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A Methodology for Empirically Evaluating Passenger Counting Technologies in Public Transport

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Abstract

Interest in Automatic Passenger Counting (APC) systems in public transport is rapidly growing as transport providers increasingly seek accurate, real-time estimates of occupancy to provide better services to their customers. Although several technologies have been developed for APC, public transport such as buses are a noisy environment that pose unique challenges for passenger counting. In this paper, we propose a methodology for empirically evaluating passenger counting technologies in public transport. We validate the methodology through a live trial with buses carrying members of the public arranged in collaboration with Sydney Trains and Transport for New South Wales, supported by iMOVE Cooperative Research Centre. Results and outcomes of the trail and an empirical evaluation of multiple APC technologies conclude the paper.

1 Introduction

Automatic people counting (APC) is attracting increasing interest from public transport providers, with many commercial products now on the market (Tattile Automatic People Counter (T-APC) 2019; NEC FieldAnalyst 2019; Video Turnstile 2019). While the majority of academic studies to date have focused on visual counting (Wang, Chang, and Wu 2017; Subburaman, Descamps, and Carincotte 2012; Chen et al. 2014, Lengvenis et al. 2013), there is growing interest in a range of other technologies (sensor modalities), motivating demand for empirical comparisons to evaluate the viability of such technologies. The general problem of APC is a well explored, with a number of technologies potentially well-suited to the public transport context. However, APC on public transport - particularly on buses - poses a unique set of challenges that must be considered when evaluating such technologies. Challenges include the at-times dense accumulation of people, the varying numbers of people between stops, and sensor instability due to jolts and jitters experienced both while in motion due to uneven road surfaces, as well as engine vibration when idle at a bus stop. Thus, people counting systems in a vehicle do not necessarily produce the same quality of estimate as in a stationary environment. While previous studies including study by Myrvoll et al. 2017 have investigated APC systems on long-distance coaches, and urban buses studies by Oransirikul et al. 2014; Brandon 2015; Mikkelsen et al. 2016, there remains a need for a methodology that can provide the foundations to conduct thorough empirical comparisons of multiple APC technologies under similar real-world conditions.

Conducting a live APC trial with members of the public as passengers require careful planning and consideration. Countries vary in their stringency of privacy laws, and local rules have to be satisfied to obtain ethics approval. Sensors require prime locations to provide accurate readings, but may not be installed where they can induce injury. Third party liability insurance is generally a requirement, and it may be necessary to confirm with the insurer that a particular study is covered. Such logistical challenges mean studies often only provide theoretical results of their passenger counting technologies (C.-H. Chen et al. 2008), or rely on pre-captured datasets collected in labs (Escolano et al. 2016). Even when such studies do consider on-bus performance (e.g., Yahiaoui, Khoudour, and Meurie 2010; Yang et al. 2010; Lengvenis et al. 2013), there is only limited detail given regarding trial design considerations, or basis for underlying methodology applied.

In this paper, we propose and evaluate a methodology for empirically evaluating APC technologies in public transport. We highlight some of the key requirements and design decisions that needed to be considered during the development of such a methodology. In collaboration with Transport for NSW (a statutory authority of the state government of the Australian state, hereafter TfNSW) and its rail network operator Sydney Trains, and supported by iMOVE Cooperative Research Centre, we conducted a live trial with members of the public as passengers where we empirically evaluated four APC technologies namely, Video sensing, WiFi sensing, 3D-Infrared sensing and Pressure (mat) sensing, under identical conditions for bus services operating in and around Sydney's metropolitan area using the proposed methodology. We present comparative results from a trial on live bus services, outlining key insights to guide future APC field trials.

2 Background

Between July and December 2018, Swinburne's research team, in partnership with TfNSW and Sydney Trains, conducted a comprehensive evaluation and comparison of state-of-the-art APC technologies. Specifically, the study aimed to evaluate real-time automatic passenger counting technologies in buses within Sydney's metropolitan area. The participation of Sydney Trains was motivated by their use of buses as a rail replacement service during maintenance. Having access to real-time passenger occupancy data addresses a pressing problem faced by all transport operators: the need to provide sufficient, but not excessive, numbers of services to avoid passenger discomfort and cost blowout.

Other motivations for APC include the desire to enhance passenger experience through the publishing of accurate and near real-time bus occupancy numbers (availability), locations and capacity for waiting passengers (wait-times) via a mobile device and/or web-based application.

Evaluations of APC technologies for bus services must consider a range of criteria. In the context of this project, specific points to address were identified in consultation with project partners (TfNSW, Sydney Trains). For example, the timeliness of updates, with a potential for a real-time data transfer, cost-per-bus, scalability, technology security and ease-of-installation were all listed as high priority criteria to address, reflecting the practical intent of the study to inform possible deployment choices in the near-term. Based on these criteria, the research team was tasked with developing a methodology that will help identify viable state-of-the-art technology options and conduct a live trial to evaluate the performance of each technology option.

3 Methodology

A two-phase evaluation methodology for the comparison of technologies in real bus settings is proposed as illustrated by the flowchart in Fig. 1, which shows the pilot trial on the left and the live trial on the right. These trial phases are preceded by several steps including procurement of relevant components for the specific APC technology and integrating and testing them within a lab environment. In the methodology's implementation, both trials were also preceded by visits to the local bus depot of the respective bus operator to discuss safety and suitable positioning of the devices.

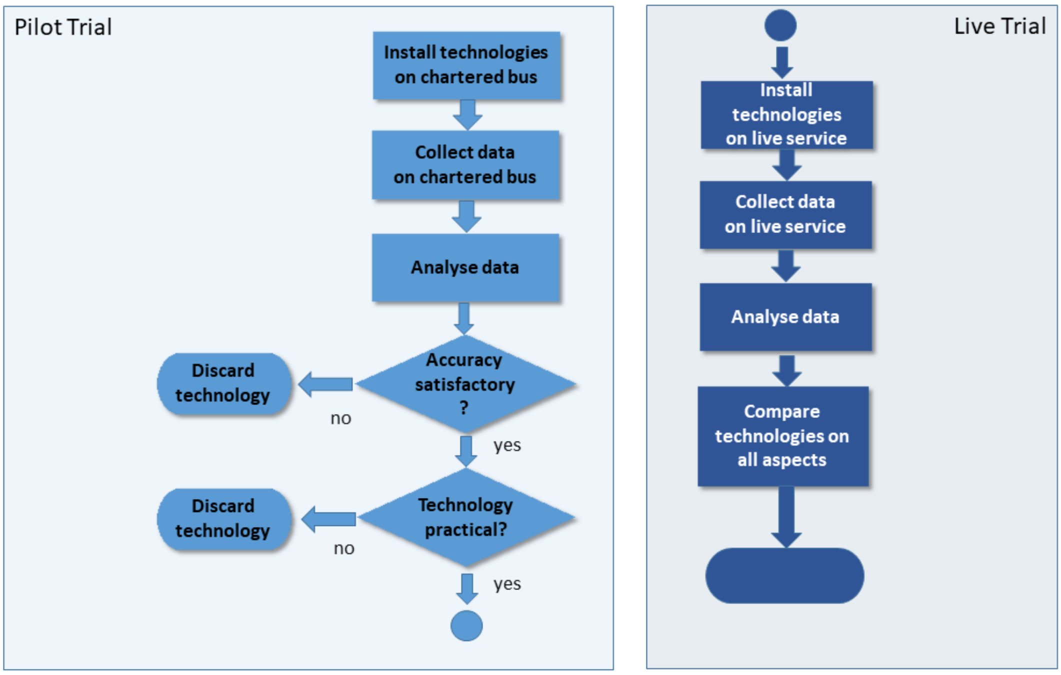


Figure 1: Flowchart of methodology. The light blue items are part of the pre- trial, the dark blue fields describe the live trial with members of the public.

3.1 Pilot trial with volunteers

The pilot trial, a simulated passenger-carrying trial using a chartered bus in Melbourne (close to Swinburne University's campus), aimed at validating each technology's accuracy and viability, as well as evaluating specific installation requirements for each technology option. It consisted of two hours of installation/maintenance and two hours of data collection over two days, one week apart. This was preceded by a visit to the bus depot, where possible installation conditions and restrictions were discussed and identified (e.g. the video-based solution had to capture the image of a passenger as they were boarding the bus or alighting from it).

At the start of both days of the pilot trial, a chartered bus was equipped with the devices needed for each technology option. Each technology collected data that was captured for post-processing and analysis. The bus was parked at a provisional bus stop which was not used by active services at the time. At this stop, volunteers boarded and alighted as the bus completed multiple circuits, as shown in Fig. 2a where the bus's location is traced from the output of a GPS module installed on the bus. Ground truth data for each stop was collected by one team member counting the persons boarding and alighting. Between 6 and 15 members of the team and their associates volunteered as passengers.

The Melbourne-based pilot trial was designed to provide the following outcomes:

- A cost-efficient pre-evaluation of all technology options developed by Swinburne, allowing Sydney Trains/TfNSW to select technology options to proceed to full prototyping in Sydney;
- A cost-efficient evaluation of operational requirements for all technology options, informing further research and development requirements for the Sydney Trial;
- Refinement of trial design and data analysis needs and
- Improved familiarity and experience working with buses representative of those to be used in the Sydney trial, allowing technologies to be refined, and calibration requirements to be better understood. This in turn will greatly reduce the risk of unforeseen complications inhibiting data collection in the Sydney-based trial.

As Fig. 1 shows, after the data analysis, the accuracy achieved by each technology were presented to Sydney Trains/TfNSW and a decision was made whether to discard the technology. Insights gained in the pilot trial about installation, positioning, cost and related considerations were also presented to Sydney Trains/TfNSW.

3.2 Live trial on metropolitan bus routes

The live trial was conducted in Sydney with a bus company that operates several of the bus services on routes in central Sydney. The knowledge gained from the pilot

(a) Route of charted bus obtained from GPS (b) Charted bus

Figure 2: Route and chartered bus

helped refine the installations for each of the technology options thus reducing the downtimes in data collection.

The trial was conducted over seven days using two buses. The buses serviced routes in and around Bondi Junction, with buses originating from the Waverly bus depot. On Saturday and Sunday, the two buses were used to provide a replacement service during train line maintenance between Sydney Central and Bondi Junction. Regular bus services spend 1 - 2 minutes on a leg between two stops, whereas train replacements typically take 7 minutes between stops.

Every day before the start of the shift of a driver, each of the four technologies were installed on each bus. The Swinburne project team members were available in each

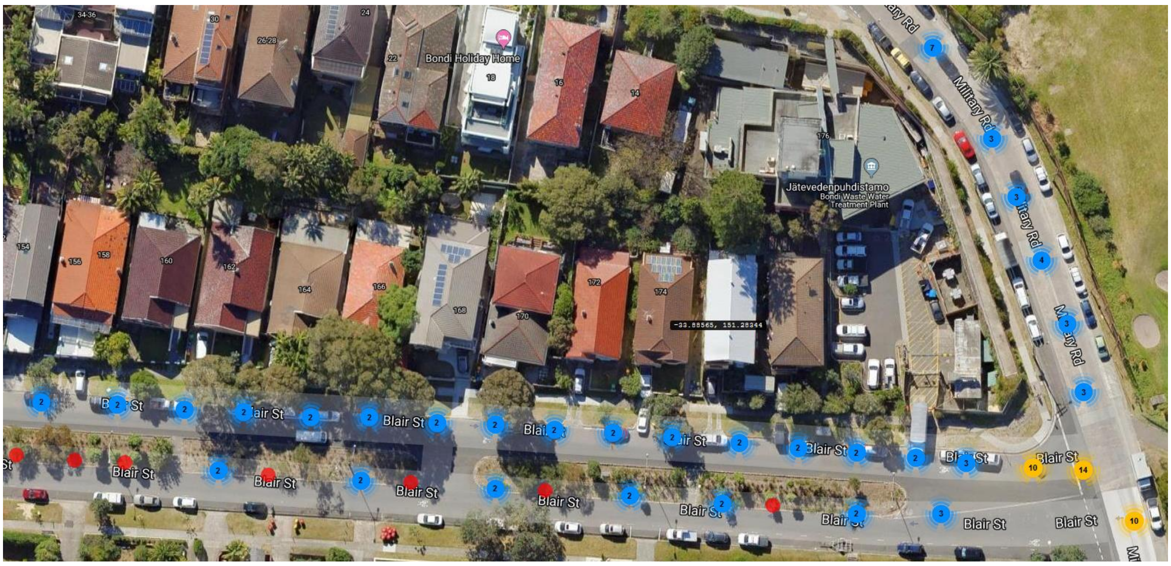


Figure 3: Bus route plotted using marker icon captured by GPS probes

bus for customer queries, counting passengers (capturing ground truth used later for analysis) and watched over the devices installed. Sensors collected data between the beginning of the shifts around 7.30am and continued until approximately 3.30pm on weekdays.

According to the workflow shown in Fig. 1, based on the data collected in this live trial, the technologies were compared according to aspects of performance, cost and technical details and the results presented to Sydney Trains/TfNSW. Recommendations were made as to the suitability of the technologies for deployment on bus services.

4 Automatic passenger counting technologies

4.1 Video-based sensing

Two cameras were mounted per bus, the front one shown in Fig. 4a, providing visual coverage of the front and rear door-ways of both buses. RGB image frames were captured at 640×480 pixel resolution, and 30 frames per second utilising software running on an adjacent Raspberry Pi 3B+ (RPi), powered by a 20,000 MAH Powerbank. Data was stored on an SD card mounted in the Raspberry Pi.

A detection-based vision algorithm was developed in which passengers are initially detected, and then tracked to ascertain the direction of their movement. Passenger detection is achieved using the pre-trained convolutional neural network, MobileNet SSD (Single Shot Detector) [16], chosen on the basis of its accuracy and relative efficiency compared with other comparable networks.

Passenger detections are stored as ’track’ objects, and initialised with the detection confidence output of the MobileNet network. Future detections of the same track object are established based on a calculation of the Intersection of Union (IoU) between bounding boxes in consecutive frames. If a new detection bounding box, when compared to an existing track object bounding boxes, achieves an IoU of greater than 40%, it is considered an update of the pre-existing track object, and thus replaces the previous one. Track objects that are not updated at a particular point in time, have their confidence progressively reduced each frame, and if below 20% confidence, are deleted from the track object list.

Enter and exit counts for each door are maintained based on movement of tracked passengers across two virtual parallel lines positioned within the camera view frame during calibration. An enter or exit event is triggered if and only if a track object passes both lines in order to reduce false positive responses. Recorded timestamps of passenger exchange events allow front and rear door counts to be combined to calculate the total passenger exchange at each stop.

4.2 3D Infrared sensing

Two Orbbec Persee devices were installed in each bus to cover both of the front and rear doors as shown in Fig. 4b. The Orbbec devices were powered by CYGNETT 27,000 MAH power banks that supply the power needed by these devices. Depth and infrared data were collected for 6 days. Each device collected around 70GB of videos per day.

In order to count number of people from the infrared and depth data, classification techniques were trained on four classification training sets, depth and infrared data for the front and rear doors. This training aimed to identify the heads of the passengers while they were entering or exiting the bus.

4.3 Mobile WiFi sensing

The mobile sensing technology counts the number of devices in a defined space based on probe request messages the devices send when they are not connected to a network. The decision whether a device is inside this space is made using the spatial and temporal overlap of the probe requests sent by this device. The spatial overlap is achieved by positioning several mobile WiFi sensors around the bus. 4 - 5 sensors were used in the live trials, and the variations shown in Fig 5 were explored.

To count the people on the bus based on their devices (assuming we cannot account for people who do not carry them), we relied on the MAC addresses and their repetitions across time and sensors to decide whether each MAC address belonged to a device inside or outside the bus.

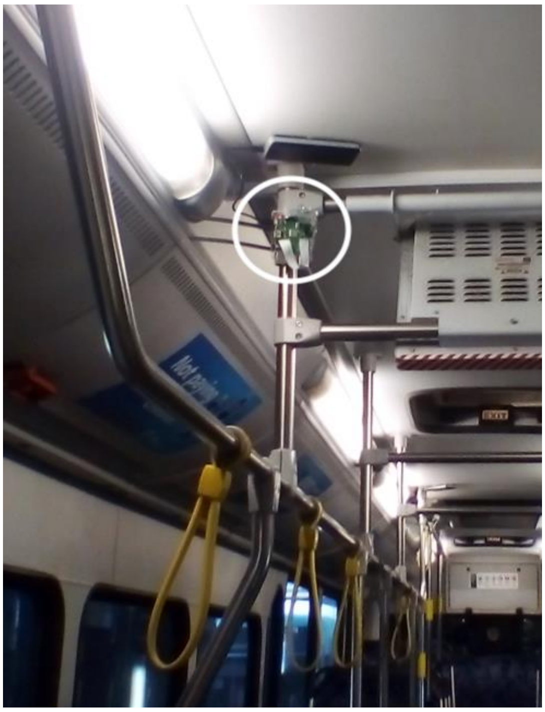
The most successful algorithm used the following rules:

1. Remove all probe requests from all sensors' data that have an RSSI of less than -100.
2. Remove all MAC addresses whose first and last message (regardless of sensor) are less than 50% of the leg's distance apart.
3. Remove all MAC addresses whose first and last message are 55% of the leg time apart (the time between stops).
4. Remove all MAC addresses which have not been recorded at least 3 times.

4.4 Sensor mat

A sensor-grid mat was placed at the rear door of the bus. Data recorded by the sensor was computed using an algorithm that calculates the centre of pressure movement when passengers step on and off the mat. The calculation of the centre of pressure is possible due to the presence of a piezo-resistive material (pressure-sensitive layer) divided into a sensor grid. This allows for the detection of the direction of movement (on or off the bus) and the achievement of accurate counting of the number of passengers boarding and descending the bus. All data were recorded on a SD card, then post-processed and compared to the ground truth count as well as the video camera count.

For the live trial, two sensor mats with 24 sensing nodes each, designed and built at Swinburne University, were taped down on the entrance floor. Each mat was centred on the available floor space in the direction of travel and placed as closely as possible to the edge of the bus entrance in the direction orthogonal to travel. Each mat was connected to an SD card to record continuous pressure data output from the mat (8-10 hours of data, approx. 60MB). The SD card for each mat was contained in a box and connected by wire to the mat and taped to the vertical surface closest to the door in a way that did not interfere with the opening doors as shown in Fig. 4d. To simulate a real-life use of the sensor mat, passengers were not made aware of the mat. Sensor mats could only be fitted at the rear door of each bus. The mat was initially installed at



(a) Video sensing (front-door install)

(b) 3D Infrared Sensing

(c) Mobile WiFi Sensing

(d) Sensor Mat

Figure 4: Sensor Installation for all four APC Technologies Evaluated

the front door, however the frame of the doors prevented the doors from opening and closing properly.

5 Results and insights

The two-phased technology evaluation methodology (Fig 1) we are proposing was applied to the evaluation and comparison of the four above-described technologies. Below we report key results achieved during each phase of the evaluation, and discuss both challenges and insights gained through the implementation of the methodology proposed.

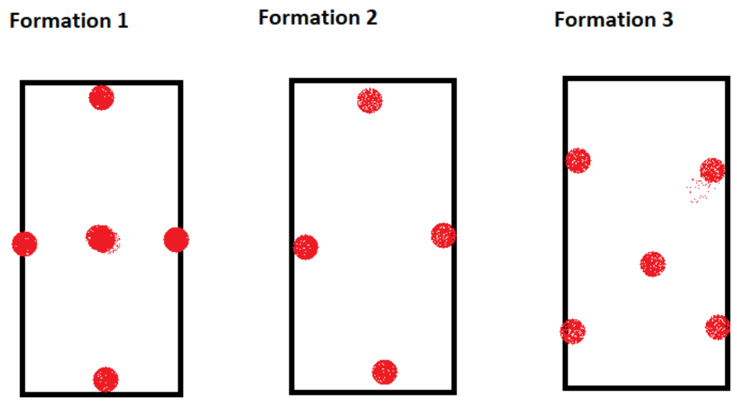


Figure 5: Mobile WiFi Sensing – Installation Configuration Options

5.1 Pilot results

The primary motivation of the pilot phase was to provide opportunities to eliminate potential causes of error, and better understand the bus operating conditions in preparation for live trialling. Of chief concern for both video-based and 3D Infrared development teams was the positioning of sensors to best suit processing needs. To this end, numerous positions were trialled, with multiple cameras positioned to capture data of the front door from varying positions. For video-based, three locations were trialled: above the driver, in front of the driver on top of the main console, and behind the driver, above the centre aisle of the bus. The latter position proved to be best in terms of accuracy (reported in Table 1), and was thus selected for live trialling. Positioning of the 3D Infrared sensor was similarly varied throughout the pilot, allowing post analysis of the captured data to determine best location for the live trial.

Key issues to address for the sensor mat development team were the fitting of the mat securely and safely to the bus entrance area, and the embedding of associated electronics and wiring. The mat's integration with the bus's hinged wheel chair access ramp also proved a non-trivial issue to be resolved for a live trial with members of the public as passengers.

The WiFi sensing team explored installation options for their sensors, and tested power requirements for the sensors. It was found that the AA-based battery banks did not provide sufficient power, causing WiFi modules to reset periodically. Thus, higher capacity power banks were selected for the live trial.

Table 1 presents preliminary results that were collected and analysed in the pilot trial. As can be seen, all technology options achieved accuracy scores of between 70 and 90%. Detailed estimates per trip were reported by the sensor mat and WiFi teams, while the video-based team distinguished between boarding and alighting events, but did not detail the trips. The 3D Infrared sensor team was not able to collect data of a quality that could be transformed into meaningful estimates, but gained insights into appropriate sensor positions. The sensor mat team discovered an issue arising from two persons stepping on the mat at the same time, which led to the estimation algorithm misinterpreting either the number of passengers or the direction in which they were heading. These issues were remedied before the live trial.

As shown in Fig. 1, after the data analysis the decision was made whether the results warranted further investigation of a technology. Sydney Trains/TfNSW appraised the results and decided that the accuracies of all technologies were sufficient for a live trial. Installation details, costs and other insights gleaned in the pilot were also presented to Sydney Trains/TfNSW. It was decided that none of these details were grounds for eliminating a technology from the trial. Consequently, it was decided to proceeded with all four technology options for live trials in Sydney.

Table 1: Accuracy scores of APC technologies from Pilot Trial

<table>
<tr><th rowspan="2">Trip No</th><th colspan="3">Passenger numbers on each leg</th><th colspan="3">Accuracy</th></tr>
<tr><th>Actual</th><th>Sensor Mat</th><th>Mobile WiFi Sensing</th><th>Video Sensing</th><th>Sensor Mat</th><th>Mobile WiFi Sensing</th></tr>
<tr><td>1</td><td>12</td><td>11</td><td>8</td><td rowspan="7">Boarding – 97% Alighting – 71% Mean – 84%</td><td rowspan="7">Mean – 90%</td><td rowspan="7">Mean 80%</td></tr>
<tr><td>2</td><td>10</td><td>16</td><td>7</td></tr>
<tr><td>3</td><td>13</td><td>19</td><td>10</td></tr>
<tr><td>4</td><td>13</td><td>14</td><td>15</td></tr>
<tr><td>5</td><td>16</td><td>No data</td><td>16</td></tr>
<tr><td>6</td><td>17</td><td>No data</td><td>14</td></tr>
<tr><td>7</td><td>16</td><td>16</td><td>No data</td></tr>
</table>

5.2 Live trial results

A live trial of all technology options was performed over the week of December 10-16, 2018. Normal bus services were used during the weekdays and replacement bus services over the weekends. Throughout the trial, at least one research team member accompanied each bus to supervise technologies, and obtain passenger counts as ground truth data for subsequent analysis. After the trial, manual passenger counts were cross-checked with video footage to ensure correctness. The first day of operation was designated as a setup day, and any data collected used only to inspect and, if needed, adjust operational settings. Days thereafter were official trial days.

Table 2 presents a summary of accuracy results for each door-based technology option (i.e., video-based, 3D Infrared, and Sensor Mat), based on all passenger exchanges from across the trial. Here, results are presented using data collected from the morning peak period of regular week days, and all day on weekends, showing the percentage of boarding and alighting event counts that were correctly identified across this period. To assist interpretation, results are broken down to each individual event (e.g., Front in, Rear out), as well as combined for each door, and for both doors (i.e., Total). As can be seen, results vary between technology options, and also with respect to different passenger exchange events.

WiFi sensing is presented separately due to the fact that it does not estimate bus occupancy by counting boarding and alighting events, but directly by sensing devices during transit. Thus, Table 3 presents accuracy results for the WiFi sensing option, showing accuracy as the percentage of total passengers accounted for on the bus between each adjacent bus stop. In this case, results for weekdays and weekend are presented separately to highlight a notable difference in accuracy achieved. Clearly, the weekend accuracy (75%) significantly out performs the weekday accuracy result of (16%), a likely result of the much shorter intervals between stops on weekday services (1-2 minutes) compared to weekends (6-7 minutes on average). Weekday bus legs appear to provide insufficient time for the heuristic (described in Section IV.C) to ascertain a device is really on the bus, and not in its surroundings. As the weekend involved rail replacement services, legs between stops were much longer, thereby explaining the large discrepancy in accuracy.

Conducting trials with members of the public provided new opportunities to discover unexpected difficulties for the technologies, such as a WiFi sensor being stolen. For each technology, we report below the issues that need preparing for if a technology is to be implemented as a people counting solution.

Table 2: The percentages of boarding and alighting events identified accurately by each of the technologies RGB, 3D Infrared and sensor mat.

	Total	Front door	Rear door	Front in	Front out	Rear in	Rear out
Video	57%	70%	33%	76%	47%	0%	35%
3D Infrared	55%	74%	20%	93%	0%	100%	20%
Sensor mat	83%	N/A	95%	N/A	N/A	64%	93%

Table 2: Percentage accuracy of WiFi sensing on weekdays compared to week- ends

	Transit Weekdays	Transit Weekends
WiFi Sensing	16%	75%

5.2.1 Video-based sensing

Results from Table 2 indicate that the video-based APC method achieves reasonable accuracy on the front door, but a clear decline in accuracy for the rear door. Notably, however, passenger detection itself was observed to be reasonably robust, and efficient enough to achieve real-time performance on the Raspberry Pi 3B+. Inspection of the video data indicated the difference between front and rear door was a likely result of passenger crowding within the rear door area between stops (causing false positives), as well as more variability in the entry point of alighting passengers within the camera's view, which depended on which part of the bus the passengers approached from. Determining a camera position and angle that both satisfied the need for sufficient visual coverage and other factors such as sensor security was found to be significantly more challenging than the front door. Future work may consider a wider fish-eye lens for increased visual coverage.

Other well documented challenges for video-based people counting were also encountered such as multiple passengers entering/exiting too fast or too close together, causing loss of tracking. Missed detections due to passengers occluding each other was also observed regularly. While improved training of the existing network may improve performance, a stronger solution would likely entail a complete end-to-end trained CNN architecture specifically targeting bus passenger counting. In addition to improved accuracy, efficiency gains are also likely achievable through use of a smaller, more refined network architecture (unlike the more general MobileNet architecture). This was not possible to explore in the current study due to time constraints, but offers an attractive path for future development. Camera positioning may also be revisited, including consideration of a top-down vantage point above door-ways to remove passenger occlusions, and simplify the calibration of virtual lines for counting. Combining RGB video processing with depth sensing (i.e, such as the Orbbec Persee utilised by the 3D Infrared APC method) may also be considered to improve accuracy and efficiency.

5.2.2 3D Infrared sensing

3D Infrared Sensing achieved similar results to video-based overall, with particularly strong results for entering passenger counts, but a clear drop off in performance for exiting passenger counts on both doors. This is a likely result of a lack of training for detecting passengers from behind, as well as issues with occlusions.

Other issues were also observed during the live trial. Lidar depth sensing and Infrared, for example, were observed to be sensitive to the bus vibration, causing blurring of object boundaries. Notably, vibration was greatest when the bus was idle (e.g., at bus stops), however the Haar feature-based classify was not sufficient to overcome this. Like video-based, an end-to-end trained CNN using data collected from the live trial is the most likely direction for future work. Sensor stabilisation itself should also be addressed in future work for this approach.

As with video-based, people standing in front of the camera during bus movements was observed to impact counting accuracy due to false positive counts. Limiting data collection to only when the bus stops is a possible work-around, which may be achieved using an acceleration sensor to trigger data collection.

5.2.3 Mobile sensing

As is evident from Table 3, mobile sensing accuracy during weekdays is considerably lower than during the weekends, a likely result of large differences in travel time (1-2 minutes during weekdays compared to 7 minutes during weekends). The WiFi solution is thus unique compared to other solutions in that its performance depends on the travel duration of the bus between stops. To address this issue, the interpretation of the data could be changed so as to process probes across the boundaries of stops. For example, if a device has been sensed before the current stop, and it is encountered again, this points to a high probability of the device (and its owner) being on the bus rather than outside. Notably, performance on the weekend rail replacement bus services is comparable with other options, and indeed, offers the advantage of a direct occupancy count. This is compared with passenger exchange estimating technologies (video-based, 3D Infrared and Sensor Mat) in which accumulating error over time may impact occupancy estimates if not corrected for.

In contrast to the pilot trial, it was observed during the live trial that when passenger numbers exceeded 40, estimated bus occupancy decreased to very low numbers, suggesting high passenger density may attenuate the WiFi signal. Consequently, the positioning of devices was varied again during the live trial, and the configurations shown in Fig. 5 were explored. Configuration 1 (Fig 5a) led to the best accuracy. This was unexpected, as the sensors in the middle of the bus are barely a metre apart.

Counteracting the shielding effect of bodies presents a challenging issue, and having a dense distribution of sensors all over the bus appears to be a good solution, when the algorithm that interprets the data relies on multiple sensors receiving probes from the same device. Alternatively, the provision of a WiFi service for the passengers to connect to on the bus offers another possibility, however more investigation of this issue is required. Notably, the identification of such practical issues for APC deployment is testament to the two-phased empirical methodology applied, where the contrasting performance between simulated and live trials enables the isolation of specific issues to address under real-world conditions.

5.2.4 Sensor mat

Sensor mat results were obtained only for the rear-door, and were generally strong. Observing rear door boarding and alighting events only was an unavoidable limitation due to installation issues with the front door. While easily addressed in future designs of the mat, it was not possible to fix this during the live trial in Sydney. Future designs will explore reducing the thickness of the mat, and also explore alternative configurations to more easily integrate with wheelchair access ramps.

The greatest impediment to counting accuracy with the Sensor Mat was people standing on the mat while the bus was in motion. This was most prominent when the bus was full, and standing room was limited. In addition to possible algorithm improvements, restricting counting to when the door is open (using, for example, an optical sensor to trigger boarding/alighting events) would largely address this issue. Unusual events such as dogs, prams, shopping trolleys were also observed to effect accuracy.

6 Future directions

6.1 Practical implementation

The ticketing system is not installed on all rail replacement buses, especially in non-metropolitan areas. Four APC technology options are trialled to fill in these gaps and allow operators to better understand customer demand under planned rail disruptions and better bus provision planning. The exact technology option to be implemented is still to be confirmed, but video sensing and infrared sensors are favoured because they have demonstrated a potential to count passengers with good accuracy. Capturing passenger numbers in real time is necessary if customers are to be provided with improved information for journey planning and trip decisions. The sensor mat shows no strength in real-time analysis, as data collected cannot be instantly accessed. The accuracy of video sensing and infrared sensors will be further assessed in real-time.

7 Conclusion

We have presented a methodology for the empirical evaluation of Automatic Passenger Counting (APC) systems for possible deployment on public transport bus services. With focus on four state-of-the-art APC technology options video-based, 3D Infrared, WiFi sensing and a pressure-based Sensor Mat, we have demonstrated how the methodology we proposed can be applied to compare technology options in an authentic, real-world operational context, and inform the future development of each technology option as a deployable APC option. Central to our approach has been the adoption of a two-phased trial methodology, allowing initial piloting to occur in a less formal, exploratory manner, before embarking on an authentic live trial with members of the public. We have shown that while this methodology is resource-intensive, it offers key benefits over more theoretical comparisons, or simulated trials alone. The most prominent is the ability to gain an understanding of the practical requirements of a fully deployed APC system, not only in terms of technology-specific challenges, but also general issues with APC deployment in a given environment. Results for all four technology options established their feasibility under specific conditions, but also highlighted areas in need of improvement. In addition to counting accuracy, each option offers a range of trade-offs associated with cost, ease-of-installation, security and scalability. While not all these issues were addressed in this paper, it is clear that the proposed methodology provides the scope for evaluating all these factors, allowing public transport providers to make informed decisions, appropriate for their context.

Acknowledgments

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