duodenoscopes (10%) are not adequately clean. Figure 2 shows a box-plot analysis of the data set by endoscope type and by site. There is significant ($P < .005$) site-to-site variability for all endoscope types as demonstrated by variation in mean values, box size, and many outliers. **Conclusions:** This study highlights the importance of using a quantitative cleaning verification method to better understand process capability and to provide more robust quality assurance for manual cleaning. Significant differences were detected in the level of cleanliness between upper GI scopes and lower GI scopes and bronchoscopes. When compared to a literature-supported level for adequate cleanliness, upper GI scopes exhibited failure rates in excess of 10%. Furthermore, significant site-to-site variability occurred, and many outliers fell well beyond the normal process envelope, representing significant cleaning lapses. Root causes to these concerning findings could range from inadequate execution of the cleaning protocol, to device design, to age and existing damage that could prevent achieving adequate cleaning and possibly impair the effectiveness of HLD.

Fig. 1.

Presentation Type:

Distinguished Oral

Mining Camera Traces to Estimate Interactions Between Healthcare Workers and Patients

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Background: Simulations based on models of healthcare worker (HCW) mobility and contact patterns with patients provide a key tool for understanding spread of healthcare-acquired infections (HAIs). However, simulations suffer from lack of accurate model parameters. 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 near a patient. These data can inform modeling efforts for understanding HAI spread. **Methods:** Three Kinect cameras (left, right, and door cameras) were placed in a patient room to track the human body (ie, left/right hands and head) at 30 frames per second. The results reported here are based on 7 randomly selected days from a total of 308 observation days. Each tracked body may have multiple raw segments over the 2 camera regions, which we "stitch" up by matching features (eg, direction, velocity, etc), to obtain complete trajectories. Due to camera noise, in a substantial fraction of the frames bodies display unnatural characteristics including frequent and rapid directional and velocity change. We use unsupervised learning techniques to identify such "ghost" frames and we remove from our analysis bodies that have 20% or more "ghost" frames. **Results:** The heat map of hand positions (Fig. 1) shows that 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. HCW visit frequency per hour (mean, 6.952; SD, 2.855) has 2 peaks, 1 during morning shift and 1 during the afternoon shift, with a distinct decrease after midnight. Figure 2 shows visit length (in minutes) distribution (mean, 1.570; SD, 2.679) being dominated by "check in visits" of
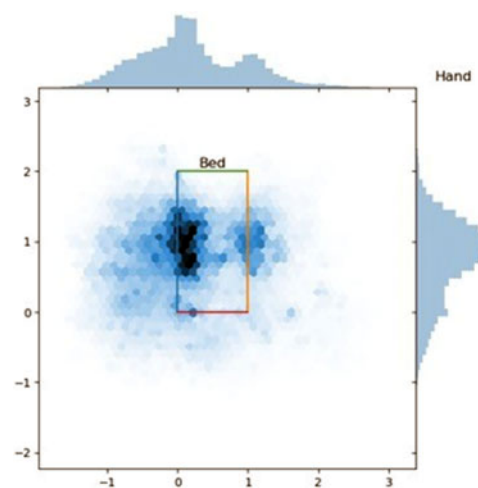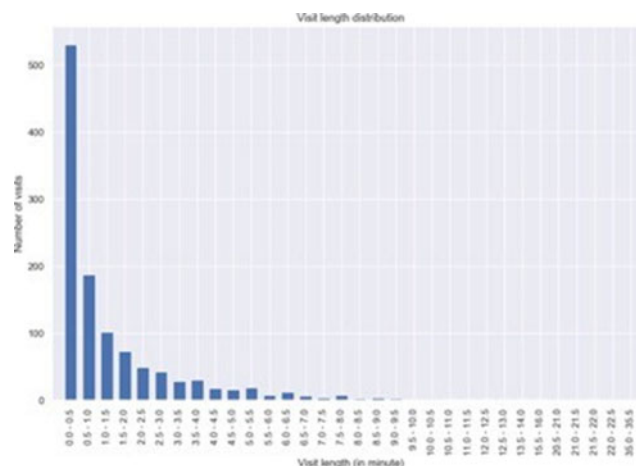

Fig. 2.

<30 seconds. HCWs do not spend much time at touching distance from patients during short-length visits, and the fraction of time spent near the patient's bed seems to increase with visit length up to a point. **Conclusions:** Using fine-grained data, this research extracts distributions of these critical parameters of HCW–patient interactions: (1) HCW visit length, (2) HCW visit frequency as a function of time of day, and (3) time spent by HCW within 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.

Presentation Type:

Distinguished Oral

Novel Methodology to Measure Preprocedure Antimicrobial Prophylaxis: Integrating Text Mining With Structured Data

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