Mining Kinect Traces to Estimate Interactions between Healthcare Workers and Patients

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Introduction

A Healthcare Acquired Infection (HAI) is obtained while a patient is in a healthcare facility being treated for some condition. Clostridiods difficile (CDI) and Methillin-resistant Staphylococcus aureus (MRSA) infections are among the most common HAIs. HAIs are a major challenge for today’s healthcare system, especially because many of these infections are becoming resistant to antibiotics.

Discrete-event simulations based on models of healthcare worker (HCW) mobility, contact patterns with patients, patient demographics, patient admission-transfer-discharge patterns, and pathogen load on surfaces, provide a key computational tool for understanding HAIs-spread and potential interventions [1]. However, discrete-event simulation models require accurate parameters for the models they are based on.

This research uses Microsoft Kinect cameras placed in a patient room in the Medical Intensive Care Unit (MICU) at the University of Iowa Hospitals and Clinics (UIHC) to obtain reliable distributions of HCW visit-length and time spent by HCWs within touching distance of the patient, and how these patterns change over the course of a typical day. These data are expected to inform modeling efforts that are critical to understanding the spread of HAIs.

Dataset

3 Kinect cameras, placed in a patient room, capture images at 30 frames per second (fps).

Left and right camera track human body (i.e., left hand, right hand, and head) position, while door camera tracks the door.

No overlap between camera views; individuals often move from one field of view to the other.

Body Stitching

- Each body may have multiple raw segments over the two camera regions that need to be “stitched” up.
- A body may also be temporally occluded by another person or object in the room and split into multiple raw segments.

Figure 3: A trajectory of movement showing 1 second of movement per image.

We used two types of stitching:

- **End-to-end stitching**; stitch up ending point of a body with starting point of another body based on a feature matching method.
- **Interior stitching**; fit a broken segment into the main segment, also using a feature matching method.

This reduces the total 688x captured “raw” bodies to 2xx “stitched” bodies over the 7-day period.

Figure 4: Distribution of number of raw bodies merged into a stitched body.

Figure 5: Number of raw and stitched bodies per day.

- Feature matching: We assigned each body an entry time and exit time based on their first and last appearance. When a body \( P \) (referred to as “old” body) exits, we designate 5 candidate “new” bodies as those with the temporally closest entry times. We then calculate a matching score between the old body and the candidate new bodies using following features extracted from the last 10 frames of old body and the first 10 frames of each candidate new body.

- Spatial gap
- Temporal gap
- Directional similarity
- Velocity difference

An old body is then stitched to a new body with best matching score, provided a matching score threshold is met.

Figure 6: Normal vs. Ghost body

Ghost Detection

We define a human body as ghost if most of its traces shows some unnatural characteristics over a period of time.

- Ghost characteristics include frequent directional change, being stuck at the same spot, discordant head and hand velocities, tendency to jitter or rapidly change velocity, and repetitive motion over a small region.
- These ghost bodies, unless removed, affect the correct estimation of HCW-patient interaction parameters.
- For each frame, we used a sliding window of size 20 frames (~0.67 seconds) to extract the following features and then applied unsupervised learning to classify the frame as either a ghost or a normal frame. A body with at least 60% normal frames (between its entry and exit) is classified as normal body; all other bodies are labeled ghost bodies. This yields 1404 ghost bodies out of total 2666 stitched bodies.

Figure 7: Head locations

Validation

After stitching, ghost removal, we examine the resulting body trajectories.

- Figures 7 and 8 illustrate head and hand heatmaps from the remaining traces. High frequency locations are clustered around the bed and more to the patient’s right in accordance with the general medical practice of performing patient exams from their right side.
- Figure 7: Head locations
- Figure 8: Hand locations

Results

- Figure 9 shows the distribution of the number of HCW visits per hour (mean 6.952, std dev 2.855).
- HCW visit frequency two peaks, one during morning shift and one during the afternoon shift. As expected, there is a distinct decrease after midnight.
- Figure 10 shows visit length (in minutes) distribution (mean 1.579, std dev 2.679).
- Most of the visits are just “check in visits” of under half a minute.
- Figure 11 illustrates the fraction of visit time HCWs spend at touching distance from the patient as a function of visit length.
- HCWs don’t spend much time near patient during short length visits. The fraction of time spent near patient bed seems to increase with visit length up to a point.

Figure 9: Visits per hour

Figure 10: Distribution of visit lengths (in minutes).

Figure 11: Fraction of time near patient bed as a function of visit length.

Conclusions

Using fine-grained data, this research extracts distributions of these critical parameters of HCW-patient interactions: 

(i) HCW visit length, 
(ii) HCW visit frequency as a function of time-of-day, and (iii) time spent by HCW in touching distance of patient as a function of visit length.

To the best of our knowledge, we provide the first reliable estimates of these parameters. Our results are preliminary; we have 300 days of additional sensor data to analyze, and we have yet to incorporate data from the third overhead door sensor, which may improve accuracy of results significantly.