Road Extraction from High Resolution Satellite Imagery

H. S. Bhadauria[1], Annapurna Singh[2], and Ashish Arya[3]
[1,2,3,]G. B. Pant Engineering College,

ABSTRACT:
This paper describes the task of extracting road from a satellite image. Road information is essential for automatic Geographical Information System (GIS) application, such as cartography, military, traffic controlling software and infrastructure planning. Automatic and semi-automatic, two types of techniques for road extraction, have improved the extraction rate of road networks. In this paper a methodology is introduced to predict the performance of road detection from high resolution satellite image. Extented Kalman Fiter (EKF) is used for single road detection. While in typical areas, where there are obstacles, Particle Filter (PF) with EKF has been used. In contrast to previous work on road detection, the focus is on characterizing the road detection performance to achieve reliable results of the detection when both human and computer resources are involved.

KEYWORDS: *Road map extraction, satellite imaging, Extended Kalman filtering, particle filtering.*

I. INTRODUCTION

Preparing new maps and updating the existing maps, from satellite images and aerial images is a necessary task now these days which has huge usage in various applications. Road network extraction from images depends on human labor, which makes networks database development an expensive and time-consuming. Automated and Semiautomatic road extraction can significantly reduce the time and cost of data acquisition and update, database development and turnaround time. Therefore, automated and Semi-automatic road extraction has been a hot research topic over the past two decades. Road is an important man-made object whose information is important in cartography, traffic controlling, urban planning and industrial development. Road extraction methods are categorized into automatic and semiautomatic methods. In Automated method there is no interaction of human operator with the process while in Semi-automatic method, human operator interacts with system regularly. Road detection and tracking requires knowledge about the road database as well as image related knowledge [1], including previous processing results, rules, and constraints [2]. Most of road tracking methods make assumptions about road properties like

- roads are elongated,
- there is enough contrast between road and adjacent areas,
- surfaces are usually homogeneous

as discussed in the work, proposed by Wang and Newkirk [3], Vosselman and Knecht [4], Mayer and Steger [5], Katartzis et al. [6], Bentabet et al. [7], Zlotnick and Carnine [8], Mckeown et al. [9], Tupin et al. [11].
Problem with these systems is that assumptions are pre-defined and fixed whereas image road properties may change. For example:

- Road surfaces may be built from several materials that can cause change in radiometric properties.
- Roads may not be elongated at junctions, bridges, and inclined surfaces.
- Land objects such as trees, buildings, vehicles and shadows may occlude the road.

Such properties cannot be predicted completely and establish a source of problems incomplete automated systems. The solution to such problem is to follow a semi-automatic approach that holds human in the entire process where computer vision algorithms are used to help humans performing these tasks [12]. McKeown and Denlinger [10] used a semiautomatic road tracking technique working on road profile correlation and road edge detection. The user initialized the tracker to find out starting values for position, direction and width of the road. The axis points of road were drawn by the road trajectory and correlation model. A road tracker based on a single-observation Kalman filter was introduced by Vosselman and Knecht [4]. To initialize the state of the Kalman filter and to extract a template for road profile human input was used. The Kalman filter then updated its state to find out the road axis points from matching the template profiles to the mentioned profiles. Baumgartner et al.

[13] proposed a model based on the above method. An interaction interface was projected to organize actions of human operator with computer predictions. Gruen and Li [14] used Semi-automatic approaches which includes the least squares template matching methods. These semi-automatic systems grant human operator to start the road tracking and to stay connected with system in entire tracking process. Xiong and Sperling [15], presented an another semi-automatic system which shows a semi-automatic tool that assist the user to check and correct the errors resulting while performing road network matching. This paper represents a different approach that uses a semi-automatic road tracking approach working on human– computer interaction. It also uses the Bayesian filtering as shown by Arulampa-lam et al. [16]. Extended Kalman filters and particle filters, two models of Bayesian filters, are used to calculate the current state of the system based on past and current observations. When the tracking is fail, a human operator finds out the cause of the failure and initializes another filter. The Observation profiles are created from the road texture described by its 2D features. The current state of the Bayesian filters and the multiple observations are used for optimal profile matching. Therefore, the road tracker is flexible enough in handling the different types of road including obstructions like trees, bridges, vehicles, shadows road surfaces changes and more. These approaches consist of beginning of the road. One limitation of the past work, mentioned in the road extraction methods [4,16] is the restricted processing of the image. These algorithms use EKF and PF for a given seed point on the road tostart the tracing. These stop their processing when an occlusion is occurred, a junction, or even a sudden variation in the direction of the road is encountered.This paper provides a practical solution to the applications used in image processing and remote sensing areas. There are various automatic algorithms have been generated, but a very few of them have been used practically [18].

II. PREPROCESSING

2.1.Road width estimation

In the previous work of semi-automatic road trackers, proposed by McKeown and Denlinger [10]; Baumgartner et al. [13] and Vosselman and Knecht [4], the human operator is required to enter the road width at the starting of the tracking process. Road width is required to determine whether the road profiles are extracted correctly or not, whereas in our system, the road width is calculated automatically at the starting of the tracking process. A road segment is entered by the human operator. In this work an assumption is taken that the roadsides are straight and parallel lines to each other on the both side of the road axis. We need to calculate the distance between the roadsides to figure out the width of the road.To detect the road edges, the selection of edge detectors is important for the generation of appropriate edge information.The Sobel, Robert and Canny detectors are commonly used edge detectors. Sobel cannot provide satisfactory results because some redundant edges within the roads can also be detected, but cannot be removed due to the fixed parameters set in the Sobel. The Robert edge detector can easily achieve a clear and proper edge image from a Quick Bird Pan image. However, some detailed edges in indistinct edge areas cannot be detected. The Canny edge detection algorithm is known as an optimal edge detector, which needs to adjust two thresholds and a standard deviation of a Gaussian smooth mask to yield a proper result.So we have applied the Canny edge detector. The main reason to use the Canny edge detector is, the edges from the Canny detector are thin. But, edges in blurred areas can be clearly delineated. That means it provides good results while dealing with low resolution images.

(a) (b)

Figure 1 a) Satellite image and, **b)**Edge detection using Cannyedge detector.

2.2 Profile extraction

An reference profile from the road segment inputted by human operator is created as a vector of grey levels. The new profiles are then generated from another road segments inputted by human operator and kept into a list, called profile list, for using next time. To increase the performance robustness of the system, we use the two-dimensional features of the road. We seek along a line that is perpendicular to the road direction, and also seek a line along the road direction. Finally, we combine the both Profiles that were extracted in both. The parallel profile is required in grey level values which change little with respect to the road direction, whereas this will not work on off-road areas. So the chance of tracking the off-road is reduced and, the result, there are less tracking errors.We find a profile sequence, containing the information about the road texture which may include occluding objects, from the human input. For a following sequence of road profiles P=[p_1, p_2,…, p_n], the process profile extraction goes as follows. First of all, we need to compute an average profile. Then each profile is cross-correlated with this average profile sequentially. If the correlation coefficient is less than a threshold, fixed to 0.8, the profile is discarded from the profile list sequence. Following this way, all points on the road axis are calculated and also road profiles generated from noisy areas, for example, where cars, bus and other vehicles are present, are discarded. The algorithm keeps repeating the entire process until a sequence of new profiles is created. The average profile of the new sequence is considered as the final profile for the road segment. The strength of the noise removal process is influenced by road conditions and its texture. This method very effective if there is less occlusion on the road. When, the road is populated with more occlusions, for instance, roads with a traffic jam, or roads under the shadow of trees, the system may result some noisy reference profiles. In such type of cases, the efficiency of the system falls.

III. ROAD PATTERN

We are required to find coordinates of the road median on an image to apply EKF to trace a road in satellite images. There is an initial point on the road is required so that EKF can start its operation. This initial point can be inputted by a human operator or through an automatic approach. Once initial point is inputted, the EKF starts its process and sequentially look to the next point on the road according to some defined time step.

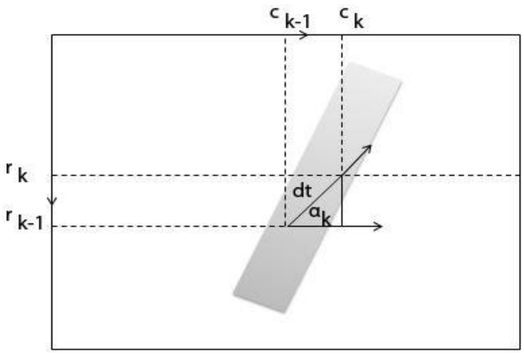


Figure 2 The Road Model.

The process takes the noisy measurement to get the best estimation of the state of the road at the given point. Therefore, an equation can be used to the system with the artificial time step as follows:

$$\boldsymbol{a_k = f\,(a_{k-1}) + m_k} \quad \textbf{(1)}$$

where a_k represents the position of the k^{th} point while tracing the median of the road, and m_k represents the process noise, measured from variation of the road position from one point to the next. The measurement vectorn_k is related to the state vector a_k and the measurement noise v_k through the following stochastic difference equation referred to as themeasurement equation:

$$n_k = h(\,a_k\,) + v_k \quad \textbf{(2)}$$

We used a 4-D state vector in the formulation of the road-tracing, as in [2], as follows:

$$a_k = [r_k \quad c_k \quad \alpha_k \quad \gamma_k]^T \quad \textbf{(3)}$$

where r_k and c_k shows the row and the column numbers of the center of the road, α_k is the direction of road, andγ_k is the change in direction of the road curvature in the k^{th} step. Fig. 1 shows the relationship between the road center coordinates at step k and the road center coordinates at step k−1. Applying the following relationship, the system equation becomes

$$a_k = \begin{bmatrix} r_k \\ c_k \\ \alpha_k \\ \gamma_k \end{bmatrix} = \begin{bmatrix} r_{k-1} - dt.\sin(\alpha_{k-1} + \gamma_{k-1}dt) \\ c_{k-1} - dt.\cos(\alpha_{k-1} + \gamma_{k-1}dt) \\ \alpha_{k-1} + \gamma_{k-1} \\ \gamma_{k-1} \end{bmatrix} + w_k \quad \textbf{(4)}$$

The measurement equation given by

$$n_k = H_k a_k + v_k \quad \textbf{(5)}$$

H_k can be defined by the following matrix

$$H_k = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \quad \textbf{(6)}$$

where v_k is the measurement noise found in the process of finding the measurement in the k^{th} step.

IV. EKF AND PF

4.1 Extended Kalman filtering

Extended Kalman filtering is used to solve non-linear time series [19] when the posterior density is taken as Gaussian. First, we will compute Φ, which holds the coefficients of the linear time update equations

$$\Phi_k = \frac{df_k(x)}{dx} |x = x'_{k-1} \quad \textbf{(7)}$$

The covariance matrix of the predicted state vector is given by

$$P_{k|k-1} = \Phi_k P_{k-1|k-1} \Phi_k + Q_{k-1} \quad \textbf{(8)}$$

After the state update, the EKF continues the iteration by solving the given update equations:

$$K_k = P_{k|k-1} J^T (J P_{k|k-1} J^T + R_k)^{-1} \quad \textbf{(9)}$$

where *J* is measurement matrix shown as follows

$$J = \begin{pmatrix} 1 & 00 & 0 \\ 0 & 10 & 0 \end{pmatrix} \quad \textbf{(10)}$$

and R_k is covariance matrix of measurement noise

$$R_k = \tau^2 \begin{pmatrix} sin^2(\alpha_k) & sin(\alpha_k)cos(\alpha_k) \\ sin(\alpha_k)cos(\alpha_k) & cos^2(\alpha_k) \end{pmatrix} \quad \textbf{(11)}$$

where τ^2 is the variance in the observation. The initial state of the Extended Kalman filter is set to $a_k = [r_k \quad c_k \quad \alpha_k \quad \gamma_k]^T$,where r_k and c_k shows the row and the column numbers of the center of the road, α_k is the direction of road, and γ_k is the change in direction of the road curvature in the kth step. Vosselman and Knecht [4] in road tracking, proposed covariance matrix Q_k of the process noise, decided by the difference between the constant road curvature and the actual curvature changes.

4.2 Particle filtering

We assume that the standard deviation $\tau = \sqrt{2}$ and so the observation is as follows:

$$P(z|x^i)\alpha \frac{1}{\sqrt{2\Pi}} exp\left(-\frac{d_i^2}{2\tau^2}\right) \quad \textbf{(12)}$$

where d_i is the Euclidean distance between the location of particle x^i and the observation. The particle filter arranges the weights of each particle in the entire process. Lee et al. [20] worked on Particle filtering in non-linear and non-Gaussian processes modeling. The filter figures the posterior density p ($P_k|z_k$) by the following particle set {s_k^i, w_k^i, *i*=1,2,...N} in every time step k, where w_k^i is weight of the particle s_k^i.Given the particle set {s_{k-1}^i, w_{k-1}^i, *i*=1,2,...N} at time k–1, the iteration k of the particle filter can be summarized as follows:

1. Build a density function$\{c^i_{k-1}\}$ on the particle set. Prepare N particles$\{x^i_{k-1},\ i = 1, \dots, N\}$ according to thedensity function. Sample the i^{th} particlex^i_{k-1}according to a unvarying random number u^ion [0, 1] and explore for the first particles^i_{k-1} in such a way so that$c^i_{k-1} \geq u^i$.
2. Modify every particle to create new particles $\{x^i_k$, i=1,…,N}. In the state updation process, the road curvature γ_k is affected by a zero mean Gaussian random variable.
3. For each particle estimate new weights, according to how easily they match the observation z_k. The weightis then normalized and is proportional to $P(z|x^i)$. This is a way to create a new particle $\{s^i_k, w^i_k$, i=1,…,N}.

The approximated state at time k is therefore.

$$E(x_k) = \sum_{i=1}^{N} s^i_k w^i_k \tag{13}$$

V. TRACKING PROCESS

5.1 Stopping criteria

The stopping criteria in tracking the road, the observation of Vosselman and Knecht [4], is accepted. They define some threshold. If the coefficient is below the threshold, and some other criteria are met (e.g. a high contrast between the profiles), the observation is refused. The jump-over strategy is used while considering the small occlusions on the road, for example, cars and other vehicles. To skip road positions, where there is occlusion, the jump over scheme uses an incremented time interval, so that a state without any occlusions can be achieved. In real applications, road properties are complex enough.A road profile can be generated by cross-correlating a profile which is extracted from a non-road area with grey level. Moreover, the Bayesian filters might fail because the predicted position may not hold an observation profile that could match with the reference profile. For example, when occlusions are present on the road, and there is a small match between reference and observation profiles. There is a rejection of observation. Therefore the system then needs an interaction with human operator, resulting tracking process less efficient for the user.

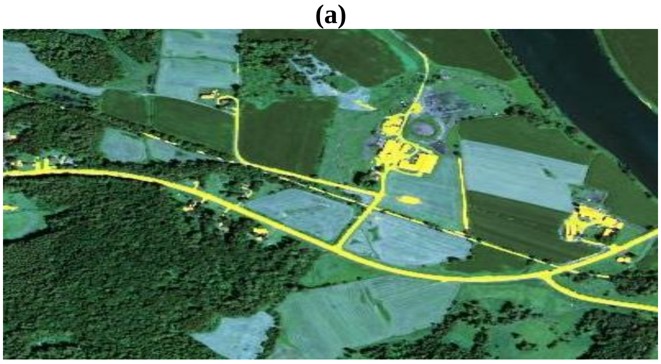
5.2 Improving efficiency

The algorithms of Vosselman and Knecht [4]Baumgartner et al. [13] used previously, it is required to extract a new reference profile each time when the old reference profile was discarded. We define a system in which all reference profiles are held and the road tracking process collects knowledge about the road status. The latest profile is keeps the highest priority while matching the profile. The Bayesian filter seeks the list of reference profiles for a match if matching is failed. To show the little change in the road texture, the reference profile is modified by matches attained through weighted sum technique. Here we proposed an algorithm that uses the observation-reference profile together, in combination. The search space *V=<X,Y,Θ>* is described by the current state a_k, where *X*, *Y* and *Θ* are limited by a small neighborhood of r, c and α respectively. LaBerge [21], propose an approach in which humans use multi-scale attention to concentrate on significant features and to mitigate the effects of distracters. We adopted a step prediction scheme to increase the efficiency of road tracking to model such behavior. The Bayesian filters, helps to calculate the time interval τ. The value of the initial prediction scale is set to 1.When there is a successful match occurs, the value of the scale parameter is incremented by 1. On the other hand, if fails, the prediction scale is again fixed to 1. Following this way, we can automatically adjust the time interval. If the road is very long, straight and homogenous in texture, the road tracking process can assume the next point on the road axis using a larger scale and dismissing some details on the road and hence enhancing the speed of the road tracking process.

VI. ROAD EXTRACTION RESULT

We have applied our method to a real satellite image. The satellite image is a taken from Indian Remote Sensing (IRS) satellite with 5-m spatial resolution. Our algorithm needs an initial point on a provided road segment, as an initial point, to start the road tracking process. This initial point can be entered by a human operator, or we can get it through an automatic method. We have used different parameters for EKF module and the PF module, because the jobs of these modules are different. Our work shows the process of extraction of road segment by the EKF module, until it meets the junction. The EKF delivers the process to the PF module. The algorithm continues its operation in the same fashion until it detects all the road segments. If a road intersection is encountered, the PF keeps looking for all road branches devised from that intersection. On the other hand, if a dead-end road is encountered, the PF module decides that there is an end of the road. The PF module stops the processing of dead end following of all branches using the branch validation criterion method. For measuring the results, we have employed an image generated by operator that have used as reference for a road network axis in our work. The results are measured with the help of evaluation metrics addressed correctness and completeness, as it has been used in [22] and [23].

(a)



(b)

Figure 3 a). High resolution image taken from satellite, **b).**Extracted road from high resolution satellite image.

Correctness indicates how much the extracted road match to a real road while completeness shows an amount of how much the extracted results are completed. We have used the EKF module to detect the measurement for correctness of our results. On the other, the center points gained from the PF module on considering areas have been rejected because they are noted picturing a clear road axis location.

6.1 Some Other Results

(a) **(b)**

Figure 4 a). Satellite Image **b).**Extracted Road.

VII. CONCLUSION

We introduced an algorithm based on the combination of the EKF and the PF for tracking the road from satellite images. This algorithm is tested on an IRS satellite image with 5-m spatial resolution. In this paper we have used an interaction model between human and computer to make the road tracking process effective. Our algorithm can reduce human labor. It also ensures accurate results. To match observation profiles to reference profiles we have used road tracking method, based on Bayesian filters. The tracker measures the result by using cross- correlation between road profiles extracted from previous and current position respectively. Furthermore, our algorithm stays robust no matter how drastic changes in the road direction and change in the road width. One limitation of our algorithm is that it has slow processing for the PF module. As algorithm uses the PF module only on road intersections and road obstacles, the slow processing of it does not influence the entire road tracking process. The proper inputting of the parameters of algorithm impacts the effectiveness of the road network extraction. Moreover, the algorithm is required to check its performance on complex urban, which may require the need of some modifications in the future work.

REFERENCES

[1]Crevier, D., Lepage, R., 1997. Knowledge-based image understandingsystems: a survey. Computer Vision and Image Understanding 67(2), 161–185.
[2]Baltsavias, E., 1997. Object extraction and revision by image analysis using existing geodata and knowledge: current status and steps towards operational systems. ISPRS Journal of Photogrammetry and Remote Sensing 58 (3–4), 129–151.
[3]Wang, F., Newkirk, R., 1988. A knowledge-based system for highway network extraction. IEEE Transactions on Geoscience and Remote Sensing 26 (5), 525–531.
[4]Vosselman, G., Knecht, J., 1995. Road tracing by profile matching and Kalman filtering. Proceedings of the Workshop on Automatic Extraction of Man- Made Objects from Aerial and Space Images, Birkhaeuser, Germany, pp. 265–274.
[5]Mayer, H., Steger, C., 1998. Scale-space events and their link to abstraction for road extraction. ISPRS Journal of Photogrammetry and Remote Sensing 53 (2), 62–75.
[6]Katartzis, A., Sahli, H., Pizurica, V., Cornelis, J., 2001. A model-based approach to the automatic extraction of linear feature from airborne images. IEEE Transaction on Geoscience and Remote Sensing 39 (9), 2073–2079.
[7]Bentabet, L., Jodouin, S., Ziou, D., Vaillancourt, J., 2003. Road vectors update using SAR imagery: a Snake-based method. IEEE Transaction on Geoscience and Remote Sensing 41 (8), 1785–1803.
[8]Zlotnick, A., Carnine, P., 1993. Finding road seeds in aerial images. CVGIP. Image Understanding 57 (2), 243–260.
[9]Mckeown, D., Bullwinkle, G., Cochran, S., Harvey, W., McGlone, C., McMahill, J., Polis, M., Shufelt, J., 1998. Research in image understanding and automated cartography: 1997–1998. Technical Report. School of Computer Science Carnegie Mellon University.
[10] McKeown, D., Denlinger, J., 1988. Cooperative methods for road tracing in aerial imagery. Proceedings of the IEEE Conference in Computer Vision and Pattern Recognition, Ann Arbor, MI, USA, pp. 662–672.
[11] Tupin, F., Houshmand, B., Datcu, F., 2002. Road detection in dense urban areas using SAR imagery and the usefulness of multiple views. IEEE Transaction on Geoscience and Remote Sensing 40 (11), 2405–2414.
[12] Myers, B., Hudson, S.E., Pausch, R., 2000. Past, present, and future of user interface software tools. ACM Transactions on Computer–Human Interaction 7 (1), 3–28.
[13] Baumgartner, A., Hinz, S., Wiedemann, C., 2002. Efficient methods and interfaces for road tracking. International Archives of Photogrammetry and Remote Sensing 34 (Part 3B), 28–31.
[14] Gruen, A., Li, H., 1997. Semi-automatic linear feature extraction by dynamic programming and LSB-snakes. Photogrammetric Engineering and Remote Sensing 63 (8), 985–995.
[15] Xiong, D., Sperling, J., 2004. Semi-automated matching for network database integration. ISPRS Journal of Photogrammetry and Remote Sensing 59 (1–2), 35–46.
[16] Arulampalam, M., Maskell, S., Gordon, N., Clapp, T., 2002. A tutorial on particle filter for online nonlinear/non-Gaussian Bayesian tracking. IEEE Transaction on Signal Processing 50 (2), 174–188.
[17] M. Bicego, S. Dalfini, G. Vernazza, and V. Murino, "Automatic road extraction from aerial images by probabilistic contour tracking," in Proc. ICIP, 2003, pp. 585–588.
[18] Glatz,W., 1997. RADIUS and theNEL. In: Firschein,O., Strat, T. (Eds.), RADIUS: Image Understanding for Imagery Intelligence, pp. 3–4.
[19] Brown, R., Hwang, P., 1992. Introduction to Random Signals and Applied Kalman Filtering, second ed. Wiley.
[20] Lee,M., Cohen, I., Jung, S., 2002. Particle filterwith analytical inference for human body tracking. Proceedings of the IEEE Workshop on Motion and Video Computing, Orlando, Florida, pp. 159–166.
[21] LaBerge, D., 1995. Computational and anatomical models of selective attention in object identification. In: Gazzaniga, M. (Ed.), The Cognitive Neurosciences. MIT Press, Cambridge, pp. 649–664.
[22] C. Wiedemman, C. Heipke, H. Mayer, and O. Jamet, "Empirical evaluation of automatically extracted road axes," in Empirical Evaluation Techniques in Computer Vision. Piscataway, NJ: IEEE Press, 1998,pp. 172–187.
[23] C. Wiedemann and H. Ebner, "Automatic completion and evaluation of road networks," in Proc. Int. Arch. Photogramm. Remote Sens., 2000, pp. 979–986.