Making sense: Sensor-based investigation of clinician activities in complex critical care environments

Thomas Kannampallil *, Zhe Li, Min Zhang, Trevor Cohen, David J. Robinson, Amy Franklin, Jiajie Zhang, Vimla L. Patel

Center for Cognitive Informatics and Decision Making, School of Biomedical Informatics, University of Texas Health Science Center, Houston, TX, United States

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ABSTRACT

In many respects, the critical care workplace resembles a paradigmatic complex system: on account of the dynamic and interactive nature of collaborative clinical work, these settings are characterized by non-linear, inter-dependent and emergent activities. Developing a comprehensive understanding of the work activities in critical care settings enables the development of streamlined work practices, better clinician workflow and most importantly, helps in the avoidance of and recovery from potential errors. Sensor-based technology provides a flexible and viable way to complement human observations by providing a mechanism to capture the nuances of certain activities with greater precision and timing. In this paper, we use sensor-based technology to capture the movement and interactions of clinicians in the Trauma Center of an Emergency Department (ED). Remarkable consistency was found between sensor data and human observations in terms of clinician locations and interactions. With this validation and greater precision with sensors, ED environment was characterized in terms of (a) the degree of randomness or entropy in the environment, (b) the movement patterns of clinicians, (c) interactions with other clinicians and finally, (d) patterns of collaborative organization with team aggregation and dispersion. Based on our results, we propose three opportunities for the use of sensor technologies in critical care settings: as a mechanism for real-time monitoring and analysis for ED activities, education and training of clinicians, and perhaps most importantly, investigating the root-causes, origins and progression of errors in the ED. Lessons learned and the challenges encountered in designing and implementing the sensor technology sensor data are discussed.

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1. Introduction

Critical care environments are characterized by distributed, inter-dependent, episodic and non-linear work activities. The dynamic nature of the care process in critical care environment affects the nature and timing of work activities of clinicians, and often increases the possibility of errors. Studying the work activities of clinicians in such environments can help us understand the care delivery process, workflow, and interruptions that affect clinical work. Exploratory investigations of clinician activities are often performed using observational methods. While these methods provide a descriptive depth that cannot be matched by automated methods, use of participant observation methods [1,8,10,13,14,16] in a critical care setting is often challenging, as capturing the work activities of multiple clinicians requires several observers who must be closely synchronized during their data capture sessions. In this paper, we propose the use of multi-sensor technology as an approach to complement human observation in critical care settings, to capture highly detailed and precise information regarding certain work-related activities of clinicians. We believe that such a hybrid approach that combines human observation and sensor-based data capture facilitates a holistic mechanism for understanding and evaluating a complex critical care environment.

Two of the easily discernable clinician activities in the ED are movement of the clinician across various locations and their interactions with other clinicians. The mobility and interactions of the clinicians are an inherent part of the work activities as they go through the patient care process. The complex nature of the work activities in the ED is likely to result in fairly complex mobility and interaction patterns. Studying the nuances of these patterns can provide insights into how the complexity of the environment affects the clinician work activities. Our approach for this study...
was predicated on prior research [24,27,28], where it was found that sensor-based technologies could be used to reliably capture mobility and interaction of clinicians. One of the challenges of studying an environment such as the ED is that the complexity is often caused by several contributing factors. If the randomness in the mobility or interaction patterns among the clinicians in the ED environment is very high, then it is unlikely that there are trends or patterns within such activities. In contrast, if the randomness falls within certain established boundaries, it provides an opportunity to investigate the underlying patterns within such activities. We use entropy to measure of the degree of randomness in the environment. Based on a detailed entropy analysis of the movements of physicians within the ED (considered as a system), we found that there was a high likelihood of underlying patterns in the clinician movement and clinician interactions. We also established the significant correlation between human observation and sensor data, which provides validity for using the sensor data as a measure for capturing clinician activities.

The entropy computation and the strong correlation between observed and sensor data provided a basis for using sensor data for “piecing together” ED work activities. By tracking clinician movement and their interactions with co-workers (i.e., other clinicians), we developed a trace of their workflow along the following dimensions: location, time spent at a location, transitions across different locations in the ED, and finally, their collaboration with other clinicians in the ED. In other words, we created a workflow of the clinician activities that provided significant insights into the work patterns, resource utilization, overheads and potential for the occurrence of errors. We also describe the implications of the use of sensor technology in critical care settings in terms of its use for monitoring and management of resources, as resource for training in virtual environments such as Second Life, and most importantly, as a useful source of highly precise data for investigating the origin, causes and progression of errors in the ED.

2. Background

The study of complex systems draws together emerging approaches from several diverse fields including economics, physics, biology, mathematics and computer science on the common ground of complexity. This interdisciplinary effort seeks to formulate unifying principles of complexity. Several authors have proposed that the healthcare system or elements thereof can be characterized as a complex system [3,17–19,21,25]. For example, Smith and Feied [21] argue that an emergency department is a paradigmatic complex system. This argument rests on the unpredictability of both patients’ clinical conditions and clinicians’ work patterns, the vast decision space and incomplete evidence that complicate clinical decision-making and the inherent unpredictability of the system as a whole.

Several concepts drawn from the complex systems literature are pertinent to the study of a critical care unit as a complex cognitive system. A cogent and readable account of the ways in which concepts from the complexity literature might be applied to social systems has been developed by the Complexity in Social Science (COSI) project [9]. Complex systems are by their nature non-deterministic and dynamically structured. That is to say, it is not possible to predict the behavior of a complex system by studying the function of its components in isolation, and furthermore the study of the behavior of any such component reveals little about the system as a whole. Likewise, the process of clinical care emerges from a series of dynamic and flexible interactions between patients, health-care providers and outside influences [4]. While this argument applies readily to workflow, it also relates to the cognitive processes that underlie critical care decision making, as the cognitive processes in critical care settings are distributed across the minds of the clinical team and a range of physical media [7]. Given the complex nature of system behavior, it is not possible to predict the knowledge, expertise and information that will be available at the point in time at which clinical decisions are made. Similarly, for transfer of information, it has been observed that within complex social systems the flow of information is determined somewhat serendipitously by the geographical location of team members [6], which is influenced in turn by the complex dynamics of the system as a whole.

These aspects of the critical care workplace present challenges for the human-intensive ethnographic methods we have employed in our previous research [7,14,16], as these have tended to focus on the shadowing of individual clinicians. However, complex systems theory suggests that only limited insight into system behavior can be obtained through the study of component parts. Consequently, in our recent work we have explored the use of automated sensors through which we aim to complement the human-intensive focused data collection we have employed previously [24]. While not able to capture the depth and richness of representation that are possible through ethnographic methods, these sensors offer certain advantages in that it is possible to collect data concerning a geographically mobile clinical team over an entire shift. This is desirable, as even an exceptionally well-funded research program that may be able to employ multiple well-trained human observers is likely to experience problems integrating a team of observers into a busy clinical environment without obstructing patient care.

In this paper, we present an overview of our work in which we use sensors in a real-world clinical environment to try to characterize the movements of, and interactions and collaboration among members of a clinical team in the ED setting. Data captured from these sensors are interpreted in the light of human-intensive observations of key team members captured contemporaneously. We present a series of analyses of these data, and discuss their significance for the study of complex social systems. In addition, we share some lessons learned with respect to the use of automated sensors in a complex clinical context.

3. Methods

In this section we describe the study setting, data capture using the sensors and human observers, data synchronization and analysis. Detailed description of the sensor setup, physician shadowing, and data analysis are also provided.

3.1. Study setting

The study was conducted in a certified Level 1 Trauma Center in the Emergency Department of a large teaching hospital located in the United States. The hospital provides 24/7 emergency and trauma care to approximately 52,000 patients a year. The ED is separated into distinct units caring for pediatric patients, general medicine patients and those requiring trauma care. The physical setup of the trauma side of the ED includes eight trauma patient beds and five urgent care beds. In times of high patient volume, additional chairs and beds are placed in the open spaces as needed. The care team for trauma ED typically includes one attending physician, two resident physicians and two trauma nurses, an urgent care nurse, a charge nurse, one technician, and a respiratory therapist shared by the entire ED. The trauma center is also supported by a dedicated trauma team, consulting physicians and the staff from other units of the ED (including off-service providers) as needed.
3.2. Participants

Observation and tagging occurred on four separate shifts over a 2-month period at the trauma center. During each observation session, the attending physician, two resident physicians, and two trauma room nurses, were solicited for participation. Informed consent was obtained from all participants before the start of each data collection session. Participants were instructed to go about their usual activities. The Institutional Review Board (IRB) approved the study.

3.3. Sensor setup

RID (Radio-Identification) sensor technology used for this study is composed of tags and base stations which are used to capture the movement and interactions between the clinicians in the ED. Tags are mobile devices that help in the tracking of moving objects. Base stations are stationary devices that provide radio coverage and tracking of the tags. The tags and base stations communicate using a vendor-customized IP-Lite radio connection protocol. During the study sessions, members of the core care team carried the RID tags in the pockets of their coats. Base stations were placed at key locations in the ED to capture their movements and the transitions between spaces such as patient rooms. As a clinician carrying a tag comes in close proximity with a base station, a ping event is registered with that base station. This is referred to as a tag–base ping. The strength of ping event is measured in terms of received signal strength index (RSSI). Additionally, when two clinicians come in close proximity to each other, a tag–tag ping is registered. As with the tag–base pings, the relative physical distance between the clinicians is reflected in the signal strength of the tag–tag pings. The tags and base stations send pings at approximately 3-s intervals. In other words, for every three seconds, each tag registered with a corresponding base station in its vicinity.

Fig. 1 shows the configuration of tags and base stations and how ping events are registered between them. In Fig. 1, interactions between three tags and one base station are shown. The tags register pings with each other (tag–tag pings, represented as n1, n2 and n3) and, concurrently register pings to the common base station (m1, m2 and m3 pings). The tag–tag and the tag–base pings are used for the identification of the location of a clinician (or multiple clinicians) and their collaborators at any particular point in time. The tag–tag interactions provide an additional dimension (of co-location of clinicians) through which to interpret the actions of the clinicians in the ED.

A total of ten (10) base stations were placed across the trauma rooms, physician station, nurse station, CT room and urgent care rooms. The tags were distributed among the attending physician (1), residents (2) and nurses (2). The sensor data included the tag–tag and tag–base pings along with their corresponding signal strength and time-stamp. Sensor data on the tags and base stations was then formatted and uploaded to a MySQL database server. The spatial orientation of the base stations is shown in Fig. 2.

One of the critical factors in effectively using the sensor technology is the calibration of the sensors to filter “good” signals from noise. Prior research has used a variety of mechanisms to filter the

![Fig. 1. Tag-tag and tag-base configuration. Three tags and one base station is shown in the figure with interactions between them represented by pings (tag-tag and tag-base).](image-url)
sensor signals. In general, threshold signal strength is often established as a baseline measure. In our experiments, we used a RSSI signal strength value of -70 dB (decibel) as our cut off signal strength. This value was based on manufacturers specification and our calibration tests verified this threshold.

3.4. Shadowing

In order to validate and complement the information provided by the sensor data, human observers shadowed the “tagged” clinicians. The purpose of shadowing the clinicians was twofold: first, to confirm the accuracy of the location estimations made by the tags and second, to get additional information on the activities of clinicians. The attending physician was shadowed for two sessions, while in the other sessions, a resident and nurse was followed.

To assist observers with their shadowing tasks, we used the UObserve suite of data logging tools [15]. UObserve is a mobile platform that provides researchers with the ability to conduct field observations using standard templates to ease data collection, and importantly the capacity to precisely record the time of recorded events. The UObserve tool is based on the work domain ontology of the ED environment (see e.g., [15]). The use of UObserve allowed for precision and ease in capturing events (e.g., time, place, participants, and activities) and synchronization with the tagging data. For this study, observers were provided with a version of UObserve, which had a list of ED-specific locations (based on the base-station locations) and collaborating clinicians at that location. At every instance when the tagged subject changed location, the observer noted the location on the UObserve tool. Additionally, other clinicians who came in direct contact with the shadowed clinician were also noted.

For each location selection, a time-stamp was automatically added by the system. This time-stamp was synchronized with the time-stamps on the sensors. The data from UObserve was uploaded from the mobile device to an encrypted server. A companion application was developed to export the data in customizable data formats. A sample screen shot from one template in the UObserve interface is shown in Fig. 3.

3.5. Data collection

Four data observations of the core trauma care team (1 attending, 2 residents, 2 trauma nurses) occurred over a two-month period. One clinician was shadowed per session by an observer. Prior to collecting the data in the ED, the tags and base stations were extensively tested in the laboratory and in the ED (in pilot experiments) to ascertain their accuracy and effectiveness. During each of these sessions, both sensor and shadowing data were captured. On average, each of the data collection sessions lasted about three hours (mean = 3.2 h, s.d. = 0.14 h) and was conducted from the start of attending shifts during both afternoon and night periods. While all five team members wore RID tags, only selected team members were shadowed. Clinicians varied across the sessions.

3.6. Data analysis

In this section, a detailed explanation of the various measures that were used to analyze the sensor and observation data is provided. Particular attention is given to the manner in which the data from the sensors are extracted, processed and analyzed. We specifically investigate two characteristics of clinician activities: movement of clinicians and their interactions with each other. Based on these two specific characteristics, we investigate the following: time spent at a location, time spent with other clinicians, transition between various locations and collaborative work activities.

3.6.1. Entropy or “degree of randomness”

In order to investigate the work activities in a complex environment, we have to first establish that the order and progression of work activities had any underlying repeating pattern. If the activities were indeed random, then it would be impossible to establish inherent patterns within the ED work activities. For this purpose, we first compute the entropy of the “ED system” in terms of movement and interaction patterns of the clinicians.

Entropy is the degree of randomness or disorder in a system and has been proposed as one of the measures that can be used to characterize the predictability of human behavior [22]. In other words, the degree of randomness in the environment in terms of the clinician mobility and interactions is representative of the complex nature of the work activities. If the entropy (i.e., the degree of randomness) were low, then it would be relatively easy to predict the mobility and interaction patterns, while higher entropy would imply greater difficulty in predicting such patterns. In a dynamic environment such as the ED, higher entropy would suggest that...
the work environment is relatively complex making it difficult to predict the movement or interactions of the clinicians.

We computed the entropy measures for mobility and interaction in the following manner: the tag–base and tag–tag pings below the threshold values were first filtered out (see section above on the determination of threshold values). The rest of the data (approximately 70% of the total data collected) was used to extract a time-series of valid, tag–base and tag–tag pings. For example, tag A attached to an attending physician recorded a sequence of locations: (Trauma Bed 1, Trauma Bed 2, Nurse Station, Physician Station, . . . ), which represents the set of locations that were visited by the attending physician. Similarly, a sequence of clinicians who were in proximity to the attending physician can also be extracted. For every session, we extracted the location and interaction information. We computed the estimated mobility and interaction entropy based on the modified Lempel–Ziv [30] data compression algorithm. The Lempel–Ziv algorithm is a lossless data compression algorithm, which codes the unique strings of characters with codes of a fixed number of information bits. For a time-series of length \( N \), the entropy is estimated as

\[
S_{\text{est}} = \frac{\log_2(N)}{\frac{1}{2}\sum A_i}
\]

where \( A_i \) is the length of the shortest sub-string at position \( i \) and the sub-string does not previously appear from position 1 to \( i - 1 \). We also computed the baseline measure of entropy assuming all behavior to be completely random, \( S_{\text{rand}} \).

\[
S_{\text{rand}} = \log_2(N)
\]

where \( N \) is the number of possible behaviors. We used the random entropy computation as the basis for determining relative degree of randomness of the ED system entropy (both mobility and interaction) in comparison to the random entropy value. In other words, if the baseline random entropy measure \( S_{\text{est}} \) is less than the \( S_{\text{rand}} \), then it is highly likely that we will be able to make predictions about the mobility and interactions of the clinicians in the ED. A detailed analysis of the measurement of entropy can be found in Zhang et al. [27,28].

3.6.2. Time spent at a location and in proximity to other clinicians

Collaborative work is often done within the specific context of location and people [2]. By ascertaining the location of a clinician and subsequently the time spent at that location, it is possible to make preliminary judgments on the work activities of the clinicians.

The location of a clinician is determined based on the tag–base pings and the shadowing data. For determining the time spent by the clinicians at a location, we use the tag–base ping events that were retrieved from the base stations. The time spent by a clinician in proximity to a base station is determined by aggregating the tag–base pings at each identified base station with the highest threshold signal strength value at that particular time. Like time spent in a location, time spent in proximity to others is measured by pings over the threshold response level. Unlike time at a location (tag–base pings), time spent in proximity to other clinicians is computed as an aggregate of the tag–tag pings. If there were multiple tag–tag pings at a particular time, then all possible pairs of tag–tag pings were aggregated for this computation.

3.6.3. Transitions between locations

One of the ways to investigate the workflow of clinicians is to trace the movement patterns of the clinicians. As explained earlier, work activities are often context (and location) dependent. In other words, locations can be used as a general proxy for certain types of activities. For example, the presence of an attending or resident at a trauma bedside can be considered as a “patient care” activity. Similarly, a physician at a physician workstation can be construed as the physician performing a documentation task. On account of the hands-on nature of clinical work in this setting, transitions between locations provide a preliminary account of the workflow in a collaborative setting. For example, the movement of the attending physician across various locations with in the ED over the period of a shift can be used to gauge their work pattern. If the attending physician was at their workstation for most of a shift, then we can make predictions about the low degree of activity during that shift. In contrast, if there is significant amount of movement by the attending physician across various trauma rooms, then we can make predictions about the high degree of activity during a shift. While these examples are extreme scenarios, it is important to note that transitions between different locations can be used as a basis for determining the nature of activities in the ED. In short, the transition between locations provides a trace-based illustration of the workflow. Similar approaches have been used to describe cell-phone use behavior [22] and EMR use behavior [1].

In order to develop the transitions between locations in the ED, we identified 10 locations in the ED where the base-stations captured significant signal strength. These locations were: CT Room (CT), Nurse Station (NS), Image Browsing Station (PACS), Trauma Bed 1A (T1A), Trauma Bed 1B (T1B), Trauma Bed 2B (T2B), Trauma Bed 3B (T3B), Trauma Bed 4A (T4A), Urgent Care Beds [10]. Based on the tag–base pings at these locations, we first developed a transition probability matrix of location transitions for each clinician.

A location-based transition probability matrix represents the transitions between a set of selected locations. Each cell in the matrix represents the total count of the transitions between the two locations. For example, if the cell value between the CT room and the Nurse’s Station for the attending physician was 25, it means that the physician moved from the CT room and the Nurse’s Station a total of 25 times during the shift. The transition probability matrix is also often referred to as an antecedent-consequent matrix, since it provides the counts of the number of transitions between the antecedent and consequent events. We developed a 10 \( \times \) 10 matrix for the location-based transitions (for the 10 locations described earlier in this section) for each of the clinicians, per session.

In order to develop the transition probability matrix, we first filtered the tag–base pings that were above the threshold value. Using a sliding window with an interval of 15 s, we temporally collected the locations of all clinicians within this time-window. The location with the highest RSSI strength per clinician was then separated out. This process was applied to the entire data set till all locations of all clinicians were obtained over their entire shifts. The temporal sequence of locations was then converted into a matrix of location-based transitions for further analysis.

3.6.4. Collaboration: aggregation and dispersion

Highly complex environments are often characterized by collaborative interactions to maintain the continuity of work activities. The collaborative interactions can be characterized in terms of three key concepts: the size of the collaborating team of clinicians, the length of their collaboration and the location at which the interactions of the team occurs. The knowledge of these three concepts is useful in developing a “blueprint” of the collaborative activities within the ED. We use the tag–base pings between clinicians to estimate the collaborative interactions between them. Using physical proximity as an indicator for interaction, we identify the following: first, the pair-wise interactions between all the clinicians and the locations at which these interactions take place were identified (based on tag–base pings). Then, the location and size of the largest group of clinicians are detected using matrix-based algorithm.
While, we use the term “interaction” in a general sense, meaning physical proximity between clinicians, it can be argued that close proximity at a particular location in an emergency care setting (e.g., at a specific trauma bed) would indicate that the clinicians are together for a common purpose or goal (e.g., care for a patient at a location). Thus, even though the clinicians may not be verbally communicating with each other, a common goal of being at the same location can be considered as a measure of a shared collaborative activity. We use this concept to measure the degree of team aggregation and dispersion in the ED.

As explained earlier, we first identify the pair-wise interactions between all pairs of clinicians. For the sensor data, we focus primarily on the pair-wise interactions of the attending physician, as they are central to controlling the workflow in the ED. For ascertaining the pair-wise interactions, the sensor data was first “chunked” into intervals of 30 s, after testing with intervals ranging from 30 s to 180 s. To be considered as a “valid tag–tag ping” at a particular location several conditions were first evaluated. We describe these conditions with an example. Consider two tags, tag1 and tag2 at a location B1 (base station location). A valid tag–tag ping between these two tags would involve the following interactions: tag1→tag2 ping, tag2→tag1 ping, tag1→B1 ping and tag2→B1 ping. Additionally, all these pings have to occur within the selected 30-s interval.

After obtaining the pair-wise interactions (and their locations), we evaluated the formation (aggregation) and dissipation (dispersion) of larger clinician groups. The identification of large groups was progressively more complex than the pair-wise comparisons. Since groups (size > 2) take longer time to form (and disperse), we considered time intervals of 100 s for this analysis. The time period of 100 s was arrived after testing with various “time-chunks”, discussions with ED attending physicians and our own observation data. Based on our observation data and discussion with ED clinicians, we evaluated the average group formation (for groups of different sizes) time across each shift. A 100-s interval was found to be an appropriate time-span for capturing the formation (and dispersion) of groups of sizes varying from two to four. The groups were ascertained in the following manner: first, the presence of a group within the considered time interval was determined. Second, it was verified whether the interactions were occurring within the same location. We explain the aggregation algorithm with an example.

For every 100-s interval that we considered, we developed a two-dimensional matrix similar to the one shown in Fig. 4. There are two types of information that is encoded in the matrix: the tag–tag interactions (represented as a binary operator between tags T1–T5 in the left half of the matrix) and the tag–base interaction (represented as a binary operator between base stations B1–B10). From the example matrix (see Fig. 4), we generate all possible tag–tag interactions. In this case, the only tag–tag interactions are with tag 1 (T1) with (T2 and T3). The interactions of all other tags (T2, T3 and T4) are with only with T1. Thus, the direct interactions in this period of time are (T1, T2, T3). Next, we investigate the reverse tag pings (i.e., from T2 to T1, T3 to T1, etc.). For this, we evaluate the column values for T1: (T2, T3, T4). The intersection set between direct and reverse set of tag–tag pings gives us the set of tags that were interacting in this time period. In our case, we get the set of tags as (T1, T2, T3). This means that the clinicians carrying the tags T1, T2 and T3 were in close physical proximity to each other.

The last step in the algorithm is to establish the location where the clinicians were together. For this, we use the identified set of tags and compare it with the common set of locations at which these tags were present. In other words, we explore the columns for the base stations (B1–B10) that have non-zero values in the cells for the set of identified interacting tags. In the case of the example provided, the only location where the base station has non-zero value is for the column pertaining to B2 (see Fig. 4). Consequently, a group will only be considered as such if all members ping one another, as well as the location base station during the same 100-s time period. Thus, we can identify the largest group during this time period as (T1, T2, T3) at location (B1). The highest signal threshold values were taken into consideration if there were multiple possible locations for the identified group. There was less than 5% incidence of multiple locations for a group across all sessions. We computed the size of the largest group for every 100-s interval for the all the four sessions.

4. Results

In this section, we report on the results from the sensor and observation data. First, we validate the correlation between sensor and observed data. Based on this validation (i.e., the plausibility of using tags as a data collection mechanism), we investigated the relative entropy of the ED system. Then we report on the workflow of the ED clinicians based on their location transitions and interactions with other clinicians. Finally, we describe the formation and dispersion of teams as a measure of collaboration in the ED.

4.1. Validating sensor and shadowing data

In order to evaluate the degree of association between the sensor and shadowing data, we computed the correlation between these data sets for both mobility and interactions among clinicians. A high correlation between the sensor and observed data validates the accuracy of the sensor data in capturing the location and interactions among the clinicians. We computed the Pearson moment-correlation between the location determined by the sensor data and location determined by human observers. We obtained a statistically significant correlation between the observed and sensor-based location data ($p < 0.01, R = 0.96$) (see Fig. 5A).

Similarly, we also computed the correlation of proximity between the clinicians as determined by the sensors and shadowing observer. Based on Pearson product-moment correlation, we found significant correlation between co-location of the physicians as
determined by the sensors and by the observers ($R = 0.98$, $p < 0.001$) (see Fig. 5B). In other words, physicians (attending and the two residents) were more likely to be co-located than the nurses. The inherent lack of co-location of nurses can be attributed to the significant percentage of nurse activities are often performed in isolation from other physicians (e.g., documentation, care coordination). Hendrich et al. [11] reported similar results where they found that that nurses spend significant amount of their time at nurse stations performing documentation and care coordination activities. The mobility and interaction correlations were computed from data across all sessions.

The significant correlation between the sensor and observed data provides an initial validation for the accuracy of the sensor data in capturing the location and interactions of clinicians in the ED. A comprehensive knowledge about the location and interactions is instrumental in real-time monitoring of emergency environments. Such monitoring can provide useful insights into the activities around specific events such as arrival of a patient with severe acuity or a mass emergency event (e.g., a train accident) and for the study of errors. These concepts are further explored in Section 5.

4.2. ED entropy or degree of randomness in the ED

As described earlier, we computed the mobility and interaction entropy of the clinicians across the four data collection sections. The estimated entropy ($S_{est}$) was compared with the baseline random entropy, $S_{rand}$ (see Eq. (2)). The value of random entropy ($S_{rand}$) calculated based on the assumption that subsequent locations are completely random, was 3.32. Fig. 6 shows the average mobility entropy of all the clinicians across the data collection sessions. The average mobility entropy values of the clinicians were computed as follows: attending (mean = 0.85, s.d. = 0.18), resident 1 (mean = 0.76, s.d. = 0.12), resident 2 (mean = 0.61, s.d. = 0.24), nurse 1 (mean = 0.65, s.d. = 0.35) and nurse 2 (mean = 0.92, s.d. = 0.31). From the entropy computation we can see that the mobility entropy of the physicians (residents and the attending physician) is relatively more stable across the sessions and remains relatively high. At the same time, it is much more difficult to predict the relative entropy of the nurses since the variance of the entropy across sessions is relatively high.

Comparing the estimated entropy values with the base line entropy value ($S_{rand} = 3.32$), we found that the clinicians’ actual estimated entropy values were significantly lower ($p < 0.05$). Due to high variability in the nurse mobility patterns across sessions we could not make any predictions regarding their mobility behaviors. But, in the case of physicians (attending physician and residents), the estimated entropy values indicate that their underlying movement patterns are very likely to be reasonably predictable. This relatively lower estimated entropy values provides us a basis for further investigations into the nuances of the mobility patterns (especially those of the physicians). In the next section, we trace the movement patterns of the physicians using the location-based transition probability matrices.

Similar to the mobility entropy, we computed the interaction entropy among the clinicians. As described earlier, the physical proximity among clinicians is broadly used as a measure of interaction in this context. The estimated interaction entropy for the clinicians was computed as follows: attending (mean = 0.82, s.d. = 0.15), resident #1 (mean = 0.84, s.d. = 0.22), resident #2 (mean = 0.56, s.d. = 0.24), nurse #1 (mean = 0.95, s.d. = 0.15) and nurse #2 (mean = 0.87, s.d. = 0.21). Based on the estimated entropy computations from the data from these sessions, we can draw several conclusions regarding the interactions between the clinicians.

First, we found that the computed entropy was less than the base line entropy value ($S_{rand} = 2$). This means that there is likely
to be a predictable pattern that underlies the interactions between
the clinicians. Second, the entropy values across all the clinicians
are relatively similar (except for resident 2), which shows the like-
lihood that there are similar degrees of interaction among the
team members. This also is highly indicative of collaborative work prac-
tices. We explore the nature of collaborative interactions among
the team of clinicians in subsequent sections. The detailed entropy
computations can be found in Zhang et al. [27,28].

4.3. Time spent at locations and in proximity with other clinicians

Based on the tag–base pings, we computed the time spent by
the clinicians in various ED locations. As described earlier (see Sec-
tion 1), the time spent was computed based on the aggregation of
tag–base pings at each location over time. Fig. 7 shows the time
spent by the clinicians at the various locations in the ED. The x-axis
shows the different ED locations (same as those marked up in
Fig. 2) and y-axis is the time spent at each location in seconds.

From Fig. 7, we found that: clinicians spent most of their time in
the trauma rooms (at the various trauma beds 1A, 1B, 2B, 3B, 4A
and 4B); the residents and nurses spent significantly more time
in the trauma rooms (i.e., beside the patients) than the attending
physician. This is primarily a function of the care process in large
teaching hospitals where residents (along with the support of
nurses) manage the care process under the supervision of the
attending physician.

In a similar manner, we also computed the time spent by the
attending physician with other clinicians based on the tag–tag
pings. We found that the attending physician spent considerably
more time with other physicians (residents) than nurses
\(^{1}\) (\(p < 0.01\)). This was expected considering as the study was con-
ducted at a teaching hospital.

4.4. Transition between locations

In order to investigate the clinician workflow we traced the
transitions between various locations by the clinicians. The transi-
tions were determined based on the transition probability matri-
ces. Fig. 8 shows the counts of transitions between various
locations by the attending physician in the four sessions. The x-axis

represents the originating location and y-axis represents the termi-
nating location for each transition. The diagonal of the matrix rep-
resents instances where the attending physician was in the same
location for consecutive time intervals. Significant differences in
the transition patterns can be gleaned from the analysis of the four
graphs. In session 1, the attending physician was fairly sedentary at
the nurse station (NS). This was probably due to a relatively slow
shift.\(^{1}\) In sessions 2–4, we can see that the attending physician
moved across the various trauma rooms and had a “foot print”
across all the locations in the ED. It can also be observed that a sig-
nificant time was spent in the trauma rooms (darker squares in the
cells representing the trauma rooms).

We also developed similar location matrices for other clinicians.
In the case of residents, we found that the transition pattern of one
resident was complementary to the other. In other words, we
found that, one resident was invariably present at a set of trauma
rooms (and absent from the rest of the trauma rooms), while the
second resident was present at the remaining trauma rooms. This
is consistent with the demands of their shared workload and divi-

dion of patient care duties. This is further investigated in the next
section on collaborative patterns. We found no consistent patterns
in the location transitions among the nurses.

4.5. Collaboration: aggregation and dispersion

We computed all pair-wise co-occurrences between the attend-
ing physician and other clinicians. As expected, we found consis-
tent co-location of the attending and the residents in the trauma
rooms. This was further confirmatory evidence for the likely com-
plementary role that each of the residents took for the patient care
activities. In other words, we found that one resident had a prom-
inent “role” with respect to the treatment of a specific patient. This
can be seen in terms of the pair-wise co-location probability (see
Fig. 9) where one resident is more likely to be present along with
the attending physician in a trauma room. The high co-location
probability of one resident was highly correlated with a low co-

\(^{1}\) In fact, our observation data shows that during this session, the attending
physician spent a considerable portion of this slow shift teaching the residents at the
Nurse’s station.
Fig. 8. Location transition matrix for the attending physician from the four sessions. The x-axis shows the originating location and the y-axis shows the terminating location during the transition. The counts in the diagonal matrix show the instances where the attending physician did not move in consecutive time intervals.

Fig. 9. Pair-wise co-location probability between the attending and the residents.
location probability of the other resident being in the same trauma room. We did not find any consistent patterns with respect to the co-location between nurses and the attending physician.

While the interaction between pairs of clinicians is interesting, complex settings are characterized by a significant amount of collaborative activity. Consequently, we were interested in the behavior of the team as a unit, in addition to that of individual clinicians or clinician pairs. We investigated the formation and dispersion of larger groups (>3) in the ED. Based on our algorithm described earlier we computed the team size dispersion over the data collection sessions. On average we found that there was a high percentage of two and three-clinician groups across all sessions (Fig. 10). We found several interesting patterns with respect to the aggregation and dispersion of teams across the ED.

First, the incidence of larger clinician groups (4 and above) was very low. On average, there were less than 15 such group occurrences. These clinician groups always included the physician, both residents and one of the nurses. The low occurrence of the larger groups was probably due to a combination of factors: first, such large groups would entail the majority of the care team. From observations, we know that these large groups typically come together during a major trauma and quickly disperse to care for the other patients in the ED center. During occasion of lower patient volume, large groups might congregate in central locations with team members entering and exiting freely. These circumstances of high demand and low volume are relatively infrequent. Second, our algorithm that determined the presence of teams was extremely stringent in terms of the requirements that ascertained the presence of a group (multiple tag→tag and tag→base pings within a short interval). While, this may ignore extremely slow forming groups, we believe that the ED is an extremely fast-paced environment where the formation and dispersion of groups are in response to rapidly emerging situations.

Second, larger clinician groups (size greater than or equal to 4) always congregated in one of the trauma rooms. This is highly likely in ED settings where the arrival of a patient with high acuity levels triggers significant activity around that patient. While, we cannot directly verify the acuity of the patient at the times where the larger groups congregated, in our future work we plan to retrospectively investigate the arrival acuity levels of patients for the sessions in which we collected sensor data. Third, team size of three almost always (90% of the cases) involved at least one resident and a nurse. The third participant in such three-person groups was either the resident or the attending physician. About 60% of such 3-person groups were formed in the trauma rooms, while the rest were primarily split between the nurse station (NS) and physician station (PACS). Two clinician pairs were very common and we found significant variability among these pairs. But, about 50% of the two-clinician groups identified consisted of the physician and one of the residents. This is typical considering the dual role of the attending physician in patient care and medical education.

An example of how the overall size of the largest ED team changes over a data collection session is shown in Fig. 11. The x-axis shows the time while the y-axis represents the size of the largest group at that point in time. As can be seen from the figure, the size of the group varies between 2 and 3 and for a short time a group of size 4 congregates together.

5. Discussion

We used RID sensors to capture the work activities of clinicians in the trauma room of a high-volume emergency department. The sensor data were supplemented with human observation data from clinician shadowing. We found significant consistency between the data sets in terms of the clinician location, movement and interactions. Additionally, we also found that the entropy of

![Fig. 10. Size of the team across various sessions.](image1)

![Fig. 11. Team size dispersion across a data collection session (session 2). The x-axis shows the time distribution (i.e., the time over a data collection session). The y-axis shows the size of the team.](image2)
We found several patterns of team composition, formation and aggregation and dispersion of teams in the ED. We found that it is possible to predict mobility and interactions in the ED system was below the expected threshold values, which indicates that it is possible to predict mobility and interactions among the clinicians. Using this as the basis, we investigated the collaborative activities of clinicians, such as pair-wise interactions and the formation of teams in the ED. We found several patterns of team composition, formation and aggregation and dispersion of teams in the ED. The purpose of this research effort was to investigate the appropriateness of using sensors to study work activities in complex environments such as the ED. With significant consistency between the observed and sensor data, we were able to establish the viability of using sensors in the ED. While we used limited data collection sessions, our results provide significant support for more extensive use of sensors for studying complex activities in the ED. With human observers, we are definitely required to collect highly nuanced information about the activities in complex environments, sensors are a reasonably reliable complementary data collection mechanism. Combining sensor data with other readily available clinical information (such as patient arrival information, condition and acuity) can help in developing flexible mechanisms for monitoring and managing the resources of complex environments. Additionally, sensor data also has significant use in retrospective study of errors in the ED.

In the rest of this section, we describe the potential applications and uses of sensor technology in critical care settings. While the healthcare community has adopted the use of sensors in various settings, our purpose is to describe the opportunities for the use of this technology for investigating clinical workflow and clinician activities. We propose three primary applications for sensor data: for real-time monitoring of activities and resources in the ED, for training new clinicians in virtual settings, and finally, for the study of the cause and propagation of errors.

5.1. Real-time monitoring of activities and resources in the ED

Sensor technology has been significantly useful in the remote and real-time monitoring of activities in various environments such as nursing activities [11] elderly care [6], telemedicine [20]. Monitoring and management of resources in a highly dynamic and complex setting requires significant amount of data with respect to the activities and happenings within that setting. Data from the sensors (both mobility and interaction) provide information regarding the clinician (in terms of their location and co-location with other clinicians) with great precision and detail. Additionally, this information is time-sequenced. As a result, a real-time feed from the sensor data can be used to develop a trace of events in the ED. For example, the rapid formation and dispersion of large teams at different trauma beds may indicate the possible arrival of several patients with high acuity. Hospital administrators can use the data from the sensors to ascertain the “status of the ED”. This information is critical in deploying additional resources, both in terms of personnel and equipment, to the ED. Additionally, sensor data can have potential applications when changes are introduced in a critical care environment. For example, the introduction of new health information technology (HIT) creates significant changes in work activities. The application of new quantitative methodologies to sensor data, such as those described in Zheng et al. [29], can provide valuable insights for studying changes in workflow patterns, disruptions in workflow and fragmentation of work activities.

5.2. Resources for training and education

Medical education relies extensively on real-world scenarios for teaching and training purposes. Patient cases are often used to help students develop an understanding of the complex critical care environments. With the widespread popularity of virtual environments such as Second Life (www.secondlife.com), it is relatively easy to replay real-world scenarios in a seemingly contextualized environment. For example, the sensor data regarding clinician location, movement and interaction can be incorporated into a Second Life environment where an entire sequence of real-world events can be replayed. In other words, virtual avatars can be used to replay an emergency case scenario that can potentially be used for teaching medical students about the nature of ED work. This scenario can be then analyzed in terms of resource utilization (e.g., number of clinicians who gathered at the patient bed-side), attention to other patients during this time, interactions between clinicians (i.e., who were at the bed side) and dynamics of team activity. We can generate greater utility for training by overlaying additional information (e.g., patient condition) into the virtual world environment. For example, medical instructors can center their discussion and teaching on case scenarios of how an ED team worked under different workload (busy vs. non-busy shifts) and patient acuity conditions. Potential best practices can also be pointed out to trainees in a much more effective manner in such a visual environment.

Recent research [5,24] has reported on the potential of online 3-D virtual environment for medical education and learning. Online virtual environments provides an informal environment in which the learners can understand the norms, practices and challenges of working in a complex environment and integrate such information through repetition and group interactions [26].

5.3. Framework for studying errors

The study of errors in emergency care settings has received significant attention in recent times (e.g., [12]). While sensor technology has been minimally used in the investigation of origin and propagation of errors in the ED, it is a viable mechanism for this purpose. From our sensor data, we developed normative and predictive models of clinician activities in the ED. These activities can be retrospectively used to investigate the temporal events and activities that surround reported error incidents.

What is missing from most prior studies on the tracing of errors in critical care environments is the detailed information regarding clinician activities around the time at which the error occurred. The continuous monitoring using sensors provides a large database of clinician location, movement and interaction events. Using the methods described earlier (e.g., transition patterns, group formation and interactions), it is possible to re-create the distribution of attention and resources in the ED around the time at which the error was reported. Such a “replay” of events can help in tracing potential activities that could have been avoided and may have contributed to the error. We will use an example to describe this.

Consider that an attending physician self-reports an error regarding the delayed administration of a drug to a patient in trauma-bed 4 at 530 ET on June 1, 2010. The error report also includes the arrival condition of the patient, history and other patient-relevant information. There are two sets of information that can be used to develop a trace of the events that happened prior and after the error occurred. The sensor data can be used to identify the patterns of interactions, movement and collaboration among the clinicians around the time at which the error happened (say, from 5 to 6 p.m. on June 1, 2010). The clinical information on the patient along with observation (audio or field notes) can be used as supplementary evidence to develop a much more richer perspective of the activities surrounding the reported error event. Thus, a detailed sequence of events can be used to track the possible contributory activities that possibly led to the error event. This
framework, which combines sensor data and clinical data, for studying errors is shown in Fig. 12.

This framework for investigating the origin and propagation of errors has several advantages. First, the data collected from using the sensors can be retroactively combined with the clinical data. Self-reported errors in an emergency setting are usually very low. As such, it is important to be able to trace the events that happened around the time the error incident was reported. Sensors provide a viable mechanism by which data can be collected for extended periods of time and then be retrospectively used for evaluation and analysis. Second, sensors can be used as a passive data collection mechanism with minimal interference with the clinician’s work activities. Third, the relatively long battery life of most sensors makes it feasible for running long data collection sessions (e.g., 20–30 days) without any breaks in data capture. Such an arrangement with human observers is extremely costly and labor-intensive. Our future research work involves the use of the framework to investigate the activities of clinicians in the ED around self-reported errors.

5.4. Challenges and lessons learned

In summary, there are several potential research and applied opportunities for the use of sensor technology in complex critical care environments. In spite of the significant challenges for designing, calibrating, collecting and analyzing sensor data, we believe that sensor technology has exciting prospects for developing insights of the work of complex critical care environments, which would otherwise be impossible due to significant time and cost burden of using human observers. The calibrating and setting up of the sensors in an ED setting required extensive pilot testing to ascertain the exact positioning of the base stations to get maximum coverage. We also had to ensure that our technology did not cause adverse effects on medical equipment and devices. Per our manufacturer’s description, our sensor technology operates in the same frequency range as the WiFi/Wireless, which is ubiquitous in hospital settings. While, we did not extensively test for adverse effects of sensors, we believe that our technology does not cause adverse effects on medical devices as argued by van...
der Togt et al. [23]. Some clinicians were concerned about their privacy issues due to the use of sensors during their shifts. We collected no physician or patient-identifying information and all IRB-regulated protocols were followed for assuring data protection and privacy. For example, all data was saved on an encrypted drive and all identifying information (e.g., time) was removed prior to data analysis. Another significant challenge that we faced was the cost involved in managing the sensor technology. Due to the significant amount of data generated from the sensors, we developed algorithms for compressing and storing the data. This volume of data also required us to develop computationally efficient algorithms for analysis.

6. Limitations

While, sensor-based technology provides flexibility in data capture in complex environments, we encountered several challenges while conducting this work, which resulted in some limitations. Below, we list some of the limitations of our study and describe the some of the workarounds we employed to mitigate them.

First, we used the correlation between the observation and sensor data as the basis for our analysis on transitions between locations, pair-wise co-location and collaborative patterns. As we did not have multiple observers shadowing all the clinicians, we used the agreement between observer and sensor for a single clinician across an entire session as our primary basis for our analyses. Given our focus on developing a preliminary perspective on the viability of the use of sensors in critical care environments, we believe that our evaluation study and results provide a promising first step. Second, we encountered some technical issues with our multi-sensor data system that made it difficult to time-synchronize some instances of our data (hence, the less than 100% correlation) and, are working with the manufacturers to surmount these obstacles.

Consequently, our future research program will focus on developing a tightly-synchronized multi-observer data collection protocol, which would provide a richer context in a more nuanced level. The algorithm that was developed for identifying the pairs and groups had a purposeful “redundancy” factor associated to it. As such, we believe that some of the potential data discrepancies may have been accounted for. But, without multi-observer clinician shadowing, it would be impossible to empirically establish this fact.

7. Conclusion

Studying complex critical care environments with significant interactions between clinicians is a challenging task. While, human observers are able to provide nuanced descriptions of the work activities, they are often unable to capture the spatially distributed activities of multiple clinicians. In this paper, we reported on the use of sensor technology as a feasible mechanism to complement human observation in critical care environments. Based on our study, we found that we can use sensors to:

- Effectively identify patterns of movement and interactions between clinicians. A trace of the mobility and interaction patterns is useful as a measure of complexity in the environment.
- Identify the location, composition and formation of groups in the ED. The collaborative aggregation and dispersion acts as an indicator of the workflow of clinician activities in complex critical care environments.
- Potential opportunity for the use of sensors as a complementary data source for retrospective evaluation of the origin and progression of errors in a complex environment. Sensors can be used to retrospectively trace the activities of clinicians, which can act as a basis for possible identification of the root-cause of errors arising from the workflow of the clinicians.

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