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Incorporating RTLS-Based Spatiotemporal Information in Studying Physical Activities of Clinical Staff *

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Abstract— **Clinicians and staff who work in intense hospital settings such as the emergency department (ED) are under an extended amount of mental and physical pressure every day. They may spend hours in active physical pressure to serve patients with severe injuries or stay in front of a computer to review patients' clinical history and update the patients' electronic health records (EHR). Nurses on the other hand may stay for multiple consecutive days of 9-12 working hours. The amount of pressure is so much that they usually end up taking days off to recover the lost energy. Both of these extreme cases of low and high physical activities are shown to affect the physical and mental health of clinicians and may even lead to fatigue and burnout.**

In this study Real-Time location systems (RTLS) are used for the first time, to study the amount of physical activity exerted by clinicians. RTLS systems have traditionally been used in hospital settings for locating staff and equipment, whereas our proposed method combines both time and location information together to estimate the duration, length, and speed of movements within hospital wards such as the ED. It is also our first step towards utilizing non-wearable devices to measure sedentary behavior inside the ED. This information helps to assess the workload on the care team and identify means to reduce the risk of performance compromise, fatigue, and burnout.

We used one year worth of raw RFID data that covers movement records of 38 physicians, 13 residents, 163 nurses, 33 staff in the ED. We defined a walking path as the continuous sequences of movements and stops and identified separate walking paths for each individual on each day. Walking duration, distance, and speed, along with the number of steps and the duration of sedentary behavior, are then estimated for each walking path. We compared our results to the values reported in the literature and showed despite the low spatial resolution of RTLS, our non-invasive estimations are closely comparable to the ones measured by Fitbit or other wearable pedometers.

Clinical Relevance— **Adequate assessment of workload in a dynamic care delivery space plays an important role in ensuring safe and optimal care delivery [7]. Systems capable of measuring physical activities on a continuous basis during daily work can provide precious information for a variety of purposes including automated assessment of sedentary behaviors and early detection of work pressure. Such systems could help facilitate targeted changes in the number of staff, duration of their working shifts leading to a safer and healthier environment for both clinicians and patients.**

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I. Introduction

In the era of big data and connected devices, hospitals can capture, store, and analyze large volumes of data to extract managerial insights that help enhance the quality of care and reduce the potential burden for the care-team staff. One area that recently attracted interest in hospital settings is the monitoring of clinicians' physical activity and reduction of sedentary activities among the hospital staff. Lack of physical activity and increased sedentary lifestyle is reported by the World Health Organization as one of the top 10 causes of mortality and morbidity [1]. The American Heart Association recommended at least 150 minutes of moderate-intensity activities per week such as walking at a brisk pace and reducing the amount of sitting at the workplace, to prevent chronic diseases such as coronary heart disease, stroke, depression, and cancer [2, 3]. Researchers were also encouraged to utilize advanced healthcare technologies to uncover trends and find meaningful relationships to support informed decision-making that enhances the work pressure and productivity of staff [4, 5].

Recent advancements in wearable technologies provide novel methodologies for continuous and granular evaluation of system status [6]. Several technologies have been used in monitoring physical activities in hospital settings, but much research is directed toward the application of wearable activity trackers such as Fitbit and pedometers. Yu, et al. [7] used wearable sensors to measure nursing workload as a major contributor to patient safety in a simulated environment. Hampers, et al. [8] implemented an electronic patient tracking system, which resulted in improved resource utilization and system productivity. A study of 45 anesthetists reported a median of 3694 steps while at work [9], which is much lower than the numbers reported by Schofield, et al. [10] for office workers (5380) or nurses (5446), as shown in Table 1. Peters, et al. [11]'s pedometer-based study of physical activity among 51 emergency physicians reported that resident physicians walked an average of 5068 steps and 2.6 miles per shift compared to attending physicians who walked an average of 4722 steps and 2.4 miles per typical shift of 8.5 hours. Meanwhile, Atkinson, et al. [12] reported 4647 and 4822 steps respectively for medical and surgical consultants. Another study by Welton, et al. [13] on 146 nurses reported they walk an average of 4-5 miles during a 12-hour shift, whereas Chowdhury and Khosla [14]'s study on 767 nurses showed

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they walked between 2.4 and 3.4 miles per 10 hours day-shifts and 1.3 to 3.3 miles per night-shifts. The discrepancy among the reported estimations of average physical activities in the hospital settings may be due to the differences in their environmental settings. It can also be due to human or device-related errors. For example, when a hand-worn device counts every hand movement as a walking step, or when the human subjects forget to charge the device after a few days or decide to take the device off during some activities. This variation highlights the need for utilization of remote and noninvasive devices that do not interfere with the normal working activities of the target population and require minimal maintenance by the user.

TABLE 1. LITERATURE REVIEW ON ESTIMATION OF WALKING DISTANCE AND DURATION IN THE HOSPITAL SETTINGS.

Paper	Count	Steps	Miles	Hours
Cuthill, et al. [9]	45	3694	-	8.2
Schofield, et al. [10]*	63	5380	-	-
	11	5446	-	-
Peters, et al. [11]*	34	5068	2.6	8.6
	17	4722	2.4	8.5
Atkinson, et al. [12]*	4	4647	-	< 9.5
	4	4822	-	< 9.5
Welton, et al. [13]	146	-	4-5	12
Chowdhury, et al. [14]	767	-	3-5	12

* indicates papers with two set of reporting variables

Real-time location systems (RTLS), while not specifically designed to capture individual steps, have been used in real-time tracking of hospital patients, staff, and equipment [14],[15]. They can also provide discrete localization information for the human targets including the real-time assessment of patient per provider ratio [16], the contact time [17], and other valuable temporal information [18]. Li, et al. [19] designed an activity recognition system by utilizing radiofrequency identification (RFID) technology to monitor the object-use status of 10 objects in a trauma room of an ED. RTLS not only tracks the location of each subject over time but can also provide valuable data about the sequence of locations they passed through (walking path). We propose the use of RTLS recordings to extract important information such as walking distance, walking duration, and walking speed.

II. Method

The methods section describes our method to prepare the RAW data, identify walking paths, and estimate factors of physical activity as visualized in Fig. 1. We start with the extraction of RFID data and the geometric location of readers inside the ED, followed by an intensive 4-stage data cleaning process. We then defined "walking path" to be used for the classification of movements in the ED into different activity levels and then extracted statistics from these measurements aggregated over all subjects in an annual perspective.

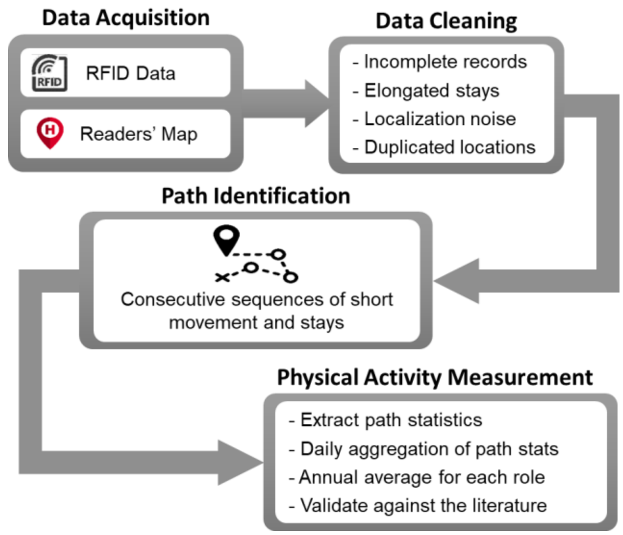

Figure 1. Proposed data flow from raw RFID to cleaning, path identification, and physical activity measurements.

A. Data source

The emergency department at Mayo Clinic's St. Mary's Hospital in Rochester, Minnesota, has 73 rooms and is treating more than 190 patients per day. RFID systems have been used in the ED since 2016, with 292 readers being installed in the ceilings of every room and hallways as shown in Fig. 2 and Fig. 3. All clinical and non-clinical personnel in the ED have been wearing RFID trackable tags inside their badges, with readers throughout the department. The location of each tag is being computed using a triangulation algorithm to find the closest reader to each tag. The RFID data is being stored in an event-based fashion where each row consists of a subject ID (RFID tag), their location, the time they entered that area (start time), and when they left that reader's immediate area (end time). This database has accumulated approximately 8.5 million historical records since 2016. In the current study, we focused on the records from Sep 2018 to Sep 2019 where we had the maximum number of monthly events with a stable number of users.

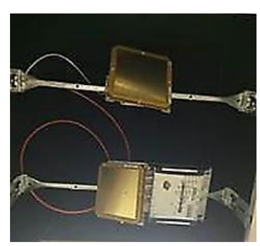

Figure 2. RFID readers are installed hidden in the ceiling to monitor the movement of different RFID tags.

We have organized the data based on their location type and the role type of tag holder. The raw RFID dataset contains information about the type of locations that RFID readers are installed (e.g. corridor, patient room) and the role of subjects that appear to be at each location (e.g. Physician, Resident). Table 2 provides an overview of the number of database records separated by the type of location and the role category of subjects. It contains a unique number of subjects for each category including a total of 38 physicians, 13 residents, 33 staff, and 163 nurses for the selected period of time. The total duration of stay in hours is also provided for each category.

B. Data cleaning

we had to overcome the following major data issues:

- **Incomplete records:** There were 5000 records without any time-out. We update these locations based on the time-in of the same record:

$$Record_{time\_out} \leftarrow Record_{time\_in} + 1\ second$$

- **Elongated stay at one location:** There were about 59000 records where the subject stays in the same place for more than 5 hours. We suspect that these are related to the situations where the individual leaves their RFID-tag inside the ED and go home after their shift. We updated \the time-out of these records based on their time-in values:

$$Record_{time\_out} \leftarrow Record_{time\_out} + 1\ second$$

- **Localization Noise:** We have about 33000 records where a person seems to jump to a random location and stay there "for zero seconds". We believe this happens due to a triangulation error, thus we removed them.
- **Duplicated locations:** After identification and removal of the localization noise records, we ended up with about 195000 rows with consecutive instances of the same user at the same location. All consecutive records were merged after identification.
- **Duplicated records:** We also identified and removed about 280000 duplicated records with the same user, location, and timings.

Figure 3. Mayo Clinic's Saint Mary's ED and the density map of staff's average time spent at each RFID reader.

C. Definition of the walking path

Staff movements within the ED may go through multiple readers including the operation room, hallway, patient room, or other places such as the restroom. They may pass through those readers in less than a few seconds (walking in the hallway) or may stop underneath a reader to perform a task, such as visiting with a patient. We defined the path as such random sequences of movements and intermediate stops. Each path starts and ends with an exceptional event such as elongated stay or inter-node duration of more than one hour:

$$Record2_{time\_in} - Record1_{time\_out} > 1\ hour$$

A cumulative sum of inter-node distances would result in an estimation of the total distance (length) for each path. Similarly, the cumulative summation of elapsed times under each reader would result in the total duration of that path.

D. Computing walking duration and speed

Having the length and duration of the walking path, we can easily compute the average path speed. However, stops in different locations during a path will cause an unwanted reduction in the estimation of walking speed. In other words, we should not include times when an individual was stationary at a location into the estimation of moving speed. To resolve this, we clipped the duration of stays at each reader and include at most 30 seconds of that in the estimation of walking duration.

$$Walking_{dur} = \sum Min(Stay_{dur}, 30\ Sec.)$$

E. Estimating the daily number of steps

It is clear that current RFID systems are not designed for, and are not capable of, counting the number of steps; nevertheless, we are looking for a rough relative estimation of the number of steps to provide the basis for future comparison against the state-of-the-art publications on the monitoring of physical activity. We propose to approximate the number of daily steps based on walking distances. To do so we used the values reported in the literature (Table 1), to convert walking distance back to the estimated number of steps:

$$Inverse\_coef = X/Y$$

$$Step\_count = Walking\_Dist * Inverse\_coef$$

F. Estimating sedentary activities

While RTLS systems cannot provide high-resolution information about minor and in-place activities (e.g., short walks in small distances inside a room), they can capture major displacements between readers (e.g., walking in a hallway). We consider the lack of major activities as a proxy for sedentary behaviors, especially if they happened in a confined area. In other words, whenever a subject stays long enough at a designated staff room, it raises the chance of inactivity and sedentary behavior. To reconcile this, we first segment out the "walking" periods from all movements and call the remainder the "stationary" periods. This period is then divided into two categories of "very short stay" where the subject passes a reader for a few seconds, and the "sedentary" periods for the longer duration of stays. For further analysis, we defined two severity levels for the sedentary behaviors based on the minimum stationary time. The low sedentary duration is the accumulative sum of times that a subject stays underneath the same reader for at least 20 seconds, which includes many short stays as well. The high sedentary duration is only considered when the stationary times are more than 20 minutes:

$$Sedentary\_Dur_{low} = \sum Min(Stay_{dur}, 20\ Sec.)$$

$$Sedentary\_Dur_{high} = \sum Min(Stay_{dur}, 20\ Min.)$$

III. EXPERIMENTAL RESULTS

In this section, we demonstrate our RFID-based estimated measurements for physical activity and sedentary behavior of 857 ED professionals over the course of one year. To preserve the privacy of individuals all data were first de-identified, and all evaluations were aggregated over employment role categories. Each readers' Euclidean location and the distance between each pair of them were manually measured as described in the methods section. After cleaning the data, path information was extracted and aggregated over the entire timespan for each role. This section covers a general overview of how each measurement showed up.

A. Monitoring moving patterns

Having the Cartesian location of readers on the map provides valuable location-based information about trackable activities within ED. We can now study temporal and spatial variations in the distribution of target activities within the ED and monitor changes over time. This provides the ability to study not only the movement path but also the duration and speed of each section. Fig. 4 represents a sample path for physicians (left) beside a sample movement path from a random nurse (right). Lines on the map are color-coded by the duration of each section and are inversely related to their speed.

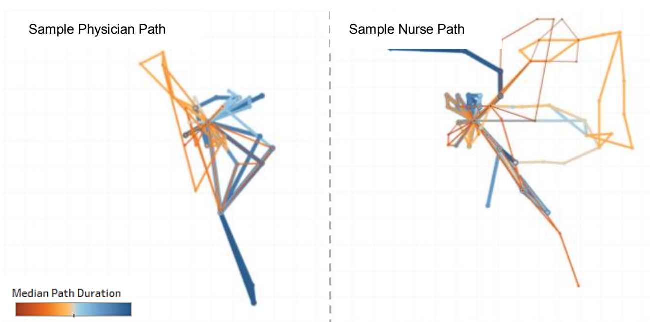

Figure 4. Using our method, not only we can monitor the daily movements of care providers, but we also can analyze their speed at each movement.

B. Estimating sedentary behavior

As described in the methods section, we propose a new idea to overcome the low spatial resolution of the RFID system in the identification of sedentary behaviors. Based on this definition sedentary behavior covers only a small portion of the "stationary" period that is longer than a threshold. A histogram of the duration of stays in Fig. 5 shows most of the time (75% quantile) individuals stay less than two minutes at a single location. We define high sedentary stays to be longer than 2 minutes. On the other hand, very short stays of up to 9 seconds (25% quantile) are considered active stays and not sedentary.

We have reported our estimations for the duration of the walk, sedentary, and active stationary in Table 2. Active stationary time is simply computed by subtracting these values from the shift duration. Physicians dedicate one last hour of their shift to documentation and the EHR system. This last stationary activity is currently discarded in our algorithm, which makes their shift to become less than 8 hours.

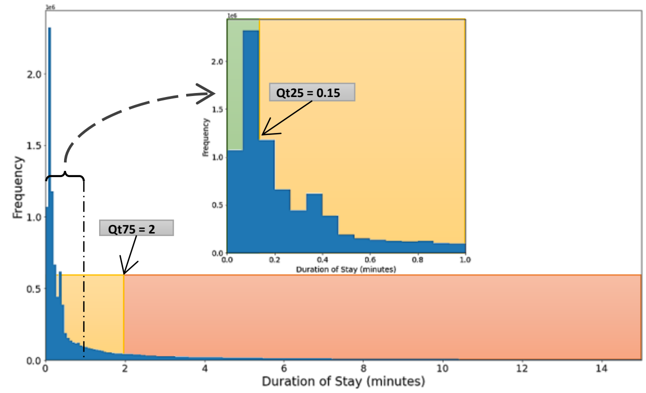

Figure 5. Histogram of the duration of stay at each location is used to provide an intuitive way to separate the RFID records into three categories of "long stay" which covers most of the sedentary behaviors in the staff area, "short stays" which presumably covers passing along the hallways and the ones that will not fit in either of the two categories mostly due to the low spatial resolution of RFID, that we call "active stays". We used 0.25 quantiles for the first and 0.75 quantiles for the second cut-offs.

TABLE 2. THE ESTIMATED DURATION OF PHYSICAL ACTIVITY FOR CLINICIANS IN THE ED

Role Category	Physician	Resident	Nurse	Staff
Shift Duration	7:13:40	7:58:38	10:32:33	8:27:36
Walk Duration	0:26:26	0:22:51	0:58:23	0:32:20
Sedentary Duration	4:30:37	4:34:30	5:19:51	4:24:11
Stationary Duration	2:16:37	3:01:17	4:14:19	3:31:04

C. Continuous activity tracking

After dividing individuals' daily movements to separate sequences of walks around the ED and between rooms, we can monitor absolute and relative variations in different parameters such as walking distance, walking duration, and walking speed using the following formula:

$$Walk\_speed\ = Walk\_distance\ /\ Walk\_duration$$

D. Daily steps estimation

In order to map the walking distance to the number of steps, we first needed to decide on a typical stride length, which varies among individuals based on their gender, height, age, and walking speed. We cannot attribute the actual value since our RFID data is de-identified and lacks such information about the subjects. Meanwhile, as we are only interested in the average values for different workers in the ED environment, we decided to use the existing literature and first estimate the average stride length for a typical ED professional and then use it to estimate the number of steps. Using the information in Table 1, we have three references with both distance (in miles) and the number of steps:

$$Stride_{miles} = \frac{1}{2} * \left(\frac{2.6}{5068} + \frac{2.4}{4722}\right) = 5.11e^{-4}\ miles$$

Now we can roughly estimate the number of steps using this formula:

$$Num\_steps = \frac{Distance_{miles}}{Stride_{miles}} = \frac{Distance_{miles}}{5.11 * e^{-4}}$$

Table 3 demonstrates our estimation of physical activity among ED clinicians and staff. We used all the previously mentioned techniques to estimate information about the walking paths of each individual and also their sedentary behaviors. These measurements include the number of individuals in each role (population), the average duration of their shift, walking time, sedentary behavior (separate for each of the three categories of active, low, and high sedentary), as well as walking distance and walking speed. We also have provided for each category, our estimation for the average number of steps per working shift. All these values were aggregated for the four role categories of physician, resident, nurse, and staff.

While our estimation of shift duration for residents, nurses, and staff (7:58:38, 10:32:33, 8:27:36) matches both literature and our expectation, this estimation for physicians (7:13:40) is almost one hour less than the expected value, possibly due to the way we split the movements into paths which discarded physician's final documentation hour. Similarly, while the estimated walk distance for both physicians and nurses (2.34 and 4.79 miles) nearly matches the values reported by Peters, et al. [11] and Welton, et al. [13] (2.6 and 4-5), our estimation for residents walking distance (1.8 miles) is less than the expectations. This may be because the residents spend some part of their work outside the ED which also reduces their number of measured steps. Accordingly, our estimated number of steps for physicians and staff (4585 and 5772 steps) matches the values of the literature (4722 and 5380 steps), but our estimation for nurses (9371 steps) is much higher than others. This perhaps is related to a higher workload on the ED nurses compared to other hospital-based nurses in the literature, especially when their walking distance is in range. We should note again that our estimation of walking steps is done by mapping the length of walk divided by the "approximate stride length" from the literature shown in Table 1. These values are subject to errors not only because of the individuals' stride length but also their walking speed.

TABLE 3. ALL AGGREGATED ESTIMATIONS FOR EACH ROLE OVER THE ONE-YEAR PERIOD OF SEP 2018 TO SEP 2019.

Measurement	Physician	Resident	Nurse	Staff
Population	68	235	263	273
Shift Duration	7:13:40	7:58:38	10:32:33	8:27:36
Walk Duration	0:26:26	0:22:51	0:58:23	0:32:20
Active Stationary	2:16:37	3:01:17	4:14:19	3:31:04
Low Sedentary	4:30:37	4:34:30	5:19:51	4:24:11
High Sedentary	4:22:05	4:28:56	5:01:36	4:17:23
Walk Distance (m)	2.34	1.86	4.79	2.95
Walk Speed (mph)	5.34	4.84	4.90	5.49
Steps per shift	4585	3630	9371	5772

IV. Conclusion

This paper presents a novel perspective for the utilization of RTLS in the continuous and unobtrusive assessment of physical activity in activities in health care environments such as the ED. Traditionally RTLS has been used in hospital settings for timing and localization of staff and devices. To our knowledge, this is the first time that RTLS devices have been used to estimate the duration, length, and speed of movements within hospital wards such as the ED. It also is the first effort to utilize non-wearable devices to measure sedentary behavior inside the ED.

We used spatiotemporal information collected by non-wearable environmentally mounted RTLS sensors to automatically measure the level of physical activities of ED physicians, residents, nurses, and staff. We start with the extraction of RFID data and the geometric location of readers inside the ED, followed by an intensive data cleaning process. We then defined "walking path" to be used for assigning the captured human movements into different activity levels including sedentary, active stationary, and walking. We then extracted statistics from these measurements aggregated over all subjects with an annual perspective.

Our long-term goal is to use such information to investigate the amount of workload and pressure asserted to the workers which may cause performance loss, fatigue, and burnout. This information can also be used in health-promoting programs to reduce sedentary behaviors at work and the risk of obesity and cardiac disease. In addition to evaluating the relative activity levels among care team members, the use of RTLS to assess care team movement may also provide information to guide improvement projects to reduce waste, inform future facility design to take into account staffing and workflow needs.

Limitations

Although our experiment shows reasonable results compared to the literature, there is still space to improve. The current triangulation algorithm that is used by the RTLS system generates a tremendous amount of noise which makes it difficult to extract the most relevant information. We believe that overlapping the area under the coverage of the RFID readers is the main source of these noises. Also, we have multiple assumptions to simplify the search space which may result in reduced accuracy. For example, our clipping method to threshold the maximum duration of stay at each point is shown in Table 3 to misrepresent the duration of shift specifically for physicians. That perhaps is due to an hour that physicians spend at the end of each day to review and update their EHR records, which is being dropped out by our algorithm assuming that they have exited the ED.

On the other hand, in our approach, we assigned a period to the sedentary behavior if the individual stays on the board of a single reader for a long enough time. We used 30% and 70% quantiles of time spent at the readers to separate active stays versus low and high sedentary behaviors. This is due to the RFID's lack of high-resolution localization which only records entering and exiting from each reader's range. While being in such an area, the individual may still perform some physical activities which are hidden due to the low spatial resolution of the RFID system.

Further evaluation and comparisons against the state-of-the-art wearable devices are postponed to after COVID-19, which could further validate the accuracy of the findings and provide insights for a more targeted data preprocessing.

FUTURE WORK

Future work includes incorporating the care provider team's working hours from the EHR and analyzing the variations in the daily or hourly walking trends. These trends can be found in the form of repeating patterns caused by different system-level factors such as the number of visits or the working patterns of the clinicians in their prior shifts. Combining activity information at the three levels of the individual, team, and role category may provide insights about the underlying mechanism for handling variations in the workload.

Meanwhile, studying the correlation between daily activity trends and other workload measurements such as the patient to provider ratio is suggested to clarify a quantitative index for the amount of work pressure. Such measurements can predict the risk of burnout and fatigue among the clinicians which may lead to an increased chance of error in the diagnosis process. On the other hand, context-based preprocessing of the raw data and taking into account exceptional cases (such as the physicians' end of day hours with the EHR) will help to keep as much valuable information as possible.

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