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Foundation Technology for Development of an Autonomous Complex Dwell Time Diagnostics 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 crowds 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 at 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 tool, a low cost technology, capable of providing information on dwell events in real time. At present, operators are not able to access reliable and detailed 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 comprises a 3D image data based autonomous system capable of detecting dwell events during operations and creating business information that can be accessed by service providers in real time during rail operations. The technology has been tested at Brisbane Central rail station and results are presented in tandem with an analysis of QR dwell time operating procedures to identify and show how a user interface can be developed to assist operators with both long term operating procedure development and real-time operations.

1. Introduction

The increase of the demand for rail services has become a real concern in major cities [Henn et al., 2011]. The appearance of large crowds of rail passengers during the dwell period generally results in a congestion phenomenon destabilizing the proper functioning of the dwell operations [[Gray, 2013], [Veitch et al., 2013] and [Wang and Legaspi, 2012]] and leading to an extended dwell time which will affect the headway, and consequently imply many trains delayed [[Carey and Crawford, 2007], [Kang et al., 2015] and [Li et al., 2014]]. Various aspects of dwell can be managed by influencing the passengers' behaviours using special operating procedures: signs, barriers, flags, agents, etc. However, prior to service providers require high quality data to target treatments to stabilise or reduce the dwell time.

Even though operators are sufficiently motivated to treat dwell time issues, this is problematic. At present operators do not have to access to reliable, detailed or comprehensive enough data on the dwell events to properly manage them. The dwell time realities and complexities makes data collection, usually manual, limited and expensive in terms of time, money and efforts. This complexity can be reduced by expressing the dwell as a set of events: train operations and passengers' events. But a new way monitoring the dwell is still required. This clear breakdown provides clues on the sensing and perception capabilities required in such a monitoring approach, but also highlight the high volume or frequent data points to be captured, suggesting a considerable manual labour expenditure or perhaps motivating an autonomous system.

This paper explores the development of an autonomous system capable of robust and reliable detections of dwell events with an on-board preliminary analysis enabling outputting business information. This technology will provide the basis for identifying and designing a user/operator interface for assisting operators managing the dwell in real time.

The different points of this paper are presented as follow: section 2 provides a background by analysing the main problem presented by the extended dwell time. Then, section 3 details our approach developing an autonomous dwell time diagnostics tool helping fixing it. An evaluation of this experimental system, at Brisbane Central rail station, is presented in section 4. And finally, conclusions, limitations and future work are proposed in section 5.

2. Background

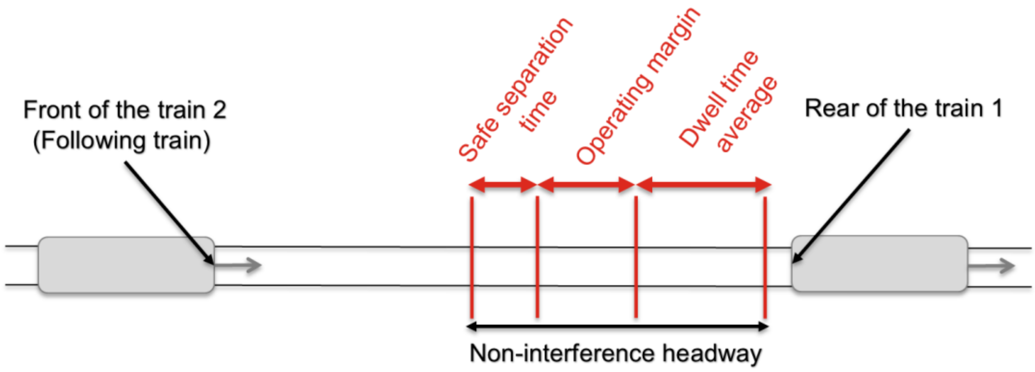
The development of an autonomous tool capable of outputting sufficient information to service providers first requires an understanding of the consequences presented by an extended dwell time, as well as the factors that can lead to such a phenomenon. This section presents on the one hand the influence of the extended dwell time on the headway, and on the other the main reasons leading to an increase of the dwell events occurrence time.

2.1 The headway

Rail systems rely on a signal system to maintain a safe separation between trains operating along a section of line for a period of time [Ryus et al., 2013]. This minimum distance has to be long enough for the following train to completely stop with a suitable margin with the rear of the train ahead if needed. In such, irregularities in the first train schedule will result on a delay for the following one.

This delay for the following train is 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 the safe separation, is typically set up. However, a dwell time exceeding the average plus the operating margin will create a first delay for the following train which will corrupt the network causing a cascade of delays for the other ones 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 unquestionably wasteful and is further exacerbated as with limited data the fluctuations in the dwell are not well understood and the operating margin is expanded to absorb this variance.

Figure 1: The non-interference headway.



This leads to increased cost and management effort by the service providers. However, rich knowledge of the dwell composition is required to identify the critical events which generally lead to an extended dwell time or dwell time fluctuations in order to manage them and allow operating and dwell time average margins to be reduced – allowing additional train paths.

2.2 The dwell time

"*The dwell time is the time that a transit vehicle spends at a station or stop while passengers board or alight*", [Widanapathiranage et al., 2013].

The dwell is generally expressed as two elements. The train operations corresponding to the different states a train can take during the dwell time: arriving, stopped with the doors opened, the doors closed, or leaving the station; and the passengers' events representing people behaviours on the platform: waiting, boarding or alighting a train. These two elements are inherently connected and generally high passengers' volume during peak time leads to a congestion phenomenon increasing dwell. For instance, people waiting to board at the same doors impede the alighting of the other passengers and subsequently increase the time the doors remain open. This situation may be avoided by providing rich information to the service providers about the different dwell events so that they can be actively managed.

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

3. Methods

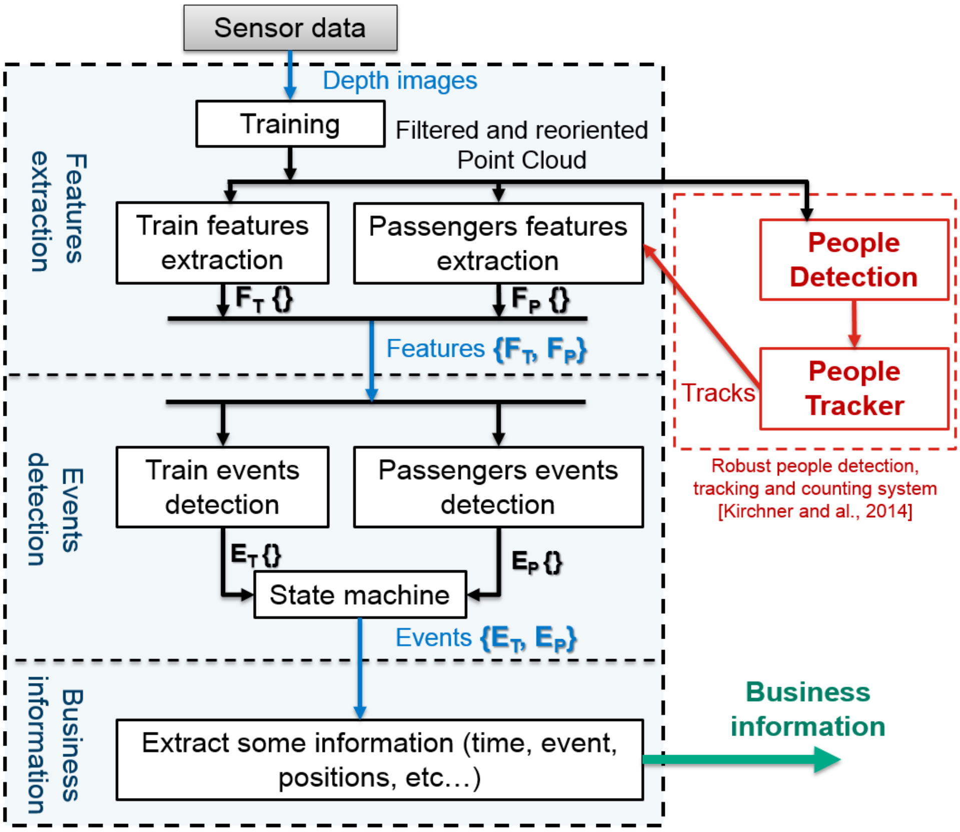
In order to pursue this, an Autonomous Complex Dwell Time Diagnostics Tool was devised. This section presents our methods towards developing this autonomous system which built on our previous work "Sensing Hardware Platforms (SHP) for robust people detection, tracking and counting" [Kirchner et al., 2014] through the addition of capabilities for autonomous detection of the dwell events and outputting the aforementioned operator need driven business information.

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 the detection. *Events detection:* this level allows the events detection by using the previously extracted features. *Business information:* this last stage contributes to create the business information usable by the operator. The stages are detailed in the following sub sections.

3.1 Features extraction

The sensing data frontend is acquired by our aforementioned SHPs [Kirchner et al., 2014]. From this data the autonomous system needs to detect the different dwell events to extract usable business information. However, these events are not easy to automatically detect on data such as depth image; which 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 the different events. These features include: information on the platform and tracks geometric position obtained during a calibration phase, train characteristics (windows, size) and people movements.

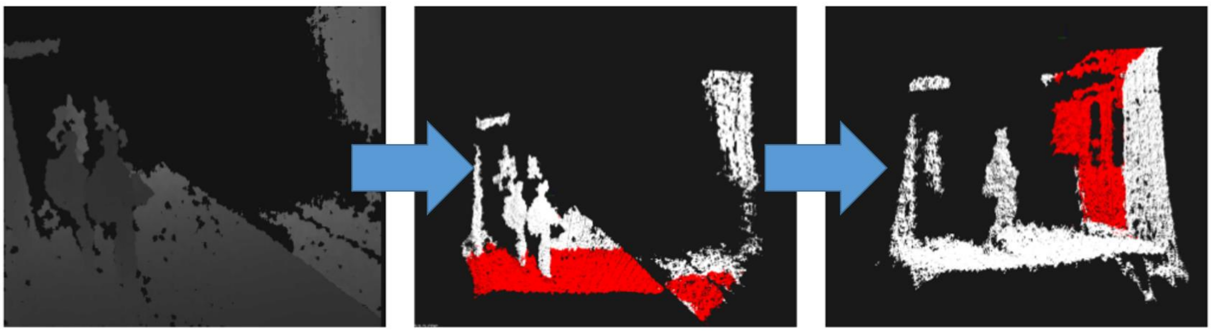
Figure 2: The Autonomous Complex Dwell Time Diagnostics Tool System Overview.



3.1.1 Training

Due to environment constraints, the SHPs are set up in different positions and situations in the train station. It not feasible to mount them at exact same position and orientation, consequently nor is it feasible to use the same detection process for each installation. However, the depth data produced by the SHPs provides sufficient information to automatically detect the floor orientation and platform edge and tracks (shown in Fig. 3). These features, extracted once only during the training phase, are used to align scene in the global coordinates enabling the general detection methods which 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) and the cloud is reoriented to finally find the train surface (in red) 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 feature detection methods. This information is obtained as follows. Having 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 are computed for all staying 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, means and voting points).

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 will provide 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 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 the train surface one. 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 and provide important clues for the dwell events detections.

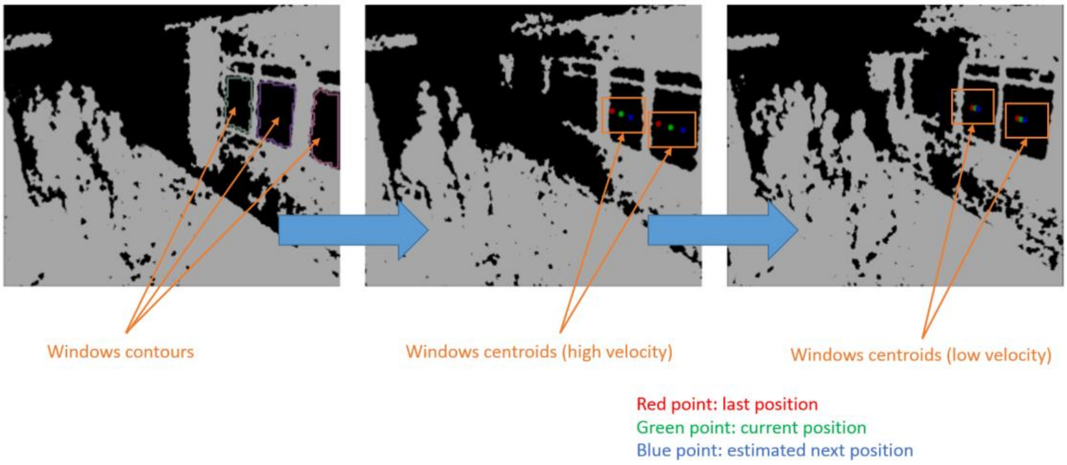
3.1.2.1 Train windows

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

After the aforementioned 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 match a same window with two images: windows directions follow the platform one.

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



3.1.2.2 Train size

The train length and the height is retrieved by first creating a 2D-histogram image where each pixel intensity corresponds to the number of points found on 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 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 extract.

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 the 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 the people's head, neck and shoulders to achieve robust person recognition [7]. The SHPs data 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 passengers' events, and later, the train operations. This is illustrated in Fig. 5.

3.2 Dwell events detection

The main function presented by this Autonomous Complex Dwell Time Diagnostics 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: the train appearance, stopped, doors opening, doors closed, departure and finally disappearance; and passengers' events: the passengers flow (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 in such 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.

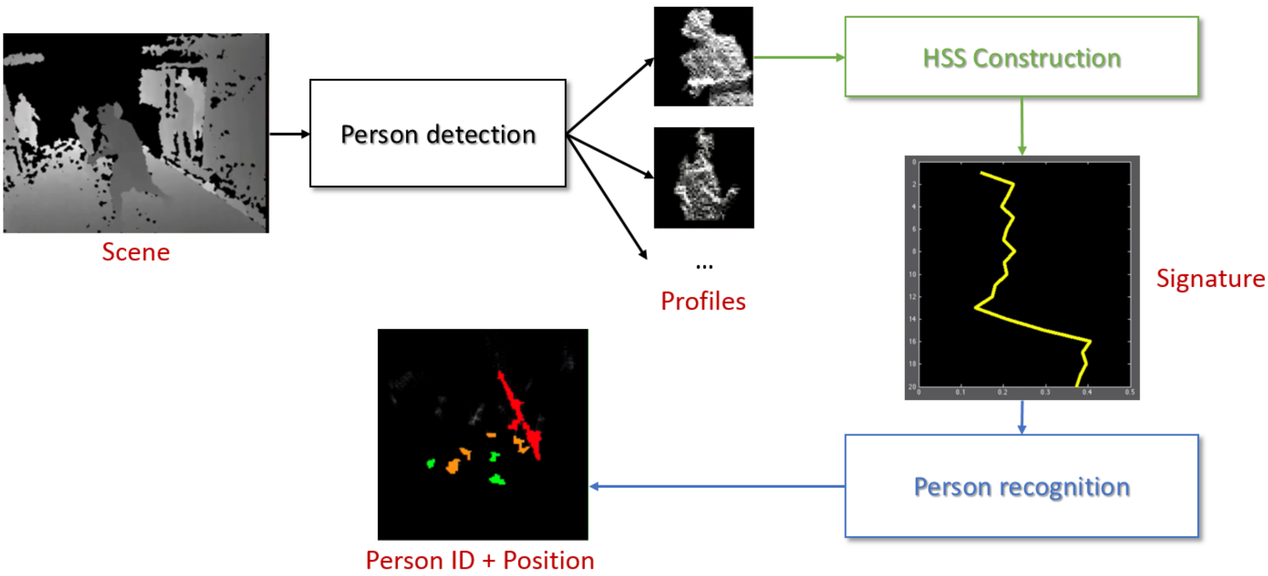
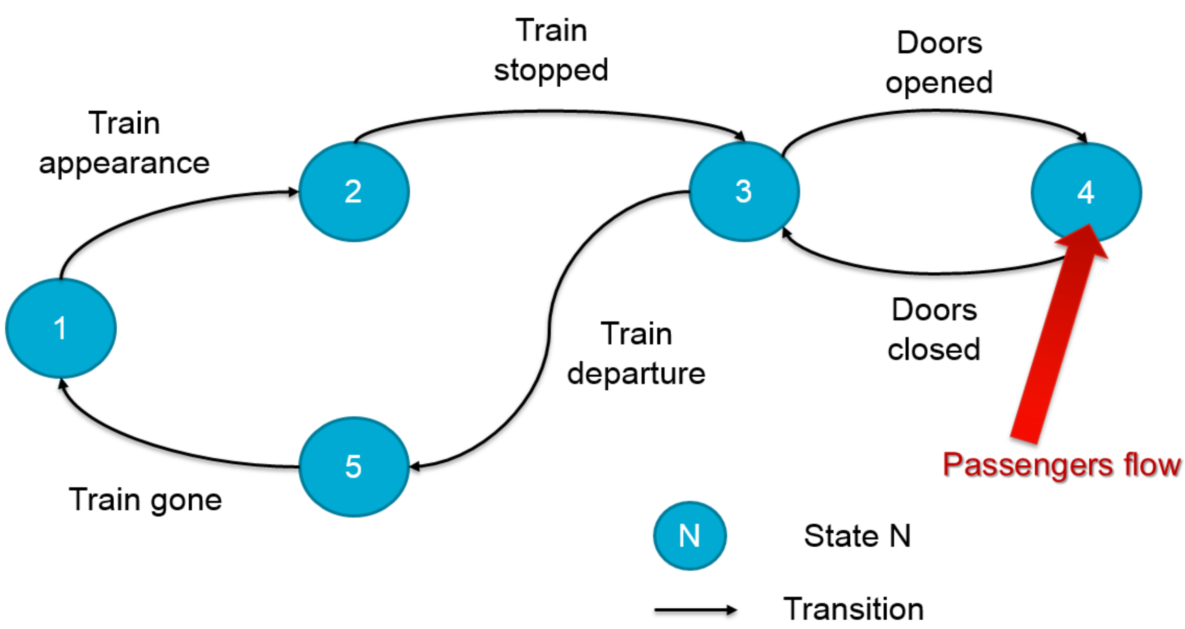


Figure 6: State machine representing the different train states during the dwell. The states: "train is gone, system is waiting for a train to arrive" (1), "train detected, waiting for it to stop" (2), "train is stopped with the doors closed, waiting for the doors to open or the train to leave the station" (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 passengers 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 first appearance on the depth images, this event can be detected when at least one window, generally the driver one, and an appropriately sized object appear on the tracks (the train).

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 station on the 2D-histogram image.

3.2.3 “Doors opened” detection

Doors are detected as opened when they are detected to start opening on the 2D-histogram image: people are generally leaving the train before the doors are fully opened. This detection is realised by computing the distances between the train windows: the distance between the doors windows and their neighbours (in the direction of the door window opening) will decrease when the distance between the doors will increase, 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 windows positions on the 2D-histogram image with their original ones saved before the doors stated opening.

3.2.5 “Train departure” detection

A train is considered in departure when the train starts moving to leave the station i.e. its velocity is greater than zero as determined by all train windows being observed to moving 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 the train dimensions are detected on the tracks, the train is supposed to be gone.

3.2.7 “Passengers flow” detection

The passengers’ features allow the detection and tracking of people all along the platform by providing the person position associated with a unique ID. When coupled with the train operations, it is possible to determine the passengers’ behaviours: waiting, boarding or alighting the train. For example, a passenger moving forward the platform limit when the train is not here is considered as waiting.

3.3 The business information

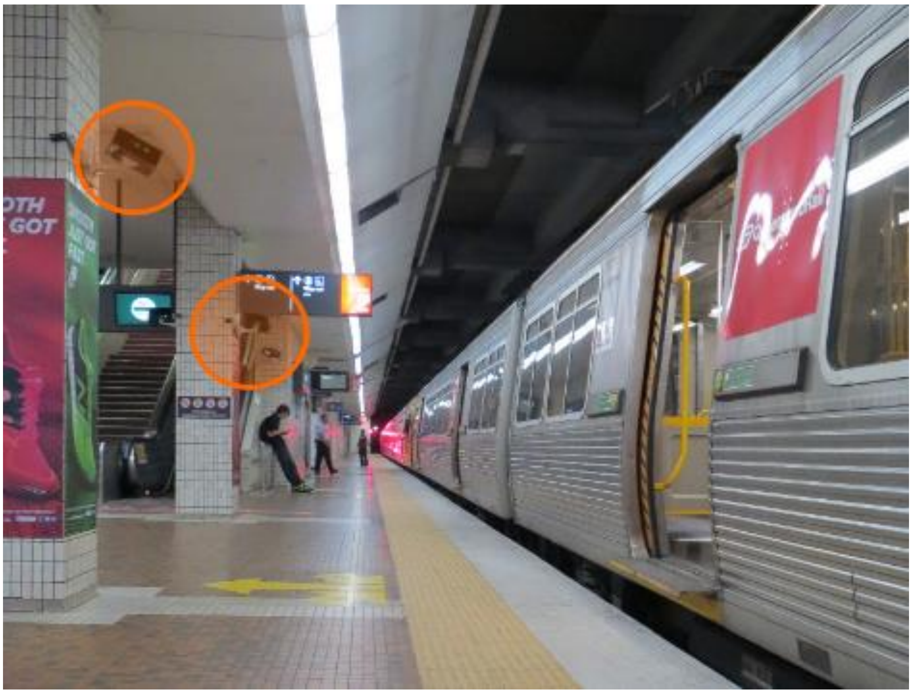
Service providers need to access rail operations data in real time. This information has to be rich enough to enable managing and preventing eventual extended dwell events leading to an increase of the dwell time. The Autonomous Complex Dwell Time Diagnostics System was designed to output relevant data based on the dwell events detections.

By interrogating the various dwell event detections outputted during a period of time, operators can have a direct access to information on train operations: for each train, the different states, time of appearance and doors positions; the passengers' data: unique IDs and position during time; and the train position: the limit between the tracks and the platform. Furthermore, these data provide high quality information on the main components generally leading to an extended dwell time: the time doors stay opened, the time between the doors closed and the train departure, the time the doors stay opened after the passengers flow stopped, the time for the passengers to board and alight the train, and the presence of a crowd front of the doors [Ryus et al., 2013].

4. Results

The Autonomous Complex Dwell Time Diagnostics system was tested at Brisbane Central rail station to explore the feasibility of autonomously detecting the different dwell events on an extended period and outputting relevant information for operators. This section presents an evaluation of the methods detection for the set of 10 trains which transited on 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 our SHP was used to evaluate our methods described above in a piecemeal fashion. Namely, an evaluation of the core autonomous detection of the dwell operations was conducted on the data without employing the aforementioned state machine. This was done to give an indication of the worse case performance with the assumption that the state machine relationships built on the dwell a priori would alleviant 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 dwell event should occur, in indicated by cell shading. Cells are shaded green in the table when our system reported detected events, or a lack thereof, and manual coding agreed. Orange shaded cells indicate instance where our system detected events and manual coding disagreed that they should have been – note, 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 event occurrence in the data. Problematic detection rates (both false positives and false negatives) are highlighted in orange text.

As previously mentioned, the state machine was not employed during this evaluation – if it had of been the overall detection rate would improve, so too would have the false detections. For instance, the instances of detection of the doors opening whilst the train is still moving would be discarded by the state machine layer as a priori information dictates that this not likely. Similarly, a priori knowledge precludes a train from stepping 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 performace. These results clearly show that automatic core dwell event detection is feasible. Furthermore, these results highlight the value of encapsulating a priori of the dwell process within a state machine.

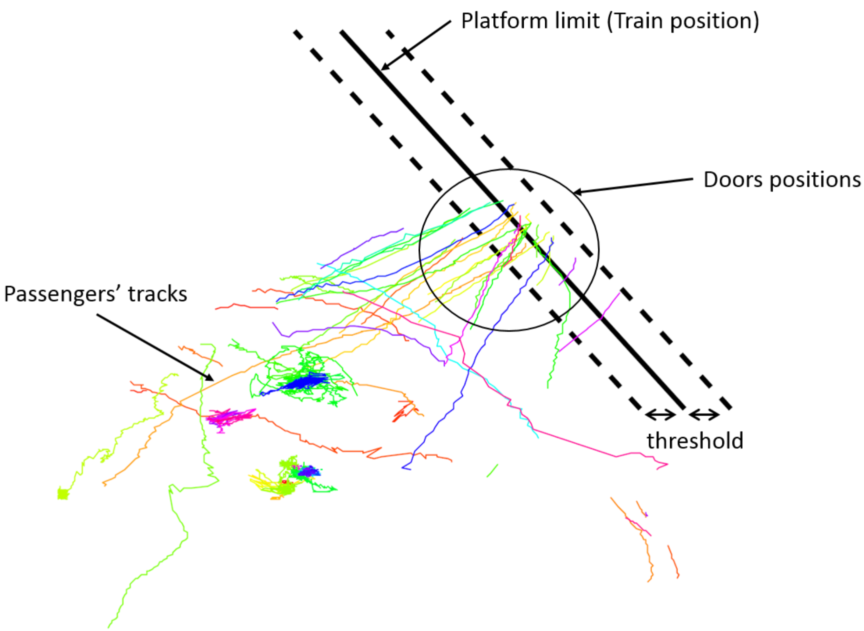
Table 1: Detection rate of our system Vs manually coded ground truth of dwell events (%)

		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 detections outputs were automatically collected in a file and a demonstrate of a potential analysis of a dwell time component conducted. In this case, passenger flow while the train is present and the doors are ajar. A representation of the passengers’ positions during the dwell of a train knowing the train and the doors positions was created. This information, presented in Fig.8, can be accessed during the dwell and provides operationalisable data such as the number of person 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 perhaps more operations focused version of this question is ‘what should be do to discourage this now that we know how prevalent it is?’. Moreover, the train operations parameters, such as the doors opened or closed, and the passengers' positions during this period of time 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 by this paper confirm our hypothesis that the Dwell, expressed as a set of train and passengers' 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 within. The data acquired during the detections allowing to outputting rich information enabling service providers to manage dwell time at a higher fidelity. Moreover, the analysis of the dwell time operating procedures gave insights to create an operator suitable interface for providing dwell information in real time: such as the train and doors position and the number of passengers on the platform.

The findings here within provide evidence for the feasibility of developing, and motivation to pursue further developments of, an Autonomous Complex Dwell Time Diagnostics Tool that will deliver valuable and operationalisable information to operators in the form of business information.

The work presented here is not without limitations. The limitations are primarily related to the features extraction errors. Noise in the SHP data effects the robustness of the 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 draw to the issue of the system recovering from an incorrect state transition. Future work will focus on further investigation on the multi-sensors detection, optimal sensor positioning, a deeper exploration of the dwell organisation in order to create more robust detection methods and increase the reliability of the Autonomous Complex Dwell Time Diagnostics Tool by service providers.

Acknowledgment

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References

[Carey and Crawford, 2007] Carey, M. and Crawford, I. (2007). Scheduling trains on a network of busy complex stations. *Transportation Research Part B: Methodological*, 41(2):159-178.

[Gray, 2013] Gray, J. (2013). Rail simulation and the analysis of capacity metrics. In *Australasian Transport Research Forum (ATRF), 36th, 2013, Brisbane, Queensland, Australia.*

[Henn et al., 2011] Henn, L., Douglas, N., and Sloan, K. (2011). Surveying Sydney rail commuters' willingness to change travel time. *Paper presented at the 33rdAustralasian Transport Research Forum, Adelaide, Australia.*

[Kang et al., 2015] Kang, L., Wu, J., Sun, H., Zhu, X., and Wang, B. (2015). A practical model for last train rescheduling with train delay in urban railway transit networks. *Omega*, 50:29-42.

[Kirchner, 2015] Kirchner, N. (2015). PCT Patent 2015900381 - Devices, frameworks and methodologies configured to enable automated monitoring and analysis of dwell time.
[Kirchner et al., 2014] Kirchner, N., Alempijevic, A., Dai, X., Plöger, P., and Venkat, R. (2014). A robust people detection, tracking, and counting system. In *IEEE International Conference on Robotics and Automation.*

[Kirchner et al., 2012] Kirchner, N., Alempijevic, A., and Virgona, A. (2012). Head-to-shoulder signature for person recognition. In *Robotics and Automation (ICRA), 2012 IEEE International Conference on*, pages 1226-1231. IEEE.

[Kirchner, 2012a] Kirchner, N. (2012a). PCT Patent 2014000086 - Crowd influencing system.

[Kirchner, 2012b] Kirchner, N. (2012b). PCT Patent 2014000087 - Transport passenger guidance system.

[Li et al., 2014] Li, D.-J., Goverde, R. M., Daamen, W., and He, H. (2014). Train dwell time distributions at short stop stations. In *Intelligent Transportation Systems (ITSC), 2014 IEEE 17th International Conference on*, pages 2410-2415. IEEE.
[Ryus et al., 2013] Ryus, P., Danaher, A., Walker, M., Nichols, F., Carter, W., Ellis, E., Cherrington, L., and Bruzzone, A. (2013). Transit capacity and quality of service manual, chapter 8. *Transportation Research Board, Washington DC., Rep. TCRP Report*, 165.

[Veitch et al., 2013] Veitch, T., Partridge, J., and Walker, L. (2013). Estimating the costs of over-crowding on Melbourne's rail system. In *Australasian Transport Research Forum (ATRF), 36th, 2013, Brisbane, Queensland, Australia.*

[Wang and Legaspi, 2012] Wang, B. and Legaspi, J. (2012). Developing a train crowding economic costing model and estimating passenger crowding cost of Sydney cityrail network.

Submitted for presentation at the 2012 Australasian Transport Research Forum, Perth, Australia.

[Widanapathiranage et al., 2013] Widanapathiranage, R., Bunker, J. M., and Bhaskar, A. (2013). Modelling busway station dwell time using smart cards. In *Australasian Transport Research Forum 2013 Proceedings*. Australasian Transport Research Forum.