation scenarios are commonly utilised in undergraduate nursing education. They expose students to real-world scenarios using a variety of technologies and modalities within a safe environment [4]. *Debriefing* with an educator after the simulation is critical for learning and improvement [3]. Although it is commonplace to video record simulations, video's utility is often constrained by the tutor's ability to document, in real time, key moments s/he wants to return during debriefing. One key feature of high performance teams attending to a patient is their ability to position themselves correctly at critical points. Currently, the educator has limited capacity to track each participant's positions along with other aspects of a team's performance.

Previous work on indoor location analysis in healthcare scenarios has shown the potential of these systems to monitor and model patients' behaviours with the purpose of providing better assistance [2, 9]. For example, a recent study showed the potential of visual representations of participants' movement and location during healthcare simulations, as they can augment the post-simulation debriefings and foster workflow management changes [7]. However, there has been little research concerning the automated analysis of indoor location in healthcare simulations and in *educational* contexts in general. Tracking movement may be particularly critical to carry human factors analysis in situations where teams are developing clinical and/or teamwork skills by engaging in activities that involve the psychomotor realm and reflecting explicitly on the scope for improvement. Our prior work has demonstrated the feasibility of using multimodal data capture and analysis to generate visualizations of student movement, talk and treatment actions [5, 6]. The limitation to date has been the need for manual steps in the analytic workflow. This paper reports progress in the challenge of using multimodal analytics and Internet of Things (IoT) sensors to capture and analyse teamwork activities by tracking individuals to potentially identify pitfalls regarding clinical procedures, towards providing near real-time feedback.

2 Pilot Study

Nine second and third year undergraduate students from the UTS Bachelor of Nursing program volunteered to participate in a simulation scenario. We randomly organized students into three teams (of 2, 3 and 4 students each; Teams 1, 2 and 3 respectively). A cardiac-arrest scenario was designed by a teacher in the context of caring for a deteriorating patient requiring basic life support. The simulation scenario ran for approximately 12 minutes and involved five sub-tasks that students were meant to perform sequentially (see Table 1, column 1). Each student had a specific role (RN1-4) with an associated set of subtasks (Table 1, columns 3 to 6). Depending on the number of students, the subtasks associated which each role were distributed among the team members (e.g. RN2 and RN3 were merged into one single role for the team with two students).

Students' movement data was logged through wearable badges[1]. We automatically recorded *student-id*, *x-position*, *y-position, timestamp* or each student every second. Since the data gathered contained noise from the positioning system, we applied a Kalman filter [1] to improve further calculations. Some student actions (*timestamp, action-name*) were automatically logged by the high-fidelity manikin[2] (for reference see Table 1, Column 2). In addition, all the simulations were video-recorded for further analysis.

Table 1. Sub-tasks and actions logged by the manikin given specific roles.

Sub-tasks	**Actions logged by the manikin**	**RN1**	**RN2**	**RN3**	**RN4**
ST1: Oxygen Therapy	Place oxygen mask Set oxygen level	x			
ST2: Assessment of chest pain (PQRST)	Attach NIBP Measure blood pressure	x			
ST3: One dose of Anginine	Administer medicine	x	x		
ST4: Connection to a 3-lead monitor and heart rhythm identified	Attach 3-lead ECG			x	
ST5: Life support according to the DRSABCD protocol	Start CPR Stop CPR	x	x	x	x

[1] Indoor localization system: *Pozyx* (https://www.pozyx.io)
[2] Simman 3G: Laerdal (http://www.laerdal.com)

3 Indoor-location Analysis

Following the methodology proposed in [5], we performed the following steps to generate team's and individual's movement visualisations:

Clustering. From the educator's perspective, we coded 4 meaningful locations that students usually cover around the room: 1) head of the bed, 2) bedside, 3) bed-footer, and 4) far away from the bed and 5) by the trolley (which contains an automated external defibrillator). These physical areas are often associated with meaningful tasks that nurses commonly perform. For example, a nurse located at the head of the bed is usually there to hold the patient's head during a CPR intervention. Nurses at the bedside are commonly interacting with the patient directly; while nurses closer to the bed-footer are there commonly to read the notes about the patient or discuss the case. With this information, we assigned a location (from 1 to 5) to each logged position in our dataset.

Visualisations. We generated a set of network graphs to the nurses' space usage around the patient's bed. Fig. 1 shows how the meaningful locations became the nodes of the network graph. The links between the nodes represent the movement of each nurse from one area to another. In case the nurse spent time in the same area, it is represented with a lasso. Each nurse is assigned with a different a colour (RN1-brown, RN2-blue, RN3-red and RN4-green). The width of the links represents the time the nurse spent in that area.

Segmentation. We divided the dataset into meaningful segments from the manikin actions. This helped us into to understand roles and team performance by stages. Table 1 shows the manikin actions according to each subtask. Since the manikin actions did not log starting points (except for CPR), we manually set the starting point of the sub-task by watching the videos. The timestamp from the manikin's logs served as the ending point of the sub-task.

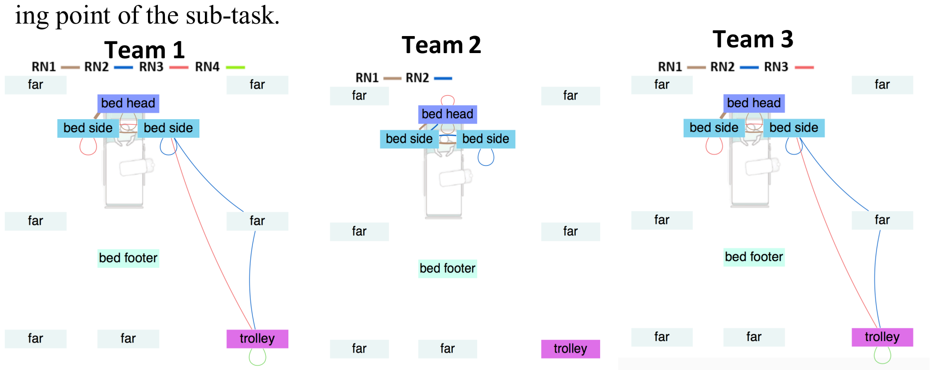

Fig. 1. Network graph representing team and individual locations (coloured lines) from the beginning of the simulation until patient received *oxygen therapy* (ST1).

Making Sense of Location Patterns. Our analysis explored how each individual and team movement data could support educator's insights and how these relate with the learning activity. Due to space limitations, we describe one possible way to make sense of this information. In a post-hoc interview, an educator expressed that Team 1 and Team 2 were high-achieving teams, whereas Team 3 was a low-achieving team.

Overall performance and team movement. We observed that each team occupied the room in different ways, yet we can see some similarities. It seems that all three teams moved around *bed sides*, *bed head* and the *trolley* more often. This behaviour is appropriate for the task, given that participants had to provide basic life's support near the patient (e.g. oxygen therapy, vital signs).

Individual performance and role movement. From the examples depicted in Figure 1, we observed that role **RN1,** often occupied the *bed head* and *bed sides* areas, to assist the patient. Mapping the role movement with their assigned task, we can see that, RN1 have been assigned the communication with the patient. Thus, we expected that RN1's presence would be associated with areas in close proximity to the patient (e.g. at the *bed head* and *bed sides* areas). Regarding **RN2**, in teams 1 and 3 this role showed a similar trajectory: both nurses occupied the *trolley* area at some point. However, the nurse in Team 2 spent most of the time in *bed sides* area. From the commentaries made by the teacher about Team 2 performance, we could say that both RN1 and RN2 shared the same locations because RN2 was helping RN1 to provide basic life support. Finally, observing **RN3**, we can appreciate that RN3 in Team 1 covered the *bedsides*, *bed-footer* and *trolley* areas. By contrast, RN3 in Team 3 only occupied one *bed side* and a *far* area. This is in line with the comments made by the teacher, which expressed that RN3 in Team 3 should be more aware and responsive.

4 Conclusions and Further Work

In this paper, we have presented an approach to track and visualise how teams of students occupy the physical learning space in the context of healthcare simulation. Drawing from the learning design, we segmented our dataset by giving meaning to the locations in the space. We explored the potential of visualising the location data in helping explain the behaviour of teams from a teacher's point of view. Whilst additional contextual information would be needed to fully understand the activities unfolding in those locations, this work can be seen as an initial step towards automatically visualising and making sense of team movement in learning spaces. Our overarching aim is to make processes and performance more visible in physical learning spaces, both for teachers and students. However, more work is still needed to connect these data with higher order aspects of learning and collaborative activity. Additionally, a larger dataset would allow us to apply machine learning techniques to this kind of location data that can point at frequent patterns that may differentiate individuals, roles or teams. In order to support the sensemaking process on these data, our next steps will include exploring what additional data sources can help us build a richer model of team's actions and activities performed by each student according to their role. As our ultimate goal is to provide feedback to teachers and students, we are planning to validate an improved version of these visualisations with prospective users. Currently, we are involving teachers and learners into the design of such visual representations using participatory designed techniques [8] tailored to data-intensive educational scenarios.

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