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Abstract - A typical way to update map is to compare recent satellite images with existing map data, detect new roads and add them as cartographic entities to the road layer. At present image processing and pattern recognition are not robust enough to automate the image interpretation system feasible. For this reason we have to develop an image interpretation system that rely on human guidance. More importantly road maps require final checking by a human due to the legal implementations of error. Our proposed technique is applied to IRS and IKONOS images using Unscented Kalman Filter(UKF) . UKF is used for tracing the median axis of the single road segment. The Extended Kalman Filter (EKF) is probably the most widely used estimation algorithm for road tracking. However, more than 35 years of experience in the estimation community has shown that is difficult to implement and is difficult to tune. To overcome this limitation,UKF is introduced in road tracking which is more accurate, easier to implement, and uses the same order of calculations as linearization. The principles and algorithm of EKF and UKF were also discussed. The core of our system is based on profile matching.UKF traces the roadbeyond obstacles and tries to find the continuation of the road finding all road branches initializing at the road junction.The completeness and correctness of road tracking from the IRS and IKONOS images were also compared.

Keywords:- IKONOS, Extended Kalman Filter,Unscented Kalman Filter.

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I. INTRODUCTION

Network of roads is an essential mode of transportation, and provides the backbone for human civilization. Hence, it is vital to maintain and restore roads to keep our transportation network being connected. Roads usually appear as dark lines while viewing from satellite images which are mostly true in rural as well as sub-urban areas. 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 post-processing stage. Some of the automatic initialization system has been proposed based on Geographical Information System(GIS) or geographical database has been reviewed in [1] and [2],and on heuristics [3] ,[4] or an stochastic assumption [5]. In a semi-automatic method human intervention is required at the initial stage and at times during the processing stage.

This paper proposes a method based on UKF. The UKF component is responsible for tracing axis coordinates of a road beyond obstacle or an intersection, tracing road branches on the other side of a road junction. There are also other improvements in our works in comparison with previous methods.The most common way of applying the KF to a nonlinear system is in the form of the extended kalman filter(EKF).In the EKF,the probability distribution function(pdf) is propagated through a linear approximation of the system around the operating point at each time instant.In doing so,the EKF needs the Jacobian matrices which may be difficult to obtain for higher order systems.Further,the linear approximation of the system at a given time instant may introduce errors in the state which may lead the state to diverge over time.In order to overcome the drawbacks of the EKF,other nonlinear estimators have been developed such as the unscented kalman filter(UKF),the ensembled Kalman filter(EnKF).The overall impression is that the performance of the UKF is better than the EKF in terms of robustness and speed of convergence.The computational load in applying the UKF is comparable to the EKF.The principels and algorithm of EKF and UKF are described in Section IV-A and B.The results of the road tracking and junction detection using UKF is presented in Section V.

II. SYSTEM OVERVIEW

The road tracking process starts with an initial human 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

A. Prototype of the road tracking system

In most of the road tracking methods the following assumptions are made regarding road characteristics as mentioned in [7]:

- Roads are elongated,
- Road surfaces are usually homogeneous,
- There is adequate contrast between road and adjacent areas.

However these assumptions are not always true. In curved areas or ramps, the road may not be elongated. The road surface may be built of various materials that appear quite difference in the image. Background objects such as trees, houses, vehicles and shadows may occlude the road surface and may strongly influence the road appearance. Road surfaces may not have adequate areas because of road texture, lighting, and weather conditions. . Figure.1 shows a typical example of a high resolution IKONOS image to provide information for map revision purposes.

Figure.1 A sample of a high resolution IKONOS image

The system is composed of preprocessing and tracking modules. The human and machine interact during the production process. The tracking results and the reference profile extracted from human input are stored so that the computer-based tracking module can access them whenever necessary.

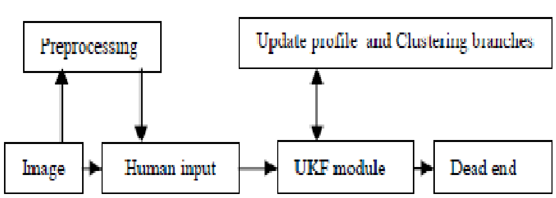


Figure2.Prototype of the proposed system

Preprocessing stage includes the reference profile extraction and seed point selection. Monochromatic imagery is utilized in this technique. The tracking module is composed of the UKF module. The starting point includes the co-ordinates of the road center, road direction and a course estimate of the road width at that point. The architecture of the proposed system is shown in Figure 2.Starting from the initial point ,UKF module can sequentially proceed to the next point on the road by using some artificially defined time step.The distance along the road is considered to be as the time steps.In each step the process uses noisy measurement to obtain the best estimate of the state of the road at that point, with reference with the updated profile. Since road profile is usually different at the intersection (ie) it is usually wider, hence the result of the profile matching is not reliable for obtaining measurement. The UKF will stop after S number of steps. The value of S must be large enough to let the PF module to pass over regular-sized obstacles and junctions. If UKF module cannot find any valid road branches after S steps, it will announce that the road is a dead-end road.

III. PREROCESSING

The preprocessing module consists of two components namely reference profile extraction and estimation of road width.

A. Reference profile extraction

An initial reference profile is extracted as a vector of grey levels from the road segment entered by the human operator. Later, new profiles are extracted from new human inputs and placed into a profile list for further use. To improve robustness of the system, we use two-dimensional road features, i.e. in addition to searching along a line perpendicular to the road direction; we also search a line along the road direction. The method in [6] uses the least square error profile matching to measure the similarities between any two profiles and also to estimate the optimum shift that exist between them. Profile are extracted in both directions and combined. The parallel profile is useful since grey level values vary little along the road direction, whereas this is not the case in off-road areas. Thus the risk of of-road tracking is reduced and, in turn, tracking errors are reduced. From each human input, we obtain a profile sequence that contains the road surface texture information which may include occluding objects. A road profile x is associated with a label y .Y, where *Y* is defined as

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

For a sequence of road profile P = [p1; p2;. …… pn], profile extraction proceeds as follows. First, an average profile is calculated. Then each profile sequence is cross-correlated with the average profile. Whenever the correlation coefficient is below a threshold (set to 0.8), the profile is removed from the sequence. In this way, all axis points are evaluated and road profile extracted from noisy axis points, for example, where cars and trucks are presented, is removed. The algorithm iterates through all the profiles until a new profiles sequence is generated, and the average profiles of the new sequence is taken as the final road segment profile.

B. *Extraction of road width*

Road width determines whether road profile can be correctly extracted or not. In our approach the road width is the road width is estimated at the beginning of the tracking.A road segment is entered by the human operator with two consecutive mouse clicks with the axis joining the points defining the road center line.We assume that the roadsides are straight parallel lines on both sides of the road axis.Road width can be estimated by calculating the distance between the roadsides.Road edges, in turn can be calculated by means of sobel gradient mask.The gradient of the profile along the profile direction is calculated and one point is selected at both sides of the axis point where the largest gradient is found.

IV. PRINCIPLES AND ALGORITHM OF EKF AND UKF

The state vector contain the variable of interest.It describes the state of the dynamic system and represents its degree of freedom.The variable in the state vector cannot be measured directly but they can be inferred from values that measurable.In case of road tracking from an image,it includes where r_k and c_k are the coordinates of road axis points, θ_k is the direction of the road, $\dot{\theta}_t$ and is the change in road direction.The distance along the road is considered to be as time variable.

A. *EKF*

To illustrate the principle behind the EKF, consider the following example. Let W be a random vector and

$$y = g(x) \qquad (1)$$

be a nonlinear function, $g : R^n \rightarrow R^m$. The question is how to compute the pdf of y given the pdf of xi For example, in the case of being Gaussian, how to calculate the mean (y) and covariance ($\sum_y$) of y> If g is a linear function and the pdf of x is a Gaussian distribution, then Kalman filter (KF) is optimal in propagating the pdf. Even if the pdf is not Gaussian, the KF is optimal up to the first two moments in the class of linear estimators [8]. The KF is extended to the class of nonlinear systems termed EKF, by using linearization. In the case of a nonlinear function (g(x)), the nonlinear function is linearized around the current value of x, and the KF theory is applied to get the mean and covariance of y. In other words, the mean $\left(\bar{y}^{EKF}\right)$ and covariance $\left(P_y^{EKF}\right)$ of y, given the mean (x) and covariance (P_x) of the pdf of x are calculated as follows:

$$\left(\bar{y}^{EKF}\right) = g(\bar{x}) \qquad (2)$$

$$\left(P_y^{EKF}\right) = (\nabla g)\, P_x\, (\nabla g)^T, \qquad (3)$$

where (∇ g) is the Jacobian of g(x) at $\bar{x}$.

Algorithm. Let a general nonlinear system be represented by the following standard discrete time equations:

$$x_k = f\,(x_{k-1}, v_{k-1}, u_{k-1}) \qquad (4)$$

$$y_k = h\,(x_k, n_k, u_k) \qquad (5)$$

where $x \in \mathbb{R}^{n_x}$ is noise, $v \in \mathbb{R}^{n_v}$ the process the noise, $n \in \mathbb{R}^{n_n}$ the observation noise, u the point and the noisy observation of the system. The nonlinear functions f and h are need not necessarily be continuous. The EKF algorithm for this system is presented below:

- Initialization at k = 0:

$$\hat{x}_0 = E[x_0],$$

$$P_{x_0} = E[(x_0 - \hat{x}_0)(x_0 - \hat{x}_0)^T],$$

$$P_v = E[(v - \bar{v})(v - \bar{v})^T],$$

$$P_n = E[(n - \bar{n})\,(n - \bar{n})^T],$$

For k = 1, 2, ... ∝.

(1) Prediction step.

(a) Compute the process model Jacobians:

$$F_{x_k} = \nabla_x f\,(x, \bar{v}, u_{k-1})\,|_{x=\hat{x}_{k-1}},$$

$$G_v = \nabla_v f\,(\hat{x}_{k-1}, v,\, u_k)\,|_{v=\bar{v}}$$

(b) Compute predicted state mean and covariance (time update)

$$\hat{x}_k^- = f\,(\hat{x}_{k-1}, \bar{v}, u_k),$$

$$P_{xk}^- = F_{xk} P_{xk} F_{xk}^T + G_v P_v G_v^T.$$

(2) Correction step.

(a) Compute observation model Jacobiansu

$$H_{x_k} = \nabla_x h(x, \bar{n}, u_k)\,|_{x=\hat{x}_k^-},$$

$$D_n = \nabla_n h(\hat{x}_k^-, n,\, u_k)\,|_{n=\bar{n}}$$

(b) Update estimates with latest observation (measurement update)

$$K_k = P_{xk}^{-} H_{xk}^{T} (H_{xk} P_{xk}^{-} H_{xk}^{T} + D_n P_n D_n^{T})^{-1}$$
$$\hat{x}_k = \hat{x}_k^{-} + K_k [y_k - h(\hat{x}_k^{-}, \bar{n})]$$

$$P_{xk} = (I - K_k H_{xk}) P_{xk}^{-}$$

B. UKF

Consider now the same example as in the previous section. The question is how the UKF compute pdf of y given the pdf of x, in other words, how to calculate the mean $(\bar{y}^{UKF})$ and covariance (P_y^{UKF}) of y, in the case of beingGaussian.Consider a set of points

$x^{(i)}$, i ∈ {1, ..., p}, p = 2n + 1,

(similar to the random samples of a specific distribution function in Monte Carlo simulations) with each point being associated with a weight $w^{(i)}$ K These sample points are termed as sigma points. Then the following steps are involved in approximating the mean and covariance: Propagate each sigma point through the nonlinear function,

$$y^{(i)} = g(x^{(i)})$$

- the mean is approximated by the weighted average of the transformed points,

$$(\bar{y}^{UKF}) = \sum_{i=0}^{p} w^{(i)} y^{(i)}, \Sigma w^{(i)} = 1$$

- and the covariance is computed by the weighted outer product of the transformed points,

$$(P_y^{UKF}) = \sum_{i=0}^{p} w^{(i)} (y^{(i)} - \bar{y})(y^{(i)} - \bar{y})^T$$

Algorithm

Let the system by represented by (4) and (5). An augmented state at time instant k,

$$x_k^a \stackrel{\Delta}{=} \begin{bmatrix} x_k \\ v_k \\ n_k \end{bmatrix} \quad (6)$$

is defined. The augmented state dimension is,

$$N = n_x + n_v + n_n \quad (7)$$

Similarly, the augmented state covariance matrix is built from the covariance matrices of x, v, and n,

$$P^a \stackrel{\Delta}{=} \begin{bmatrix} P_x & 0 & 0 \\ 0 & P_v & 0 \\ 0 & 0 & P_n \end{bmatrix} \quad (8)$$

Where P_v and P_n are the process and observation noise covariance matrices.

- Initialization at k = 0:

$$\hat{x}_0 = E[x_0], Px_0 = E[(x_0 - \hat{x}_0)(x_0 - \hat{x}_0)^T)$$

$$\hat{x}_0^a = E[x^a] = E[\hat{x}_0 \;\; 0 \;\; 0]^T$$

$$P_0^a = E[(x_0^a - \hat{x}_0^a)(x_0^a - \hat{x}_0^a)^T] = \begin{bmatrix} P_x & 0 & 0 \\ 0 & P_v & 0 \\ 0 & 0 & P_n \end{bmatrix}$$

- For k = 1, 2, ..., ∞

1. Calculate 2N + 1 sigma-points based on the present state covariance :

$$X_{i,k-1}^a \begin{cases} \stackrel{\Delta}{=} \hat{x}_{k-1}^a, i = 0, \\ \stackrel{\Delta}{=} \hat{x}_{k-1}^a + \gamma S_i, i = 1, \ldots, N, \\ \stackrel{\Delta}{=} \hat{x}_{k-1}^a - \gamma S_i, i = N+1, \ldots, 2N, \end{cases} \quad (9)$$

where S_i is the ith column of the matrix,

$$S = \sqrt{P_{k-1}^a}.$$

Where γ is a scaling parameter,

$$\gamma = \sqrt{N + \lambda} \quad \lambda = \alpha^2 (N + k) - N,$$

where α and k are tuning parameters. We must choose k ≥ 0, to guarantee the semi-positive definite ness of the covariance matrix, a good default choice is k = 0. The parameter α, 0 ≤ α ≤ 1, controls the size of the sigma-point distribution and it should ideally be a small number. The ith sigma point (augmented) is the ith column of the sigma matrix,

$$X_{i,k-1}^{\alpha} = \begin{bmatrix} X_{i,k-1}^x \\ X_{i,k-1}^v \\ X_{i,k-1}^n \end{bmatrix}$$

where the superscripts x, v and n refer to a partition conformal to the dimensions of the state, process noise and measurement noise, respectively,

2) Time-update equations :

Transform the sigma points through the state-update function,

$$X_{i,k/k-1}^x = f(X_{i,k-1}^x, X_{i,k-1}^v, u_{k-1}), \; i = 0, 1, \ldots, 2N. \quad (10)$$

Calculate the a priori state estimate and a priori covariance.

$$\hat{x}_k^- = \sum_{i=0}^{2N}\left(w_m^{(i)} X_{i,k/k-1}^x\right) \tag{11}$$

$$P_{\hat{x}k} = \sum_{i=0}^{2N} w_c^{(i)} \left(X_{i,k/k-1}^x - \hat{x}_k^-\right)\left(X_{i,k/k-1}^x - \hat{x}_k^-\right)^T \tag{12}$$

The weights $w_m^{(i)}$ and $w_c^{(i)}$ are defined as,

$$w_m^0 = \frac{\lambda}{N+\lambda}, i = 0,$$

$$w_c^{(0)} = \frac{\lambda}{N+\lambda} + (1-\alpha^2+\beta), i = 0,$$

$$w_m^{(i)} = w_c^{(i)} = \frac{1}{2(N+\lambda)}, i = 1,\ldots., 2N,$$

where β is a non-negative weighting parameter introduced to affect the weighting of the xzeroth sigma-point for the calculation of the covariance. This parameter (β) can be used to incorporate knowledge of the higher order moments of the distribution. For a Guassian prior the optimal choice is $\beta = 2$.

3) Measurement-update equations:

Transform the sigma points through the measurement-update function

$$Y_{i,k/k-1} = h\left(X_{i,k/k-1}^x, X_{k-1}^n, u_k\right), i = 0, 1, \ldots . 2N \tag{13}$$

and the mean and covariance of the measurement vector is calculated,

$$\hat{y}_k = \sum_{i=0}^{2N} w_m^{(i)} Y_{i,k/k-1}$$

$$P_{\bar{y}k} = \sum_{i=0}^{2N} w_c^{(i)} \left(Y_{i,k/k-1} - \hat{y}_k^-\right)\left(Y_{i,k/k-1} - \hat{y}_k^-\right)^T.$$

The cross covariance is calculated according to

$$P_{x_k,y_k} = \sum_{i=0}^{2N} w_c^{(i)} \left(X_{i,k/k-1}^x - \hat{x}_k^-\right)\left(Y_{i,k/k-1} - \hat{y}_k^-\right)^T$$

The Kalman gain is given by,

$$K_k = P_{x_k y_k} P_{\bar{y}k}^{-1},$$

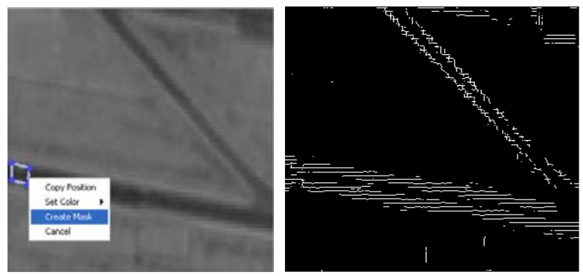
and the UKF estimate and its covariance are computed from the standard Kalman update equations.

$$\hat{x}_k = \hat{x}_k^- + K_k(y_k - \hat{y}_k^-),$$

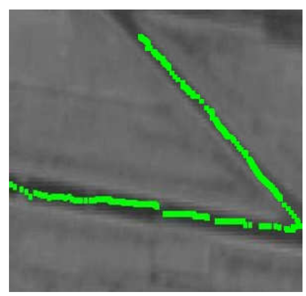
$$P_{xk} = P_{xk}^- - K_k P_{\bar{y}k} K_k^T)$$

V. RESULTS AND DISCUSSION

Road extraction from remote sensing images has its applications in cartography, urban planning, 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, according to [8] and [9]. 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.Figure.4 shows the road tracking results by unscented kalman filtering.For larger dk, progress of the UKF will be faster on the image; however, the resolution of the resulting road center points will be coarser. The system error covariance matrix is a measure of how our road model matches the road behavior



(b)

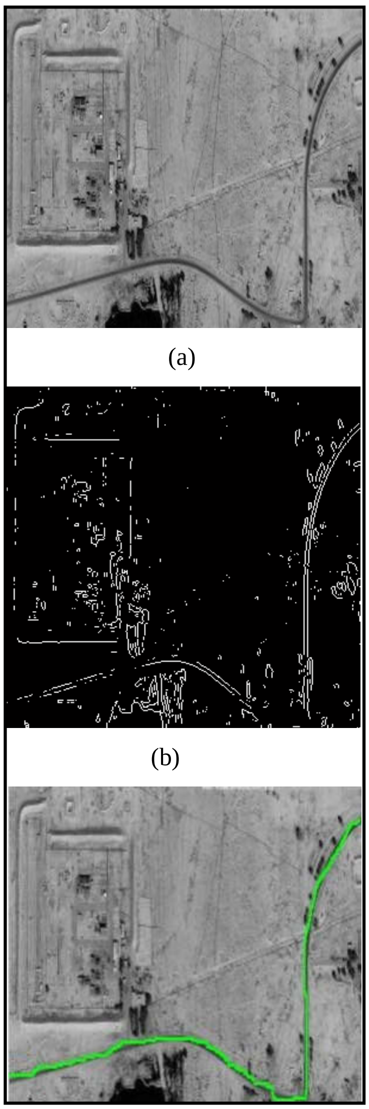


(c)

Figure.4.Road tracking results from IRS image (a)Reference profile extraction. (b)Edge detection using Sobel gradient mask (c) Road tracking by UKF

If the roads in the image are changing direction rapidly, we have to set high values for the elements of covariance matrix.. The measurement error covariance matrix models the behavior of the error resulted from our measurements from the image. Using UKF instead of the combination of EKF in the LLPF improves the performance. The EKF and UKF operate in the frame work of Gaussian approximation for the posterior density function which makes them simple to implement and fast to execute.

The results of the road tracking from an IKONOS image is shown in Figure.5.First the reference profile and seed point is extracted manually by the human operator.Then the edge of the road is detected using Sobel gradient mask.Then the road network is tracked by UKF beyond road junction or obstacles. The completeness and the correctness of the IRS and the IKONOS image is compared and their performance is analysed as shown in the Figure.6. 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, about 0.93 and completeness is about 0.95. For IRS images used in this experiment, the correctness values are very high, about 0.89 and completeness is about 0.83. The completeness of the result depends on the complexity and properties of the road network.



(a)

(b)

(c)

Figure.5 Road tracking results in an IKONOS image. (a)Reference profile extraction. (b)Edge detection using Sobel gradient mask (c) Road tracking by UKF

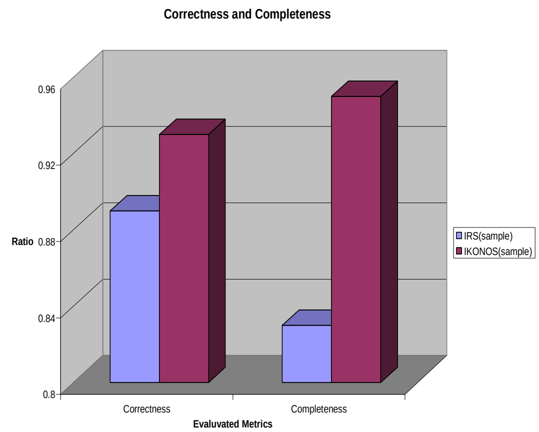


Figure.6 Comparison of correctness and completeness of IRS and IKONOS image

VI. CONCLUSION

The method of extraction developed in this research, and the proposals for future work aimed at automating the initial step of the identification and selection of road segment points, may only work on high-resolution images. As, these processes need edge information for extraction, and geometric (width)and radiometric radiometric/intensity variation) characteristic information across the road along the direction of road, to identify and select road segment points. This information may exist only in high-resolution images, where roads exist as long continuous features with uniform width; in the case of low-resolution images, roads exist as long bright lines that may disappear or exist as very thin features after the pre-processing step. 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 uran areas is yet to be evaluated,which might necessitate some modifications in the way measurements are required.

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