Foundation technology for developing an autonomous Complex Dwell-time Diagnostics (CDD) Tool

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Abstract

As the demand for rail services grows, intense pressure is placed on stations at the centre of rail networks where large crowds of rail passengers alight and board trains during peak periods. The time it takes for this to occur — the dwell-time — can become extended when high numbers of people congest and cross paths. Where a track section is operating at short headways, extended dwell-times can cause delays to scheduled services that can in turn cause a cascade of delays that eventually affect entire networks. Where networks are operating at close to their ceiling capacity, dwell-time management is essential and in most cases requires the introduction of special operating procedures.

This paper details our work towards developing an autonomous Complex Dwell-time Diagnostics (CDD) Tool — a low cost technology, capable of providing information on multiple dwell events in real time. At present, rail operators are not able to access reliable and detailed enough data on train dwell operations and passenger behaviour. This is because much of the necessary data has to be collected manually. The lack of rich data means train crews and platform staff are not empowered to do all they could to potentially stabilise and reduce dwell-times. By better supporting service providers with high quality data analysis, the number of viable train paths can be increased, potentially delaying the need to invest in high cost hard infrastructures such as additional tracks.

The foundation technology needed to create CDD discussed in this paper comprises a 3D image data based autonomous system capable of detecting dwell events during operations and then create business information that can be accessed by service providers in real time during rail operations. Initial tests of the technology have been carried out at Brisbane Central rail station. A discussion of the results to date is provided and their implications for next steps.

1. Introduction

Globally, there has been an increase in the demand for public transport and rail services in recent years and this has become a real concern in major cities (Henn *et al.*, 2011). The emergence of large crowds of rail passengers during peak periods often results in congestion at key rail platforms, disrupting scheduled operations (Gray, 2013; Veitch *et al.,* 2013; Wang and Legaspi, 2012) and leading to extended dwell-times while passengers alight and board that affect train headways creating delays (Carey and Crawford, 2007; Kang *et al.,* 2015; Li *et al.,* 2014). Various aspects of the dwell-time can be managed by influencing passenger behaviour using special operating procedures including announcements, signs, barriers, flags, agents, etc. However, to do this most effectively, service providers require high quality data to target treatments.

While rail operators are highly motivated and keen to treat dwell-time issues, often they do not have access to reliable and comprehensive data on dwell events. Dwell-time realities and complexities make opportunities for manual data collection limited and expensive and in practice, many data forms would be most useful during operations rather than after the fact.

Consequently, there is a need to find new ways of monitoring dwell-times to assist rail operations.

This complexity can be reduced by expressing dwell-time as a set of events — train operations and passenger behaviour events. This breakdown provides clues on the sensing and perception capabilities needed for monitoring behaviour while highlighting the high volume of data points needed, pointing to the potential merits of developing an autonomous dwell-time monitoring system.

This paper explores the development of an autonomous system capable of robustly and reliably detecting dwell events with a preliminary analysis that shows the kind of business information that could be produced by it. This technology will provide the basis for identifying and designing a user/operator interface for assisting operators managing dwell-times in real time including the detection, and ultimately prediction of passenger crowding for the purposes of reducing its impacts on train operations, prediction and potential influence of passenger walking trajectories, detection and reporting of final passenger boardings to assist with train departure. Moreover, an offline analysis on the outputted data should allow service providers to identify some obscure factors that can lead to extended dwell-times, such as the influence of the train station configuration and train arrival velocity on passenger behaviour.

The different points of this paper are presented as follows: Section 2 provides some background on the issues surrounding train dwell-times. Then, Section 3 details our approach for developing an autonomous CDD tool that might help operators addressing some of these issues. An evaluation of the sensing and perception technology needed to do this based on results from on-site testing at Brisbane Central rail station is presented in Section 4. And finally, conclusions, limitations and future work are proposed in Section 5.
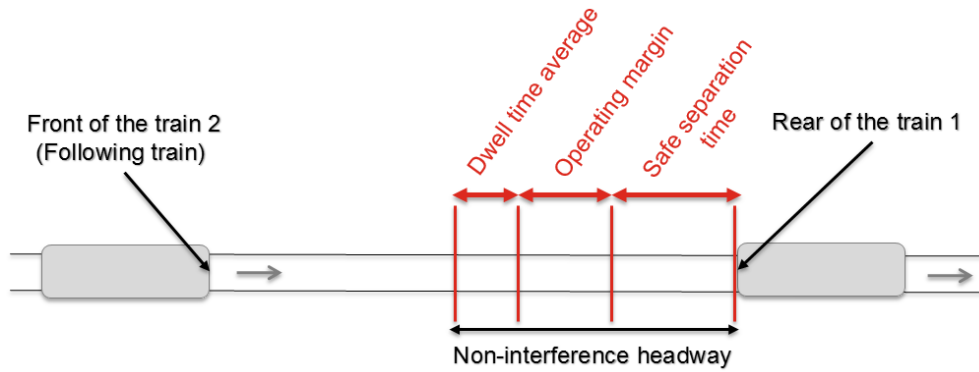
2. Background

The development of an autonomous CDD first requires an overview of the consequences presented by an extended dwell-time as well as the factors that can lead to it. This section discusses the influence of extended dwell-times on headways and some of the dwell events that can lead to increased dwell-times.

2.1 The headway

Rail systems rely on a signalling system to maintain safe distances between trains operating on a given track section during a given time period (Ryus *et al.,* 2013). This minimum distance has to be long enough for the following train to completely stop with a suitable margin at the rear of the train ahead if needed. In practice, irregularities in the first train schedule will create delays for those following.

Delay for following trains are problematic. In order to accommodate these irregularities, a non-interference headway (shown in Fig.1), composed by the dwell-time average plus the operating margin and safe separation, is typically set up. However, a dwell-time exceeding the average plus the operating margin will create a delay for the following train which will potentially corrupt the network schedule causing a cascade of delays for following trains in the same section. Furthermore, the average dwell, by definition, over estimates the actual dwell allowance component of the headway for 50% of all services. This is wasteful and exacerbated by the limited data available on the reasons for dwell-time fluctuations — which are not well understood as a consequence — so that the operating margin is expanded to absorb the variance.

Figure 1: The non-interference headway.

This leads to increased cost and management effort by service providers. However, a detailed knowledge of the dwell composition can assist in identify critical events that lead to extended dwell-times and fluctuations needed to manage them and allow operating and dwell-time average margins to be reduced to allow additional train paths.

2.2 The dwell-time

The dwell-time is the time period a public transport service spends at a station or stop to enable passengers to alight or board (Widanapathiranage et al., 2013). In the case of train services, it is generally expressed as two elements. The first are train operations corresponding to the different states a train can take when stopped at a station, including arriving, stopped with doors opened, doors closed and departing the station. The second comprise passenger events including passenger behaviours on the platform such as waiting, boarding or alighting a train, standing in positions that obstruct other passengers from moving. These two elements are inherently connected and generally high passenger volumes during peak periods leads to congestion that can increase dwell-times. For instance, people waiting to board at the same doors can impede other passengers alighting and subsequently increase the time the doors need to remain open. This situation may be avoided by providing rich information to service providers about dwell events so they can be actively managed.

Opportunities exist for operators if empowered with real time access to this information. However, these data are non trivial, and expensive, to obtain with current approaches that rely heavily on manual intervention. Clearly, an autonomous system for detecting dwell events and outputting the information required for managing dwell-times would be advantageous and of value.
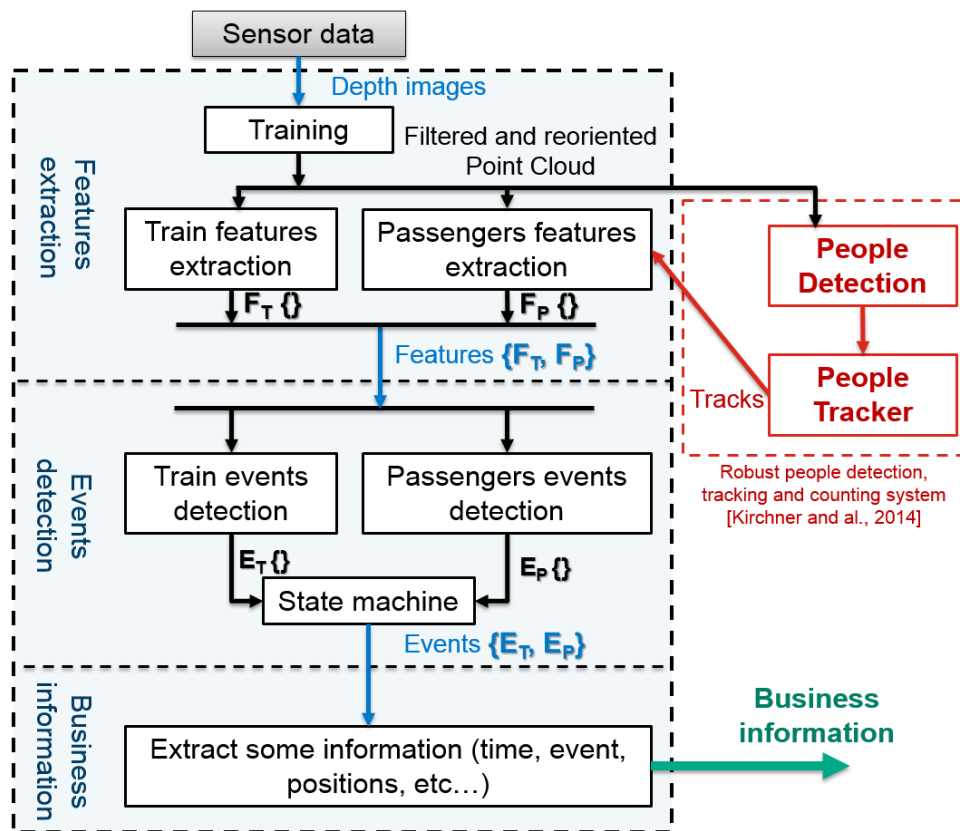
3. Methods

In order to pursue this, an autonomous CDD tool has been devised. This section presents our methods toward developing this autonomous system that builds on previous work using Sensing Hardware Platforms (SHP) for people detection, tracking and counting (Kirchner *et al.,* 2014) through the addition of capabilities for autonomous detection of the dwell events and outputting business information able to serve operator needs.

Figure 2 details the framework of our approach. *Features extraction:* this stage exploits the data directly acquired from the SHPs to detect the platform properties and extract the required features for detection. *Events detection:* this level allows the events detection by using the previously extracted features. *Business information:* this last stage creates the business information to be used by the operator. The stages are detailed in the following sub sections.

3.1 Features extraction

The sensing data frontend is acquired by our SHPs (Kirchner *et al.*, 2014). From this data the CDD needs to detect the different dwell events to extract usable business information. However, these events are not easy to automatically detect from depth image data that does not provide the same modality of information a passenger on the platform could use. Fortunately, some characteristics can be extracted from the data in order to be used later for the detection of different dwell events. These features include information on the platform and tracks geometric position obtained during a calibration phase, train characteristics (for example, window positions and their size) and people movements.
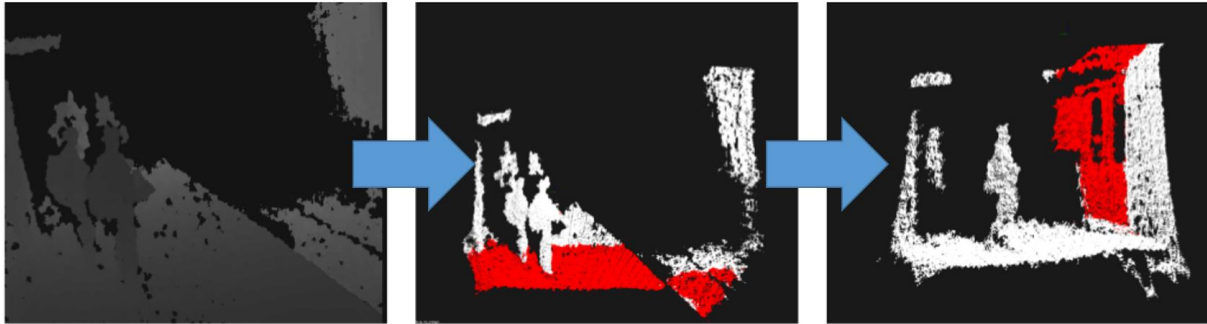
Figure 2: The Autonomous Complex Dwell Time Diagnostics Tool System Overview.

3.1.1 Training

Due to constraints in the train platform environment, the SHPs were installed in different positions within the train station and because it is not feasible to mount them at the exact same position and orientation, it was not feasible to use the same detection process for each installation. However, the depth data produced by the SHPs provide sufficient information to automatically detect the floor orientation, platform edge and tracks (shown in Fig. 3). These features extracted once only during the testing phase have been used to align the scene in the global coordinates enabling the general detection methods that follow.

Figure 3: The training process. The depth image is converted into point cloud. Then the floor of the platform is autonomously identified (in red in the image 2) and the cloud is reoriented to finally find the train surface (in red in the image 3) and by consequent the limit with the tracks.

3.1.1.1 Platform orientation

Knowledge of the platform floor position is important to correct the point cloud orientation and facilitate the subsequent features detection methods. This information is obtained as follows: after converting the depth image into a point cloud, it is filtered — using the voxelGrid method from the Point Cloud Library (PCL) — to reduce the number of points and consequently the computation time. Then the normal is computed for all remaining points in the cloud (using *normalEstimation* from *PCL*). Finally, the points with the most commonly occurring normal, typically associated with the floor surface, are used to determine the linear curve parameters of the floor in the selected frame (using scatter plots and means).

In some cases more than one floor is detected, the floor and the tracks for example. In this the curve parameters are computed re-iteratively using a distance threshold reduction. Finally, the linear parameters are converted in a rotation angle in the corresponding frame.

3.1.1.2 Platform limit

The platform limit with the tracks provides important information on the train position and orientation. But its computation time is too important to be performed in tandem with the detection process. The limit detection works using the same method as explained previously, except this time the point cloud has to be reoriented with the platform horizontally displayed, the floors removed and a train present on the tracks. The most represented normal direction will correspond to that of the train surface. From this information, the limit curve can be computed.

3.1.2 Train features extraction

Train unique features, such as the windows and the size, can be extracted from the depth images to provide important clues for detecting dwell events.
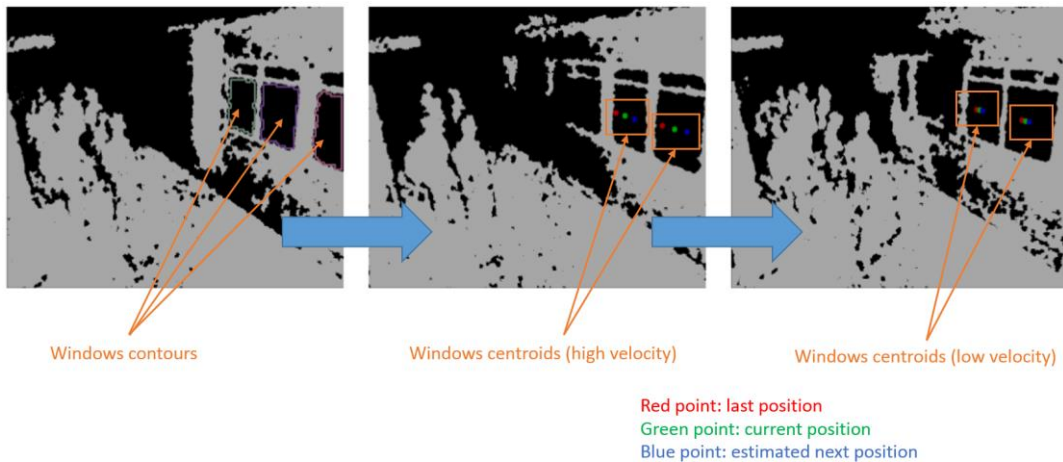
3.1.2.1 Train windows

The multiple train windows detected are exploited to extract information on the trains' velocity, position and states. However, the noise in the data and the people occlusions generally result in a change of the shapes and sizes between two images making detection susceptible to error. This section presents our approach for detecting and recognising the same window between two images taken at two different times to improve general robustness, estimation accuracy and reduction of false detections.

After the preliminary treatment, where the platform is removed and the noise reduced by dilating the image (using *dilate* from *OpenCV),* the contours of the image shapes are detected (using *findContours* from *OpenCV*) and filtered by geometric properties such as size and shape.

The detected contours are used to update a list containing the previously detected windows (shown in Fig. 4) with their last, current and estimated next shape — contour, size and position. A weight associated to each window, increased when a matching shape is found, or decreased when no corresponding shape is found in the current image, partially addresses false detections. Moreover, in the case where the window disappears between observations, the next positions will still be estimated but the trust value will decrease. The platform limit provides an important clue to matching and identifying the same window across two images: window directions follow the platform direction.

Figure 4: Windows detection. Left image shows the windows contours. Centred and right images show the windows centroids positions for images at different time t for two different velocities: t-1 (red), t (green) and t+1 (blue).

Windows contours

Windows centroids (high velocity)

Windows centroids (low velocity)

Red point: last position
Green point: current position
Blue point: estimated next position

3.1.2.2 Train size

The train length and height are retrieved by first creating a 2D-histogram image where each pixel intensity corresponds to the number of points found vertically above each bin from the reoriented point cloud with the floors removed by segmentation. This image is then transformed into a binary image and blob detection (using *simpleBlobDetector* from *OpenCV*) is performed. The blobs are then sorted by size and shape to identify the train, again using geometric a priori knowledge of a train (vertical planar surface). Finally, the train-blobs are used to identify regions in the original point cloud and the train size measures are extracted.

3.1.3 Passengers features extraction

Person recognition and behaviour extraction by a machine is non trivial and the current approaches are limited due to constraints like illumination facial expressions, etc. (Kirchner *et al.,* 2012). However, where most of the studies are based on face-area detection and facial recognition, a new method presents an innovative approach enabling the people recognition by an autonomous system. This method — called Head-to-Shoulders Signature (HSS) — uses the inter-person variation in the size of people's heads, necks and shoulders to achieve robust person recognition. Data from the SHPs is used by the HSS and enables detection of passengers on the platform, tracking their position and outputting usable clues on their behaviours, moving or standing, to detect the passenger events, and later, the train operations. This is illustrated in Fig. 5.

3.2 Dwell events detection

The main function presented by this CDD tool is the autonomous detection of the different events constituting the dwell-time in order to output rich information to service providers. However, these events are various, complex and currently no methods allow their direct

detection using depth images. This section presents a set of new methods using the previous features extracted to detect the main train operations: train appearance, stopping, doors opened, doors closed, departure and finally train disappearance; and passenger events: the passenger flows (boarding and alighting).

A state machine was designed to underpin this, shown in Fig. 6. The state machine represents the current train state during the dwell and limits the false positive detections as the meaning extracted from detections is contingent on past events, the current situation, and feasible 'next' events based on knowledge of the dwell process.

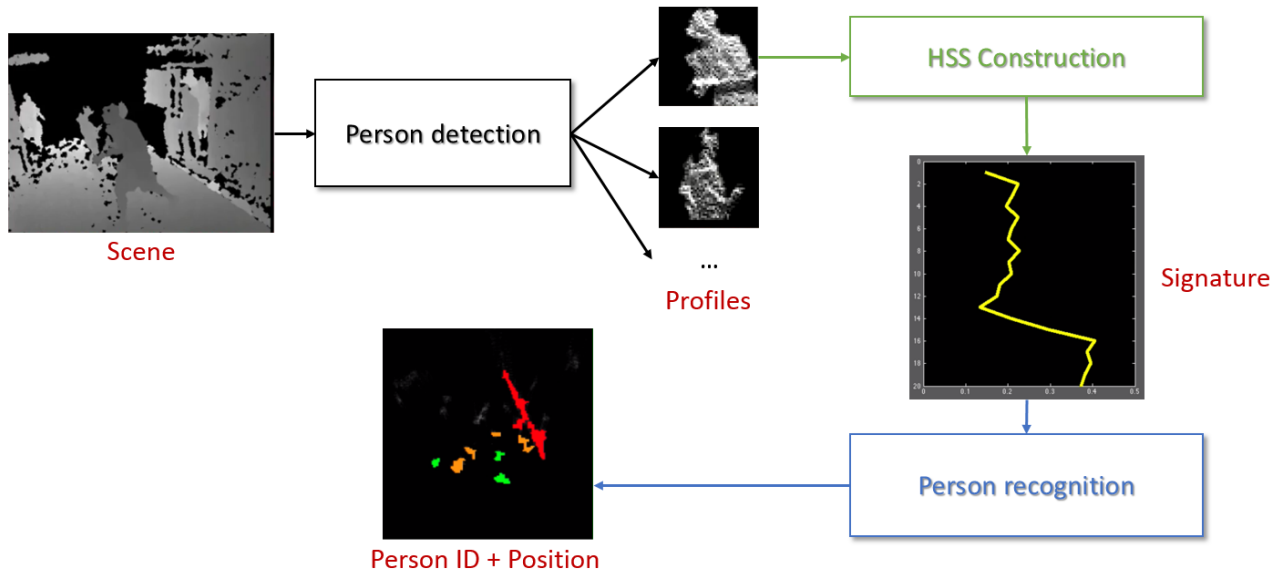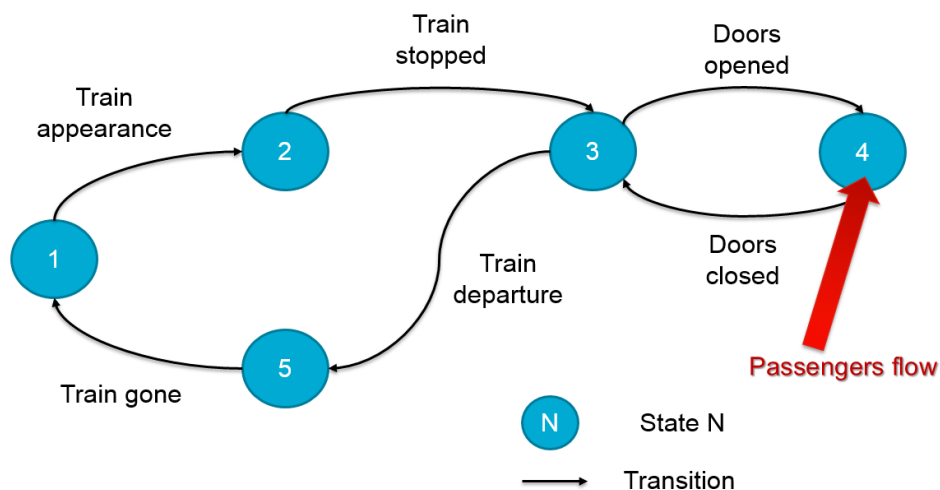**Figure 5: Head-to-Shoulders Signature detection and recognition process.**

Figure 6: State machine representing the different train states during the dwell.

The states: "train is gone, system is waiting for a train to arrive" (1), "train detected, waiting for it to stop" (2), "train is stopped with the doors closed, waiting for the doors to open or the train to leave the station" (3), "train is stopped with doors opened, waiting for the doors to close" (4), "train is leaving the station" (5); and the transitions (outputs of the events detections): "train appearance", "train stopped", "doors opened", "doors closed", "train departure", "train gone". The passenger flow occurs in state 4 but the passengers' behaviours before the doors opened is really important to help detecting the crowd formation and manage it in time.

3.2.1 "Train appearance" detection

Corresponding to the train's first appearance on the depth images, this event can be detected when at least one window, generally the driver's window, and an appropriately sized object — the train — appear on the tracks.

3.2.2 "Train stopped" detection

A train is considered as stopped when its velocity is zero. This event is detected by comparing the windows' weighted last and current positions. The window size also provides information when it becomes stationary on the 2D-histogram image.

3.2.3 "Doors opened" detection

Doors are detected as opened when they are detected as starting to open on the 2D-histogram image. Significantly people generally begin to alight from the train before the doors are fully opened. This detection is carried out by computing the distances between the train windows: the distance between windows set within the doors and their neighbours (in the direction of the door window opening) will decrease when the distance between the doors increases, creating a hole.

3.2.4 "Doors closed" detection

Doors are closed when they return to their original state. This detection is achieved by comparing the current window positions on the 2D-histogram image with their original ones saved before the doors started opening.

3.2.5 "Train departure" detection

A train is considered to have departed when the train starts moving to leave the station. Its velocity is greater than zero as determined by all train windows being observed to move in the same direction along the platform edge. Moreover, the return size of the vehicle in the 2D-histogram image changes.

3.2.6 "Train gone" detection

If no windows and no object with train dimensions are detected on the tracks, the train is considered as not present.

3.2.7 "Passenger flow" detection

The passenger features allow the detection and tracking of people along the platform by identifying the person positions associated with a unique HSS signature. When coupled with the train operations, it is possible to determine the passenger behaviours including waiting, boarding or alighting from the train. For example, a passenger moving towards the platform edge when a train is not there and remains relatively stationary is considered as waiting.

3.3 The business information

Service providers need to access rail operations data in real time. This information has to be rich enough to enable real-time management of dwell events and preventing eventual

extended dwell-times. The CDD tool is being developed to output relevant data based on the dwell events detected.

By interrogating the various dwell event detections outputted during a given time period, operators can have direct access to information on train operations — for each train, the different states, time of appearance and door positions, the passenger numbers and positions during the dwell-time and the train position. Furthermore, these data provide high quality information on the main components that can cause an extended dwell-time — the time doors stay opened, the time between the doors closing and the train departing, the presence of people in front of doors that might obstruct other passengers alighting, the time taken by passengers to alight and board the train and the time after passenger flows have ceased (Ryus *et al.,* 2013).

The data obtained by such a system can be used to make informed evidence-based decisions for public transport operators. For example, by predicting people positions and paths during the dwell-time, service providers can anticipate where congestion might occur and make a decision on the most effective way to manage it, such as an announcement requesting people to move back from the train doors to let passengers alight from the train more easily and quickly. Other difficulties might be confined to one particular section of the train and so an action that targets that area specifically might be most effective.

4. Results

The CDD system was tested at Brisbane Central rail station to explore the feasibility of autonomously detecting the different dwell events over an extended period and outputting relevant information for operators. This section presents an evaluation of the detection methods used to monitor the set of 10 trains that stopped at the platform during the 50 minutes captured by our SHP (shown in Fig. 7) and an example of business information generated for a train.

Figure 7: Picture of a 3D-RGBD sensor placed on a platform at Brisbane Central rail station.

4.1 Evaluation of the detection methods

The data captured by the SHPs was used to evaluate our methods described above in a selective fashion. Namely, an evaluation of the core autonomous detection of the dwell operations was conducted on the data without employing the state machine. This was done to give an indication of the worst case performance with the assumption that the state machine relationships built on the dwell a priori would alleviate false detections.

Table 1 presents the results of this evaluation. The columns correspond to the known dwell process state — which are also mirrored in the state machine. The rows of the table indicate detection rates of each of the detection methods for the 10 trains observed during the study.

The detection performance, found by comparing autonomously detected dwell event instances with a manually coded ground truth of when selected dwell events should occur, are indicated by cell shading. Cells are shaded green in the table when the system reported detected events — or a lack thereof — and manual coding agreed. Orange shaded cells indicate instances where our system detected events and manual coding disagreed with what they should have been, noting that in several instances these rates are low. Finally, the number within the cell refers to the detection rate; for instance, a detection rate of 90% indicates that our system detected 90% of events of that kind in the data. Problematic detection rates (both false positives and false negatives) are highlighted with orange text.

As previously mentioned, the state machine was not employed during this evaluation — if it had been the overall detection rate would improve and the rate of false detections would have declined. For instance, the cases of detection of the doors opening while the train is still moving would be discarded if the state machine layer as a priori information where incorporated as this is not likely. Similarly, a priori knowledge precludes a train from shifting directly from 'Doors opening' to 'Train gone' without the intermediate steps having been observed. This again would see the state machine drive an improvement in overall performance. These results clearly show that automatic core dwell event detection is feasible. Furthermore, these results highlight the value of encapsulating a priori knowledge of the dwell event sequence as captured by the state machine.

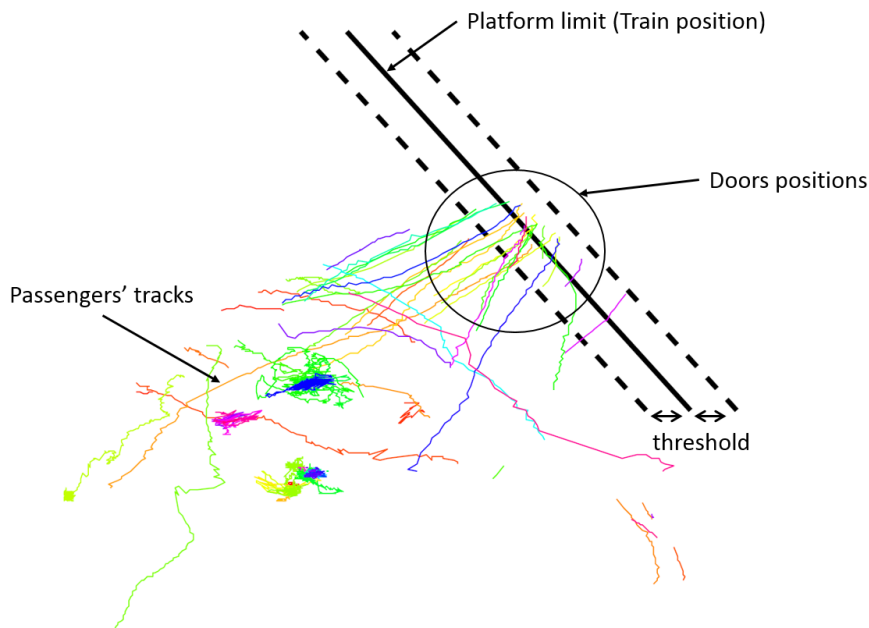**Table 1: Detection rate of our system Vs manually coded ground truth of dwell events (%)**

		No Train	Appeared	Moving (Arriving)	Stopped	Door Opened	Passenger Flow	Doors Closed	Stopped	Moving (Departure)
System Detected Dwell Event	Appearance	0	100	100	100	100	100	100	100	100
	Stopped	0	0	0	90	70	100	30	80	0
	Doors Opened	0	0	90	20	40	90	10	30	80
	Departure	0	0	100	20	50	90	40	50	100
	Gone	90	0	0	0	0	0	0	0	0

4.2 Business information example

To demonstrate the potential of outputting relevant information, these dwell event detection outputs were automatically collected in a file to demonstrate what the potential analysis of a dwell-time sequence might look like. In this case, passenger flow while the train is present

and the doors are open. A representation of the passenger positions during the dwell-time of a train service knowing the train and door positions was created. This information, presented in Fig.8, can be accessed during the dwell-time to provide operationally useful data such as the number of people currently on the platform. This provides valuable insights to operators in a form suitable for engagement. For instance, this data raises the questions *why were people lingering in front of the doors but not boarding the train?* Or a more operations focused version of this question is *what can be done to discourage this behaviour now that we know how prevalent it is?* Moreover, the train operations parameters, such as doors opened or closed, and the passenger positions during this time period can provide, for example, the time doors stayed opened after the last passenger alighted or boarded.

Figure 8: Passengers movements (as detected and recorded by our SHPs) on the platform during an entire train dwell time: the coloured curves corresponding to the passengers' tracks.

5. Conclusions and future work

The results presented in this paper confirm our contention that the dwell-time, expressed as a set of train and passenger events, can be automatically detected using our previously developed SHP, placed on a train station platform, by extracting some features and performing detection methods such as those described here. The data acquired during the detections allow a rich array of information enabling service providers to manage dwell-time more effectively.

The findings provide evidence for the feasibility of developing, and motivation to pursue further developments of, an autonomous CDD tool that will deliver valuable and operationalized information to operators in the form of business information.

The work presented here is not without limitations. The limitations are primarily related to features extraction errors. Noise in the SHP data affects the robustness of doors detection, and this needs to be addressed. Additionally, the pivotal role the state machine plays was highlighted and in such concern arouse. Specifically, it became evident that formation of the dwell a priori into a state machine directly interplays with the interpretation of detections as being false. Furthermore, attention was drawn to the issue of the system recovering from an

incorrect state transition. Future work will focus on further investigation on the multi-sensor detection, optimal sensor positioning and deeper exploration of the dwell organisation in order to create more robust detection methods and increase the reliability of the CDD tool for service providers.

Acknowledgment

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