SYSTEM AUTOMATIC TRAFFIC MONITORING TO OBTAIN THE O/D MATRIX: CASE STUDY IN BRASILIA-DF, BRAZIL

Adriel Rocha Lopes, Universidade de Brasília, adriel@aluno.unb.br

Augusto Passalaqua Martins, Universidade de Brasília, augustomartins@ceftru.unb.br

Gabriel Irribarem Soares Ruas, Ceftru/UnB, gruas@unb.br

Ticiano Augusto Callai Bragatto, Ceftru/UnB, bragatto@unb.br

Marcus Vinícius Lamar, Universidade de Brasília, lamar@unb.br

Pastor Willy Gonzáles Taco, Universidade de Brasília, pastor@unb.br

ABSTRACT

This paper proposes the use of computational vision and artificial intelligence techniques to vehicle counting and tracking in a multiple street scenario, using optical character recognition to link the same car in two different observation posts using the license plate. Besides counting and tracking, the system also classifies vehicles in four different classes: trucks, buses, van and cars. With the identification of vehicles and their classifications arise tools to plan and manage transportation data with actual road behavior. Allowing us to obtain a traffic system consistent with the reality of the urban. With Automatic Traffic Monitoring was able to get a Matrix O / D, quickly, efficiently and with little manpower.

Keywords: Matrix O/D, Computational Vision, Artificial Intelligence, transportation planning.

INTRODUCTION

Road overcrowding is a reflection of the constant increase of vehicles running in urban centers, consequently, the complexity of traffic flow management increases**.** Traffic flow management processes require information and data on the behavior and distribution of traffic flow in order to provide a basis for transportation planning and allow for corrective interventions to take place. Thus, vehicle count studies on Screen and Cordon Line, used to build the Origin/Destination (O/D) matrix, are central to convey information on demand behavior, which facilitates the planning and management of road networks.

The existing methods for estimating the O/D matrix usually demand a considerable amount of time, human and financial resources to gather the necessary data for building the model. In that context, methods for estimating the O/D matrix based on traffic volume counts in traffic networks arise.

Methods for estimating O/D matrices have been studied since the mid-1970s, when Van Zylen and Willumsen (1980) proposed the synthetic model. Since then, the method has undergone several modifications so as to provide more accurate responses (Gur *et. al.* (1978), Cascetta (1984), McNeil & Hendrickson (1984), Cascetta & Nguyen (1988), Bell *et. al.* (1991), Yang *et. al.* (1992), Lopez-Reyes (1999) and Bentoncini (2007)). This paper presents the development of an automated system for counting and monitoring vehicle flow on Screen or Cordon Line to estimate the O/D matrix.

This system has very low cost and provides high accuracy rates in measuring vehicle flow through volume counts. The portable system is capable of monitoring the flow of vehicles for long periods of time, by means of automating the monitoring process, and uses computer vision techniques to count on Screen or Cordon Line.

The automated system proposed in this paper comprises four subsystems; and each of them performs a step in the process of building the O/D matrix. In step 1, the images of the vehicles' license plates are captured and stored on video. In step 2, the vehicles' rears are located; their license plates are segmented and then the character recognition process is conducted. After the license plate is recognized, in step 3, the system generates a database which optimizes the access (e.g., manner and time) to that information. Finally, the O/D matrix is then estimated, given that we have the collected data at hand and that computational techniques are applied.

This paper is organized in 6 sections, including the Introduction. Section 2 presents the fundamentals regarding the methods for estimating O/D matrices based on volume counts. Section 3 describes the methods for classifying vehicles and reading license plates. Then, Section 4 puts forth the automated monitoring system we developed in addition to how the O/D matrix can be built from such monitoring. Section 5 presents a case study conducted to validate the technique used for building the O/D matrix. Finally, conclusions are drawn in Section 6.

BUILDING THE O/D MATRIX

Determining the amount of movements performed between origins and destinations in a given region or city is an important step in analysis and planning studies for the road system. In general, the desires for moving people or goods are represented by bi-dimensional origin-destination matrices (O/D matrices), where each element in the matrix (cell) represents the travel demand between an origin and a specific destination.

According to Cascetta, there are three methods for determining an O/D matrix. The first one is the household survey and/or interviews on site (at the road network), thereby estimating the travel demand between regions. The second one estimates trips from information regarding land use as a function of the impedance of trip generation between different O/D pairs. In addition, the gravitational model and the model intervening opportunities (Ortuzar, 1990) are examples of synthetic models used for estimating the distribution of trips between these O/D pairs. The third method comprises traffic volume counts, where the number of trips between O/D pairs is estimated from data collected at various locations on the network.

The first method mentioned, according to Ortuzar & Willumsem (1994), requires a considerable amount of time, human and financial resources for its realization. In addition, data are quickly outdated, especially in developing countries due to the constant changes in the urban setting. The second method has the same problems, given that it demands costly information over a long period for calibrating synthetic models. The advantage of these methods, according to Ortúzar & Willumsem (1994), is the amount of information gathered on the movements performed. Besides estimating movement patterns in the O/D matrix, the database obtained from these surveys enable more complex analyses to be conducted regarding the behavior of travelers in face of their travel choices (López-Reyes e Kawamoto, 2001). Additionally, calibrating trip generation models is useful for estimating future demand behavior. According to Dermachi & Bertoncini (2004), costs associated to both methods are usually justified if such surveys are the only possible alternative, such as in the case of planning a new road system.

Paramahamsan (1999) state that the operational control of transportation systems requires that the O/D matrices be dynamic, reliable and easily and quickly accessible. In that context, traffic volume counts are the most feasible tool for estimating synthetic O/D matrices because it can provide a basis for improving the knowledge on movements performed and, consequently, improve traffic management. That method caters for effective O/D matrices, i.e., matrices that faithfully replicate the traffic volume observed and cater for representing the variability of movement behavior; in addition to requiring few resources.

Ortúzar & Willumsen (1994) describe the estimation of synthetic matrices using volume counts as a very attractive data source due to its low cost and the fact that it can be done automatically, requiring few human resources (e.g., a network monitored by a central traffic control). This estimation should be interpreted as the inverse of other traffic allocation techniques (Bertoncini, 2007) because instead of obtaining data flows across the network from allocating an O/D matrix, they aim to estimate an O/D matrix that, when applied to the network, replicates the observed flows (Abrahamssom, 1998).

The main problems associated with estimating O/D matrices are the following. First, in theory, you can get multiple results for the O/D matrices from the same pool of flow data, which calls for identifying the most appropriate solution. The second problem concerns the fact that, in practice, there is usually no continuity of traffic flows at the nodes, which implies the absence of an O/D matrix replicates the observed pattern exactly. The third problem is associated with traffic jams in the network under study.

Aiming at overcoming the obstacles presented, several studies were developed, putting forth mathematical formulations and solution algorithms in order to estimate synthetic O/D matrices from traffic volume counts. Examples include Robbilard (1975), Van Zuylen & Willumsen, Cascetta (1984), Yang et al (1992), Paramahansam (1999) and Van Aerde (2003).

As mentioned before, multiple results may be obtained for the O/D matrices from the same set of flow data in order to resolve this issue, so the formulation proposed by Robillard (1975) estimates the O/D matrix is conducted with the help of the gravitational model, which used a proportional allocation model, where the routes used were defined before the O/D matrix estimation process. Van Zuylen (1978) proposed that minimizing the amount of information, involving the observed flow and the seed matrix would be able to estimate an O/D matrix. Willumsen (1979), follows a logic similar to Van Zuylen's and proposes that the maximization of entropy, where the micro-state would be represented by information regarding each trip (e.g., origin, destination, mode, time etc) and the meso-state represented by the total amount of trips between the O/D pairs would result in the O/D matrix that is most likely to occur. Demands estimated by these models, which are called synthetic demands, are estimated from traffic counts obtained on stretches of roads or intersections. These counts may acknowledge vehicle classes such as cars, trucks and buses. They can also be done in fragmented periods of time, for example, an hourly count can be divided into four 15-minute intervals, which makes the model attractive to be used in addition to traffic simulators.

The most important model for solving flow continuity problems is the one proposed by Cascetta (1984), and many other models have stemmed from his proposal. Cascetta (1984) addressed the issue using a statistical inference approach while using the least square Method.

Regarding the third issue presented, which concerns the effect of traffic jams on the estimation of the O/D matrix, models put forth the idea that the p_{ij} matrix (percentage of usage of a given arc) should no longer be fixed. Nguyen (1997), Gur et al (1978) and Fisk (1998) have made important contributions in this field by proposing the use of an interactive method which accounts for the joint use of model generation and traffic allocation as a kind of dual-level technique. The proposed method considers that the estimated trips must be dragged along the minimum cost path until that path is no longer so. Thus, all trips are allocated based on the minimum cost path. However, Yang (1992) believes that this proposal cannot fully resolve the issues linked to road congestion. Then, Yang et al (1992) presented a new proposal for the dual-level technique as an attempt to solve the issue of congested networks. The model uses least square coupled with a user equilibrium allocation technique for estimating the O/D matrix.

These works are still not widely known, so they are not normally used by researchers or transport systems analysts (Bertoncini, 2007). The very ignorance of the details of the method's theoretical grounds and the practical difficulties found in estimating trips between O/D pairs contributes to this situation (Van Aerde; Rakha; Paramahamsan, 2003).

A popular way of gathering data of an O/D matrix using traditional methods is license plate recognition. By means of recording the license plates that travel in observation stations, which are distributed throughout the study area, the trajectory of vehicles is described, thus, their origins and destinations are found. The locations of the observation stations are defined based on the proposed zoning and should at least cover the main entrances and exits of the traffic zones. After the sample O/D matrix is found, it is then expanded in order to obtain a matrix that represents the movements of the whole population.

According to Souza (2007), license plate recordings are usually sample-based due to the difficulty in manually recording the plates of all vehicles going through an observation station. This leads to many experimental errors because there are several criteria to define which vehicles will comprise the sample. Furthermore, only a portion of the plates' digits is recorded (usually the numeric ones). According to Van De Zijpp (1997), due to partially recording the license plate, ambiguous data may be collected, which happens when two different vehicles have the same partial record. Souza (2007) argues that these errors are minimized if the observation stations are equipped with camcorders or automated vehicle identification tools.

METHODS FOR CLASSIFYING VEHICLES AND READING LICENSE PLATES

Classifying Vehicles

Automatic vehicle categorization has been developed by several researchers to improve studies regarding traffic operation and planning. This modeling has been used successfully in many countries, however, as each country uses their own definitions regarding the category of vehicles, studies tend to be specific to a certain region in particular.

Categories can also be made for specific studies, such as the counting of axles (Sun *et al. (2003)*), which lends itself handy for auditing toll plazas. Categories such as passenger cars, vans, buses and trucks can be done by sensors as inductive loops (Gajda *et al. (2001)*), extensometers (Shin *et al. (2007)*) and computational vision.

Using computational vision techniques for solving this problem is a widespread practice mainly because it is a minimally invasive method (there is no need for drilling the pavement for placing the loops) and because results can be reviewed.

The categorization of computational vision is normally used in two stages: feature extraction, which synthesizes the visual information into numeric indicators, and classification, which uses artificial intelligence techniques to estimate the most appropriate vehicle category for a given set of extracted features.

Ji *et. al. (2007)* proposes using a classifier based on Gabor filters for extracting features and a minimum distance classifier to distinguish between the five classes of vehicles (Figure 1). They report a 95.17% hit rate.

Figure 1 – Categories proposed by Ji *et. al. (2007)*

Gupte *et al. (2002)* proposes only two categories: cars and not cars. The extracted features encompass length and a combination of height and width. The classification performed is conducted by means of a threshold, reaching a 70% accuracy rate.

Detecting Moving Objects

Background subtraction is a technique that aims at generating a reference image that represents the semi-static or static portion of the scene, i.e. the background. After the background is modeled, moving objects can be defined as regions that do not match the background model.

The simplest background subtraction method is using a manually chosen image. Despite its simplicity, there is an accumulation of errors due to changes in the scene that are not modeled by the static background. A way to obtain an adaptive background model is using the pixels' temporal average, as presented by Stauffer and Grimson (1999). This method, however, is only appropriate for static backgrounds and few objects in the scene.

Aiming at overcoming these limitations, while maintaining the simplicity of the average, Lai & Yung (1998) propose a background subtraction algorithm based on scoring (Scoreboard). Ridder et al (1995) model each pixel with a Kalman filter, which allows the model to adapt well to changes in lighting. This model is also unable to represent a multi-modal background, i.e., where more than one value can be considered as background in a given region. This situation can occur, for example, with flashing lights or a tree swinging in the wind A method that has a multi-modal model for the background is proposed by Friedman & Russel (1997). The authors classify each pixel into three predetermined distributions, which represent the colors of the road, shadows and vehicles. Due to the use of predefined probability distributions, this method adapts with difficulty to the different situations in which it can be applied, thus requiring manual calibration for each scene.

Stauffer & Grissom (1999) propose a multi-modal adaptive methodology. In their work, each pixel is treated as a stochastic process with a probability distribution modeled by a mixture of Gaussians. The parameters of the Gaussians are adjusted through an online Expectation Maximization (EM) algorithm. In their model, pixels are classified as background if they have a higher probability than a given threshold, according to the distribution of their respective Gaussians. However, the mixture of Gaussians is unable to ignore sudden changes in lighting, such as the ones caused by passing clouds on a sunny day. KaewTraKulPong & Bowden (2001) present modifications in the system proposed by Stauffer & Grissom to improve its performance. A weakness identified in the original paper is the long time it takes for the initial background model to load. The authors propose an accelerated initialization which uses a window with the same size of the already obtained frames to conduct the model's initial estimate. This allows a functional background model to be obtained in the first frames of the sequence, even though it runs the risk of including illegitimate information too quickly in the model. The model's update dynamic ensures that information which does not match the background image is promptly ignored by the model while more evidence can be gathered and the model becomes more stable.

Recording and Reading License Plates

License Plate Recognition (LPR) is the process of recognizing vehicle license plates automatically through computational vision techniques. Figure 2 shows typical examples of images a LPR system should be able to process. The basic method, as indicated by Anagnostopoulos, C. N. E., Anagnostopoulos, I. E., Loumos, V. & Kayafas, E. (2006) may be divided into three main stages:

1. License plate location;
2. Character segmentation; and
3. Character recognition.

FIGURE 2 – Example of images handled by a LPR system.

Location

The first step involves detecting the region of interest (i.e., license plate) in the image fed into the system. This stage is developed based on information on the plates that is already known. In LPR systems, there is usually a step of preprocessing the input image using filters for noise reduction, color conversion and correction of perspective so as to facilitate the processes conducted in the following steps.

Several works, such as Hsieh, J.-W., Yu, S.-H. & Chen, Y.-S. (2002), Hongliang, B. & Changping, L. (2004), Comelli, P., Ferragina, P., Granieri, M. & Stabile, F. (1995), Dubey, P. (2005) and Duan, T. D., Duc, D. A. & Du, T. L. H. (2004) highlight that license plates are regions with large concentration of vertical edges, due to the contrast between letters and background of the plate. By means of using edge detection techniques together with morphological filters and heuristics about the plate's shape, the authors can isolate the regions of possible license plates within an image.

Furthermore, the works of Chang, S.-L., Chen, L.-S., Chung, Y.-C. & Chen, S.-W. (2004)., Jianfeng, X., Shaofa, L. & Zhibin, C. (2003) and Yang, F., Ma, Z. & Xie, M. (2006) make use of information on possible colors of lettering and plate background to improve the recognition and segmentation of plates. Chang, S.-L., Chen, L.-S., Chung, Y.-C. & Chen, S.-W. (2004) use the possibilities of color transition for detecting edges, letters and background. Additionally, Jianfeng, X., Shaofa, L.& Zhibin, C. (2003) uses a neural network that classifies points according to possible colors in a plate. Data gathered in this stage are then used to assist the classification of objects that are likely to be license plates. These data are also used to maximize the contrast between the background and the letters. The work of Yang, F., Ma, Z. & Xie, M. (2006) performs a conversion to grayscale before analyzing the image’s central area in order to determine which binarization method provides optimum contrast.

Segmentation

In the segmentation stage, an analysis of the binary image obtained is carried out so that the characters on the plate can be separated from each other in order to be classified in the following step. The most common character separation technique is the analysis of the vertical and horizontal projection of the binary image, according to Zhang, X., Liu, X. & Jiang, H. (2007). Another widely used method is the analysis of connected components, such as data on height, width and location for detecting edges and characters, as shown by Yang, F., Ma, Z. & Xie, M. (2006). In this stage, perspective correction problems are also analyzed. These issues may be dealt with in the previous step, depending on system. In addition, elements that were incorrectly defined as being of interest at the binarization stage are analyzed.

For perspective correction, Pan, M., Yan, J. & Xiao, Z.(2007) introduce and compare several techniques for calculating the plate's inclination angle in relation to the camera so it can later be corrected using linear transformations. Besides, Zhang, X., Liu, X. & Jiang, H. (2007) present a technique for correcting skew based on Radon transform. Image noise, which are incorrectly binarized points, are commonly eliminated by using a threshold that adapts to the character limits used in the projections, as stated by Anagnostopoulos, C. N. E., Anagnostopoulos, I. E., Loumos, V. & Kayafas, E. (2006). An alternative is to use an iterative algorithm where the result of a noisy image is discarded and a new binarization, with a new boundary, is generated so it can be analyzed by the character segmenter one more time, according to Zhang, X., Liu, X. & Jiang, H. (2007).

Recognition

Before the next stage can be performed, a normalization needs to be conducted so as to undo the results of treating characters uniformly regardless of the license plate's original image size or distortions caused by perspective correction, Chang, S.-L., Chen, L.-S., Chung, Y.-C. & Chen, S.-W. (2004).

Feature extraction simplifies and reduces the amount of input data for the classification system. Among the feature extraction methods researched are topological ordering, including the number of holes, endings and nodes of three and four exits in each character, Chang, S.-L., Chen, L.-S., Chung, Y.-C. & Chen, S.-W. (2004) and Principal Component Analysis and edge detection using Kirsch Abdullah, S. N. H. S., Khalid, M., Yusof, R. & Omar, K. (2007).

After the number and letter features are extracted, data are fed into a classification system, which usually involves an artificial neural network, as in Anagnostopoulos, C. N. E., Anagnostopoulos, I. E., Loumos, V. & Kayafas, E. (2006), Wu, F., Wang, Y.-G. & Hou, X.-W. (2007), or Chang, S.-L., Chen, L.-S., Chung, Y.-C. & Chen, S.-W. (2004), which uses a Self-Organizing Map, among others.

AUTOMATED TRAFFIC MONITORING SYSTEM

Image Capture and Video Storage

First, the observation station is defined and set of camcorders are placed on the region of interest. Each camera is positioned on the road so as to monitor only one traffic lane, which facilitates plate detection and segmentation. The video signals of each lane are stored on camcorder's hard drive. The videos acquired during the session are stored in the server database, where they wait to be processed in later steps.

Vehicle Detection

The system seeks to segment vehicles from the camera's fixed viewpoint. In this situation, the objects of interest move on a relatively static scene, which is the road. Small movements that occur due to vibrations and the effects of wind are the main difficulties considering the scene as static. The system proposed by Stauffer & Grissom (1999) was chosen as a basis for performing this task; however, it was adapted according to changes proposed by KaewTraKulPong & Bowden (2001). The system needs to be adaptive in order to be used for long periods of monitoring, which means it should change its model according to variations of lighting conditions.

In the model proposed by Stauffer & Grissom (1999), each pixel is considered as an independent stochastic process. Given that the scene's composition and the intensity of lighting both vary with time, the background model must be built dynamically. The pixels' color distribution is approximated by a Gaussian mixture model. This model has several advantages over simpler techniques. For example, when an object is modeled as if belonging to the background, it does not destroy the previous model. This allows for quick recovery of the original background model, even after an object that was moving at first remains stationary for some time. It could be a parked car within the camera's field of vision which starts to move away and leaves the parking space. Only when a Gaussian becomes the least likely Gaussian, among the K used in the model, and a new color is observed that the previous model is lost.

Background subtraction results in a binary mask, where 1 represents the moving objects, i.e., the foreground, and 0 represents the background. All pixels which do not match any existing distribution belong to the foreground. Pixels that match the distribution are only classified as background if the match occurred with one of the model's B first Gaussian at that position. Otherwise, they will also be classified as foreground.

License Plate Location and Segmentation

The process of reading the license plates used in this study was the one described by Anagnostopoulos, C. N. E, Anagnostopoulos, I. E., Loum, V. & Kayafas, E. (2006).

After the car's region has been isolated from the rest of the scene, the license plate can be isolated from the rest of the vehicle because plates have a higher concentration of vertical edges. We use the Sobel edge detector in order to detect these regions. This detector uses two filters to extract the magnitude of the image's horizontal and vertical gradients. Edges are regions where the gradient's magnitude is above a certain threshold. To isolate only vertical edges, we choose only edges in which the horizontal gradient is greater than the vertical one, i.e., areas where the image's gradient has an angle close to the horizontal axis. Areas that have a high density of edges are located by applying morphological filters in image which contains the edges. First, a dilation filter is applied, which causes the edges near the image to merge, forming a block of pixels. An erosion filter is then used to erase the areas which are not big enough to be considered license plate candidates. After the morphological filters are applied, rectangular shaped areas which are roughly as big as a plate are then chosen for recognition.

OCR Technique for identifying the characters of the license plates

Once the region of interest is selected in the captured image, the image is converted to grayscale according to the formula by means of extracting the luminance component 0, 2989R + 0, 5870G + 0, 1140B. The grayscale image is then converted to black and white using the Otsu algorithm to calculate the threshold of image conversion.

Due to capture angle, a correction of perspective must also be carried out in order to align the output image as much as possible to the camera. In this step, an analysis of the elements of the binarized image is carried out to identify the biggest element, whether it is black or white, which is considered to be the plate's background. This region’s pixels closest to each of the four corners of the image are taken as the four extreme points of the plate’s rectangle and the image is transformed using a projective transformation. This process results in a binary image containing an aligned license plate.

Character segmentation is then conducted through an analysis of vertical and horizontal projection. First, a vector is obtained by counting the amount of linked elements in each column. This vector is filtered using a 5 element average filter and the resulting vector is multiplied element by element with the vector obtained by projecting (or adding up) the pixel values of each column. Intersection points between the vertical projection and the vector obtained by this multiplication are taken as character borders.

A similar analysis is conducted for the horizontal elements, and the largest element is taken as the character's upper and lower borders. License plates belonging to motorcycles are disregarded because they have only two lines.

Images of the characters are extracted from the borders obtained and all images are normalized to the same size with the letter or number in the center.

These images are divided into 3 rows and 2 columns in 6 blocks of same size and the geometric moments up to third order are calculated. These moments are normalized at an interval between 0 and 1. They are then used as input to an artificial neural network with different topology and weights for letters and numbers. The output of the neural network is taken as the result of the reading.

Vehicle Classification

A mask indicating the vehicle's position in the image is made so that vehicle classification can be conducted, as shown in Figure 3. This mask serves as a basis for extracting the features that will be used.

a b

Figure 3 – a) original image and b) resulting binary mask

The features that will be tested are main moments and moments that are invariant to translation and scaling (Mukundan e RamaKrishnan (1998)) because they have demonstrated their ability to describe objects (Hu (1962)).

After the mask is generated, these moments are extracted and normalized. Then, a feature selection algorithm is used to iteratively select the best features (Pudil *et al. (1994)*) so that the final set of features allows the classifiers to achieve higher accuracy rates more easily.

A classifier is then trained with this set of selected features. This study worked with modern classifiers (artificial neural networks – Haykin (1988) and support vector machines – Vapnik & Lerner (1963)) in addition to a classic classifier (*k Neasrest Neighbor* – Fukunage & Narendra (1975)).

The best performance is chosen based on the results of these three classifiers

O/D Matrix Construction

The method used in this work for building an O/D matrix is the detection of license plates through character recognition carried out by an automatic system. Based on the recognition of the license plates of the vehicles running on the monitored roads, it is possible to trace vehicles so as to define their origin and destination, by means of cross-checking data. Recognition is carried out at the entrances and exits of the areas under study.

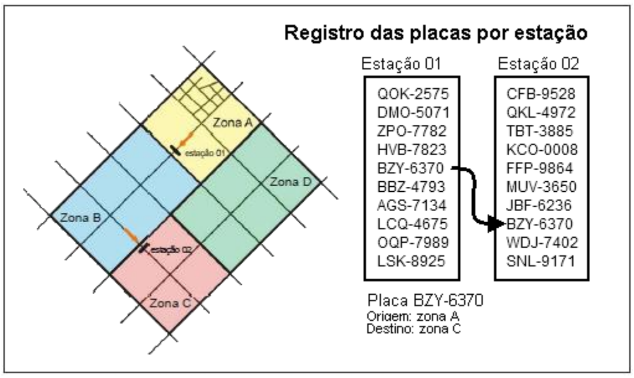

FIGURE 4 – Hellinga (2004), Adapted.

Figure 4 shows the scheme of the process of cross-checking license plate data. After the amount of vehicles that come from or go to a given traffic zone is identified, you can build and model the O/D matrix of the zone of interest.

CASE STUDY

Features of the Road Under Study

This paper presents a case study conducted at a roundabout at the University of Brasília (Darcy Ribeiro Campus), in Brasília, Brazil.

The roundabout was effective for applying volume counts because it characterizes a multiple origin/destination access system, i.e., the vehicle will have three origins and three destinations, which enabled us to produce an O/D matrix with three rows and three columns.

On the road, there is a flow inside the university campus, as well as an external access to the city of Brasília. The roundabout is an intersection (node) that divides flows headed for the South and North Zone of the University of Brasília. It is a strategic spot because it segments traffic from outside the campus.

Traffic occurs predominantly during the day, as the road is used mostly by the academic community. There highest incidence is of private cars, given that there is traffic of public transport on the two road tracks.

We use the following nomenclature to define the origin and destination zones of our matrix:

1. Origin/Destination **A**: Northern Zone of the University of Brasília;

2. Origin/Destination **B**: Southern Zone of the University of Brasília;

3. Origin/Destination **C**: Avenue L4;

Origin/Destination **A** encompasses the Dean's office, the Library and most of the University's academic infrastructure. Origin/Destination **B** comprises the Biology Institute, the Chemistry

Institute, the Medical School and the University of Brasília's Technology Park. In turn, Origin/Destination **C** is Avenue L4, which borders the entire Eastern portion of the city of Brasília. Accordingly, there are the following movement possibilities at the roundabout:

FIGURE 5 – Movement 1

FIGURE 6 – Movement 2

FIGURE 7 – Movement 3

Data Collection

Flow data were gathered at the Origin/Destination A and B from 9:28 to 12:00, on March 25th, 2010.

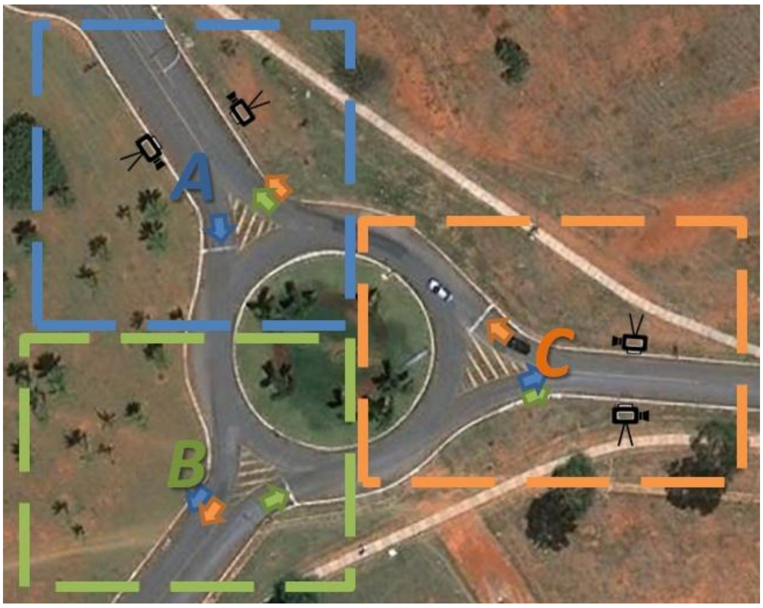

FIGURE 8 – Zones and Locations of Camcorders

The system used for obtaining the video sequences used in this study consists of a metal support, to position the camera at a vantage point. The camera model used is the Samsung HMX 10A with a resolution of 1280 x 720 pixels (HD 720p) progressive capture at 60 frames per second. Videos were stored in 16GB SDHC (Secure Digital High Capacity) memory cards for offline processing. Each card can store up to 3 hours of video in the highest quality. The support is a metallic tripod built specifically for this purpose.

a b

FIGURE 9 – a) Tripod e b) Camcorder

The tripod comprises a metal support base and a 1-meter long tubular section. The tripod is 1.85 meters high, accounting for the base and section. The camera is 1.50 meters over the floor and is attached to the tubular section through a metallic plate, which enables it to rotate in two axes regarding the tripod's axis.

After the roads were captured on film, videos were stored in a database on an Intel®Core™ i7-920 2.66GHz computer with 8GB RAM memory. Storage totaled 47 GB of images to be processed.

Information Processing

In general, in a computational vision system, the processing does not need make use of the full range of spatial detail that the image capture system provides. A moving region detected roughly in a low resolution image can be re-mapped onto the original image, which reduces the computational burden of processing. Therefore, reduced versions (160x90 pixels) of the original 1280x720 videos were used.

With the video stored in the database, background subtraction began, which is framing moving objects in a video sequence. After the background is defined, license plates were located and characters were identified using OCR (Optical Character Recognition) methods. Additionally, independently from the identification process chain, vehicles were classified into four categories: light cars, buses, trucks and vans.

During the processing, some problems made it impossible to identify vehicles, for example:

a b c

FIGURE 10 – Dirty plate, Blurry plate and Plate with non-standard characters

Categorization

Two 66-image sets were used, one for training and one for testing, for each of the classes used (cars, vans, buses and trucks), totaling 264 for training and 264 for testing.

18 features were extracted from the images using the training set (9 main moments and 9 invariant translation and scaling moments).

Feature selection was performed using the k-NN classifier with k = 1. Results are shown in Table 1, where η_{xy} represents invariant translation and scaling moments and m_{xy} represents the main moments.

Iteration	Feature	Hit Rate
1	η_{11}	45,75%
2	η_{21}	67,09%
3	η_{23}	83,11%
4	η_{12}	90,31%
5	η_{22}	93,15%
6	η_{32}	94,42%
7	η_{33}	94,35%
8	η_{13}	94,58%
9	η_{31}	94,30%
10	m_{12}	93,81%
11	m_{13}	93,25%
12	m_{33}	92,91%
13	m_{32}	92,74%
14	m_{23}	92,47%
15	m_{31}	91,92%
16	m_{21}	91,73%
17	m_{11}	91,29%
18	m_{22}	91,09%

TABLE 1 – Feature Selection

Note that the best accuracy rate occurs at the 8th iteration, reaching 94.58%, only using invariant scaling and translation moments, which proves the best performance of these features.

The classifiers were trained using the set of features composed by the eight best features. The k-*NN* is trained with *k=1* using euclidian distance (same parameters used in the feature selection process).

The neural artificial network used is a *Multi Layer Perceptron*, having 6 neurons at the intermediate layer and *BackPropagation* training algorithm.

The support vector machine had its architecture based on a one-versus-all layout, using a degree 3 polynomial kernel.

Table 2 shows the average recognition rate for the classifiers mentioned above.

Classifier	Hit Rate
K-NN	94,58 %
RNA	97,20 %
SVM	96,59 %

TABLE 2 – Classifiers Used

For the project's final version, the artificial neural network was used, which catered for higher accuracy rates among the tested techniques for the set composed of 8 invariant moments (regarding scaling and translation).

Building the O/D Matrix and Comparative Study

After having performed the whole experiment with identification and linking of information, the following O/D matrix was found:

D \ O	A	B	C	Production
A	1	171	98	270
B	233	0	268	501
C	90	220	0	310
Attraction	324	391	366	1081

Table 3 – O/D Matrix

Through automatic monitoring we were able to identify when peak traffic flow occurs. The abscissa axis of the graph represents the amount of vehicles identified every 10 minutes, which are shown in the ordinate axis. Note that there is also an increased flow trend at the end of the monitoring, at 12:00 due to the emergence of a new peak time.

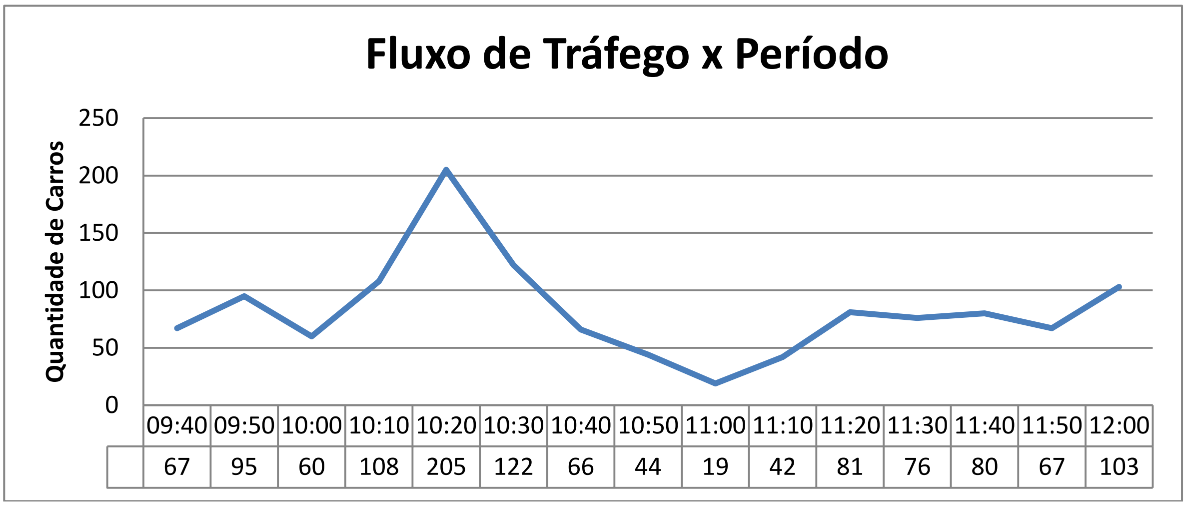

Figure 11 – Vehicle Histogram in each period

In order to validate the data used to build the O/D matrix, manual count was carried out in Origin/Destination A and B at the highest peak, from 10:10 to 10:20. The following results were found:

	Automatic	Manual	Absolute Error
Origin Road A	80	102	22
Destination Road A	46	46	0
Origin Road B	37	38	1
Destination Road B	25	31	6

TABLE 4 – Error at peak times

The largest error occurred in Origin Road A due to a traffic jam, which made it difficult for the system to read the plates, given that the were moving extremely close to each other, causing plate occlusion.

Absolute error was 13.36%; with an average error margin of 7.25 per lane and a 10.17 standard deviation.

Besides counting and identifying the vehicles, they need to be categorized in order to obtain the O/D matrix because each vehicle has a different characteristic. The amount of vehicles in each category should be acknowledged in planning because differences in size, weight and usability features change the way traffic is analyzed. Thus, the following results were found:

CATEGORY	AMOUNT
Cars	809
Buses	22
Trucks	8
Vans	16

TABLE 5 – Amount of Vehicles on the monitoring

The error margin linked with this categorization was 7.81%.

When the counting begins, some vehicles are identified only at the destination point, given that they went through the origin point after the monitoring had begun. We identified a 0.7% error margin associated to this kind of problem.

CONCLUSION

With the growth of cities and, consequently, the fleet of vehicles, traffic flow in medium and large centers eventually became a problem. Streets are badly scaled and road expansions do not keep up with urban sprawl. In addition, there is always a lack of efficient public policies on that matter. In order to prevent or correct some of these problems, engineers, who are responsible for maintaining traffic; turn to studies that make use of instruments to model the road network for planning changes and improvements on it.

In that context, the work presented here has proved to serve as a good reference for instrumentation and study of a road network. Furthermore, it has shown accurate results in studying traffic flow. By making use of automation tools, we managed to build an O/D matrix with a 13.86% error band. These automation tools also made for mitigating continuity problems (i.e., 0.7%) because time can be controlled when data is being processed, which enables the network can be regulated around the monitoring. Additionally, the automation tools enabled us to obtain results for the O/D matrices from the same pool of flow data without multiple results. Due to the identification of license plates, we were able to faithfully track the vehicle's route and print its actual trajectory within the network under study.

Because monitoring is carried out with cameras, the O/D matrix is easily obtained and requires relatively few human resources, i.e., Automated Traffic Monitoring enables us to create an O/D matrix quickly and requires less workforce if contrasted with older techniques

The biggest problem associated with filming is the occlusion of license plates in traffic jams. There was a 27.5% occlusion rate of the plates at peak times in the network shown in this work. However, this could be minimized if the camera's location in the arc under study is perfected, and more camcorders are placed in different places on the same road.

ACKNOWLEDGEMENTS

The authors would like to thank the CNPq (National Counsel of Technological and Scientific Development, in Portuguese) for the partial funding provided through the 481428/2007-0 protocol.

REFERENCES

Abdullah, S. N. H. S., Khalid, M., Yusof, R. and Omar, K. (2007). Comparison of feature extractors in license plate recognition. First Asia International Conference on Modelling & Simulation. Pp. 502–506.

Abrahamssom, T. (1998) Estimation of Origin-Destination Matrices Using Traffic Counts - A Literature Survey. International Institute for Applied Systems Analysis, Interim Report IR- 98-021, Austria.

Anagnostopoulos, C. N. E., Anagnostopoulos, I. E., Loumos, V. and Kayafas, E. (2006). A license plate-recognition algorithm for intelligent transportation system applications. IEEE Transactions on Intelligent Transportation Systems, Vol. 7, no. 3, pp. 377–392.

Bell, M. G. H. (1991) The estimation of origin-destination matrices by constrained generalized least squares. Transportation Research Part B, n. 25, p. 13-22.

Bertoncini, B. V. Uma proposta de carregamento incremental de fluxos veiculares para estimação de matrizes O-D sintéticas. 2007 137 p. Dissertação de Mestrado – Escola de Engenharia de São Carlos, Universidade de São Paulo, São Carlos, 2007.

Cascetta, E. (1984) Estimation of Trip Matrices from Traffic Counts and Survey Data: a Generalized Least Squares Estimator. Transportation Research 16B, n.4-5, p.89-299.

C. Ridder, O. Munkelt, and H. Kirchner, “Adaptive background estimation and foreground detection using kalman-filtering,” in Proceedings of International Conference on recent Advances in Mechatronics, 1995, pp. 193–199.

C. Stauffer and W. E. L. Grimson, “Adaptive background mixture models for real-time tracking,” in Computer Vision and Pattern Recognition, 1999. IEEE Computer Society Conference on., vol. 2, 1999, p. 252 Vol. 2.

Chang, S.-L., Chen, L.-S., Chung, Y.-C. and Chen, S.-W. (2004). Automatic license plate recognition. IEEE Transactions on Intelligent Transportation Systems. Vol. 5, no. 1, pp. 42–53.

Comelli, P., Ferragina, P., Granieri, M. and Stabile, F. (1995). IEEE Transactions on Optical recognition of motor vehicle license plates. Vol. 44, no. 4, pp. 790–799.

Demarchi, S. H. E Bertocini, B. V. (2004) Determinação de Matrizes O-D Sintéticas a partir de Contagens Volumétricas. Anais do XVIII Congresso de Pesquisa e Ensino em Transportes, ANPET, Florianópolis.

Duan, T. D., Duc, D. A. and Du, T. L. H. (2004). Combining hough transformand contour algorithm for detecting vehicles’ license-plates. Proceedings of 2004 International Symposium on Intelligent Multimedia, Video and Speech Processing. pp. 747–750.

Dubey, P. (2005). Heuristic approach for license plate detection. IEEE Conference on Advanced Video and Signal Based Surveillance. pp. 366–370.

Gajda, J. et al. A vehicle classification based on inductive loop detectors. In: Instrumentation and Measurement Technology Conference, 2001. IMTC 2001. Proceedings of the 18th IEEE. 2001. v. 1, p. 460–464 vol.1.

Gupte, S. et al. Detection and classification of vehicles. IEEE Transactions on Intelligent Transportation Systems, v. 3, n. 1, p. 37–47, 2002.

Fukunage, K.; Narendra, P. A branch and bound algorithm for computing k-nearest neighbors. Computers, IEEE Transactions on, v. 100, n. 24, p. 750–753, 1975.

H. S. Lai and N. H. C. Yung, “A fast and accurate scoreboard algorithm for estimating stationary backgrounds in an image sequence,” Circuits and Systems, 1998. ISCAS ’98. Proceedings of the 1998 IEEE International Symposium on, vol. 4, pp. 241–244, 1998.

Haykin, S. Neural Networks and Learning Machines. 1988.

Hellinga, B.R. (1994) Estimating Dynamic Origin - Destination Demands from Link and Probe Counts. Ph.D. Dissertation, Department of Civil Engineering, Queen's University, Kingston, Ontario, Canada.

Hongliang, B. and Changping, L. (2004). A hybrid license plate extraction method based on edge statistics and morphology. Proceedings of the 17th International Conference on Pattern Recognition, Vol. 2, pp. 831–834.

Hsieh, J.-W., Yu, S.-H. and Chen, Y.-S. (2002). Morphology-based license plate detection from complex scenes. 16th Proceedings of the International Conference on Pattern Recognition, Vol. 3, pp. 176–179.

Hu, M. Visual pattern recognition by moment invariants. Information Theory, IEEE Transactions on. v. 8, n. 2, p. 179–187, 1962.

Institute of Roads, Traffic, and Town Planning. The Technical University of Denmark, Paper 1993-3.

Ji, P.; Jin, L.; LI, X. Vision-based vehicle type classification using partial gabor filter bank. In: 2007 IEEE International Conference on Automation and Logistics. 2007. p. 1037–1040.

Jianfeng, X., Shaofa, L. and Zhibin, C. (2003). Color analysis for chinese car plate recognition. Proceedings. 2003 IEEE International Conference on Robotics, Intelligent Systems and Signal Processing. Vol. 2, pp. 1312–1316.

López-Reyes, D. E. L.; Kawamoto, E. (2001) A Influência da Segmentação da Estimação da Matriz Origem-Destino, Baseada em um Modelo de Escolha Discreta. In: Carlos Nassi, Anísio Brasileiro, Eiji Kawamoto, Luis Antonio Lindau. (Org.). Transportes: Experiências em Rede. 1 ed. Rio de Janeiro: FINEP, 2001, v. 1, p. 143-173.

Mukundan, R.; Ramakrishnan, K. Moment functions in image analysis: theory and applications. [S.l.]: World Scientific, 1998.

N. Friedman and S. Russell, “Image segmentation in video sequences: A probabilistic approach,” in Proc. of the Thirteenth Conference on Uncertainty in Artificial Intelligence (UAI 97). Morgan Kaufmann, 1997, pp. 175–181.

Nguyen, S. (1977) Estimating an OD Matrix from Network Data: A Network Equilibrium Approach. Publication 87. Centre de Recherche sur les Transports, Université de Montreal.

Nielsen, O. A. (1993) A New Method for Estimating Trip Matrices from Traffic Counts.

Ortúzar, J. de D. E Willunsen, L. G. (1994) Modelling Transport. Jonh Wiley & Sons, Chichester.

P. KaewTraKulPong and R. Bowden, “An improved adaptive background mixture model for real-time tracking with shadow detection,” in 2nd European Workshop on Advanced Video Based Surveillance Systems. Kluwer Academic Publishers, September 2001.

Pan, M., Yan, J. and Xiao, Z.(2007). An approach to tilt correction of vehicle license plate. International Conference on Mechatronics and Automation. Pp. 271–275.

Paramahamsan, H. (1999) Fundamental Properties of Synthetic O-D Generation Formulations and Solutions. M.Sc. Thesis, Department of Civil and Environmental Engineering, Virginia Polytechnic Institute and State University, Blacksburg, VA.

Pudil, P. et al. Floating search methods for feature selection with nonmonotonic criterion functions. In: Pattern Recognition, 1994. Vol. 2 - Conference B: Computer Vision & Image Processing., Proceedings of the 12th IAPR International. Conference on. 1994. v. 2, p. 279–283.

Robillard, P. (1975) “Estimating the O-D Matrix from Observed Link Volumes” Transportation Research, v. 9,p. 123-128.

Shin, P. et al. Automatic vehicle type classification using strain gauge sensors. In: Pervasive Computing and Communications Workshops, 2007. PerCom Workshops ’07. Fifth Annual IEEE International Conference on. 2007. p. 425–428.

Souza, D. D. de M. R. E (2007). Estimação Sintética de Matrizes Origem/Destino a partir de Contagens Volumétricas em Áreas com Controle de Tráfego em Tempo Real com o Auxilio do Queensod. Dissertação de Mestrado, Programa de Mestrado em Engenharia de Tansportes,, Universidade Federal do Ceará, Fortaleza, CE, 120 fl.

Sun, C.; Ritchie, S.; OH, S. Inductive classifying artificial network for vehicle type categorization. In: Computer Aided Civil and Infrastructure Engineering. 2003. v. 18, n. 3, p. 161–172.

Van Aerde, M. (1998) QUEENSOD – Release 2.10 – User´s Guide: Estimating Origin Destination Traffic Demands from Link Flow Counts. M. Van Aerde and Associates, EUA.

Van Aerde, M.; Rakha, H.; Paramahamsan, H. (2003) “Estimation of O-D Matrices: the Relationship between Practical and Theoretical Considerations”. Transportation Research Record 1831, p. 122-130.

Van Zuylen, H. J.; Willumsen, L. G. (1980) “The Most Likely Trip Matrix Estimated from Traffic Counts”. Transportation Research, v. 14B, p. 281-293.

Vapnik, V.; Lerner, A. Pattern recognition using generalized portrait method. Automation and Remote Control, v. 24, p. 774~780, 1963.

Wu, F., Wang, Y.-G. and Hou, X.-W. (2007). License plate character recognition based on framelet. International Conference on Wavelet Analysis and Pattern Recognition. Vol. 2, pp. 673–676.

Yang, F., Ma, Z. and Xie, M. (2006). A novel binarization approach for license plate. 1ST IEEE Conference on Industrial Electronics and Applications. Pp. 1–4.

Yang, F., Ma, Z. and Xie, M. (2006). A novel approach for license plate character segmentation. 1ST IEEE Conference on Industrial Electronics and Applications. Pp. 1–6.

YANG, H.; Sasaki, T.; Iida, Y.; Asakura, Y. (1992). Estimation of Origin-Destination Matrices from Link Traffic Counts on Congested Networks. Transportation Research Part B, n 26, p. 417- 434.

Zhang, X., Liu, X. and Jiang, H. (2007). A hybrid approach to license plate segmentation under complex conditions. Third International Conference on Natural Computation. Vol. 3, pp. 68–73.