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A Novel Method for Road Extraction from Satellite Images

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Abstract

Extended Kalman filter (EKF) has previously been used to extract road maps in satellite images. The extended Kalman filter in general is not an optimal estimator, if the measurement and the state transition model are both linear. In addition, if the initial estimate of the state is wrong, or if the process is modeled incorrectly, the filter may quickly diverge, owing to its linearization. In our new approach, we have combined Unscented Kalman Filter with a special Particle Filter (LLPF) in order to regain the trace of the road beyond obstacles, as well as to find and follow different road branches after reaching to a road junction. In this approach, first, EKF module starts tracing the road using the initial state and the initial profile cluster. While progressing along the road path, the profile clusters are updated, and new appropriate clusters are added as road intensities and/or widths change. Then passed it to LLPF(Local Linearization Particle Filter), which tries to find the continuation of road after a possible obstacle or to identify all possible road branches that might exist on the other side of a road junction. For further improvement, we have modified the procedure for obtaining the measurements by decoupling this process from the current state prediction of the filter.

Introduction

Road networks are essential modes of transportation, and provide a backbone for human civilization. Hence, it is vital to maintain and restore roads to keep our transportation network connected. Ongoing research has led to a gamut of methods that automate the digitization process. Digitization methods for road extraction are either automatic or semi-automatic in nature. In the literature, an automatic method implies a fully automatic process. Theoretically, a fully automatic approach requires no human intervention, but this is not practical. Consider a method of automatic method; no human intervention is needed for road feature extraction at the initial or processing stage.

In a semi-automatic method human intervention is required at the initial stage and at times during the processing stage. In both methods, human intervention is needed at the post-processing stage. Post-processing intervention is essential in both methods, to extract undetected but desired features from the raster image, and to fix incorrectly extracted features. An automatic method scores over a semi-automatic method due to its ability to automate the operations of the initiation and processing stages. Road feature extraction from a raster image is a nontrivial and image-specific process hence, it is difficult to have one general method to extract roads from any given raster image.

Remote Sensing and Geoscience

One of the primary roles of the Advisory Board on Remote Sensing (ABRS) of the International Union of Geological Science (IUGS) is to facilitate the use of remote sensing data by international geological community. Although remote sensing is a relatively young scientific discipline, its use in the geosciences over the last two decades has been quite remarkable. Several significant developments have taken place in remote sensing in terms of the uses of existing satellites and the capabilities of planned satellite that are directly applicable to the study of geosciences process. In general three methods are used to extract geological information from remote sensing data. They are the spectral, photo geological, and integration methods.

According to McKeown (1996), roads extracted from one raster image need not be extracted in the same way from another raster image, as there can be a drastic change in the value of important parameters based on nature's state, instrument variation, and photographic orientation. The existence of other features, both cultural (e.g., buildings) and natural (e.g., trees) and their shadows can occlude road features, thus complicating the extraction process. This ancillary information provides a context for many of the approaches developed. Thus, it is necessary to evaluate the extent of inclusion of other information needed to identify a road. Some extraction cases need minimal ancillary information; and some need a great deal. These limitations point to a need to develop a method to evaluate multiple criteria in detecting and extracting roads from images. Our study extracted roads solely based on the road characteristics stored in an implicit manner in a raster image.

Remote Sensing and Cartography

Remote sensing has opened up new realms of geographic information for cartographers. Extensive vegetation surveys are made from high altitudes to show the distribution of specific crops, weeds, or native plants amidst an expanse of general vegetation. High-resolution satellite cameras located at altitudes of several hundred kilo-meters can record details as small as a few meters in diameter on the surface of the Earth. Satellites such as those in the LANDSAT series sweep the globe with continuous scans to provide detailed up-to-date maps of nearly the entire Earth. Satellite imagery is also used to create up-to-the-moment weather maps. Increasingly, data obtained from remote sensing are being assembled into complex, highly refined electronic images resembling photographs that are best viewed on color computer monitors or television screens. Remote sensing is used to reveal obscure or misunderstood phenomena. An example is the recent detection of the lost city of Ubar in Oman, which was rediscovered with the help of NASA satellite radar imagery. Image analysts used cartographic methods to pick out clues from the radar images, including caravan tracks that pointed them to the buried city ruins.

Most maps and atlases use data from remote-sensing sources to create some of its maps. Remote-sensing sources used in these maps include SPOT satellite images of cities, Earth by Day and Earth at Night composite satellite images, and hypsography, or terrain and elevation data, for the entire world. The Eco-regions data in Encarta World Atlas is a combination of remotely sensed vegetation, land cover, and climate data composed in a GIS setting.

Short Outline of the Road Tracer

In case of road tracking the parameters describes the position and shape of the road. The core of our system is road tracking based on profile matching. In addition to this a method of dynamic clustering is constructed in order to maintain tracking, when the road profile undergoes some variation due to change in road width and intensity. Most road tracing algorithms consist of two steps: detection of road positions and concatenation of those positions. The detection step is supported by a prediction based on the previously detected road segment. Detection is performed by either an edge or line detection operator or an analysis of the road profile. In most cases a straightforward connection of the detected road pixels is used to describe the road.

Road Model

In order to apply EKF to trace a road in satellite images, we need to consider coordinates of the road median on an image as a random process and to develop a proper discrete state-space model to represent its behavior. The processing system, EKF, can start its operation from an initial point on the road. This initial point can be provided by a human operator or through another automatic approach that is beyond our discussion in this work. Starting from the initial point, the EKF can sequentially proceed to the next point on the road by using some artificially defined time step. In each step, the process uses the noisy measurement to obtain the best estimate of the state of the road at that point. Therefore, a stochastic difference equation, referred to as the system equation, can be used to model the evolution of the system with the artificial time step as follows:

$$xk = f(xk-1) + wk$$

In this model, xk represents the status of the kth point on the race of the median of the road, and wk represents the process noise, modeling random variation of the road status from one point to the next. In each step, the measurement, the filter's input, is independently obtained from the image. The error in obtaining the measurement is represented by what is referred toas the measurement noise. The measurement vector zk is related to the state vector xk and the measurement noise vk through the following stochastic difference equation referred to as the measurement equation:

$$zk = h(xk) + vk.$$

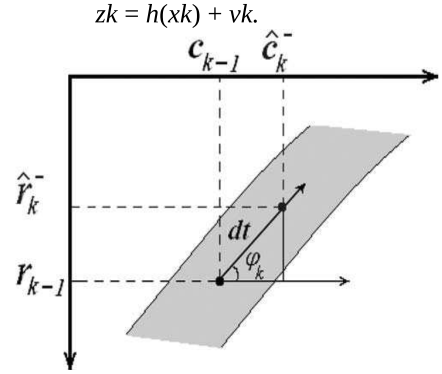


Fig.1. Graphical representation of the evolution of the coordinates of the road median from one step to the next.

The Kalman filter provides the optimum solution in the minimum-mean-square-error (mse) sense when both state and measurement equations are linear and when both system and measurement noise processes *wk* and *vk* are Gaussian.

Input Phase

A human input consists of two mouse clicks on an image, with the line joining the click positions defining a road axis and indicating the road direction. Along the road direction, a set of 2-D road profiles, which are represented as vectors of image gray levels, are extracted normal to and along the road axis at consecutive axis points. All vectors have the same length d, which is the sum of the length of the two 1-D profiles. The length of the 1-D profiles is estimated from the road width, which is calculated as the distance between the road edges. This, in turn, is obtained with a gradient-based edge detection method. We denote a 2-D road profile *is* the profile space with dimension d. A road profile x is associated with a label y .Y, where *Y* is defined as

$$Y = \left\{ \begin{matrix} 1, \text{on the road} \\ 0, \text{off road} \end{matrix} \right\}$$

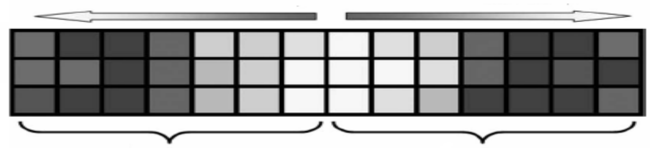
Fig.2 High resolution IKONOS image of a residential area

Edge Detection

For the gradient to better represent the road edges, the choice of Sobel mask is dependent on the road direction of the present road. Fig.3.2 shows an example of a high resolution IKONOS image. Roads have uniform width and intensity. Hence, the appropriate Sobel mask should be selected to determine the width. This algorithm searches for pixels with high gradient magnitude on each side of the road that have opposite gradient signs. The window is divided into two parts, as shown in Fig. 3.3. In each part, going from the center to the side, the first pixel whose gradient magnitude exceeds a predefined threshold is considered as the place of the road edge.

Decision on the value of this threshold is partly dependent on the image road structures. Where the roads have vivid edges (high contrast between road and off-road areas), threshold that can be set to higher values. Since the window is D × 3, in the best case, we will have three pairs of road edges (each pair is found on one of the rows of the window). From each edge pair, we can have an estimate of the road center. The final measurement value for the road center coordinates will be the median of these three estimated road centers. In order to avoid taking wrong pixels as the road edges, the algorithm checks to see whether the gradient sign of the edge pixel found on one side of the window is the opposite of the gradient sign of the edge found on the other side of the window. If the gradient sign of edge pairs is not opposite of each other, that pair is not considered as the edge pair in calculating the road center. This measurement method is independent of the road width and road profile changes.

Search for the edge Search for the edge



Side one Side two

Fig.3 searching for road edges in two parts of the window

Profile Matching

The profile matching compares the model profile with the road profile at the position predicted by the time update. The differences between the two profiles are modeled by two geometric (shift and width) and two radiometric (brightness and contrast) parameters. These parameters are estimated by minimizing the square sum of the grey value differences between the profiles after determining the optimal transformation between the profiles the matching results are evaluated by two checks. The cross correlation coefficient between the grey values of the two profiles after the transformation is required to be higher than 0.8.The estimated values of the geometric and radiometric parameters should be reasonable. E.g., if the estimated contrast parameter has a high value, say 10, the match can not be accepted. A contrast value of 10 would mean that the grey value contrast in the model profile is 10 times the contrast in the profile at the predicted position. A high contrast value therefore indicates that the latter profile hardly contains any signal and most likely does not correspond to a part of the road.

Extended Kalman Filtering

If we consider the road tracking process as a time series, it can be modeled by a state-space approach involving state evolution and noisy measurements. The state evolution of the tracking process can be defined as

$$x_t = f(x_{t-1}) + w_t$$

where x_t is the state vector at time t, w_t is the process noise .The error in obtaining the measurement is represented by what is referred to as the measurement noise. The measurement vector z_t is related to the state vector x_t and the measurement noise v_t through the following stochastic difference equation referred to as measurement equation

$$z_t = h(x_t) + v_t$$

Road Tracking Algorithm

The road-tracking algorithm consists of two main modules: the EKF module and the LLPF module. These two modules alternately hand over the control of the process to each other, explained in the following sections.

EKF Module

This module is initialized with a seed point given at the beginning of the road-tracking process. The starting point should include coordinates of the road center, road direction, and a coarse estimation of the road width at that point. The road center coordinates and the road direction are considered as the initial state of the system, namely, x1 (the fourth element of x_1 is assumed to be zero). This starting point is also used to initialize the profile cluster. The EKF module starts tracing the road using the initial state and the initial profile cluster. While progressing along the road path, the profile clusters are updated, and new appropriate clusters are added as road intensities and/or widths change.

EKF and LLPF works alternatively in accordance to the knowledge based human input .When problems become very difficult while facing obstacles the job is given to the LLPF by the human operator. Processing is done in monochromatic imagery.

Unscented transform

The unscented transformation (UT) was developed to address the deficiencies of linearization by providing a more direct and explicit mechanism for transforming mean and covariance information. Unlike the extension of KF, the UKF does not approximate nonlinear function f and h. Instead, it approximates the posterior $p(x_t|Z_t)$ by a Gaussian density hence utilizing the following relationship in hold:

$$p(x_{t-1} \mid Z_{t-1}) = N(X_{t-1}; \hat{X}_{t-1}, P_{t-1|t-1})$$

$$p(x_t \mid Z_{t-1}) = N(x_t; \hat{x}_{t|t}, P_{t|t})$$

PF MODULE

The LLPF module starts its work with a single road branch by using the last successful state estimate of the EKF module initial state x_1. This module produces N particles from x_1 proceeds with the PF algorithm based.

This approach is robust in extracting a single road track due to its interface with human experts, but it cannot identify and handle multiple road branches when it encounters an intersection of several roads.

Information about road intersections or junctions is of high importance in understanding road network topologies, junction hints are used in the network optimization process by forcing roads to pass through detected T- and L-shaped junctions. A feed forward neural network is applied on a running window to decide whether it contains a three- or a four-arm road junction. This method suffers from quite many false alarms. This algorithm finds the footprint of a pixel as the local homogenous region around the pixel enclosed by a polygon, and then, by identifying the toes of a footprint, it can track a road path, thus identifying the road intersections. But when this algorithm encounters a road width obstacle, it might lose track of the road.

Satellite Images

A total of 62 research groups were identified with some groups using up to 4 different sensors type over a number of studies. IKONOS data is used by 20 groups, and aerial imagery by 19 groups. Quick bird, SAR, and SPOT data are used by ten, seven and six groups respectively. LiDAR (Light detection and ranging) is used by 3 groups & IRS (Indian remote sensing satellite) by 2. Other data types include Landsat, Eo-1(Earth observation mission), Kompsat EOC and KVR-1000 satellite. A number of the more frequently used sensors is IKONOS. IKONOS is a satellite image which is launched in September 1999. A sample of satellite images are shown in Fig.4

Fig.4 Sample of satellite images

Road Tracking Using Particle Filter

The road tracking process starts with an automatic seeding input of a road segment, which indicates the road centerline. From this input, the computer learns relevant road information, such as starting location, direction, width, reference profile, and step size. This information is then used to set the initial state model and the related parameters are estimated the road is tracked automatically by EKF and EPF. In a road tracking procedure, when the system recognizes tracking failure, it returns the control to the human expert and uses the guidance of the human operator to update its set of profile predictors and continue tracking the road afterward.

Road Extraction Results

Road extraction from remote sensing images has its applications in cartography, urban planning, and traffic management and in industrial development. In order to evaluate the results, we compare the obtained road lane feature to a manually digitized reference road dataset. The quantitative evaluation was conducted in terms of completeness, correctness and quality index. The completeness is defined as the percentage of the correctly extracted data over the reference data and the correctness represents the ratio of correctly extracted road data. The quality is a more general measure of the final result combining the completeness and correctness. For IKONOS images used in this experiment, the correctness values are very high. The completeness of the result depends on the complexity and properties of the road network junctions. Designing an EKF for highly nonlinear processes is not a trivial task. In this work the performance of the unscented filter is compared with that of extended Kalman filter. The unscented filter produces better results without performing potentially ill-conditioned numerical calculations and linearly approximating the evolution of the state vector covariance. UKF has slightly better speed estimation performance than EKF while driven under the identical state model and parameters (covariance). First the reference profile is extracted and it is used as a template profile and during the estimation, new reference profiles were generated and stored in the road template memory for future correlation analysis, thus covering the space of road profiles. The parameters of the road are derived by means of edge detection .Once after estimating the state model, it's given as an input to the kalman filter. The Kalman filter then recursively estimates the model at each time step dt. While reaching a road junction PF is used to detect the road branches. The important parameters used in our Algorithms are specified in Table I. The step size dt determines the distance in pixels, between the process point of the algorithm at step t and t-1.W specifies the approximate road width,σ^2_φ specifies the variance of row direction measurement error. In order to evaluate the results, we compare the obtained road lane feature to a manually digitized reference road dataset. Fig.5 shows the road tracking results from IRS image.

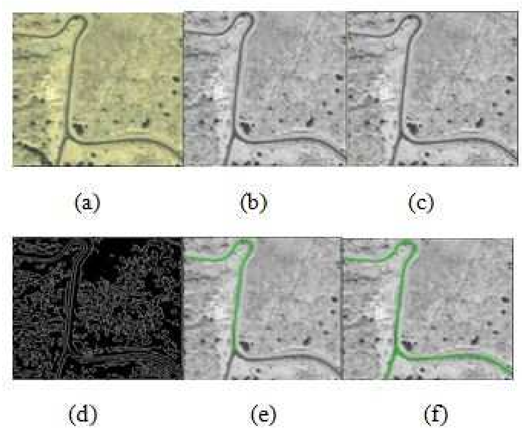


Fig.5 Automatic road tracking results from an IRS image using Efficient particle filtering (a) Satellite image (b) Monochromatic imagery (c) Automatic seeding (d) Edge detection using Canny edge detection (e) Road tracking by EKF (f) Road tracking by Efficient particle filtering and EKF

Conclusion

For road-constrained targets, the incorporation of road information into the dynamics models can greatly reduce the target motion uncertainty. Unscented Transform has been used in the kalman filter frame work and the resulting filter is said to be as Unscented Kalman Filter. Using UKF instead of EKF improves the performance. In addition to this a set of training data sequence can be used to automatically optimize the parameters of a particle filter. A variable-structure, multiple-model framework is used to address target maneuvers along the road. The proposed efficient particle filter is approximations to the optimal particle filter for jump Markov linear Gaussian systems. The main approximation of the filter is the Gaussian assumption about the conditional target state distribution given a mode sequence and observations. The efficient particle filter with 80 particles yields satisfactory simulation result.

Using UKF instead of EKF in the PF improves the performance. A deficiency of the algorithm is the slow operation of the PF module. Hence, to overcome this drawback a set of training data sequence can be used to automatically optimize the parameters of a particle filter. Furthermore, performance of the algorithm on more complex urban areas is yet to be evaluated, which might necessitate some modifications in the way measurements are required.

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