

ARVEE: AUTOMATIC ROAD GEOMETRY EXTRACTION SYSTEM FOR MOBILE MAPPING

Cheng Wang^{a,b,*}, Taher Hassan^a, Naser El-Sheimy^a, Martin Lavigne^a

^a Dept of Geomatics Eng., 2500 University Drive, N.W, The University of Calgary, Calgary, AB, Canada, T2N 1N4
chwang_nudt@263.net, tfabbas@ucalgary.ca, naser@geomtics.ucalgary.ca

^b School of Elec. Sci. & Eng., Natl. Uni. of Def. Tech., 47 Yanwachi St., Changsha, Hunan, China, 410073.

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ABSTRACT:

Land-based mobile mapping systems have yielded an enormous time saving in road networks and their surrounding utilities survey. However, the manual extraction of the road information from the mobile mapping data is still a time-consuming task. This paper presents ARVEE (Automated Road Geometry Vectors Extraction Engine), a robust automatic road geometry extraction system developed at the University of Calgary. The extracted road information includes the 3D lane lines, road edges as well as lane lines attributes. There are three innovations in this work. First, all the visible lane lines in the georeferenced image sequences are extracted, instead of only extracting the central lane line or the nearby lane line pair. Second, the lane line types are recognized, so the output is a functional description of the road geometry. Third, the output is the absolute-georeferenced model of lane lines in mapping coordinates, and is compatible to the GIS databases. Four steps are included: First, extract the linear features in each image. Second, the linear features are filtered and grouped into lane line segments (LLS). Geometric and radiometric characteristics are extracted for each LLS. Third, a Multiple-Hypothesis Analysis (MHA) method is used to link the LLSs into long lane lines 3D model. Finally, each lane line is classified into a lane line type based on the synthetic analysis of the included LLSs' features. The system has been tested on large number of VISAT™ mobile mapping data. The experiments on massive real MMS data sets demonstrate that ARVEE can deliver accurate and robust 3D continuous functional road geometry model. Full automatic processing result from ARVEE can replace most of the human efforts in road geometry modelling.

1. INTRODUCTION

Road features constitute a major part of GIS databases. Mobile Mapping Systems (MMS), such as the VISAT™ (Video-Inertial-Satellite) (El-Sheimy, 1999) developed by Absolute Mapping Solutions Inc. and the University of Calgary, Canada, provide an effective way to collect georeferenced image sequences of the roads and their surroundings. Mobile mapping has yielded an enormous time saving in road network survey. However, the manual extraction of the road information from the mobile mapping data is still a time-consuming task.

Previous researches on lane line extraction mainly focus on the traffic applications, such as traffic monitoring or autonomous vehicle guidance (Ishikawa, 1988; Kenue, 1991; Jochem, 1993; Chen, 1997; Beauvais, 2000; Paetzold, 2000; Yim, 2003; Li, 2004; McCall, 2004; Tai, 2004; Yue Wang, 2004; Hassouna, 2005; Jung, 2005; Lee, 2005; Choi, 2006), more details can be found in (Kastrinaki, 2003). In summary, the constraints used in lane line detection include: the shape, the lane lines is supposed to be a solid or dashed line with a certain width; the colour, the lane lines are usually white or yellow; and the geometry constrain, the road is flat and the lane line is with a small horizontal curvature. Lead by the application purpose, and limited by the demanding of real-time processing, these works only concerned about the lane lines that are close to the vehicle, and all the results are described within the local body frame coordinate, or even simpler within the image coordinate. In addition, only vision sensor was exploited, as a result, performances are generally not satisfying at the situation of

obscuration, shadow or worn out painting. Few works have been done for lane line extraction in image sequences, that with georeference information from other sensing modules. For autonomous vehicle guidance, Radar and camera fusion were used to locate obstacle and lane line (Beauvais, 2000); location sensing modules such as GPS were fused with vision in lane following (Goldbeck, 2000; Jin Wang, 2005). In mobile mapping, Tao (Tao, 2001) used the mobile mapping georeference to extract the 3D model of central line from mobile mapping image sequences; Roncella (Roncella, 2006) developed a semi-automatic lane line system and tested on synthetic mobile mapping data.

This work presents ARVEE (Automated Road Geometry Vectors Extraction Engine) a robust automatic road geometry extraction system for the post processing of the mobile mapping data. The input of the system is the mobile mapping data, which includes: the georeference information, the multi-camera panoramic images sequence and sensor/system calibration parameters. The output is the GIS-database-compatible road geometry information, which contains the 3D lane line model of all the lane lines covered by the cameras field of view, and the types of these lane lines. The system works fully automatic. The aim of the design is to introduce computer vision techniques to do most of the road geometry information extraction works in mobile mapping post processing, and leave as less as possible work to the afterwards manual correction.

In the sense of functionality, there are three innovations in this work. First, instead of only extracting the central lane line or the

* Corresponding author.

nearby lane line pair, our system extracts all the visible lane lines in the georeferenced image sequences. Second, the lane line types are recognized, so the output is a functional description of the road geometry. Third, the output is the absolute-georeferenced model of lane lines in mapping coordinates.

In the rest of the paper, section 2 gives the overview of the system; section 3 and 4 describe the design details of ARVEE, section 5 and 6 describe the experimental results and conclusions.

2. SYSTEM OVERVIEW

VISAT has been developed at the University of Calgary in the early 1990s- it was one of the first terrestrial MMS. Recently, an improved version was developed by Absolute Mapping Solutions Inc, Calgary, Canada (www.amsvisat.com), see Figure 1. The system's data acquisition components include a strapdown INS system, a dual frequency GPS receiver, 6 to 12 fully digital colour cameras, and an integrated DMI hookup on the speed sensor of the vehicle, and the VISAT system controller. The camera cluster provides a 330° panoramic field of view (see Figure 2). The DMI provides the van travelling distance to triggers the cameras at constant intervals. The data-logging program, VISAT Log, allows for different camera configurations and different image recording distances or trigger the camera by time if necessary (both can be changed in real-time). In terms of secondary functions, the camera cluster provides redundancy, i.e. more than two images of the same object. Using the VISAT georeferenced images, mapping accuracies of 0.1 - 0.3 m, for all objects within the field of view of the cameras can be achieved in urban or highway environments while operating at speeds of up to 100 km per hour.



Figure 1: The VISAT MMS Van

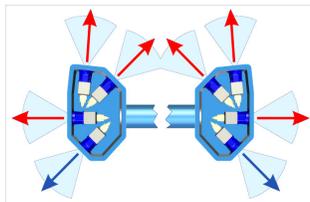


Figure 2: The VISAT Vision System

The user can then interface with the geo-referenced images through the VISAT Station™ — a softcopy photogrammetric workstation mainly designed for feature extraction from the georeferenced images, collected by the VISAT system, or any other georeferenced media. VISAT Station environment is fully integrated with ArcGIS, and permits user-friendly viewing of the imagery. Moreover, VISAT station is a client/server

application, enables many user terminals to access the same image data base and perform parallel processing.

Figure 3 shows the GIS feature extraction frame work for VISAT. The input is a panoramic georeferenced images acquired by VISAT. The extraction of 3D information is based on the integration of both image processing and photogrammetric analysis. The photogrammetric analysis uses available system parameters and geometrical constrains to provide a channel between 3D and 2D spaces. The image analysis extracts GIS-feature-related information in the images. Both results are used in a pattern recognition procedure, which locates the GIS features in the images and classify them into pre-specified categories. Then the GIS features are modelled in 3D to meet the requirements of GIS database. There are different GIS features to be extracted, these features are to be used to establish or update GIS databases.

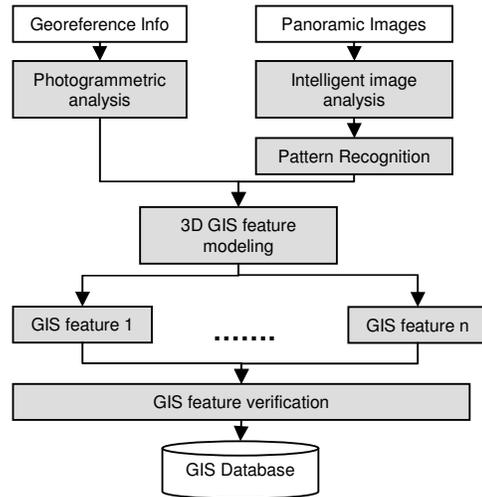


Figure 3: GIS feature extraction framework

ARVEE follows the above framework, in detail the following steps are involved. First, extract the linear features in each image. Second, the linear features are filtered and grouped into lane line segments (LLS). Geometric and radiometric characteristics are extracted on each LLS. Third, a multiple hypothesis linking method is used to link the LLSs into long lane lines. Finally, each lane line is classified into a lane line type based on the synthetic analysis of the included LLSs' features. **Figure 4** shows the flowchart of ARVEE.

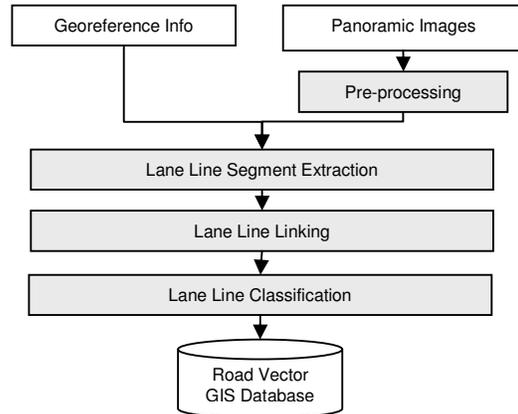


Figure 4: ARVEE Workflow

3. LANE LINE SEGMENT EXTRACTION

In VISAT, the images for all cameras are captured at the same instant, based on distance or time, at a series of points along the route using the VISAT Log data acquisition module. The data acquisition module, VISAT Log, can be configured on the fly to trigger the cameras for any desired distance. In urban surveys we usually use 3 to 5 meters intervals between image sets, which will ensure complete panoramic coverage. On highways, 5 to 10 meters intervals are typically used. At each image set, the cameras cover a wide angle of the surrounding area. The aim of LLS extraction is to extract the lane lines within the covered area from each image set. ARVEE is adaptive to different camera configurations, which greatly increase the flexibility. This convention is due to the effective LLS extraction algorithm.

For each camera, the image is applied with a linear feature extraction algorithm (Cheng Wang, 2002). All the lane line associated linear features are filtered by the following constrains: (1) Shape constrain: the lane lines is supposed to be a solid or dashed line with a certain width; (2) Colour constrain, the lane lines usually are of white or yellow colour; (3) Geometry constrain, the road is a flat surface and the lane line is with a small curvature.

The filtered out linear features from different cameras are added into the lane-line-associated linear feature set (*LALS*). All the elements in *LALS* are combined to establish the 3D model of the *LALS* in mapping frame. In this stage, more constrains are introduce to determine where is the LLSs and their central lines. These constrains are mainly from the observational correspondence across cameras. The major constrains include: (1) Space distribution correspondence, the observations to a same LLS from different cameras should close to each other in PCGP. (2) Colour distribution correspondence, the LLS should have similar colour distribution in difference observations; (3) Heading direction agreement, all the LLSs should agree to the heading direction of the road.

In this stage, feature that describe the characteristics of each LLS are also extracted. These attributes will later be used to classify the lane line type. For each LLS, as shown in Figure 5, the local image is separated into three parts: the lane line covered region *C*, the left neighbour region *L* and right neighbour region *R*.

Motivated by the common features used by human, GiFEx utilizes the following features to describe a LLS: relative position and orientation to the body frame centre; dashness (the dash-shape of the LLS); colour distribution of region *C*, *L*, *R*; the relationship between the three colour distributions; and texture features.

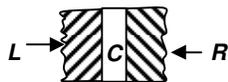


Figure 5: Local image segmentation for feature extraction

4. MULTI-HYPERTHESIS LINKING AND LANE LINE CLASSIFICATION

Given the LLSs extracted from each survey image set, the aim of lane line linking is to join the LLSs through the survey image sets to form a continuous 3D model of the lane lines. Each lane line includes several up to hundreds of LLSs. Multi-hypothesis Analysis (MHA) has proved to be successful in many applications, such as multi-target tracking (Gong, 2005). ARVEE utilizes a revised MHA algorithm to do the lane line linking. The MHA has tree steps: hypothesis generation; likelihood computation; and hypotheses management.

All the LLSs are kept in a graph structure as show in Figure 6. Each node represent to a LLS. For instance, node $L_{i,j}$ is the j th LLSs in i th survey image set.

The lane line linking develops the edges connecting the nodes. At each image set, the hypotheses are the possible connecting configurations between the ends of current maintained node to the nodes in the future image sets.

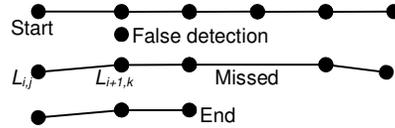


Figure 6 : Graph structure for multi-hypotheses analysis

The hypothesis generation step first calculates the possibility of the connections between the maintained graph nodes and the nodes from the current image set. The maintained nodes include the ending nodes of all the links in maintained hypotheses. They are not necessarily from the previous image set since LLS extraction may have misdetections. The connection probability is computed as:

$$P_{con} = w_p p_p + w_d p_d + w_f p_f \quad (1)$$

where p_p is the position closeness possibility between the new node to the maintained note, p_d is the direction similarity possibility, p_f is the feature similarity; and w_p w_d w_f are the weights of this probabilities. In the hypotheses generation step, all the possible connection configurations are add to hypothesis list. Then, the hypotheses with low connection possibility are pruned out of the list.

Given the hypotheses (the connections configurations) obtained from the previous processing, the likelihood calculation step calculate the likelihood of each new hypothesis. This step introduces the information of all the maintained hypotheses, to bring in an overall view of the LLS graph. The likelihood is calculated as:

$$likelihood_i = \begin{cases} likelihood_{i-1} + \sum_j^n \frac{w_{con} P_{conj} + w_{trj} P_{trj} + w_{feaj} P_{feaj}}{n} & \text{Condition*} \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

where i is the current image set number, n represent the number of objects in the current hypothesis. P_{conj} is the connection probability of the j th connection; P_{trj} is the smoothness probability of the new connection to the former link; P_{feaj} is the feature similarity possibility. W_{con} , W_{trj} , and W_{feaj} are the weights to these possibilities. *Condition** represents a set of constrains that make a hypothesis possible. The constrains include: no multiple connection; and no crossing connection. These constrains express the nature of a possible lane line.

With the increase of the survey image sets, the size of the hypothesis set might quickly explode. Hypothesis management step is designed to keep a practical-sized hypothesis set and keep the diversity of that hypothesis set as much as possible. Several rules are introduced: first, only limited amount of hypotheses are maintained; second, the hypotheses that are not change for several image sets will be combined into other hypotheses, or deleted; third, only limited hypotheses are allowed to be added at each image set.

The MHA processing goes through all the image sets. At the end, H^* —the hypothesis with highest likelihood— will be viewed as the best connection configuration of all the LLS notes. Each links in H^* is a lane line.

The feature of each LLS may be corrupted by many facts: occlusion; worn-out painting of lane lines; variation of the side pavements or grass; variance of road surface materials; and the unreliability of the feature extraction algorithms. So instead of classify the LLS, we calculate the feature of a lane line base on all the LLSs included in that lane line; and classify the type of the lane line as a whole.

5. EXPERIMENTS

ARVEE is a commercialization-targeted software system. It is designed to compatible with VISAT™ MMS developed by Absolute Mapping Solutions Inc. and the University of Calgary, Canada. ARVEE has been test over massive real mobile mapping survey data from VISAT™, including data from urban and rural areas. Test results show that ARVEE is robust and ready to serve the real world applications. Video of the results can be fund at http://mms.geomatics.ucalgary.ca/Team/Current/Collaborators/cheng/AVREE_demo/ARVEE_demo.htm

Figure 7 shows a road geometry extraction result of ARVEE. The extracted lane lines are overlapped on the original images (only two of the four cameras are showed here). There are four lane lines within this site, all correctly extracted and classified. The two lines in the middle of the road are dashed white lane line (marked as dashed white line), the one in left is a yellow solid lane line (marked as solid yellow line), and the one in right side is a solid white line (marked as solid white line). Figure 7.c is the bird view of the extracted road geometry. At this point, it should be stressed that, although there are other vehicles occlude the sight view to the right side lane line, it is still successfully extracted. This shows the robustness of the ARVEE against partly occlusion.

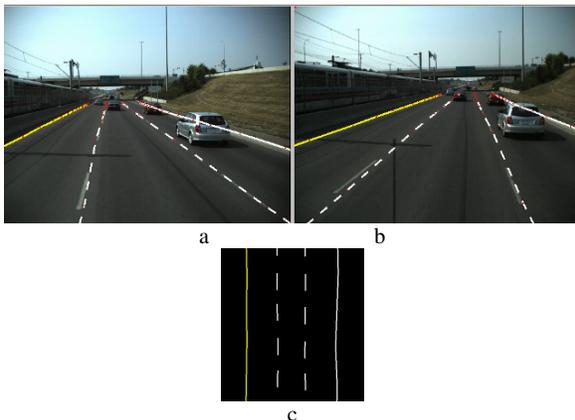


Figure 7: Road geometry result in partly occlusion

Figure 8 shows ARVEE result at a shadow occasion. Despite of the shadow from the trees, all the three lane lines are correctly detected, linked and classified. This shows the robustness of the ARVEE against shadow.



Figure 8: Road geometry result in shadow

Figure 9 shows the detected road geometry overlapped on the digital map. The extracted road geometry fits the map perfectly, but with much more details and much higher accuracy. The result can be used to greatly improve the current GIS database.

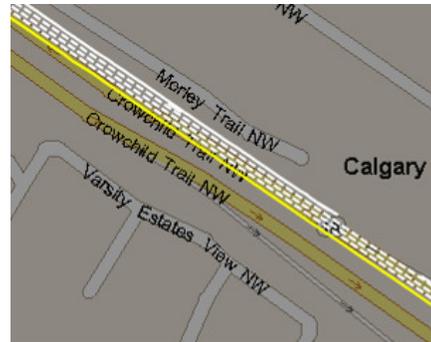


Figure 9: ARVEE result overlapped on map

In order to evaluate the misdetection rate and false detection rate of ARVEE, over 25 kilometre (more than 100,000 meter lane lines) survey data are first automatically processed by ARVEE, and then corrected manually. The manual-corrected result (MCR) is viewed as a reference, and compared with the automatic result (AR). All the lane lines appear in MCR but not in AR are count as misdetection (MD), and all the lane lines appear in AR but not in MCR are viewed as false detection. The misdetection and false detection rate is calculate based on the length of the lane lines. The statistics of the test are shown in Table 1.

Table 1: Performance statistics of ARVEE

	Length (meter)	Percentage
Total Lane Line	102,732	100%
False detection	9,889	9.62%
Miss-detection	2,510	2.4%

The major causes of the misdetection are worn-out lane lines, and heavy occlusion. The major causes of false detection are lane-line-similar structures near the road, such as the edge of side walks, or the line shapes in the nearby vehicles. Figure 10 and Figure 11 show examples of misdetection and false detection. In Figure 10, there is a worn-out dashed white lane line in the right side of the road, and is misdected.



Figure 10: Example of miss detection to worn-out lane line

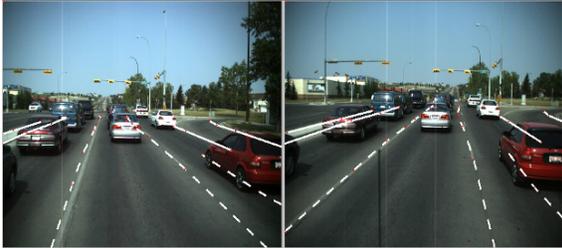


Figure 11: Example of false detection in heavy occlusion

6. CONCLUSION

MMS are efficient and cost effective tools for building and updating GIS databases. However, manual measurements of GIS features in MMS are still manpower demanding procedure. We have initiated a wide scope project for automated GIS features extraction, to decrease the most of the human work in the post-processing. In this paper, we present ARVEE, a robust automatic functional road geometry extraction system for MMS. There are three innovations in ARVEE. First, instead of only extracting the central lane line or the nearby lane line pair, our system extracts all the visible lane lines in the georeferenced image sequences. Second, the lane line attributes are recognized, so the output is a functional description of the road geometry. Third, the output is the high accurate absolute-georeferenced models which are compatible to the GIS database. Test over massive real mobile mapping demonstrate that ARVEE are ready for the real world applications.

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