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Economical Camera-based Measuring Scheme for Roundabout Traffic

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Abstract
Counting the turning movements in a four-leg roundabout is a challenging task and often executed by vehicle recognition and tracking on traffic videos. In order to obtain accurately all the 12 flow values of the origin-destination (O-D) matrix we need to measure arbitrary chosen 12 linearly independent flow values. However, the larger the area to be observed the more cameras are needed because the good pixel resolution of the vehicles and the proper camera inclination angles are essential. Here we propose a novel measuring scheme, which observes only two roundabout legs instead of observing all the four, as a result obtaining all the 12 flow values requires a reduced number of cameras. The directly measured flow values and the mathematical method of determining the O-D matrix are given in details.

Keywords
traffic, roundabout, object recognition

1 Introduction

Detailed measuring of traffic volumes determining the O-D matrix in a medium-sized or bigger roundabout is a challenging task, especially when we must do it by manual vehicle counting. One of the main reasons of this is that the paths of vehicles making straight or left-turn movements have long common parts, and the other reason is that there is no traffic light control (in most cases) while the traffic volumes can be very high.

To circumvent this problem, a number of estimation methods has been developed, which are based on measuring only the inbound and outbound traffic volumes (8 measured values in case of a four-leg roundabout) and making assumptions about the relationships between the unmeasured volumes. Pratelli et al. (2021) give a brief survey about the most promising methods together with the supposed initial state of the O-D matrix in the iterative calculation. Tettamanti (2021) compares the performances of four advanced estimation methods with the help of measurement data collected in two sub-urban roundabouts. However, these estimation methods converge fast to a solution, which is sensitive to the choice of the initial O-D matrix, thus, some prior knowledge about the turning rates is useful to improve the accuracy.

The other approach to the problem is to determine 12 easy-to-measure traffic flow values, and then a linear mathematical transformation is applied to obtain the turning movements of interest. Yousif and Razouki (2007) and later Al-Sobky and Hashim (2014) give a detailed and generalized model of this transformation. In the latter work, the authors propose the 12 necessary and easy-to-measure flows, which will be treated later in this article.

Beyond the mathematical tools the traffic counting method is also crucial. Applying manual counting observers or detector loops in case of roundabouts seems to be quite costly compared to the video-based object detecting counters. That is why a number of papers publish methods based on vehicle recognition and tracking by artificial intelligence. Crouzil et al. (2016) employ movement detection and other image processing algorithms optimized for highway traffic detection. Later, the neural network-based recognition methods ruled this field: Fedorov et al. (2019) applied a Recognition Convolutional Neural Network model, which was trained and validated by data collected by the authors. Many researchers, however, simply employ ready-to-use trained and validated neural networks, among which the most popular are the YOLO (You-Only-Look-Once) models (see e.g. Jiang et al., 2022). These models render object detection and object recognition in one inference process, which

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outputs object (vehicle) bounding boxes together with their recognized category. Oltean et al. (2019) and later Lin et al. (2021) used speed-optimized YOLO versions to achieve a real-time vehicle counting process. Majumder and Wilmot (2023) measure the accuracy of a YOLO-based counter and find that it works with an error of approximately 10% compared to manual measurements.

After the object detection phase, the recognized vehicles must be tracked along their trajectory, since in case of roundabouts certain traffic flows can be distinguished only by tracking them along an extended path not only through a certain point. Actually, these are the situations that cause most difficulties. Comaniciu et al. (2003) give a detailed survey of the image processing-based tracking methods. However, with the appearance of the effective object detection methods the combination of the object detection and the classic image tracking algorithms achieved the best results (see e.g. Dai et al., 2019 or Amitha and Narayanan, 2021).

In the next section, we analyze some of the problems of the video-based measuring methods from the camera positioning point of view. In Section 3, we propose a measuring scheme that makes it possible to use fewer cameras to obtain all 12 turning rates. In Section 4, we introduce a traffic counting measurement regarding some selected O-D matrix elements of a specific roundabout in order to demonstrate the performance of the proposed method. In the last section, we make conclusions.

2 Limitations of camera-based traffic measurements

2.1 The recognition confidence

As a result, an object detector yields a number of bounding boxes on the image together with their category labels and recognition confidences. The confidence value of a specific box shows the probability of the correctness of the recognized category. One of the factors affecting this confidence value is obviously the resolution of the object that is the size of the bounding box.

As an illustration, Fig. 1 shows a processed image of a roundabout, where the bounding boxes and their confidences are shown. The closer vehicles are recognized with higher confidence in the picture; however, this illustration does not prove anything.

In order to get a more convincing picture about this effect we collected data of approximately 120000 vehicle bounding boxes from a 1080p video clip of 3 hours length recorded in the roundabout shown in Fig. 1.

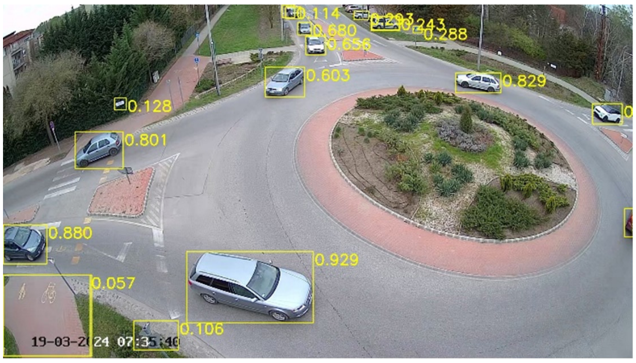

Fig. 1 An example for bounding boxes and their confidence values (The video-frame was recorded at the intersection of Kecskemét Nyíri út – III. Béla bl.)

Only one frame in each second was processed by the YOLOv5 object detector and all the observed [box-diagonal, recognition confidence] tuples were recorded in a list. The data-points of the tuples are shown in Fig. 2.

Fig. 2 demonstrates that the dataset is bounded by a curve above which there is no confidence value recorded (aside from a few outliers). For example, no confidence value measured above 0.5 when the box diagonal is smaller than 40 pixels, which is considered to be a bad resolution. However, what is more important: the change of the data distribution with the box size. In the region of below 120 pixels the vast majority of the confidences are under 0.4, while when the diagonal is greater, the confidence values are much more evenly distributed with the density maxima close to 0.8.

Accordingly, in a traffic measuring situation, we must choose low (under 0.4) limits for recognition confidence in case of a vehicle path far from the camera and yield small visual vehicle objects. This, however, will result in a high

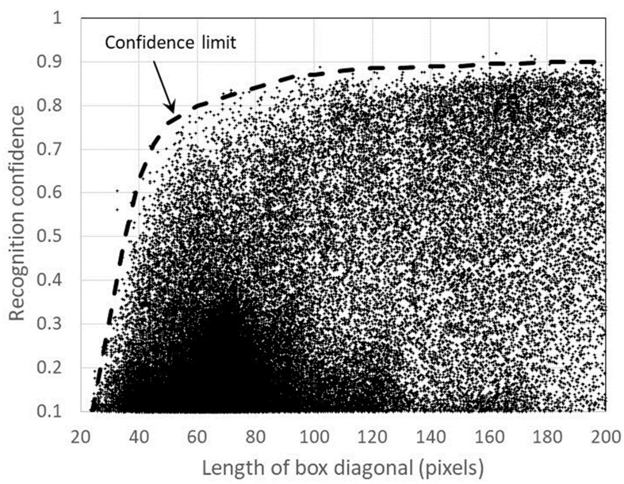

Fig. 2 The recognition confidence values corresponding to 120000 bounding boxes produced by the YOLOv5 model

rate of false positive detections, which can be observed in the upper left corner of Fig. 1, while there will be numerous false negative (unrecognized) vehicles as it is seen in the upper region of the same picture.

2.2 The problem of vehicle path separation

Regarding the vehicle tracking process a set of a prior paths must be defined on the video-image. The counter AI must determine which path was driven by the currently tracked vehicle. Obviously, the paths must be well separated from each other in the image's pixel coordinate system. To be more specific: we call two paths "well separated" if they have parts that are farther from each other than an average-size vehicle, and these parts are longer than an average-sized vehicle. It is easy to see that otherwise most vehicle trajectories cannot be related to one of the a priori paths unambiguously. Fig. 3 shows examples for a well separated and a not well separated pair of paths. This problem of separation is highly affected by the camera perspective (see e.g. Dinh and Tang, 2014). The bigger the inclination angle of the camera the easier to define well separated paths. On the other hand, however, if we have a bigger inclination, the area recorded by the camera is smaller, so we need to find a tradeoff between the two problems caused by the camera inclination.

3 The measuring scheme

The problems above are hard to solve on the image processing side but the situation can be efficiently improved by smart camera positioning and proper measured path choice. From the previous section it is clear that the larger the area to be observed the more cameras we need, otherwise we have to cope with the problem of small vehicle objects or not well separated vehicle paths.

In the measuring scheme proposed by Al-Sobky and Hashim (2014) 12 measured traffic flow data are needed to generate the O-D matrix. These are depicted in Fig. 4, O_i denotes the flows that leave the roundabout at the i-th leg, C_i denotes the flows that circulate in front of the i-th leg and M_i denotes the flow that turns right to the i-th leg. It can be seen that all four road connections must be seen by the cameras; therefore, in this scheme, we must observe a bigger area than the roundabout itself. On the other hand, these flow data are easier to measure by a human roadside observer.

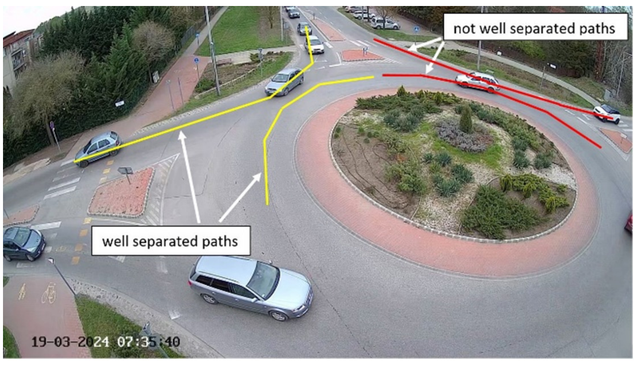

Fig. 3 An example for well separated and not well separated paths

In the present paper, the above idea of getting 12 easy-to-measure flow data is developed further. The novelty here is a new scheme that observes a smaller area, thus it requires fewer cameras to be installed and, as a result, fewer image processing work to do. In the case of a medium sized roundabout (i.e. the diameter of the central circle is not larger than 20-25 meters), we need to install at most two cameras. The proposed scheme can be seen in Fig. 5.

Here only two of the four road connections are observed, consequently only two of the four output flows are measured, i.e. O_1 and O_3, but the flows that enter the roundabout at the 1st and 3rd leg, I_1 and I_3 are also measured. Similarly, the right turn flows, Mi, are not measured but, instead of them, the C_{ij} flows are measured. Here C_{ij} denotes the flow that passes both road points in front of the i-th and the j-th leg, where the i-th and j-th legs are adjacent. In other words, measuring C_{ij} means counting the vehicles that give contribution to both C_i and C_j. Similarly to the solution proposed by Al-Shobky and Hashim (2014), these flow data are sufficient to determine the O-D matrix exactly with the premise that the number of the U turns (i.e. the flow arriving and leaving in the same leg) is zero.

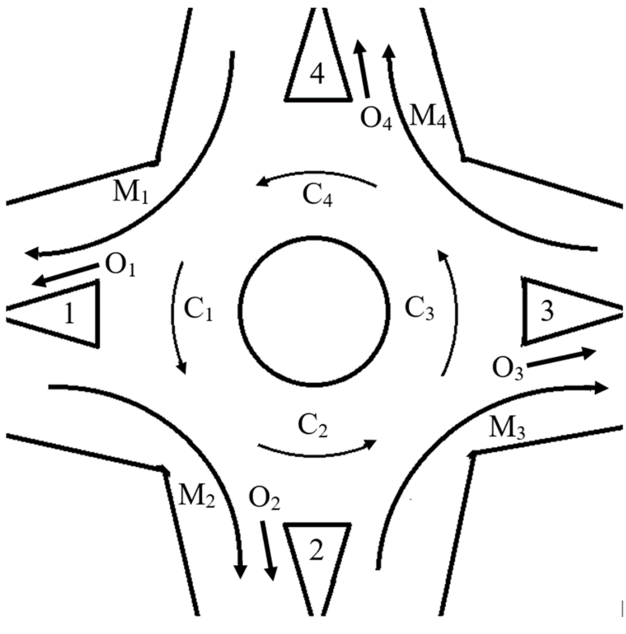

Fig. 4 The measuring scheme proposed by Al-Shobky and Hashim (2012)

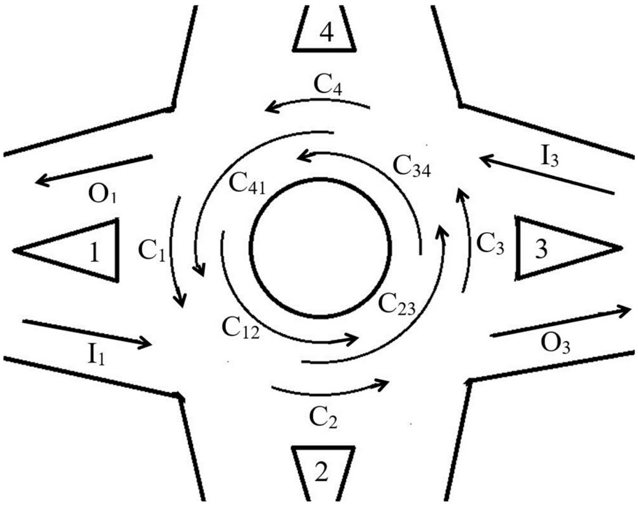

Fig. 5 The measuring scheme proposed by the present work

Let us denote the elements of the O-D matrix by F_{ij}, i.e. F_{ij} equals to the flow from the i-th leg to the j-th leg.

It is easy to see that the flow of C_2 consists of two parts: the C_{12} flow and the part of the incoming flow of I_1 that does not turn right, that is

$$C_2 = C_{12} + I_1 - F_{12} \quad (1)$$

Hence the flow of F_{12} can be expressed as

$$F_{12} = C_{12} + I_1 - C_2 , \quad (2)$$

Since the U turns are zero, the left turn flow from the 1st leg is:

$$F_{14} = C_{23} \quad (3)$$

Finally, the straight flow, F_{13}, can be obtained from

$$I_1 = F_{12} + F_{13} + F_{14} \quad (4)$$

as

$$\begin{aligned} F_{13} &= I_1 - F_{12} - F_{14} = I_1 - (C_{12} + I_1 - C_2) - C_{23} \\ &= C_2 - C_{12} - C_{23} \end{aligned} . \quad (5)$$

Applying the same calculations for the 3rd leg we obtain:

$$F_{34} = C_{34} + I_3 - C_4 , \quad (6)$$

$$F_{31} = C_4 - C_{34} - C_{41} , \quad (7)$$

$$F_{32} = C_{41} . \quad (8)$$

In the case of the flow values from the other two legs we cannot apply the above equations for the right turns, since it contains I_2 and I_4, which are not measured in the scheme. However, we have O_1 and O_3 measured, and the flow of O_1 consists of two parts: the right turn F_{41} and the difference of C_4 and C_{41}, that is:

$$F_{41} = O_1 - \left(C_4 - C_{41}\right) = O_1 - C_4 + C_{41} . \quad (9)$$

Similarly:

$$F_{23} = O_3 - \left(C_2 - C_{23}\right) = O_3 - C_2 + C_{23} . \quad (10)$$

The equations for the straight and left turning movements from legs 2 and 4 do not contain unmeasured terms, so all O-D matrix elements are expressed by the 12 measured values.

Table 1 summarizes the results of the above calculations.

Except for the left turning movements, all other movements are linear combinations of three directly measured quantities. This is similar to Al-Shobky's calculation scheme, where the right turn movements are measured directly and the others are calculated as linear combinations of three or five directly measured quantities. Let's call the calculation scheme given in Table 1 as "modified Al-Shobky" method.

4 Test measurements

As it was detailed in the previous chapter, we state that the modified Al-Shobky measuring scheme, proposed here, is more economical because it requires fewer cameras to achieve the same level of data reliability. Or, in other words, with the same number of cameras, the modified method produces smaller measuring errors in the case of computer vision counting.

In order to demonstrate the correctness of this statement, we apply both methods in a specific computer-vision-based traffic counting measurement. Three elements of the O-D matrix in the intersection of Kecskemét Nyíri út – III. Béla bl. were measured: F_{41}, F_{42} and F_{43}, i.e. the traffic volumes that come in the 4th leg of the intersection and proceed to right, straight and left, respectively. This 4th leg of the intersection at hand is the westward leg, which is the most heavily loaded one in the morning traffic. Corresponding to the original Al-Shobky method (Al-Shobky and Hashim, 2014), these three O-D matrix elements are calculated as:

Table 1 The flow values of the O-D matrix in a four-leg roundabout expressed by the 12 flow values proposed for measuring

	To 1	To 2	To 3	To 4
From 1	-	$C_{12}+I_1-C_2$	$C_2-C_{12}-C_{23}$	C_{23}
From 2	C_{34}	-	O3–C2+C23	$C_3-C_{34}-C_{41}$
From 3	$C_4-C_{34}-C_{41}$	C_{41}	-	$C_{34}+I_3$–C4
From 4	$O_1-C_4+C_{41}$	$C_1-C_{41}-C_{12}$	C_{12}	-

$$F_{41} = M_{41} , \tag{11}$$

$$F_{42} = O_1 + O_2 - M_{12} - M_{41} , \tag{12}$$

$$F_{43} = C_1 - O_2 + M_{12} . \tag{13}$$

Whereas using the modified Al-Shobky method, we need to apply the equations given in the fourth line of Table 1. So, if we are planning to apply both methods, altogether, the following eight traffic volumes need to be measured: O_1, O_2, C_1, C_4, C_{12}, C_{41}, M_{12} and M_{41}.

The measurement was performed on 19 March 2024 from 7:00 am to 9:00 am by two security cameras of type EZVIZ CB3. The traffic was counted in every 15-minute time-interval. The positions and the projected field of views of the cameras can be seen in Fig. 6. Each camera was fixed at 5.5 meters high, the diameter of the outer curb-circle of the roundabout is 35 meters.

One camera (denoted by 01 in Fig. 6) was positioned so that the traffic of the 2nd (i.e. the eastward) leg and the 3rd (i.e. the northward) leg could be seen by it, whereas the other camera (number 02) monitored the 4th (i.e. the westward) leg and the 1st (i.e. the southward) leg.

This measurement was part of a much longer (two days) measuring period, so we had to be economical with battery and storage. Therefore, the video recording was set to 15 frames per second and 1080p resolution.

As it was detailed in Section 2.2, the paths along which the counted vehicles passed were defined a priori, corresponding to the traffic flow data to be measured. The paths are shown in Fig. 7.

The paths are marked by colored polylines and the widths of the paths are denoted by circles with the same color.

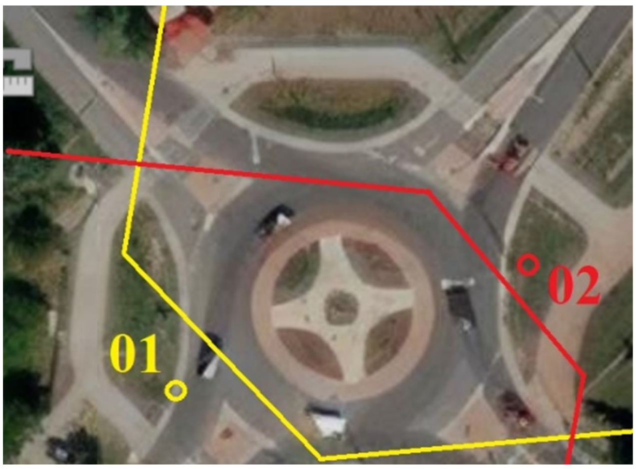

Fig. 6 The positions (denoted by yellow and red small circles) and the field of views (the two convex areas bounded by the yellow and red polylines) of the two applied cameras

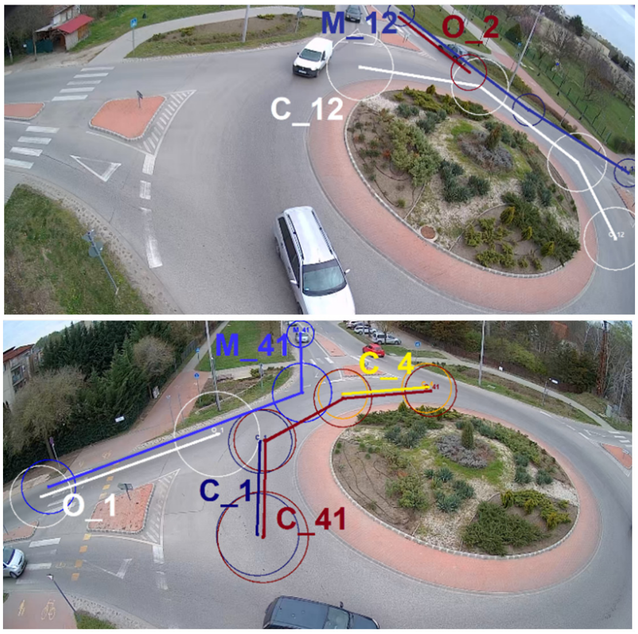

Fig. 7 The eight vehicle paths along which the computer-vision-based traffic measurement method counted the passing vehicles

The applied image-processing-based counting scheme was similar to that proposed by Majumder and Wilmot (2023): the YOLO object detecting system (version 5) was used to find all of the vehicle bounding boxes in each frame. In the next step, we kept only those vehicle bounding boxes that were positioned on one of the defined paths. Instead of a pixel-based tracking, the expected position of a chosen vehicle was determined in the image space based on its estimated velocity, and then the closest vehicle box was identified as the vehicle at hand. A similar method was used for tracking by Oltean et al. (2019). The big advantage of this bounding-box-based tracking is that it is much faster than the pixel-based methods, and it presumably performs better when the video is recorded with a low frame per second value, such as 15 fps.

The widely used YOLO object recognition system was trained on the COCO 2017 image dataset, which is divided into 128 object categories, and it can distinguish only five vehicle categories (car, truck, bus, bike, bicycle). In the present demonstrative measurement we did not distinguish these categories but joined them into a common 'vehicle' category. This made the comparison of the two methods more simple, and in the other hand, in this roundabout the rate of buses and many-wheeled trucks are low, so the number of 'vehicles' is close to the number of 'unit vehicles'.

Table 2 shows the traffic volumes F_{41}, F_{42} and F_{43} calculated by the two methods and counted by human observers. Since counting by human is considered to be much more reliable than the computer-vision-based methods, we

Table 2 Comparison of the traffic measurement results of three chosen O-D matrix elements obtained by the original calculation method by Al-Shobky, and its modified method proposed in the present paper. As a reference, the results obtained by human observers based on the video footage are included as well.

Time intervals (AM)		7:00 - 7:15	7:15 - 7:30	7:30 - 7:45	7:45 - 8:00
F_{41} (right turns)	By human	128	119	118	128
	Al-Shobky m. (2014)	119	96	107	87
	Difference to sum ratio	−4%	−12%	−6%	−17%
	Modified Al-Shobky m.	125	117	118	128
	Difference to sum ratio	−2%	−1%	0%	0%
F_{42} (straight)	By human	95	84	85	100
	Al-Shobky m. (2014)	84	108	84	125
	Difference to sum ratio	−5%	12%	−1%	11%
	Modified Al-Shobky m.	94	86	86	104
	Difference to sum ratio	−1%	1%	1%	2%
F_{43} (left turns)	By human	6	5	11	16
	Al-Shobky m. (2014)	24	6	20	35
	Difference to sum ratio	8%	1%	5%	8%
	Modified Al-Shobky m.	8	7	7	15
	Difference to sum ratio	1%	1%	−2%	−1%
Sum (F_{41} + F_{42} + F_{43})	By human	229	208	214	244

use it as reference or 'ground truth' data. These data are given first (or in the uppermost rows) in the table for each F_{4i} value. The errors of the Al-Shobky and the modified Al-Shobky methods were expressed as their difference from the reference data relative to the total in-flow traffic volume, $F_{41}+F_{42}+F_{43}$, given in percentages. That is, the corresponding error ('Difference to sum ratio') values were calculated as:

$$Diff_{4i} = 100 \cdot (CV_{4i} - R_{4i}) / \left(F_{41} + F_{42} + F_{43}\right), \quad (14)$$

where CV_{4i} and R_{4i} are the data obtained by the computer-vision-based method and the reference data. The 'Difference to sum ratio' data, rounded to integers, are listed below each computer-vision-based data in the table.

It is seen that the error values (i.e. 'Difference to sum ratio' values) of the two methods considerably differ from each other. In the case of the modified Al-Shobky method all of the errors range from −2% to 2%, while error values of the original Al-Shobky method are typically much higher. They are between −4% and −17% in the case of the right turn volumes and between −5% and 11% in the case of the straight proceeding volumes. The best result was obtained in the case of the left turn volumes: here the errors are between 1% and 8%.

This higher inexactness of the original Al-Shobky method is due to that we applied only two cameras, and though all of the necessary paths could be measured (see Fig. 7), some of the paths suffered from the problems detailed in Section 2. These problematic paths were: M_{12}, M_{41} (i.e. the right turning paths) and the O_2 path.

These paths, partly or entirely, lie in the upper quarter of the image, where the vehicle objects are smaller and usually obscure each other. Of course, these problems could be avoided by applying more cameras. However, the very aim of this measurement was to demonstrate that if we need to be economical with the number of cameras then the proposed modified Al-Shobky measuring scheme seems to be a better choice under the given circumstances and with the applied image-processing methods.

5 Conclusions

In the present work, first, the image processing problems caused by observing a relatively big area by few cameras were discussed. The identified problems derived from that the region of interest, i.e. the vehicle paths to be observed are situated in the upper region of the picture, where the observed vehicles are smaller and tend to obscure each-other. From this we can conclude that it is worth finding more economical measuring schemes requiring measurements of a smaller area. Then a measuring scheme was proposed that observes only two opposite legs of the underlying roundabout and based on the 12 measured flow values, the O-D matrix of the roundabout traffic can be calculated. This proposed method can be regarded as a modification of the method introduced by Al-Shobky and Hashim (2014). The correctness of the modified O-D matrix calculation is justified.

In order to demonstrate the practical usefulness of the proposed measuring scheme, three O-D matrix elements were measured in a roundabout (Kecskemét Nyíri út – III. Béla bl. intersection) using only two cameras and a YOLO (version 5) computer vision based object detection and tracking system. Regarding the measuring schemes, we applied both methods: the method proposed here and the original (Al-Shobky's) method. Besides, the traffic volumes at hand were counted also by human observers, and these measurement data served as ground truth reference.

It was obtained that the proposed method produced significantly smaller errors that the original one. Based on this experiment, we can conclude that if we are restricted to use only two cameras in the case of a medium sized roundabout then we can hope more exact results from the proposed measuring scheme. This statement does not hold for the case when we use four cameras, since in that case all vehicle paths involved in the original Al-Shobky scheme can be well observed. The situation probably is similar in the case of a small roundabout (when the outer curb-circle's diameter is under 20 meters): here all necessary paths can be well observed by only two cameras, so the proposed method won't produce significantly better results.

As a next step, it is worth to examine whether the performance of the proposed method is still better than the original one if we applied a more costly, pixel based, object tracking method.

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