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An innovative method for the analysis of vehicle movements in roundabouts based on image processing

Lorenzo Mussone[1]*, Matteo Matteucci[2], Marco Bassani[3] and Davide Rizzi[2]

[1]*BEST Department, Politecnico di Milano, 9, via Bonardi, 20133 Milan, Italy*
[2]*DEI Department, Politecnico di Milano, 34/5, via Ponzio, 20133 Milan, Italy*
[3]*Department of Hydraulics, Transportation and Civil Infrastructure, Politecnico di Torino, 24, corso Duca degli Abruzzi, 10129 Torino, Italy*

SUMMARY

The objective of this paper is to propose a method, based on the image processing of field survey data, to analyze vehicles movements into roundabouts. This research study consisted of three stages: a field survey to collect vehicular flow images captured by video cameras, the processing of these images using a proprietary software (VeTRA—Vehicle Tracking for Roundabout Analysis), and finally, the analysis of the collected data.

The main feature of the software is that it allows the automatic computation of the main variables necessary to rank and evaluate a generic roundabout: the entry/exit (E/E) matrix with classification of vehicles (e.g., heavy, light, and motorbikes), vehicle trajectories, and vehicular speed diagrams along the paths inside the roundabout. The processing system is robust enough to withstand classic problems affecting image processing such as variable wind conditions, cloud cover, shadows, and obstructions. Calibration and error evaluation have been deduced from data collected by a high precision Real Time Kinematic GPS video recording system mounted on a probe vehicle. Data of E/E matrices generated by VeTRA are compared with those manually counted on the corresponding video images.

A case study of an existing roundabout is featured in the paper. The results indicate that the software has a high capability of generating the E/E matrix. The analysis of vehicular trajectories with both the plot of curvature diagrams and the corresponding speed diagrams enable the evaluation of driver behavior relative to the geometric shape of the roundabout. Copyright © 2011 John Wiley & Sons, Ltd.

KEY WORDS: roundabout performance; image analysis; speed profile; E/E matrix count; Kalman filtering; trajectories; vehicular movements

1. INTRODUCTION

The roundabout, an intersection whose primary aims are increased safety and operational performance, is today one of the most widespread intersection typology in both urban and rural environments [1]. This is due to the potential benefits deriving from the reduction in both speed and the number of conflict points with respect to traditional crossroad intersections, which should, in turn, lead to improved road safety figures. However, the performance of some roundabouts cannot be considered satisfactory, and many of them could be improved in order to better match driver expectations. The fault lies with the design of roundabouts in terms of geometric dimensions and organization of roundabout elements (e.g., entry and exit lane widths, central island diameter, entry and exit angles, angles between legs, etc.). These factors combine to affect operational performance such as capacity and safety.

This finding has been supported by many studies [2] and reported in the Highway Safety Manual [3]. Under certain conditions, the conversion of a traditional intersection into a roundabout can lead

*Correspondence to: Lorenzo Mussone, Politecnico di Milano, BEST Department, 9, via Bonardi, 20133 Milan, Italy. E-mail: mussone@polimi.it

to a confidence interval of crash modification factor with values greater than one, making the roundabout less safe than the previous intersection. This result is also confirmed by Italian data collected by Sacchi *et al.* [4].

Furthermore, in many instances, geometric characteristics influence performance indicators such as capacity. In particular, some roundabout designs have failed to take all types of road users into consideration (i.e., cars, trucks, motorbikes, bicycles, and pedestrians). In general, vehicle trajectories and speeds observed under different traffic and environmental conditions differ from the predictions for same at design stage.

A knowledge of vehicle trajectories and speeds should be considered necessary when designing the geometric layout of a roundabout, and the expected speeds of vehicles should be estimated. These factors can be easily calculated by designers using swept path of turn simulation software associated with speed prediction models. Actual vehicle trajectories and speeds directly recorded at a newly constructed roundabout can confirm whether the design assumptions were valid and how reliable figures for expected performances were versus actual recorded data. In addition, it should be noted that operating speed diagrams allow us to assess whether the curvature of the four maneuvers (right turn, crossing, left turn, and U-turn) leads to an effective speed reduction.

A survey methodology based on the collection and analysis of video sequences has been developed to investigate such phenomena. Similar experiences were already worked out by Messelodi *et al.* [5] but focused on specific parts of urban intersections.

A software program, called Vehicle Tracking for Roundabout Analysis (VeTRA), was developed to obtain paths, kinematic variables of vehicles inside a roundabout, and the entry/exit (E/E) demand matrix through video recording. In VeTRA (Politecnico di Milano, Milan, Italy), a model of the background is simulated so that the image areas corresponding to moving vehicles are derived by difference. In this process, a background adaptation strategy using different learning factors, similar to the one presented in [6], has been used to cope with variable light conditions on the roads. Because the generation of E/E matrices demands the independent tracking of each vehicle from the entry and exit sections of a roundabout, multiple Kalman filters have been used to integrate information with that resulting at each frame from background difference. Vehicles are also tracked when small occlusions are present in the scene (e.g., high vegetation in the central island, electricity poles, and vehicle intersections); this is possible thanks to the use of a color model associated with each vehicle, which is fundamental for the proper interpretation of the E/E matrix. Analog experiences can be found in [7].

VeTRA-computed trajectories are compared with the positions (accurate to within a few centimeters) measured by the Real Time Kinematic (RTK) GPS receiver, which is mounted on a probe vehicle. The results show that the software has highly reliable algorithms.

This work constitutes the first stage of an extensive study that aimed to make a tool not only for the analysis of roundabout, but also for other elements of the road network. Indeed, this tool is only part of a wider rational framework for the detection and correction of geometric design flaws in existing road infrastructure. It is clear but should be underlined that, in order to produce significant analyses, collected data must contain, in a statistical sense, the features of the vehicular flow to be analyzed. Therefore, the length of recorded images varies according to the features under investigation and the variance in vehicular flow, and can be many hours or days long. This is the same as that occur in all measurement problems and image processing must also obey statistical laws.

2. EXPERIMENTAL SCENARIO AND DATA PROCESSING

The instrumentation used to collect and evaluate data consists of a vision system and a RTK-GPS system both connected to a dedicated PC. The vision system consists of a camera with a resolution of 1360×1024 pixels. The RTK-GPS system is composed of a base station (Trimble MS750 GPS with Trimble Zephyr Antenna) and a rover, which is a probe vehicle (Trimble 5700 GPS with Trimble Zephyr Antenna) connected by a radio link (DiGi XBee Pro modules in point-to-point mode) to the base station. The vision system provides information on vehicular flow through the processing of images recorded by the video camera, whereas the RTK-GPS system produces data useful for calibrating and evaluating the vision system.

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2.1. *Pre-processing*

Collected data require processing before use. In particular, images need conversion, undistortion, and rectification, whereas RTK-GPS data need data conversion (for rover data) and synchronization between the base station and rover timestamps.

2.1.1. *Video stream pre-processing*

Original images have been acquired in raw Bayer format [8] so as to reduce the total amount of storage required for the video stream by up to a third. This implies reconstructing the full color information by using a technique for Bayer demosaicing. To do so, the authors have used the “high-quality linear” algorithm described in [9].

For an accurate reconstruction of vehicle trajectories, the optical radial distortion caused by less than ideal camera lenses has to be removed so that lines and circles/ellipses in the field correspond to lines and ellipses on the image plane. Calibration data, in the form of check-board images have been used to calibrate the Bouguet camera model for the vision system using the MATLAB (MathWorks, Natick, MA, USA) [10]. The use of this model has made it possible to remove radial distortion from the acquired images. This task is necessary for image rectification.

Image rectification aims at achieving homogeneity in terms of corresponding pixels in the image plane, of the ratio between lines length and angles in a specific plane of the observed world. This requires a proper image transformation, a homography between the road surface and the image plane. Performing tracking on the transformed plane turns out to be quite effective and more accurate than on the original image. Finding a proper homography is possible when the dimensions and position of some specific elements of the observed scene are available. For example, the central island is considered circular, and it becomes an ellipse after perspective projection. The procedure is quite general, and it could be applied to any planar element with known geometry and, thus, to any shape of intersection with few modifications.

First of all, a model of the external circle of the central island is built using (0,0) as central coordinate and the true radius. By applying the camera perspective transformation to this model, the edge of the elliptical central island projection on image plane is obtained.

However, the true coordinates of the camera with respect to the island are unknown, and these extrinsic parameters need to be estimated.

In VeTRA, this is done by applying a genetic algorithm optimization procedure in order to minimize the reprojection error of the central island on the image plane. This is obtained by minimizing the sum of the distances of pixels in the contour of the real island of the image from the projection of the island model using camera (intrinsic and extrinsic) parameters. Among these, intrinsic parameters are obtained by the initial calibration procedure, and unknown extrinsic parameters are the variables to be optimized by the genetic algorithm.

At the end of the optimization process the full camera model parameters provides a complete projective transformation from the 3D world to the 2D image, by constraining world points to lie on the ground. The transformation becomes the homography from the ground plane to the image plane, and a rectified image is obtained having the roundabout in the center of the image, which occupies the whole frame (Figure 1).

2.1.2. *Real Time Kinematic GPS streams pre-processing*

Data acquired by the RTK-GPS receivers are in NMEA 0813 format [11]. These have been transformed from the geodetic coordinate system into a local reference frame in two steps: from WGS84 polar coordinate to earth-centered, earth-fixed Cartesian coordinates on the reference ellipsoid and from the latter to east–north–up Cartesian coordinates on the tangent plane to the reference ellipsoid.

For convenience, the origin of this final reference system has been located in the center of the roundabout. GPS systems produce data at 5 Hz, and each RTK-GPS record is internally time-stamped by using the GPS clock (accurate to a tenth of a second). The computer on the probe vehicle and the one acquiring the images add a local timestamp to the RTK-GPS record using the local clock, and

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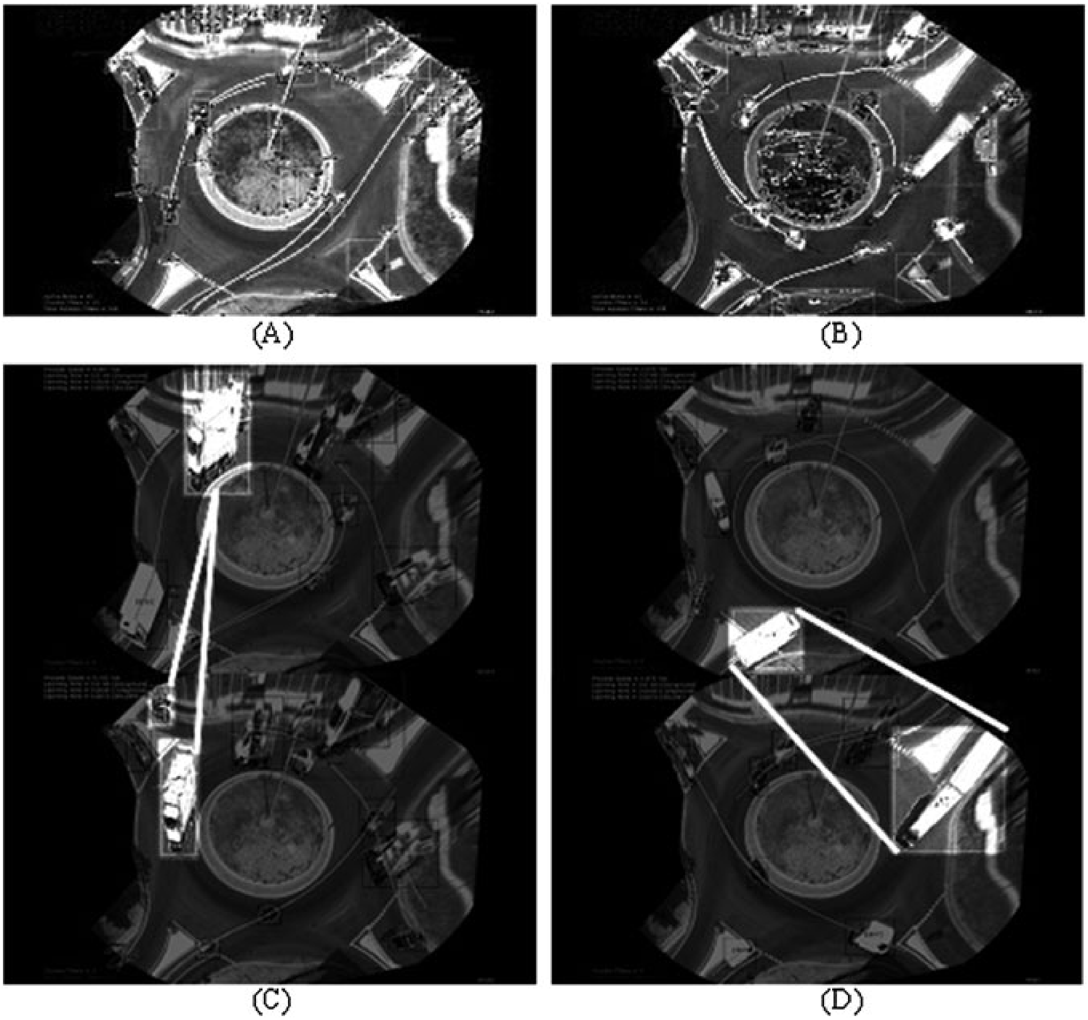

Figure 1. Four different causes of error in trajectory tracking: (A) wind; (B) cloud passage; (C) occlusion; (D) perspective deformations.

the same is done for the images. By using the timestamps in the RTK-GPS records, it is possible to link the clocks of the two machines and to synchronize the images to the RTK-GPS data as well.

2.1.3. Relevant issues

A few issues confronted in VeTRA should be highlighted as they illustrate how robust and accurate the software is (Figure 1):

- Changeable wind conditions can induce the classic "waving trees" effect and can cause the camera to move as well. In the latter case, the movement results in a complete shift of the scene captured by the camera (Figure 1A), and spurious objects may appear in the proximity of image edges.
- Sudden changes in light conditions because passing clouds might be too fast to be managed by the adaptive background learning strategy (Figure 1B).
- Occlusions might occur because of fixed objects (e.g., trees, poles) or moving vehicles. When an occlusion occurs as a result of crossing vehicles, it is not always possible to distinguish them just by tracking (Figure 1C).
- Perspective deformation modifies the shape of moving objects significantly, and this has to be taken into account when performing data association (Figure 1D).

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2.2. Image processing and vehicle tracking

The key algorithm of the VeTRA tool is the tracking system, which performs the following functions:

(1) Adaptive background modeling and subtraction to detect moving objects in the scene.
(2) Foreground identification through shadow and noise removal to give image areas representing vehicles (hereafter referred to as "blobs").
(3) Association of newly detected blobs with previously tracked vehicles.
(4) Trajectory update for the tracked vehicles according to new information.

All these activities rely on a proper model of the background that has to be sufficiently robust to contend with changes in light conditions and camera movement. In VeTRA, this is achieved by the adaptation mechanism introduced by Bonarini *et al.* [6], whereby each pixel is updated in the model by using a convex combination between its present value and the observed image. This updating mechanism is continuously performed in the areas of the image where no vehicles are present.

Once the background model is available, vehicles can be extracted by simply subtracting the current frame and the background model. Pixels differing from the background by more than a given threshold (different for each pixel and derived from an estimate of the image noise for that pixel) are considered to be vehicles.

The aforementioned process overestimates the vehicle size because of the presence of shadows. Because a shadow affects the intensity of the pixel and not its hue and saturation components, the use of a threshold on the intensity channel of each pixel in the blob can help the program to establish whether it belongs to the vehicle shadow or to the vehicle itself. Morphological operators are applied to the binary mask obtained at this stage to improve its quality by removing "salt and pepper" noise and by filling gaps created by shadow removal.

Each vehicle in the image is tracked across the image sequence by using a Kalman filter [12] on the image plane. The Kalman filter provides the *a-posteriori probability* of a vehicle position in the frame through the integration of the position of vehicle silhouettes extracted by image processing. This estimate implies a linear motion and a linear measurement model both affected by Gaussian noise. When such models are not linear, it is possible to use the extended version of the filter. The output of the Kalman filter is an estimate of vehicle position, and the Gaussian uncertainty of such an estimate. This uncertainty information can be used to compute the Mahalanobis distance between the predicted position of the tracked vehicle and its measured position. The Mahalonobis measure of distance is based on correlations between variables, and it can be reduced to the Euclidean measure when the covariance matrix between variables is the identity matrix. The general formulation for two random vectors, for example, $\boldsymbol{x}$ (e.g. the predicted position of the tracked vehicle) and $\boldsymbol{y}$ (e.g. the measured position of vehicle), is as follows:

$$\mathrm{d}(\boldsymbol{x},\boldsymbol{y}) = \sqrt{(\boldsymbol{x}-\boldsymbol{y})^{\mathrm{T}}\boldsymbol{S}^{-1}(\boldsymbol{x}-\boldsymbol{y})}$$

where $\boldsymbol{S}$ is the covariance matrix of $\boldsymbol{x}$ and $\boldsymbol{y}$.

In VeTRA, the state of each Kalman filter corresponding to a tracked vehicle includes both the vehicle position on the image plane and its derivative, in other words the vehicle speed on the image plane.

To update a filter it is necessary to associate the correct blob extracted by image processing. This is obtained by testing the following: (i) the Mahalanobis distance between the predicted vehicle position and the blob; (ii) the similarity of the color histogram of the tracked vehicle and the color histogram of the blob; and (iii) the similarity of the tracked vehicle area and the area of the blob. If these three tests are positive, the blob is associated with the tracker, and the filter is updated; otherwise, a new Kalman filter is created to track the new vehicle. Kalman filters that have not been updated for a long period are discarded.

2.3. Post-processing

Trajectories produced by the tracking system are processed in order to provide the following information:

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- Entry/exit matrix.
- Vehicle trajectories.
- Speed profiles.
- Vehicle classification.

2.3.1. Entry/exit matrix

The E/E matrix represents the matrix of all flow movements in the roundabout, and normally, some differences can be observed between this and the corresponding matrix of other intersections because the U-turn is not possible. In order to calculate the E/E matrix from the computed trajectories, a specific algorithm was devised. This was necessary because the tracking system is not capable of ensuring that all revealed trajectories are complete from entry to exit because of one of the aforementioned issues, such as noise, wind, shadows, and cloud conditions.

Matrix reconstruction requires the following steps:

- Deletion of trajectories with too short a length in terms of space and time (pure noise).
- Separation of overcomplex trajectories resulting from errors in blob detection and tracking.
- Reduction of points in trajectories to avoid zigzag curves due to data association errors especially near the yield line.

Flow is computed by counting the number of intersections between trajectories and segments corresponding to the E/E sections (Figure 2). This solution allows the consideration of all possible trajectories entering or exiting the circulatory roadway and avoids problems due to perspective deformations. To this end, trajectories recognized by the software are divided into four groups according to the number of intersection points and E/E segments (which can range from 0 to more than 2):

- No intersection point.
- Only one intersection point.
- Two intersection points.
- More than two points (because correct points are at most two, the others are incorrect especially with respect to circulation rules).

Trajectories with two intersections contain data ready to be used for E/E matrix estimation. The remaining trajectories are re-evaluated with an algorithm described in the E/E paragraph.

2.3.2. Trajectories

Trajectories on pavement surfaces are easily calculated from trajectories on the image plane when the homography between the two planes is known. For this task, RTK-GPS data collected by the rover on the probe vehicle were used. This was performed through the comparison of RTK-GPS and tracking system data, using the synchronization data to obtain the same amount of information. To avoid outliers due to noise or other problems that cause difficulties in the extraction of the homography between

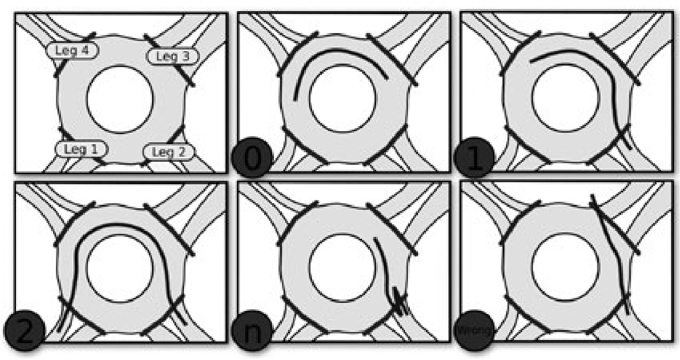

Figure 2. Possible groups of trajectories identified by VeTRA.

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the RTK-GPS data and the image trajectories, the Random Sample Consensus method of Fischler and Bolles [13] was applied in the version proposed by Zuliani [14]. Therefore different homographies are produced for each vehicular class.

2.3.3. Speed and curvature diagrams

Speed and curvature profiles are obtained by calculations based on vehicle position and time. Speed is calculated for two consecutive points by simply dividing the distance between points by the elapsed time (nearly equal to a frame rate of the camera). To build the average profile, it is necessary to merge all trajectories of the same E/E couple. Because vehicles travel on trajectories of different lengths, all trajectories are centered in the middle between entry and exit points (indicated by a 0) into the circulatory roadway. For curvature diagrams, calculated as the inverse value of the local radius, 31 consecutive points of the trajectory (1 second) have been considered when calculating the corresponding radius.

2.3.4. Flow classification

Classification of flow is necessary to improve the overall performance of flow count, speed diagram, and trajectory path. A classification has been carried out in order to detect three classes of vehicle:

- Bikes and motorbikes.
- Light vehicles, vans, and campers.
- Heavy vehicles.

Classification consists of a local classifier and a voting system. The local classifier determines, for each frame in the trajectory, the vehicle class according to the position and area of the blob within the image. The position is necessary because the same vehicle has different areas in different points of the image because of perspective deformations and was built up by a feed-forward neural network. The voting system collects the results of local classifiers for all points in the trajectory, and then, it selects the most frequent among the three different vehicle classes.

3. RESULTS

The findings presented here are based on a survey carried out at a four-leg roundabout located in a typical Italian urban environment. The external diameter of the roundabout is 50 m, and the circulatory roadway width is 13 m with an apron of 1.5 m. With respect to the legs, the average width of the entry ones with two lanes is 8 m and is 6 m for the exit ones. It must be noted that, because of the particular position of the camera with respect to the center of the roundabout, the circulatory roadway between legs 3 and 4 presents the maximum occlusion effect.

3.1. Entry/exit analysis

In Table I the number of trajectories computed by VeTRA is reported. The table indicates the number of paths distinguished on the basis of the number of intersection points with the entry or exit portal derived directly from the image analysis (first step). Because the number of paths with less than two intersection points is not nil, a controlled extension of the remaining trajectories was performed. In step 2, only those trajectories with one intersection are extended by linearly stretching one extremity until it

Table I. Paths considered for the derivation of the E/E matrix.

No. of intersections	1st step (1)	2nd step (2)	Δ(2–1)	3rd step (3)	Δ(3–1)
0	115	115	0	24	−91
1	984	610	−374	672	−312
2	1786	2077	291	2092	306
>2	4	5	1	5	1
n (with at least a wrong way)	26	108	82	122	96
Total	2915	2915	0	2915	0

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reaches the intersection point. Finally, in step 3, the same operation is applied to trajectories with no intersection points. Consequently, a new set of results has been derived with 2092 trajectories, 17% more than the initial figure.

Approximately, 70% of the trajectories recorded and not discarded during the post-processing phase are correctly classified. The remaining 823 are re-analyzed by another two step process in order to obtain the final E/E matrix (Table II):

- An *a-priori* probability is calculated for valid trajectories (those with two intersection points).
- All trajectories with only one intersection point are assigned to the matrix according to the *a-priori* probability.

Table II. Entry/exit (E/E) matrix estimates by software VeTRA and manual estimation (percentages refer to the matrix total).

VeTRA (E/E%) (1)					
Entry/exit links	1	2	3	4	Total
1	0.593	3.376	20.331	0.444	24.743
2	2.488	0.256	4.801	6.866	14.411
3	21.126	2.600	0.000	8.679	32.405
4	2.709	13.266	12.239	0.277	28.411
Total	26.916	19.498	37.370	16.216	100.000
Average estimate of three operators (E/E%) (2)					
Entry/exit links	1	2	3	4	Tot.
1	0.399	2.929	20.905	0.466	24.700
2	3.262	0.200	4.660	7.856	15.979
3	19.774	4.727	0.266	7.124	31.891
4	2.064	11.917	13.116	0.333	27.430
Total	25.499	19.774	38.948	15.779	100.000
Difference (1–2)					
Entry/exit links	1	2	3	4	Tot.
1	0.193	0.466	−0.575	−0.022	0.043
2	−0.774	0.056	0.140	−0.990	−1.568
3	1.353	−2.127	−0.266	1.555	0.514
4	0.645	1.349	−0.877	−0.106	1.011
Total	1.417	−0.276	−1.578	0.437	0.000

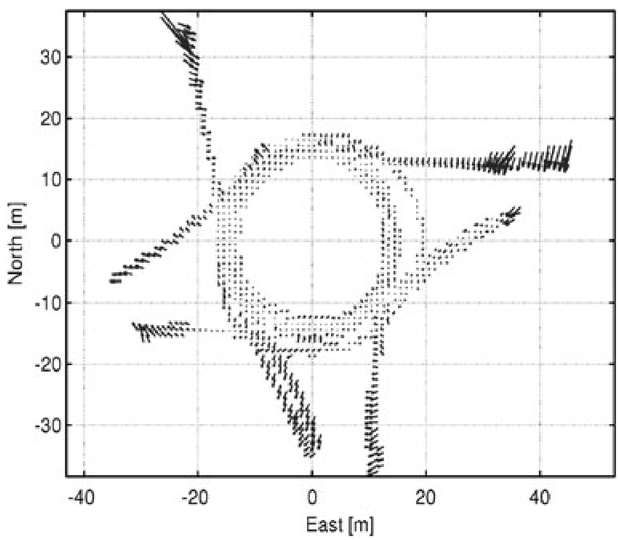

Figure 3. Distance between points extracted by VeTRA and the corresponding ones collected by the RTK-GPS system (the arrows represent the distance between two correlated points).

The relatively high number of trajectories not assigned at the first step of VeTRA is mainly due to occlusions and could be countered by using more cameras.

This approach has been confirmed by a detailed check of all trajectories with one intersection point, where limited performance is due exclusively to occlusions. The percentage of correctly assigned trajectories is nearly 100%.

By evaluating manual measurements carried out by three operators on the same video recording, it was possible to test the performance of this process. The data showed in Table II are a percentage of the total movement recorded by VeTRA and the three operators. In the last section of the table, the percentage difference between the two estimates confirms that there is an acceptable maximum divergence of 1.5%. It should be noted that this result is influenced by the position of the camera. In fact, the trajectories coming from links 3 and 4, and those directed to exits 1 and 2 are underestimated, because they cross the zone affected by occlusion effects.

3.2. *Flow classification*

The local classifier can correctly classify about 98% of blobs in the trajectories. No ambiguity arises for heavy vehicles, but the distinction between some small vehicles and motorcycles appears to be less reliable. The voting schema was then able to group vehicles in 100% of cases.

3.3. *Trajectories and speed profiles analysis*

Position data derived from the image analysis were compared with the corresponding positions as per the RTK-GPS. All results available are plotted in Figure 3, where it can be observed that the area of greatest divergence between correlating points is mainly at the legs.

This divergence is due to the limited field of view of the camera and can be simply avoided by using additional cameras or wide-angle lens. It is clear that the task of collecting the set of data useful for describing in great detail all the features of vehicular flow in a roundabout is a challenging one, and for this reason, accurate planning is essential.

When a restricted analysis on the circulatory roadway is performed, distances between correlating points are smaller. This leads to the conclusion that for measurements regarding this case study, data

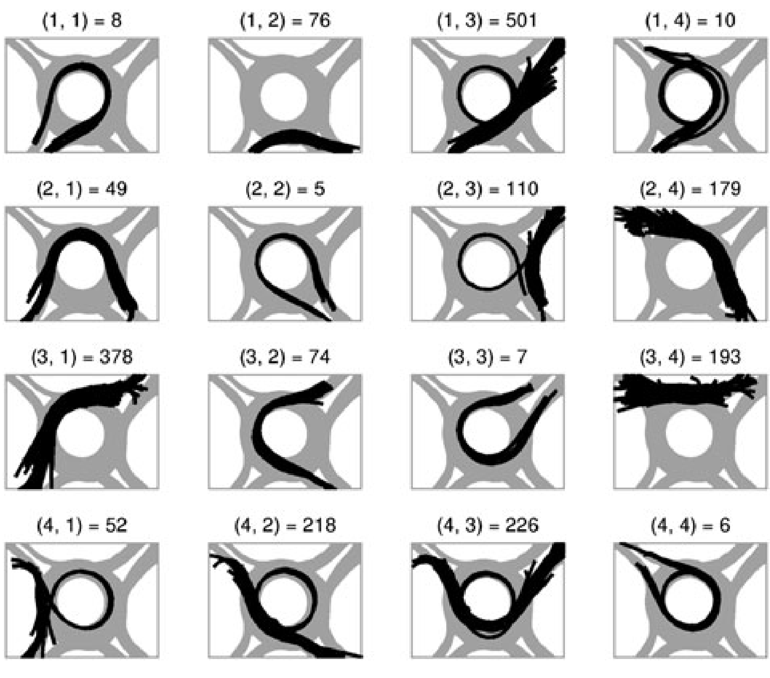

Figure 4. Bundles of trajectories for all possible maneuvers.

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on legs need a more specific acquisition and, therefore, are excluded from the dataset; for software validation purposes, only data in the circulatory roadway will be considered hereafter.

For each E/E combination, Figure 4 shows both planar path representations and the corresponding curvature diagrams are plotted in Figure 5. As can be noted in Figure 4, some maneuvers are indirect because some vehicles execute a full turn around the central island before exiting, and they are not considered for curvature and speed analysis. Curvature diagrams in Figure 5 show how curvature changes along the trajectory and how far from theoretical diagrams they are for all the possible maneuvers. In the diagrams, positive and negative values are considered according to the usual sign rule: right turns are positive, left ones are negative. Curvature lines are in grey; entry and exit sections are in red, whereas the average curvature line is black. All data are reported along the trajectory inside the roundabout and have its middle point (0m) as a reference.

Data plotted in the graphs in Figure 5 show that the average curvature of all the maneuvers is lower than $0.1\,\mathrm{m}^{-1}$, so the average radius is greater than 10m. The right-turn and left-turn maneuvers curve trends are quite regular and similar, whereas the crossing maneuver curve trend is different. In particular, the maneuver (1,3) presents a smaller curvature than the corresponding (3,1). This means that, in this case, a lower level of speed control is evident at the roundabout, so higher operating speeds can be expected.

Speed profiles have only been derived for those cars entering onto the roundabout with a speed equal to/greater than 5km/hour because, when operating speeds have to be derived, only isolated or nonconditioned cars should be considered. In fact, operating speed is the most common variable for

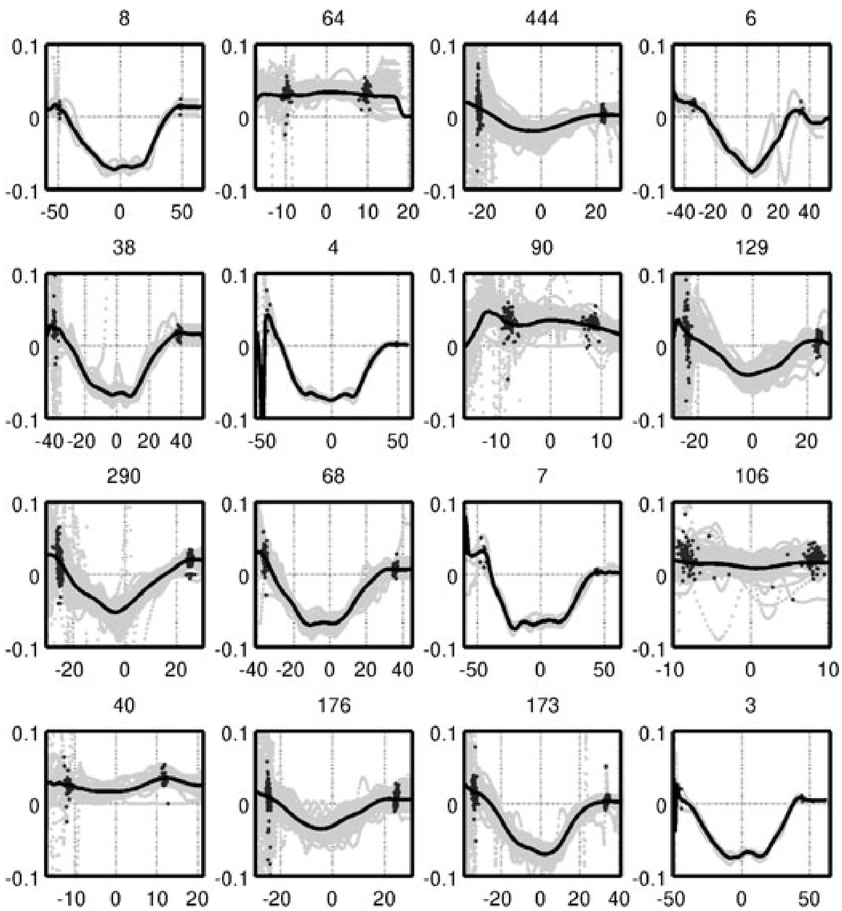

Figure 5. Curvature (grey curves) and average curvature (black curve) profiles of the trajectories worked out by VeTRA, dots represent entry and exit points in roundabout (numbers above figures refer to counted vehicles; *x*-axis is in meters, *y*-axis in meters^{-1}).

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evaluating the consistency of roadways or localized elements like intersections. The 85th percentile of a sample of speeds is a good estimate of operating speed in a specific location. Figure 6 shows the speed profiles of each vehicle (grey curves), the entry and exit points in the circulatory roadway (in black), the average speed (black curve), and the 85th percentile speed (dark-grey curve). Average and operating speeds are affected by a moderate level of tracking system noise. It should be noted that in those combinations where a large number of curves are present (e.g., maneuvers (1,3), (3,1), (2,4), and (4,2)) speed profiles are more regular than in other cases. In Figure 7, the comparison between curvature and operating speeds is illustrated. In general, it can be observed that operating speeds in the circulatory roadway are lower than 40 km/hour (24.86 mph). This means that a good degree of speed control is evident at the intersection, while the only exception is represented by (1,3) maneuver, characterized by a lower curvature.

Distance errors have been analyzed and classified in percentage terms (Figure 8A). The analysis of VeTRA statistical parameters demonstrates the accuracy of the software:

- The median is equal to 0.375 m.
- The median of absolute deviations is equal to 0.179 m.
- The inter-quartile range is 0.399 m.

The comparison between speed values derived by VeTRA and those determined by the RTK-GPS system is summarized in Figure 8B. Taking the GPS data as a reference, the error rate of VeTRA has a mean equal to 0.11 km/hour and a standard deviation equal to 2.71 km/hour. Those data have been calculated on the 2.80 km traveled by the probe vehicle. In this case, it should be appreciated that when speed is considered, the profiles derived are reliable.

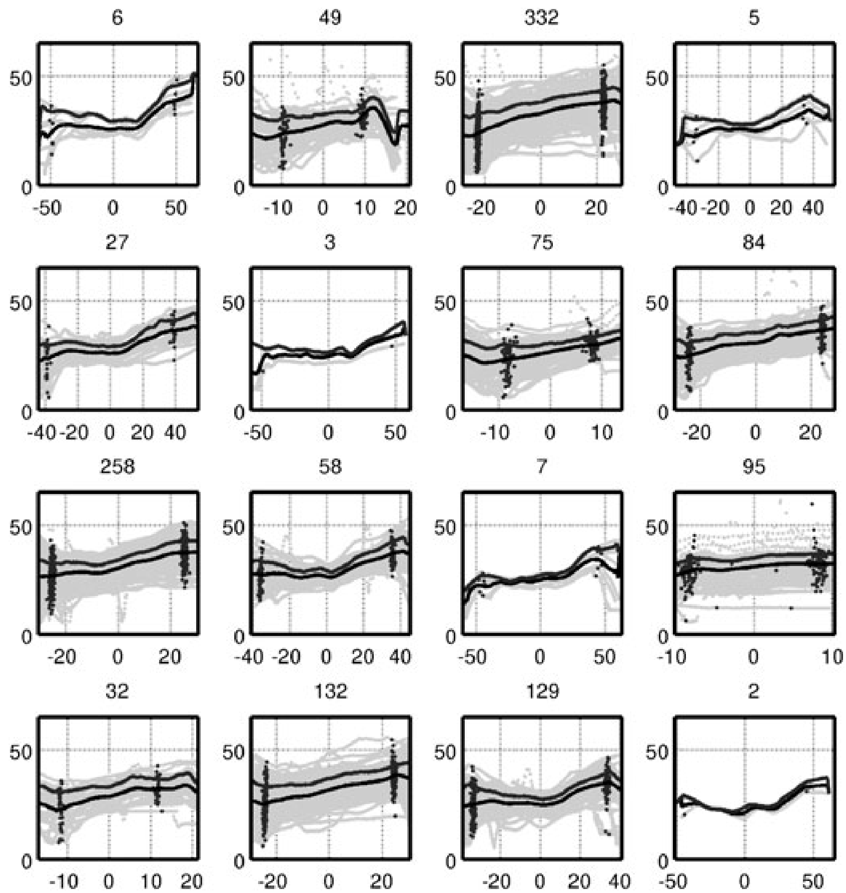

Figure 6. Speed profiles (grey curves), average speed (black curve) and operating speed (dark-grey curve), dots represent entry and exit points in roundabout (x-axis is in meters, y-axis in km/hour).

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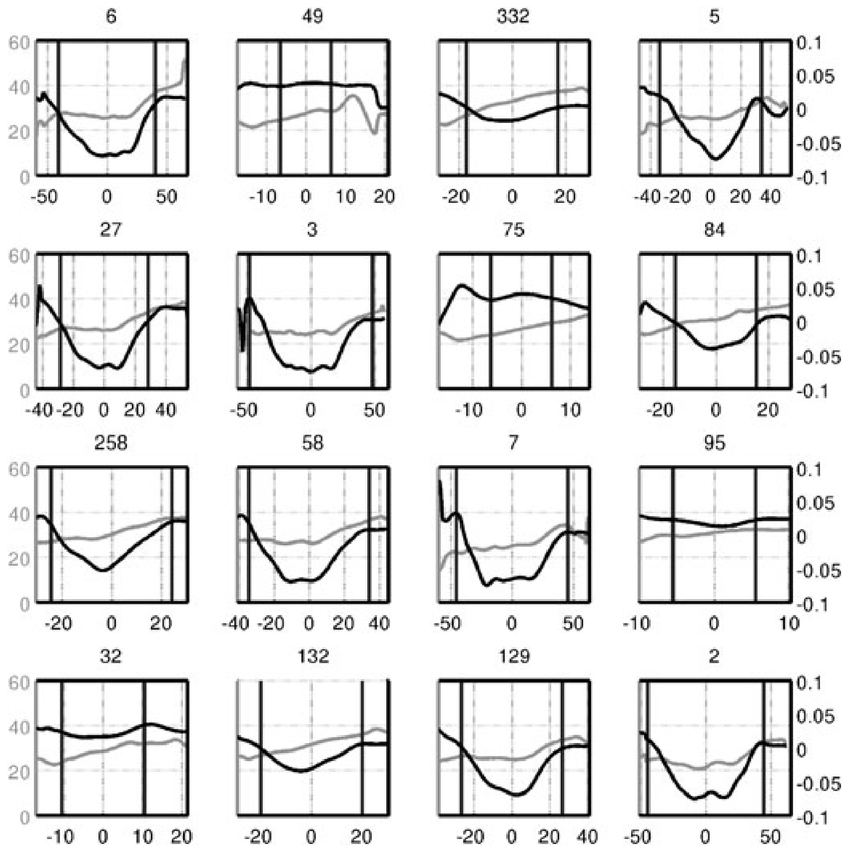


Figure 7. Comparison between curvature (grey curves) and operating speeds (black curves, shown also in Figure 6) (the left *y*-axis refers to speed in km/hour, and the right one refers to the curvature in meters^{-1}).

4. CONCLUSIONS

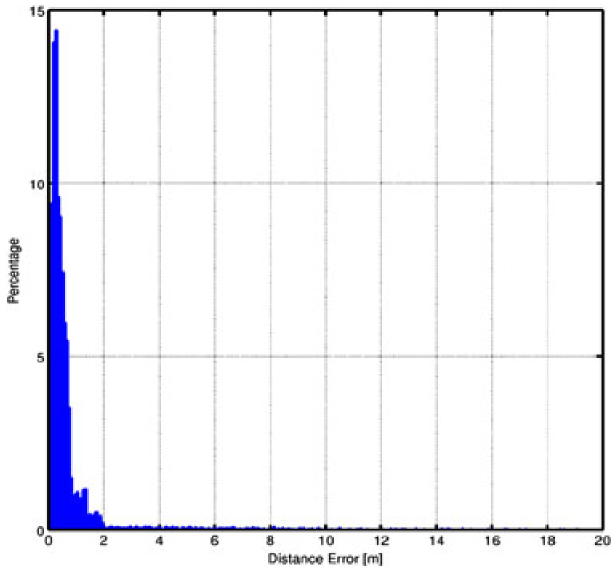
This research incorporates the development of a method for the analysis of vehicular movements in roundabout based on image processing and the elaboration of resulting data. For this purpose, a program (VeTRA) was developed and tested using a real case study. Results show that the software is very efficient in the evaluation of variables such as E/E flow matrix, trajectories, speed profiles and curvature of trajectories. These results, in particular those for trajectories, are not attainable by other methods in use at present. For this reason many researches are now based on the use of recorded images. The application shows that the proposed method is demanding in terms of time for survey setup and computing but otherwise more or less similar to other measurement systems it could be reduced if the roundabout is built taking into account the necessity of these types of survey, with the presence of poles or other holders for cameras.

Flow analyses computed by VeTRA are reliable as the software is able to reduce the number of errors caused by occlusions. Comparisons with data derived by manual counting show a very low absolute average error of 0.7%, with a peak value of 2.1%. In addition, vehicle classification is reliable in all cases.

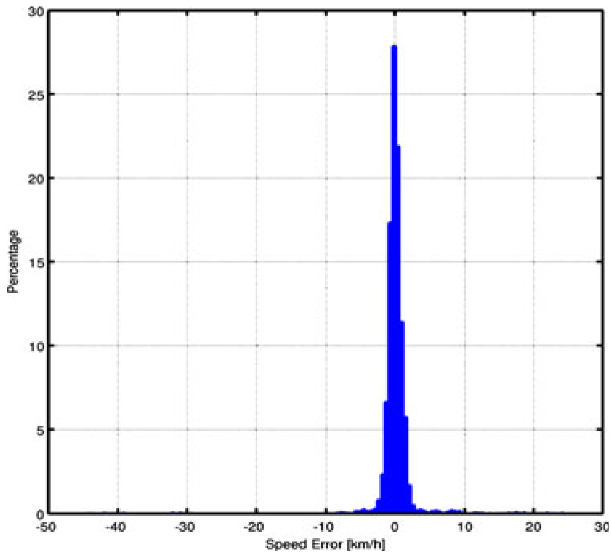
The trajectory reconstruction leads to good results when analysis is confined to points close to the camera. Speed profiles are almost insensitive to tracking system errors. In a few cases, outliers and noise limited the performance of VeTRA, and thus, a smoothing algorithm has been created to achieve more reliable results.

The performances outlined above encourage further VeTRA improvements for the following aspects:

- An algorithm for the division and fusion of blobs to limit the effects of moving occlusions.
- An improved background modeling and foreground extraction system for optimization in presence of clouds, low light, and reflections.



(A)



(B)

Figure 8. Distribution of errors in space (A) and speed (B) between VeTRA and RTK-GPS data (circulatory roadway data only).

- An image stabilization system to remove the effects of camera oscillations due to wind.
- A motion model of the Kalman filter for the improvement of curvature results measured on vehicles' paths.
- A simulation system in which vehicles are substituted by a 3D model in order to generate a further more precise relation between the real position of cars and their position on the image plane.

Four additional case studies have been examined subsequent to this one, and, as might be expected, the program performs better in line with the quality of the recorded images. High-quality images are characterized by elevated point of view, few occlusions and illumination problems, and reduced shadows.

For these reasons, the authors are working on new surveying approaches regarding camera arrangement. At the moment, two different options are being considered: the vertical position in the center of the central island and the lateral/central position of three cameras operating simultaneously. In both cases, the aim is to significantly reduce the number of errors relating to occlusion and to heavy vehicle height.

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