

## A Novel Visualization System for ICU Clinical Activity Tracking

Peng Guo<sup>1</sup>, Yeong Shiong Chiew<sup>1</sup>, Lei Shao<sup>1,2</sup>, Adrian Clark<sup>3</sup>, J Geoffrey Chase<sup>1</sup>

<sup>1</sup>*Department of Mechanical Engineering, University of Canterbury, New Zealand  
(Tel: 0064-0221071218 e-mail: peng.guo@pg.canterbury.ac.nz)*

<sup>2</sup>*School of Electrical Engineering, Tianjin University of Technology (e-mail: Lei.shao@tjut.edu.cn)*

<sup>3</sup>*HIT Lab NZ, University of Canterbury (e-mail: adrian.clark@canterbury.ac.nz)*

---

**Abstract:** Patient and nurse interaction in the Intensive Care Unit (ICU) is important as it influences the patient outcomes. Optimizing the nurse-to-patient ratio can reduce the mortality of patient, prevent nurse burnout, and reduce costs in the ICU. However, there is a lack of methods to quantify and evaluate these bedside interactions. This paper presents a Clinical Activity Tracking System (CATS), which was designed to track and evaluate nursing motion at the patient bedside, aiming to quantify how nurses spent their working time. CATS utilizes the Microsoft Kinect, a motion sensing device containing an embedded camera and infrared sensor. For CATS, the Kinect is fixed on the ceiling, facing downwards to track clinical activity at the patient bedside. The system was set up in an experimental environment to simulate the ICU bedside activity, and different motion paths and test candidates were tested over 5 iterations to evaluate the performance of the system. The total tracking area for the CATS can reach  $2.3 \text{ m} \times 1.6 \text{ m}$ , which mimics to the ICU bedside area. The system can track candidates with different heights from 1.52 m to 1.90 m. The system can also track different motion patterns consistently, with median percentage tracking error 2.30% (Inter-quartile range (IQR): [0.72%, 4.25%]). The system can also track multiple candidates with median percentage error 1.75% (Inter-quartile range (IQR): 0.97%, 4.57%). The results show that the system can be used in real-time applications to track bedside clinical activity. This system is capable of evaluating the ICU nursing activity, with the ultimate aim to generate appropriate nurse-to-patient ratio to prevent nurse burnout and increase patient care. Also, it is able to track different candidate heights, adapt to different motion paths, different dwell time, and identify multiple people simultaneously. The results revealed that the system can be used to quantify and evaluate bedside clinical activity.

---

### 1. INTRODUCTION

Patient and nurse interaction in the Intensive Care Unit (ICU) influences patient care, recovery and outcome (Egerod et al., 2013, Kim et al., 2012, Rose et al., 2011). Low nurse-to-patient ratio is associated with high mortality (Aiken et al., 2010, Tourangeau et al., 2007). In addition, low nurse-to-patient ratio increases nurses workload, resulting in burnout and job dissatisfaction (Aiken et al., 2002). Alternatively, higher nurse-to-patient ratios lead to significant financial burden (Walleck, 1994), and it is reported that up to 50% of hospital expenditure is spent on nursing labour (Reis Miranda and Jegers, 2012). For these reason, it is important to determine an optimal nurse-to-patient ratio system for ICU.

It is difficult to establish optimal nurse-to-patient ratios for acute care hospital units. The ideal goal is to provide each patient with the level of care from nurses to their illness and condition demands. However, measuring illness level is an inexact science. Existing evaluation systems, such as SAPS-II (Le Gall et al., 1993), SOFA (Vincent et al., 1998) or TISS-28 (Reis Miranda et al., 1996) can provide useful information in guiding nurse-to-patient ratio. However most of these systems are solely patient oriented, focusing on assessing a basic level of patient condition without any resolution between levels. Other nurse-to-patient ratio systems, such as EURICU-1 (first European intensive care

unit) (Adomat and Hewison, 2004) or the OMEGA system (Carayon and Gurses, 2005), are also developed based on variety of severity of illness scoring systems to optimise nurse-to-patient ratio. The assumption made in these evaluation systems is that the sicker the patient, the higher nursing care provision is required, however these systems are broad and general checklists cannot easily differentiate patients needing more or less care. Finally, there is no standard method to consistently quantify patient and bedside nurse interaction, where the level of interaction is important and may better reflect the actual patient's nursing requirement.

Adomat et al. used a video camera to record nursing activity in ICU (Adomat and Hicks, 2003) and concluded that nurses may spend less time with more critically ill patients. Thus, there is a clear contradiction in the existing evaluation system to optimise patient-nurse ratio, based on severity scores. Adomat et al. were able to provide a novel method to classify patient-nurse interaction. However, this technique remains intuitive and qualitative. It requires experienced nurses to classify the nursing activity and behaviour. Thus, there is a clear need of an automated system that can measure activity non-invasively and without identity to overcome these obstacles.

In this paper, a Clinical Activity Tracking System (CATS) which aimed to address this issue is presented. This system is

developed to track and evaluate nursing activity at the patient bedside. It aims to quantify the time nurses spend on nursing activities, such as nursing interventions, observing the patients, and talking with visitors based on motion and location around the bedside. The ultimate target is to assess activity with respect to quantitative and qualitative assessment of patient illness severity. This paper presents the system setup and design, and validates its ability to track nurse motion in a bedside area. Several clinically relevant nursing activity evaluation metrics are developed and presented in the validation tests. This validation is a required first step before being able to test the situation clinically with patients and nurses.

## 2. PROPOSED METHOD

### 2.1 The Clinical Activity Tracking System (CATS)

The Clinical Activity Tracking System (CATS) utilizes the Microsoft Kinect, a motion sensing input device with an embedded camera and infrared sensor. In this system, the Kinect is fixed on the ceiling facing downwards. A schematic drawing of the experimental set up for CATS and corresponding system variables is shown in Fig. 1. In this study, the system is set up in a laboratory environment to simulate the patient bedside area excluding the bed, as the aim is to target the nursing motion around the bed, rather than the patient.

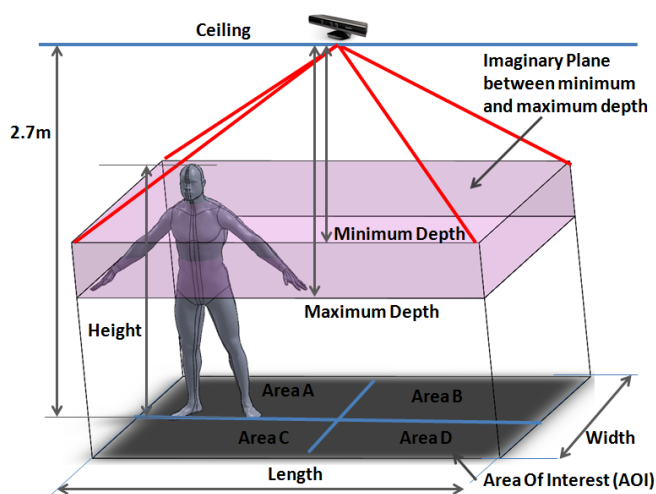


Fig. 1. CATS configuration and geometry

The total distance from the ceiling to the floor is 2.7 m, which corresponds to the actual height of the Christchurch hospital Intensive Care Unit (ICU). Several important system variables in Fig. 1 affect the total tracking area:

1. *Height*: Refers the test candidate height from the floor, which realistically varies from 1.50 to 1.90 m, including 90% of the adult population. In New Zealand, the average female height is 1.65 m and the average male height is 1.77 m (Wilson et al., 1993).

2. *Depth*: The Kinect depth sensor can maintain tracking through an extended range of approximately from Minimum Depth of 0.7 m (from the ceiling) to a Maximum Depth of 6 m. However, to capture test candidates, the Maximum Depth was set to the height of a shorter person's chest, 1.04 m from the ground, and the Minimum Depth was set above a taller test candidate's chest,  $2.7 - 0.96 = 1.74$  m from the ground.

3. *Blob size*: The contiguous objects of interest in the covered zone are filtered using several empirically determined values. Any blob size  $> 35000$  pixels ( $0.5 \text{ m} \times 0.5 \text{ m}$ ) or  $< 5500$  pixels ( $0.2 \text{ m} \times 0.2 \text{ m}$ ) are removed. This filtering thus only captures blobs similar to human size, and ignores any others.

The total tracking area for the CATS can reach  $2.1 \text{ m} \times 1.5 \text{ m}$  (Length  $\times$  Width), when the depth is set as 0.96-1.66 m from the ceiling (1.04-1.74 m from the ground). If any object shows up between 0.96-1.66 m high and the size of the object is similar to human, CATS records the objects as several blobs. Fig. 2(a) shows a sample image captured by the CATS, where three candidates were identified. Then the colour image is processed as depth image, with only blobs in a special height range and similar as human size. Every blob is identified by enclosing its contour with a rectangle, as well as a centre point. Fig. 2(b) show that when one candidate bends over, which means he is out of the detection height, the blob disappears. This function can prevent CATS detecting patients at any time to protect their privacy. Up to 4 blobs may be detected and tracked simultaneously, which is a realistic maximum for the area and intended scenario. The centre positions of the blobs and the time are recorded for further analysing.

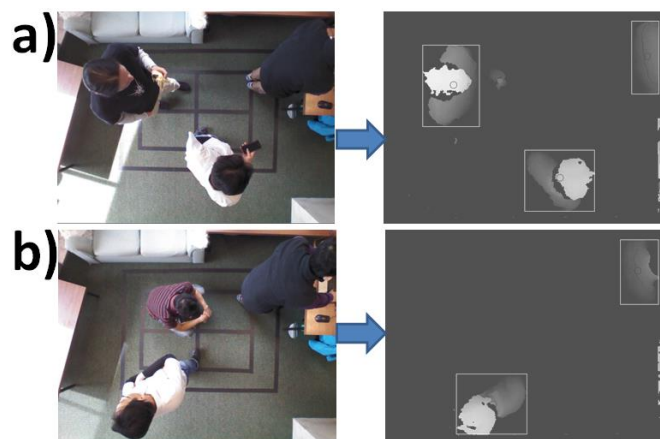


Fig. 2. Transfer the colour image into depth image and filter the blobs in a special height range and similar as human size.

### 2.2 Metrics:

Two metrics were developed to assess ICU nurse motion in the patient bedside area:

#### 1. Distance

Distance is defined as the distance between the nurses and a Fixed Point, as shown in Fig. 3. This Fixed Point is set near

to the patient head, which is where the ventilator and infusion pumps are typically located. Distance can be tracked every frame, creating a full trajectory for each interaction in the space. The distance Metric is quantified in Pixels instead of meters. Fig. 3 schematically shows an example view of CATS in an ICU bed space with the captured area of interest and the distance recorded.

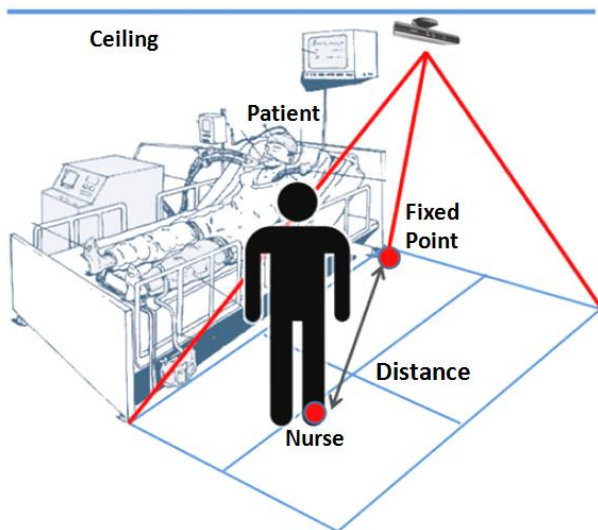


Fig. 3. The distance between each nurse and the fixed point

## 2. Dwell time

Time is recorded along with object's position if any object shows up in the depth image. Dwell time can be calculated when a test candidate is not moving in the area of interest. The main purpose is to capture those locations and time periods spent stationary at a fixed location, such as adjusting the ventilator, as these periods may capture severity and difficulty managing the patient. These two metrics can be further processed for each event to assess nursing activity and effort, to eventually determine individual patient nursing demands.

### 2.3 Walking patterns for test candidate:

To test and validate CATS performance, three candidates with different heights of 1.74 m, 1.52 m and 1.90 m performed several motion patterns in the tracking. The optimal CATS settings were determined using a test candidate with height of 1.74 m. After the optimal settings are found, 2 other test candidates of 1.52 m and 1.90 m performed several motion patterns to test the system consistency.

The tracking area is divided into 4 zones, and labelled as A, B, C and D, as shown in Fig. 4. In the tracking area, 9 distinct feature points are labelled, which are used to help indicate where to stop for each pattern. Test candidate performed several different walking patterns, with each pattern repeated 5 times. The times in each region indicate times where the person stopped walking at a specified location and was assessed as dwell time.

For two candidates, the first candidate walked along the solid arrow, and the second candidate walked along the dash arrow. There are 4 different walking patterns are designed to test the system, as shown in Fig. 5. The comparison between Fig. 5 (a) (b) and (c) can test the system consistency about different dwell time. The comparison between Fig. 5 (b) and (d) is to test system consistency to different paths. The system consistency for different candidate's heights is tested with pattern in Fig. 5 (a).

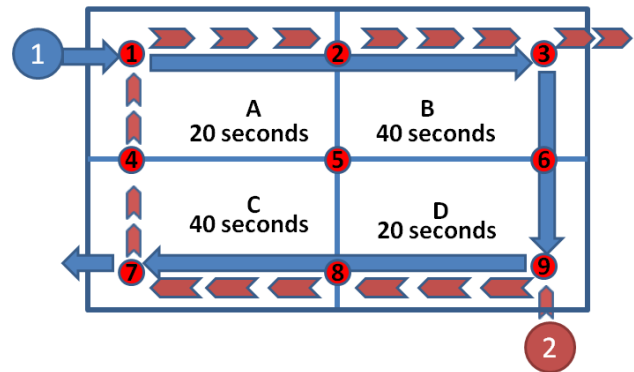


Fig. 4. The walking pattern for multiple candidates.

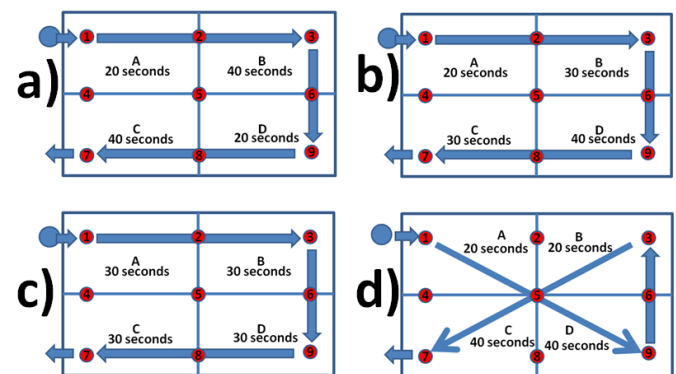


Fig. 5. Different motion paths and timing for the single candidate tests. The time in each region indicate times where the person stopped walking and will be assessed as dwell time.

### 2.4 Testing Process

The test regime was designed as follows:

1. Find the tracking area and find the best system parameters: A test candidate with 1.74 m height performed the walking pattern shown in Fig. 5(a). The pattern was walked as consistently as possible and dwell times were held using a stopwatch and directed by an external person. Several optimal system parameters were found, such as Maximum Depth, Minimum Depth and blob filter.
2. Validation for different walking paths: To prove CATS suits for different walking paths, the optimal settings obtained from steps 1 were used to test different patterns in

Fig. 5 (b) (d), calculating the consistency, using one test candidate with 1.74 m height.

3. Validating CATS suit for different heights: After optimisation with the 1.74m tall person in steps 1-2, the system was tested for heights ranging from 1.50-1.90 m using the pattern of Fig. 5 (a). The results were used to determine a system setting would work for the majority of the population.

4. Validating CATS suit for multiple tracking: To test the system for multiple concurrent people, the optimal setting was tested for the 1.67 m and 1.90 m candidate simultaneously using the patterns shown in Fig. 4.

### 2.5 Absolute percentage error (APE) of motion tracking

The system's ability to capture motion information during the conditions of different heights and other simulated situations was investigated using absolute percentage error (APE):

$$APE(t) = \left| \frac{\text{Distance}(t) - \text{Average Distance}(t)}{\text{Average Distance}(t)} \right| \times 100\% \quad (1)$$

The Distance (t) represents the distance between the candidate and the fixed point at time of 't'. There are 5 iterations, which generates 5 distances. Each person repeat the movement 5 time. The Average Distance is the average of 5 iterations, and it is used to normalize error as a deviation from expected.

The Median, inter-quartile range (IQR) and 90% confidence interval (CI) of the APE are calculated. These metrics, along with dwell time, assess the system's ability to accurately and consistently capture the test candidates or nurses trajectory when moving in the space.

## 3. RESULTS

### 3.1 Area covered and system parameters

In this study, the size of the tracking area varies depending on the value of the Maximum Depth. Several combinations of minimum and maximum depth were tested and the optimal parameters are found. This study was performed with a test candidate at the height of 1.74 m. Table 1 shows the combinations tested and their resulting total tracking area.

**Table 1. Tracking area based on maximum and minimum depth variables**

Candidates Body Part	Depth		Total Tracking Area(m ×m)
	Minimum Depth(m)	Maximum Depth (m)	
Head (0.96 m-1.16 m)	2.7-1.74=0.96	2.7-1.54=1.16	1.38×1.00
Chest (0.96 m-1.46 m)	2.7-1.74=0.96	2.7-1.24=1.46	1.90×1.40
Thigh (0.96 m-1.96 m)	2.7-1.74=0.96	2.7-0.74=1.96	2.30×1.60

From the results above, the optimal Minimum and Maximum Depth was set as 0.96-1.66 m from the ceiling. The optimal blob filter is found as 5500-35000 pixels to filter blobs too large or too small, only keep blobs similar as human size.

### 3.2 Validation of different paths:

Two different walking patterns, as shown in Fig. 6 (a) (b), were used to compare the consistency of different walking paths and different dwell times. The results are shown in Fig. 6, demonstrating the ability of CATS motion tracking to adapt to different walking patterns. Fig. 6 (c) (d) shows the consistency of the system. The Y-axis indicates the distance from the fixed point A measured pixels. Each test-iteration is represented by an individual line. Fig. 6(e) (f) shows the dwell time of first trial. For example, in Fig. 6 (e), test candidate stay in Area A for 20 seconds, Area B for 30 seconds, Area C for 30 seconds and Area D for 40 seconds, this is corresponding with the design. The bottom row shows the Median, IQR and 90% CI of Error from 5 trials.

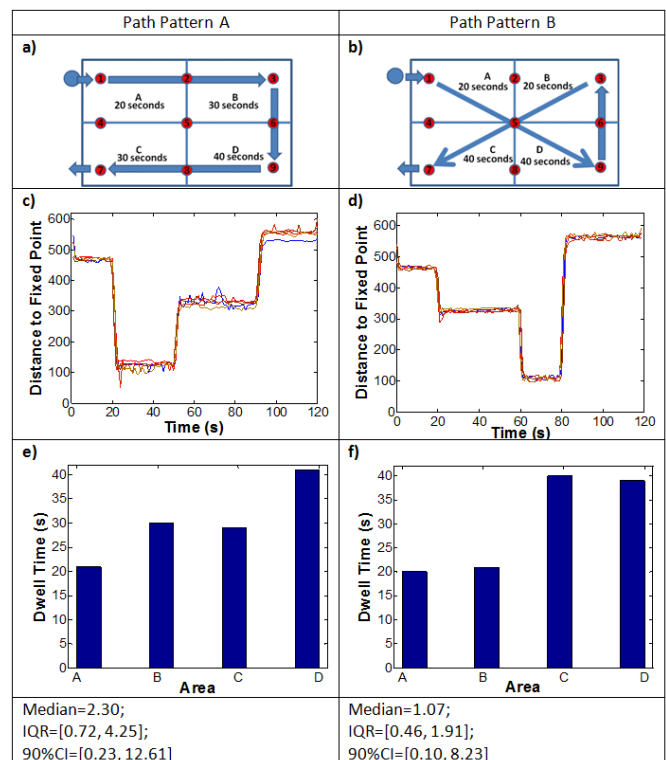


Fig. 6. The consistency of tracking with different paths

### 3.3 Validation of candidate heights

The walking pattern in Fig. 5 (a) was used to test system consistency for different candidate heights. The results for the two different candidate heights of 1.52 m and 1.90 m are shown in Fig. 7. The results show that the CATS was able to map motion paths of two candidates with different heights. Fig. 7 (a) (b) shows the distance between candidate and the fixed point. Fig. 7 (c) (d) shows the dwell time of the first

trial. The bottom row shows the Median, IQR and 90% CI of Error.

### 3.4 Validation for multiple candidates tracking

Fig. 8 shows the result for two candidates simultaneously walking along the path in Fig. 4. The candidates were 1.90 m and 1.67 m in height. Fig. 8 clearly shows the system's ability to track two candidates simultaneously. In addition, it was able to differentiate the path of each candidate clearly. Fig. 8 (a) shows the distance between candidate and the fixed point, one is 1.90 m and one is 1.67 m. Fig. 8 (b) (c) shows the dwell time of the first trial. The Median, IQR and 90% CI of Error were also calculated in the bottom row.

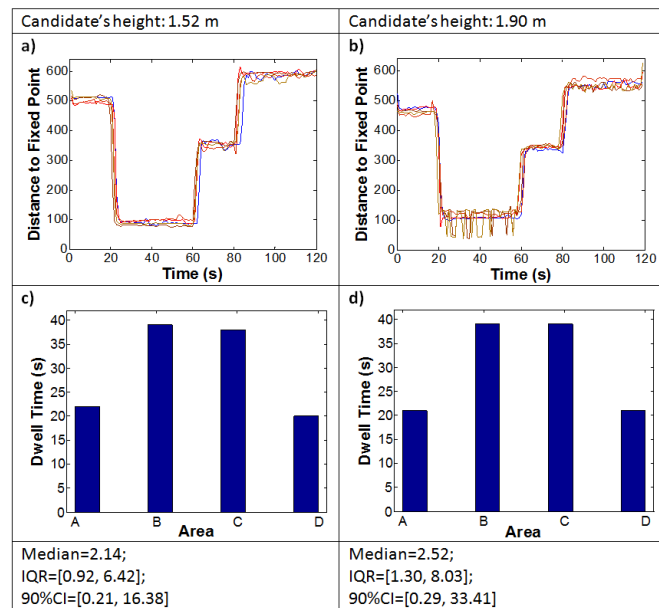


Fig. 7. The consistency of tracking different heights

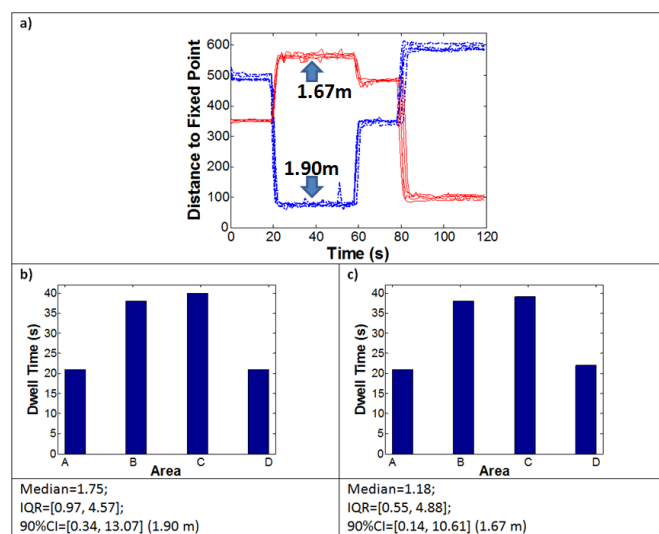


Fig. 8. Multiple candidates monitoring using walking pattern from Fig. 4

## 4. DISCUSSION

This study has shown that CATS can be used to accurately track test candidate motion and dwell time inside the tracking area. The system is mounted on the ceiling, reducing interruption to staff movements. Another significant advantage of the CATS is that no image or identifying data was stored, protecting nurse and patient privacy, which can impact ICU working environments. As found in Table 1, the system can cover an area bigger than 1.90 m × 1.40 m. This area corresponds to the actual patient bedside area where most nursing activities occur.

Also, CATS was able to detect different walking patterns, people of different heights, as well as multiple simultaneous candidates, as shown in Figures 6-8. For people with different heights, CATS can adapt to a range from 1.50 -1.90 m. For multiple candidates, CATS is capable of identifying each person by retrospectively analysing the data and record each person's trajectory.

In this study, two evaluation metrics were developed to monitor patient-nurse interaction. The first metric was the distance of the nurse from a fixed point. If the distance is small, it is an indication that nurse is near patient. If the measured distance is larger, it may be an indicator that the nursing activity is focused on medical data recording, or other less intensive preparation. The second metric is dwell time. By retrospectively analysing the dwell time, the relationship between nursing activities and patient situation can be determined. Hence, for patients with different illness scores, it is possible to know how much labour each patient needs. Hence, it is possible to calculate how many nurses an ICU needs in total, relative to the number and illness of the patients. In particular, for patients with the same illness score, it is possible to determine why they need different amounts of care and thus which type of diseases requires more nursing staff.

There are several limitations of the CATS that need to be addressed before clinical deployment:

1. CATS cannot identify the person in the tracking area because of the health and privacy issue of the working area. Thus, the system tracks everyone, including non ICU staff such as technicians and family members. This global tracking may potentially affect the data recording. However, as the occurrence of non ICU staff in the tracking area is limited, CATS can easily separate nursing activities and non nursing activities. In particular, in Christchurch Hospital ICU, family members typically sit outside the proposed tracking area, and the tracking area can be adapted to minimize this effect. It is important to note that this system is a motion tracking system and more detailed nursing activities, such as that described in the literature were not distinguishable (Adomat and Hicks, 2003, Miranda, 2003, Vincent et al., 1998).

2. CATS can only detect some of nursing activities because of the limitation of detection area. However, this problem can be solved through using multiple systems to cover larger areas of interest if needed. It is also important to note that nurse-patient interactions occur primarily in the area near the

patient. Thus, CATS will correspond to the more 'interactive' area.

## 5. CONCLUSION

A system to monitor nursing activities near the ICU patient bedside was developed and tested in a simulated experimental environment. The results showed that CATS is able to track candidate of different heights, adapt to different motion paths and identify multiple people simultaneously. The CATS uses two metrics, distance and dwell time, to evaluate nurse-patient interaction. The system performance indicates that it will work for actual clinical usage. This system can be implemented to evaluate nursing time and activities in ICU, helping the ICU to find more appropriate nurse-to-patient ratio, divide the work force based on care required, prevent nurse burnout, reduce operational costs and decrease patient mortality.

## 6. ACKNOWLEDGEMENT:

The authors thank Geoff Shaw for his assistance in experiment design and thank for Richard Green for his assistance in computer vision programming. Also, the authors thank CSC and UC doctoral scholarship supporting this research.

## REFERENCES

- Adomat, R. and Hewison, A. (2004). Assessing patient category/dependence systems for determining the nurse/patient ratio in ICU and HDU: a review of approaches. *Journal of Nursing Management*, **volume 12**, 299-308.
- Adomat, R. and Hicks, C. (2003). Measuring nursing workload in intensive care: an observational study using closed circuit video cameras. *Journal of Advanced Nursing*, **volume 42**, 402-412.
- Aiken, L. H., Clarke, S. P., Sloane, D. M., Sochalski, J. and Silber, J. H. (2002). Hospital nurse staffing and patient mortality, nurse burnout, and job dissatisfaction. *JAMA*, **volume 288**, 1987-93.
- Aiken, L. H., Sloane, D. M., Cimiotti, J. P., Clarke, S. P., Flynn, L., Seago, J. A., Spetz, J. and Smith, H. L. (2010). Implications of the California Nurse Staffing Mandate for Other States. *Health Services Research*, **volume 45**, 904-921.
- Carayon, P. and Gurses, A. P. (2005). A human factors engineering conceptual framework of nursing workload and patient safety in intensive care units. *Intensive Crit Care Nurs*, **volume 21**, 284-301.
- Egerod, I., Albarran, J. W., Ring, M. and Blackwood, B. (2013). Sedation practice in Nordic and non-Nordic ICUs: a European survey. *Nursing in Critical Care*, **volume 18**, 166-175.
- Kim, J. H., Hong, S.-K., Kim, K. C., Lee, M.-G., Lee, K. M., Jung, S. S., Choi, H. S., Lee, J. H., Jung, K.-S., Lee, S.-S., Cho, J. H., Koh, S. O., Park, M. S., Seo, K. W. and Koh, Y. (2012). Influence of full-time intensivist and the nurse-to-patient ratio on the implementation of severe sepsis bundles in Korean intensive care units. *Journal of Critical Care*, **volume 27**, 414.e11-414.e21.
- Le Gall, J. R., Lemeshow, S. and Saulnier, F. (1993). A new Simplified Acute Physiology Score (SAPS II) based on a European/North American multicenter study. *JAMA*, **volume 270**, 2957-63.
- Miranda, D. R. (2003). Nursing activities score. *Critical Care Medicine*, **volume 31**, 374-382.
- Reis Miranda, D., De Rijk, A. and Schaufeli, W. (1996). Simplified Therapeutic Intervention Scoring System: The TISS-28 items--Results from a multicenter study. *Critical Care Medicine*, **volume 24**, 64-73.
- Reis Miranda, D. and Jegers, M. (2012). Monitoring costs in the ICU: a search for a pertinent methodology. *Acta Anaesthesiologica Scandinavica*, **volume 56**, 1104-1113.
- Rose, L., Blackwood, B., Egerod, I., Haugdahl, H., Hofhuis, J., Isfort, M., Kydonaki, K., Schubert, M., Sperlinga, R., Spronk, P., Storli, S., Mcauley, D. and Schultz, M. (2011). Decisional responsibility for mechanical ventilation and weaning: an international survey. *Critical Care*, **volume 15**, 1-8.
- Tourangeau, A. E., Doran, D. M., Hall, L. M., O'brien Pallas, L., Pringle, D., Tu, J. V. and Cranley, L. A. (2007). Impact of hospital nursing care on 30-day mortality for acute medical patients. *Journal of Advanced Nursing*, **volume 57**, 32-44.
- Vincent, J.-L., De Mendonca, A., Cantraine, F., Moreno, R., Takala, J., Suter, P. M., Sprung, C. L., Colardyn, F. and Blecher, S. (1998). Use of the SOFA score to assess the incidence of organ dysfunction/failure in intensive care units: Results of a multicenter, prospective study. *Critical Care Medicine*, **volume 26**, 1793-1800.
- Walleck, C. A. (1994). Nursing and labor cost reduction. *New horizons (Baltimore, Md.)*, **volume 2**, 291-295.
- Wilson, N., Russell, D. G., Wilson, B., New Zealand. Hillary Commission for Sport, F., Leisure, Activity, U. O. O. L. I. N. Z. and Unit, H. R. (1993). Size and Shape of New Zealanders: New Zealand Norms for Anthropometric Data, Life in New Zealand Activity & Health Research Unit, University of Otago.