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Can movement types provide better insights than DCA (Definitions for Classifying Accidents) codes for crashes involving pedestrians?

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Abstract

Police-reported crash data is widely used to understand the characteristics and factors of pedestrian-involved crashes. Among various factors considered in existing studies, crash type is one of the key factors used to understand how the movement trajectories of crash-involved road users influence crash occurrence and injury severity levels. The DCA (Definitions for Classifying Accidents) data field is often used to classify crashes into different types. While the DCA codes provide some details of vehicle and pedestrian movements during a crash, the majority of the DCA codes include information about the trajectories of crash-involved vehicles only and there is only a limited number of DCA codes available which are specific to pedestrian-involved crashes. As such, this paper investigates the use of movement trajectory information, as an alternative to the DCA codes, for better understanding the characteristics of pedestrian-involved crashes. Results obtained from a case study of pedestrian crashes in Metro Melbourne during January 2010 - June 2019 showed that more in-depth insights could be obtained by using the data about movement types of pedestrians and vehicles than using DCA codes alone. These movement types can be used in isolation for pedestrians and vehicles, as well as by combining the categories of both types of road users for greater insights.

1. Introduction

To analyse the safety of pedestrians at intersections and to understand trends and causes of crashes, police-reported crash data from various jurisdictions are often used by researchers and practitioners. The police-reported datasets typically contain information about crashes, crash locations, crash situations (e.g., date, time, road and atmospheric conditions, crash type), person and vehicles involved in crashes, etc. To examine the factors of crash occurrence and crash outcomes, such as injury severity levels, many studies around the world have modelled crash counts (e.g., Ye et al., 2009) and crash outcomes (e.g., Kim et al., 2008, Kim et al., 2010, Mohamed et al., 2013, Moudon et al., 2011, Chung, 2018, Kim et al., 2017, Samerei et al., 2021). These studies showed that the likelihood of crash occurrence and injury severity levels vary by types of crashes, i.e., how pedestrians and vehicles interact during a crash event. For example, crashes occur if there are conflicts between crossing pedestrians and turning vehicles (Ye et al., 2009). More severe crashes occur when pedestrians are crossing a carriageway (Senserrick et al., 2014, Samerei et al., 2021) and the risk of severe injury or fatality increases by four times when pedestrians are crossing at unsignalised intersections (Moudon et al., 2011).

On the other hand, crash severity is lower when the conflict is with a reversing vehicle (Mohamed et al., 2013), as the speed of the reversing vehicles are considerably low.

While many studies have examined the relationships between crash types and pedestrian crashes (likelihood and injury severity levels), limited attention was given to understanding if pedestrian-vehicle trajectories (i.e., detailed description of movement types) can provide better insights about these relationships. The crash types in Australia are typically defined by a crash classification scheme, known as the Definitions for Classifying Accidents (DCA), which uses collision diagrams to classify crashes into different types and DCA codes (Andreassen, 1994). Australian jurisdictions have adopted the DCA codes to establish codes suitable for individual jurisdictions.

While the DCA codes provide some details about vehicle and pedestrian movements during a crash, the majority of the DCA codes include information about the trajectories of crash-involved vehicles only. A limited number of codes are specific to pedestrian-involved crashes (e.g., 10 codes in the DCA chart used in Victoria are specifically related to pedestrians). This small number of codes indicates that the DCA codes may not provide in-depth information for all pedestrian-involved crashes. For example, each crash is designated with a single DCA code that specifies the trajectories of two road users (e.g., a pedestrian and a vehicle in a pedestrian-vehicle crash). For crashes involving multiple pedestrians or vehicles, a single DCA code is unlikely to accurately represent the crash situations where the crash-involved vehicles and road users have more than two types of trajectories. Moreover, for crashes involving a vehicle and a pedestrian, the DCA codes do not necessarily provide details about the movement trajectories of pedestrians. As such, it is important to understand if other data fields in the police-reported crash datasets, as an alternative to DCA codes, could provide additional insights about pedestrian-involved crashes.

To address this important gap in the literature, this paper aims to investigate the use of movement trajectory information in better understanding the factors of pedestrian-involved crashes. This investigation was done using a case study of pedestrian-involved crashes in Victoria.

2. Data and Method

This research was conducted in the state of Victoria, Australia, using police-reported crash data obtained from Victoria's interactive crash statistics application CrashStats. The dataset contains information on the location and time of a crash, characteristics of road users and vehicles involved in a crash, weather and environmental conditions, and roadway characteristics. It is worthy to note that the crash database is validated with TAC (Transport Accident Commission) data regarding injury severity. The dataset was filtered to obtain crashes that occurred during January 2010 - June 2019 at road intersections in the Metropolitan Melbourne area. The intersection crashes refer to the crashes occurring within 10 meters of the intersection. Given the focus of the current study, crashes involving at least one pedestrian were considered. No filters were applied for the other parties involved in these crashes.

A total of 5,241 crashes met these study criteria which involved 5,601 pedestrians. Out of these crashes, 4937 crashes involved a single pedestrian, 265 crashes involved 2 pedestrians, 37 crashes involved 3-5 pedestrians, and 2 crashes involved more than 5 pedestrians. A total of 5529 vehicles were involved in these selected crashes, which includes 5380 motor vehicles (light and heavy vehicles), 75 motorcycles and 74 bicycles.

The crash dataset has a DCA code applied for each crash using the available DCA codes 100-199. The movement trajectories of pedestrians and other road users involved in crashes are available for each of the individuals and vehicles involved in a crash. Pedestrian movement types are categorised into 10 categories (see Table 2), whereas the movement types of vehicles are presented in 41 categories (see Table 3). Combinations of these two movement types can provide useful information about how different road users interacted in the event of a crash. In this study, these combinations are considered as an alternative to the DCAs for understanding trends of pedestrian crashes by crash types.

The crash data was analysed in SPSS 26 to derive descriptive statistics for different types of DCA codes and movement trajectory types. The descriptive statistics of these variables were compared to derive an understanding of the usefulness of the movement trajectory type data as an alternative to the DCA codes.

Analysing pedestrian crash data by DCAs to understand the distributions of crashes across all DCA types can be done both at crash-level and individual-level data, as the DCA codes applied to a particular crash and to the individuals involved in that crash are the same. However, the movement types are associated with individual road users and vehicles. As such, this paper analyses the crash data at individual level, i.e., for each pedestrian involved in a crash. This was done to allow undertaking comparative analysis for multiple pedestrians involved in a crash where the pedestrians' movement trajectories were different. While the DCA codes apply at the crash level (i.e., same DCA for multiple pedestrians involved in a crash), the movement trajectory data could have information about trajectories of individual pedestrians. Note that the movement trajectory information does not include spatial data (i.e., actual trajectories), but includes a more detailed description of the movement types.

3. Results from Case Study

Descriptive statistics results for pedestrian-involved crashes by DCA codes and movement types are presented in this section. First, the crash frequencies and proportions for different DCAs and sub-DCAs are presented. These results are then compared with those obtained for the different categories of movement trajectories.

3.1 Number of Pedestrians in crashes by DCAs

The frequencies and proportions of crashes by DCAs are presented in Table 1. As the DCA codes 100-109 are specific to pedestrians only, detailed breakdown of the frequencies and proportions are shown for these categories only. For other DCA codes, the values are presented in groups. Note that the frequencies in this table refer to number of pedestrians involved in a crash.

DCAs 100-109 include 95.5% of all pedestrians involved in the crashes. This is expected as these DCA categories are specific to pedestrian crashes. However, it was observed that 8.1% of the observations did not meet the movement types noted in 100-108 and thus coded as 109 (Any manoeuvre involving ped not included in DCAs 100-108, i.e., other types of movements). As a result, out of all observations, 87.4% had a DCA code which provided some details about the crash-involved pedestrians' movements.

Among all DCAs, the codes 100 and 102 hold the major proportion of observations (47.5% and 28.4% respectively), constituting three-quarter of all observations. While these two categories constitute more than three-quarter of all observations, the DCA codes do not provide details information about the movement trajectories of pedestrians. The codes 100 and 102 provide information about the collision type (i.e., how a pedestrian was hit by a vehicle), but do not provide any information on what the vehicle(s) and pedestrian(s) were doing at the time of crash.

Table 1: Pedestrian-Vehicle interaction by DCAs

DCA code	DCA Description	Frequency	Percent
100	Ped near side. Ped hit by vehicle from the right	2662	47.5
101	Ped emerges from in front of parked or stationary vehicle	146	2.6
102	Far side. Ped hit by vehicle from the left	1593	28.4
103	Ped playing/lying/working/standing on carriageway	121	2.2
104	Ped walking with traffic	44	0.8
105	Ped walking against traffic	20	0.4
106	Vehicle strikes ped on footpath/median/traffic island	109	1.9
107	Ped on footpath struck by vehicle entering/leaving driveway	65	1.2
108	Ped struck walking to/from or boarding/alighting vehicle	136	2.4
109	Any manoeuvre involving ped not included in DCAs 100-108	453	8.1
110-119	Vehicles from adjacent directions (intersections only)	48	0.9
120-129	Vehicles from opposing directions	23	0.4
130-139	Vehicles from same directions	44	0.8
140-149	Manoeuvring	16	0.3
150-159	Overtaking	0	0.0
160-169	On path	17	0.3
170-179	Off path on straight	52	0.9
180-189	Off path on curve	1	0.0
190-199	Passenger and miscellaneous	51	0.9
Total number of pedestrians involved in crashes		5601	100

The DCA codes 110-199 include 4.5% of all observations. These DCA codes provide information on vehicles' movement trajectories but do not provide those of pedestrians. Collectively, analysis by DCAs do not provide any details about pedestrians' movement trajectories for 12.6% of all observations.

Furthermore, for crashes involving multiple pedestrians (about 6% of all crashes in this dataset), the DCA codes will be the same for all pedestrians involved in the same crash which is not necessarily true for all crashes. As such, the DCA information for these crashes are not useful in understanding the movement trajectories of pedestrians.

3.2 Number of Pedestrians in crashes by sub DCAs

The sub DCA codes provide supplementary information for the DCA codes assigned to a particular crash. There are 25 field types for sub DCA codes which provide details about vehicles, pedestrians, sidewalks, struck objects, parking, median, etc.

The crash dataset has a total of 58 sub DCA codes. Among these, 11 codes, which start with C, D, or E, describe pedestrian movements. Type C has the details of pedestrian movements at median/safety zones (e.g., pedestrian stepped off median/ pedestrian stepped off safety zone, tram shelter etc.). Type D provides further information on DCAs 101,102, and 108. Type E provides details about pedestrians' activities (e.g., pedestrian playing, lying, standing, pushing, or working on vehicle and pedestrian activity not known).

The study crash dataset has only 4% of all observations in sub DCA types C, D, and E (0.2%, 1.6%, and 2.1%, respectively) and the remainder are of other sub DCA types. Therefore, sub DCAs do not provide much specific movement type information for individual pedestrians, in addition to those obtained from DCA codes.

Similar to the DCA codes, the crash dataset includes one sub DCA for each crash. Thus, the issues related to having a single code for crashes involving multiple pedestrians remain the same for sub DCA codes. To understand the movement trajectories of these pedestrians, it is important to consider other data variables in the crash dataset.

3.3 Number of Pedestrians in crashes by pedestrian-vehicle movement combinations

The crash dataset contains two data fields to describe 'Pedestrian movements' and 'Vehicle movements' in a crash. It also contains another data filed 'driver intent', which has values similar to the 'vehicle movements' data field, therefore, this data field was not considered in the current study. Unlike the DCA codes, which are applied to individual crashes, the pedestrian movement and vehicle movement data fields specify the movement trajectories of pedestrian and vehicles at individual road user/vehicle level. Thus, these variables can provide more specific details about the crash situations, particularly where there are multiple pedestrians or vehicles involved in a crash. Table 2 and 3 presents the categories of these variables along with frequencies and proportions of pedestrians involved in crashes. The categories are specified with 'movement type IDs', which are referred to in the combinations of these movement categories in Table 4.

Table 2: Pedestrian movement types

PM ID*	Pedestrian movement description	Frequency	Percent
1	Crossing carriageway	4405	78.6
2	Working, playing, lying, or standing on carriageway	191	3.4
3	Walking on carriageway with traffic	101	1.8
4	Walking on carriageway against traffic	109	1.9
5	Pushing or working on vehicle	35	0.6
6	Walking to, from or boarding tram	160	2.9
7	Walking to, from or boarding other vehicle	79	1.4
8	Not on carriageway (e.g., footpath)	283	5.1
9	Not known	100	1.8
10	Not applicable	138	2.5
Total number of pedestrians involved in crashes		5601	100

* PM ID: Pedestrian Movement type ID

Table 2 shows that over three-quarters of the crash-involved pedestrians were crossing a carriageway at the time of the crash. This is expected as the crash dataset considered in this study includes intersection crashes only. About 5% observations involved pedestrians on footpath. These observations could potentially include the pedestrians waiting on footpaths to cross a road while vehicles veered off carriageway and collided onto pedestrians. About 3% observations included pedestrians intending to access or disembark from a tram. Note that this study dataset includes intersections in Metropolitan Melbourne, which includes the tram routes in and around Melbourne CBD. Pedestrians being present on carriageways, other than the intention of crossing a road or accessing/disembarking from a tram/vehicle, consists of 7.1% of all observations. These categories can be further subdivided if the vehicle movement types are combined with the pedestrian movement types, as done later in Table 4, to drive further insights about the movement trajectories of road users.

Analysis results of vehicle movement types (see Table 3) shows the three major movement types for vehicles are vehicle going straight ahead, turning right, and turning left, which are the common movement types at intersections. Some other movement types also exhibit significant number of observations. For example, 2.6% observations were found when a vehicle was reversing and 2.4% were associated with vehicles stopping or slowing down. It was noted that 15 out of the 41 movement type IDs had more than 10 observations and 8 IDs had more than 30 observations. These values suggest that the vehicle movement IDs, particularly those with sufficient number of observations, can effectively be used in statistical analysis to compare trends and factors of pedestrian crashes by vehicle movement types.

The vehicle movement type IDs 17 to 40 describe the vehicle manoeuvre types in the crashes where multiple vehicles were involved. These IDs provide information for the vehicles that were involved in the initial event of a crash. The manoeuvre types of the other vehicles that were not involved in the initial event were not included in these IDs.

While the movement types of pedestrians and vehicles in isolation provides useful insights about the crash situations, combinations of these movement types could provide further insights about the mechanisms of crash occurrence. A total of 169 combinations of pedestrian and vehicle movement IDs were found from the crash dataset. It is noted that the other combinations did not have any observations, however, these are possible to have if a different crash dataset from a different time period or jurisdiction is considered.

Table 3: Vehicle movement types

VM ID*	Vehicle movement description	Frequency	Percent
1	Going straight ahead	1995	35.6
2	Turning right	1786	31.9
3	Turning left	926	16.5
4	Leaving a driveway	47	0.8
5	U' turning	27	0.5
6	Changing lanes	22	0.4
7	Overtaking	12	0.2
8	Merging	13	0.2
9	Reversing	146	2.6
10	Parking or unparking	27	0.5
11	Parked legally	5	0.1
12	Stationary accident	26	0.5
13	Other stationary	25	0.4
14	Slow/stopping	134	2.4
15	Out of control	85	1.5
16	Wrong way	6	0.1
17	Going straight ahead and turning right	38	0.7
18	Going straight ahead and turning left	9	0.2

VM ID*	Vehicle movement description	Frequency	Percent
19	Going straight ahead and leaving a driveway	2	0
20	Going straight ahead and U' turning	2	0
21	Going straight ahead and changing lanes	2	0
22	Going straight ahead and parked legally	4	0.1
23	Going straight ahead and parked illegally	1	0
24	Going straight ahead and other stationary	8	0.1
25	Going straight ahead and slow/stopping	8	0.1
26	Going straight ahead and out of control	2	0
27	Turning right and other stationary	1	0
28	Turning left and changing lanes	1	0
29	Turning left and parked legally	1	0
30	Turning left and other stationary	1	0
31	Turning left and slow/stopping	1	0
32	Changing lanes and parked illegally	1	0
33	Changing lanes and other stationary	1	0
34	Overtaking and other stationary	3	0.1
35	Reversing and parked legally	1	0
36	Parking/unparking and parked legally	1	0
37	Parking/unparking and parked illegally	1	0
38	Parked legally and out of control	3	0.1
39	Parked illegally and out of control	3	0.1
40	Other stationary and out of control	6	0.1
41	Not known	218	3.9
Total number of pedestrians involved in crashes		5601	100

* Vehicle Movement type ID

Table 4 presents a summary of the different movement ID combinations for pedestrians and vehicles. It also maps the movement ID combinations with DCA codes by reporting the percentage of observations for each pair of movement ID combination and DCA code. As the table can be rather long to show details for all 169 movement ID combinations, a simpler version of the table is presented here by combining categories for which less than 20 observations were found.

Table 4: Movement combination and DCA distribution

PVM ID*	PVM ID* Description	N= 5601	%	DCA codes										
				100	101	102	103	104	105	106	107	108	109	110-199
1-1	Crossing carriageway-Going straight ahead	1480	26.4	13.1	1.6	10.5	0.1					0.1	0.6	0.3
1-2	Crossing carriageway-Turning right	1659	29.6	16.4	0.4	11.2					0.1		1.4	
1-3	Crossing carriageway-Turning left	801	14.3	10.9		2.5				0.1			0.6	
1-4	Crossing carriageway-Leaving a driveway	22	0.4								0.2		0.1	
1-9	Crossing carriageway-Reversing	78	1.4	0.4		0.2							0.7	
1-12	Crossing carriageway-Stationary accident	21	0.4	0.2		0.2								
1-14	Crossing carriageway-Slow/stopping	101	1.8	1.1		0.6								
1-41	Crossing carriageway-Not known	131	2.3	1.2		0.7							0.3	
1-Others	Crossing carriageway-Others	112	2.0	0.6		0.4				0.1			0.4	0.4
2-1	Working, playing, lying or standing on carriageway-Going straight ahead	96	1.7	0.2			1.0						0.3	
2-Others	Working, playing, lying or standing on carriageway-Others	95	1.7				0.7						0.5	0.4
3-1	Walking on carriageway with traffic-Going straight ahead	39	0.7	0.1		0.1		0.2						
3-2	Walking on carriageway with traffic-Turning right	22	0.4	0.2		0.1								
3-Others	Walking on carriageway with traffic-Others	40	0.7	0.2		0.1		0.2					0.1	
4-1	Walking on carriageway against traffic-Going straight ahead	63	1.1	0.3	0.1	0.3			0.2				0.2	
4-Others	Walking on carriageway against traffic-Others	46	0.8	0.3		0.2								0.1
5-Others	Pushing or working on vehicle-Others	35	0.6				0.1						0.3	0.2
6-1	Walking to, from or boarding tram-Going straight ahead	112	2.0	0.2		0.2						1.3	0.2	
6-Others	Walking to, from or boarding tram-Others	48	0.9									0.4	0.1	0.2
7-1	Walking to, from or boarding other vehicle-Going straight ahead	40	0.7									0.3	0.2	
7-Others	Walking to, from or boarding other vehicle-Others	39	0.7									0.2	0.2	

PVM ID*	PVM ID* Description	N= 5601	%	DCA codes										
				100	**101**	**102**	**103**	**104**	**105**	**106**	**107**	**108**	**109**	**110-199**
8-1	Not on carriageway (e.g. footpath)-Going straight ahead	74	1.3	0.3		0.1				0.3			0.2	0.3
8-2	Not on carriageway (e.g. footpath)-Turning right	26	0.5	0.2						0.1				
8-3	Not on carriageway (e.g. footpath)-Turning left	41	0.7	0.3						0.3				
8-9	Not on carriageway (e.g. footpath)-Reversing	25	0.4								0.2			
8-15	Not on carriageway (e.g. footpath)-Out of control	42	0.7							0.4				0.4
8-Others	Not on carriageway (e.g. footpath)-Others	75	1.3								0.3		0.1	0.7
9-1	Not known-Going straight ahead	35	0.6	0.1									0.3	
9-41	Not known-Not known	28	0.5	0.1									0.3	
9-Others	Not known-Others	37	0.7	0.3									0.2	
10-1	Not applicable-Going straight ahead	46	0.8	0.2		0.1							0.2	0.2
10-2	Not applicable-Turning right	25	0.4	0.3										
10-3	Not applicable-Turning left	21	0.4	0.2		0.1								
10-Others	Not applicable-Others	46	0.8										0.2	0.4
Total		5601	100	47.5	2.6	28.4	2.2	0.8	0.4	1.9	1.2	2.4	8.1	4.5

* PVM ID: Pedestrian-Vehicle Movement ID combinations. Refer to table 2 and table 3 for the descriptions of the movement type IDs
** Cells with values ≥0.1% have been shown in the table.

Analysis by movement ID combinations shows that 34 categories of the movement ID combinations had more than 20 observations and 26 categories with more than 30 observations. These numbers are significantly larger than the 9 DCA categories available specifically for pedestrian crashes. Thus, the use of these categories as an alternative to the DCA categories in pedestrian crash analysis could provide additional insights about movement trajectories of road users in these crashes.

Table 4 shows that about 70% of all observations can be considered within three combinations (1-1, 1-2, and 1-3). These combinations refer crashes where a pedestrian was crossing a carriageway and a vehicle was going straight, turning left, or turning right. While the majority of the combination IDs include the straight/left-turn/right-turn vehicle movement IDs, several pedestrian movement IDs (e.g., crossing carriageway, walking on carriageway with traffic, and not on carriageway) were found to have at least 20 observations with these vehicle movement IDs.

Mapping of the DCA codes and movement ID combinations shows that the use of the movement ID combinations could further distribute the observations within each DCA codes. For example, DCA code 100 has 47.5% of all observations which can be considered in six major movement ID combinations (e.g., 1-1, 1-2, 1-3, 1-14, 1-41, and others). A similar distribution can be obtained from the observations of DCA code 102.

4. Discussion and Conclusions

This paper investigates the use of movement trajectories of pedestrians and vehicles in pedestrian-involved crashes, as an alternative to DCA codes, to derive understanding on trends and factors of such crashes. Descriptive statistical analysis performed on the number of pedestrians involved in crashes showed that one can obtain greater level of insights by using the movement trajectories of road users, both in isolation for each type of road users as well as by considering combinations for multiple road users.

While the DCA codes provides a simple classification of crash types, the movement types can provide a more accurate classification scheme as these consider movements of multiple road users in a crash (e.g., a pedestrian and a vehicle). In contrast, the common DCA codes in pedestrian-involved crashes do not provide detailed information about the movement of pedestrians. Moreover, the DCA codes are applied at the crash level (i.e., same DCA for multiple pedestrians involved in a crash), whereas the movement type data could have information about the trajectories of individual pedestrians.

Movement types of vehicles play a crucial role in the likelihood and outcomes of pedestrian crashes. A vehicle going straight can have better visibility to a pedestrian than a turning vehicle. Reduced visibility, which often relates to turning vehicles, is a potential contributing factor for severe crash outcomes (Li et al., 2018, Das et al., 2018, Zhang and Ma, 2014). Moreover, a vehicle going straight is likely to have greater speed than a turning vehicle, thus contributing to more severe crashes (Clarke et al., 2010, Pei et al., 2012). Thus, analysing crashes by movement types can provide more in-depth understanding about the contributing factors of crashes and their outcomes than using DCA codes alone. It is recommended that further research attention is given into exploring the use of pedestrian-vehicle movement ID combinations in analysing crash data and injury severity outcomes. Future research can examine different issues of pedestrian safety, such as analysis of crash frequencies and injury severities, using the movement trajectory data to derive more insightful understanding about the factors of crash occurrence and outcomes. Such understanding could help in developing targeted countermeasures for improving the safety of pedestrians.

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