An Implementation of Active Contour and Kalman Filter for Road Tracking

Muhammad Asif, Mohd Rizal Arshad, Muhammad Yousuf Irfan Zia and Abid Yahya

***Abstract*— In this paper an active contour based visual guidance systems for outdoor Autonomous Ground Vehicle (AGV) navigation is presented. The objective of this research is to design a visual guidance system for outdoor AGV navigation that can detect and track road boundaries. The B-spline based active contour is used to define the initial contour of road boundary on image sequences. Various image processing steps are performed on the image to extract road features. Curve fitting is used to measure the pose and orientation measurement. Kalman filter is used to track the road boundaries over time in an image sequences. Experimental results show that the design algorithm effectively track a wide range of road models.**

Index Terms— **B-spline, active contour, curve fitting, Kalman filter.**

I. Introduction

The applications of automatically guided vehicles or AGV have extensively grown in last decades. Technological enhancements in software and hardware have considerably improved the performance of AGV in many areas. The potential applications included but not limited to commercial, military, healthcare, automated warehouses and other hazardous related areas. Traditionally, AGV equipped with variety of sensors to guide and control the vehicle in unstructured and complex environment. However among these sensors, vision sensor or video camera becomes a standard tool [12]. Vision provides lots of information that can be examined by on board vision processing unit for guidance and navigation of the vehicle. The images captured by the vision system are interpreted to extract meaningful information such as position, road marking, road boundaries and direction of vehicle's heading.

Manuscript received December 23, 2006.

M. Asif is associated with National University of Computer and Emerging Sciences, Karachi, Pakistan. He is working as a researcher in the Department of Telecommunication and Computer Engineering (Phone: +92 (21) 111-128-128, Fax: +92 (21) 4100549; e-mail: muhammad.asif@nu.edu.pk).

M.R. Arshad is associate professor and researcher in School of Electrical and Electronic Engineering, University Sains Malaysia, Penang, Malaysia.

Y.I. Zia is associated with National University of Computer and Emerging Sciences, Karachi, Pakistan. He is working as assistant professor and researcher in Department of Telecommunication and Computer Engineering.

A. Yahya is PhD fellow and researcher in School of Electrical and Electronic Engineering, University Sains Malaysia, Penang, Malaysia.

Variety of methodologies and concept has been proposed by utilising various computer vision and image processing techniques for vision based road tracking system. Conventionally, these systems are either based on features or they used road model for road boundaries detection and tracking in an image sequences [1]. In feature based approach, tracking is performed by combining the low level features such as painted lines [2]-[5] or edges [6]-[7] of road boundaries. However these techniques may fail in case of noise or occlusions or in critical shadow conditions.

In contrast with feature based techniques, model based approach based on prior knowledge or model like straight line [8], [9] or parabolic [10], [11] or spline curve [1] of the tracking road. The features extracted using the various image processing techniques are matched with the prior model. This prior model can be seen as a regularization term in measurement process. In this way model based method is robust against noise and missing data compare to feature based technique.

This research presents an active contour based visual guidance systems for outdoor AGV application. The objective of this research is to design a visual guidance system for outdoor AGV navigation that can detect and track road boundaries. First, image processing is performed to reduce the noise and other artifact effects and then B-spline curve is used to define the initial contour of road boundary on image sequences. One-dimensional feature detector is used next to extract the feature points. This one-dimensional feature relies on the B-spline model use to define the road boundaries. The extracted features are matched with reference B-spline template using curve fitting technique to measure the pose and orientation of road boundaries. In order to track the road boundaries over time in an image sequences, Kalman filter is used.

The following section introduces the B-spline function for road model. Section III discusses the features extraction technique. Section IV presents the various components of road tracking algorithm. Section V presents the results and some future work. Finally section VI end the paper with conclusion.

II. Road Model

As mentioned in the section I that model based approach is the most suitable approach for tracking applications. In this project, a second order B-spline curve with 3 control points $\{Q_{-1}, Q_0, Q_1\}$ is used to define a road model. This second order B-spline gives C^{-1} continuity and represents the mid-line of the road boundary as shown in Fig. 1. A number of tracking systems [1] developed earlier use the cubic B-spline function to

(Advance online publication: 17 November 2007)

model the road boundary however to keep the computational cost low and for faster processing 2nd order B-spline is sufficient for this application. The mid-line contour $c(s) = (x(s), y(s))$ is then represented using a B-spline function is given below:

$$x(s) = \sum_{i=0}^{1} \mathbf{B}_i(s) \begin{bmatrix} Q_{-1}^x & Q_0^x & Q_1^x \end{bmatrix}^T \tag{1}$$

$$\mathbf{B}(s) = (B_0(s) \quad B_1(s))$$

where $\mathbf{B}(s)$ are the B-spline basis function and Q^x are the control points or control vectors and similarly for $y(s)$. As shown in Fig. 1, a set of control points is use to describe the mid-line of the road by using B-spline function. The contour $c(s)$ of the midline of the road is also represented by a vector $\mathbf{Q}$ with the B-spline basis $U(s)$, so that:

$$c(s) = (x(s), y(s)) = U(s)\mathbf{Q} \tag{2}$$

where $$U(s) = I_2 \otimes \mathbf{B}(s)^T$$

and $$\mathbf{Q} = (Q_{-1}^x \quad Q_0^x \quad Q_1^x \quad Q_{-1}^y \quad Q_{-1}^y \quad Q_{-1}^y)$$

The term I_2 denotes the 2x2 matrix, $\otimes$ is the Kronecker product and $\mathbf{Q}$ is the x-y coordinate of the B-spline curve [13].

III. Feature Extraction

Image processing is an important step in any vision-based system. After the exploration of potential of vision sensor, most autonomous vehicles now use onboard vision sensor for control and navigation. It can provide measurement relative to local objects. However, vision sensor requires special image processing techniques to detect object and surrounding environments in an image or an image sequences. Until now there are lot of methods proposed for image processing and feature extraction. Most of them are complex [1] and computationally expensive, as they process the entire image for feature extraction. When working on a model based approach, the image processing can effectively be restricted by defining a region of interest (ROI). It is a region where the corresponding image feature is likely to be positioned. This ROI is defined by casting normals (also called measurement line) at pre-specified points around the intial or estimated B-spline model [15] as depicted in Fig. 2. The measurement lines are unit normal vectors and the slopes of the normals are computed by differentiating the B-spline function.

$$x'(s) = \sum_{i=0}^{1} \mathbf{B}'_i(s) \begin{bmatrix} Q_{-1}^x & Q_0^x & Q_1^x \end{bmatrix}^T \tag{3}$$

To extract the features of road boundary, edge detection along the normal is performed using one dimensional convolution and subsequent thresholding. The convolution kernel used in this work can be seen in (4).

$$K = \begin{bmatrix} -0.375 & -0.625 & 0 & 0.625 & 0.375 \end{bmatrix} \tag{4}$$

After convolving the image pixels with convolution kernel, the

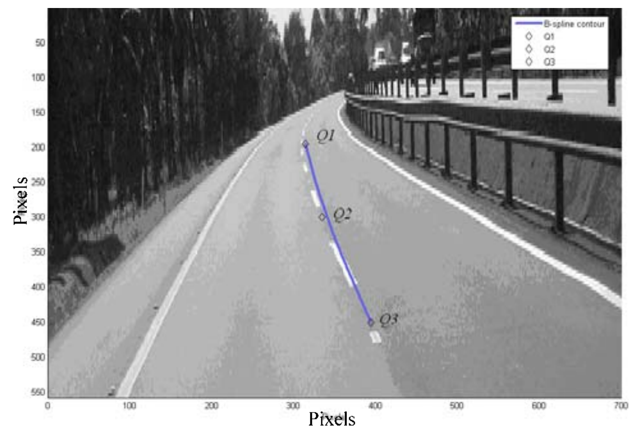


Fig.1 B-spline model represents midline of the road.

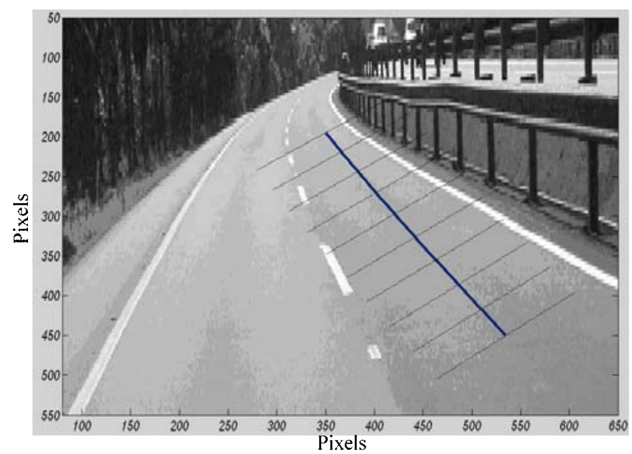


Fig.2 Normals on B-spline model for feature extraction.

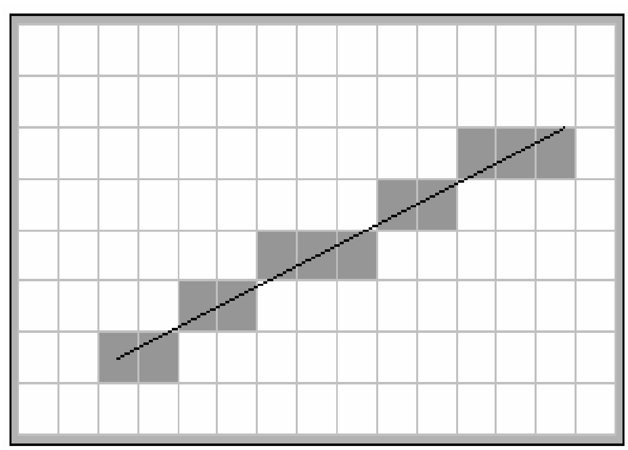


Fig. 3 Discrete nature of digital image causes multiple samples on single pixel.

pixels along the normals are classified as feature or non feature by thresholding the absolute value of the output of the convolution.

In order to perform the one dimensional convolution, the image intensity has been sampled using the Bresenham line algorithm as shown in fig 3. The Bresenham line algorithm provides convenient frame work and avoids undesirable affects such as "jaggies" or multiple samples on the same pixel value.

IV. Road Tracking Algorithm

This section explains the components of tracking system that have been implemented for road tracking application. The framework introduced by [13] is used to track the road boundaries. The developed road tracking algorithm uses the active shape modeling defined by using the B-spline curve and recursive curve fitting algorithm. The Kalman filter is used for tracking the current pose of the road boundaries over time in an image sequences. First active shape modeling is discussed and then dynamic curve fitting using Kalman filter is explained.

The shape deformation of road boundaries is defined using the non rigid contour (B-spline contour). It is assume that the variation of road boundaries in an image is linear and described by a planar affine transformation. Affine space has 6 degrees of freedom. It also gives perspective effects and can handle translation and rotation. It is computationally simple and can be applied to a template curve $c_0(s)$ as in (5).

$$c(s) = \mathbf{u} + Ac_0(s) \tag{5}$$

where u is a two dimensional translation vector, and A is a 2x2 matrix which correspond to remaining four affine motion. The affine space can be represented in a shape space [13] with template $\mathbf{Q}_0$ and shape space vector $\mathbf{X}$. A shape space is a linear mapping of a "shape-space vector" $\mathbf{X}$ to a spline vector $\mathbf{Q}$ as in (6).

$$\mathbf{Q} = W\mathbf{X} + \mathbf{Q}_0 \tag{6}$$

where W is $N_{\mathbf{Q}}$ by $N_{\mathbf{X}}$ shape matrix, $\mathbf{X}$ is a shape vector and $N_{\mathbf{Q}}$ and $N_{\mathbf{X}}$ are the dimensions of spline vector and shape vector respetively. $\mathbf{X}$ also called state vector because it represent the current state of the road boundary and $\mathbf{Q}_0$ is a template curve. The matrix W and shape space vector $\mathbf{X}$ are described as:

$$W = \begin{bmatrix} 1 & \mathbf{Q}_0^x & 0 & 0 & \mathbf{Q}_0^y \\ 0 & 0 & \mathbf{Q}_0^y & \mathbf{Q}_0^x & 0 \end{bmatrix}$$

$$\mathbf{X} = [u_1 \quad A_{11}-1 \quad A_{22}-1 \quad A_{21} \quad A_{12}]$$

The first element in shape matrix W represents the 1D translation in x-direction and remaining four columns corresponds to the other four affine motions. This transformation simplifies the contour variation and tracking in an image to a shape vector $\mathbf{X}$.

After defining the shape space, the next part of visual tracking algorithm is to use curve fitting technique to measure the current position and orientation of the road boundaries.

If $c_f(s)$ represents the image features that are obtained using the one dimensional image processing and $c(s)$ is the possible fitted curve then the fitting problem is:

$$r = \arg\min \left\| c(s) - c_f(s) \right\|^2 \tag{7}$$

which is the square of the residual norm. Generally measurements made from images are noisy, due to dynamic road environment. To overcome the effect of noise in the residual norm, Tikhonov regularization is used. It is perhaps the most common and well known of regularization schemes. It biases the fitted curve towards the mean shape $c_m(s)$ to the degree determined by regularization constant Ω as in (8).

$$r = \arg\min \left(\Omega^2 \left\| c(s) - c_m(s) \right\|^2 + \left\| c(s) - c_f(s) \right\|^2 \right) \tag{8}$$

where $c_m(s)$ is the mean shape and Ω is the regularization parameter. If the regularization parameter is very large, the term $\left\| c(s) - c_f(s) \right\|$ is negligible to that of $\Omega^2 \left\| c(s) - c_m(s) \right\|$ in (8). With a large amount of regularization, the data and any noise on the data can be ignored effectively. On the other hand if Ω is small, the weighting placed on the solution semi norm is small and the value of the misfit at the solution become more important. However, if Ω is reduced to zero, the problem reduces to the least-square case as in (7), with it extreme sensitivity to noise on the data. Equation (9) shows the fitting equation in term of shape state vector $\mathbf{X}$.

$$\min \mathbf{X} = \Omega^2 \left\| \mathbf{X} - \overline{\mathbf{X}} \right\|^2 + \left\| \mathbf{Q} - \mathbf{Q}_f \right\|^2 \text{ with } \mathbf{Q} = W\mathbf{X} + \mathbf{Q}_0 \tag{9}$$

To avoid the influence of position and orientation of the mean contour and from the features of other objects in the background in the regularization term, weight matrix L^s is introduced as in (10).

$$\min \mathbf{X} = \left\| \mathbf{X} - \overline{\mathbf{X}} \right\|^T L^s \left\| \mathbf{X} - \overline{\mathbf{X}} \right\| + \left\| \mathbf{Q} - \mathbf{Q}_f \right\|^2 \tag{10}$$

where $L^s = \Omega H$ and H is the spare of B-spline function and given below:

$$H = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \otimes \frac{1}{L} \int_0^1 \mathbf{B}(s)\mathbf{B}(s)^T \, ds \, .$$

To solve (10), a normal displacement method has been used which is a standard technique in computer vision. The normal displacement method measures the displacement between two corresponding points of the curves. If $n(s)$ is the unit normal vector to the curve $c(s)$, so (10) can be written in discrete form as follows:

$$\min \mathbf{X} \quad \left\|\mathbf{X}\text{-}\bar{\mathbf{X}}\right\|^T L^s \left\|\mathbf{X}\text{-}\bar{\mathbf{X}}\right\| + \sum_{i=1}^{N} \frac{1}{\sigma_i^2}\left(v_i - \mathbf{h}(s_i)^T[\mathbf{X}-\bar{\mathbf{X}}]\right)^2 \qquad (11)$$

where v_i and $\mathbf{h}(s_i)^T$ are given in (12) and (13) respectively. Introducing the concept of information matrix S_i and information weight sum $\mathbf{Z}_i$ from the stochastic process, the algorithm for finding the best-fitting curve is summarized as follows:

- Select N regularly equal-spaced sample points $s=s_i$, $i=1,\ldots,N$, with inter-sample space h, along the entire curve $c(s)$ so that, in the case of an open curve $s_1=0$, $s_{i+1}=s_i+h$ and $s_N=L$.
- For each i, find the position of $c_f(s)$ by applying 1D feature detector along the normal line passing though $c(s)$ at $s=s_i$.
- Initialize $\mathbf{Z}_0 = 0, \;\; S_0 = 0$

  Iterate, for $i=1,\ldots,N$

$$v_i = \left(c_f(s_i) - \bar{c}(s_i)\right).\bar{\mathbf{n}}(s_i) \qquad (12)$$

$$\mathbf{h}(s_i)^T = \bar{\mathbf{n}}(s_i)^T U(s_i) W \qquad (13)$$

$$S_i = S_{i-1} + \frac{1}{\sigma_i^2}\mathbf{h}(s_i)\mathbf{h}(s_i)^T \qquad (14)$$

$$\mathbf{Z}_i = \mathbf{Z}_{i-1} + \frac{1}{\sigma_i^2}\mathbf{h}(s_i) v_i \qquad (15)$$

  where $n(s_i)$ is the normal unit vector of curve $\bar{c}(s)$ at $s=s_i$, and $\sigma_i^2 = N_{\mathbf{Q}}$.
- The aggregated observation vector is $\mathbf{Z}=\mathbf{Z}_N$ with the associated statistical information $S=S_N$.
- The best-fitting curve is given in shape-space by:

$$\hat{\mathbf{X}} = \bar{\mathbf{X}} + (L^s + S)^{-1}\mathbf{Z} \qquad (16)$$

The term S_i (information matrix) is a measurement of the weight of each intermediate estimate $\mathbf{X}$, $\mathbf{Z}_i$ (information weight sum) accumulates the influence of the mean shape c_m. The proof of correctness of the curve fitting algorithm can be found in [13]. The pose and orientation of the tracking road boundary can be measure directly from the shape vector $\mathbf{X}$.

To track the road boundaries over an image sequences Kalman filter [14] is used. The dynamic of the road boundary is modeled using the second order auto regression processing or ARP. A second order ARP expresses the state $\mathbf{X}_t$ at time t as a combination of previous two states and some Gaussian noise. The simplest autoregressive model is the linear model where the AGV is assumed to have a constant velocity model with respect to the road boundaries. It is best described by the following equation.

$$\mathbf{X}(t_k) = A_2\mathbf{X}(t_{k-2}) + A_1\mathbf{X}(t_{k-1}) + B\mathbf{w}_k \qquad (17)$$

where $\mathbf{w}$ is a random Gaussian noise with zero mean and unit standard deviation, A and B are matrices representing the deterministic and stochastic components respectively and $\mathbf{X}(t_k)$ is the position of the curve at time t_k. If β and f are expressed the damping rate and the frequency of oscillation of the harmonic motion respectively then:

$$A_2 = a_2 I_{N_X}, \quad A_1 = a_1 I_{N_X} \quad \text{and} \quad B_0 = \frac{b_0}{\sqrt{N_{\mathbf{X}}}} H^{-\frac{1}{2}}$$

where $a_2 = -\exp(-2\beta\tau)$, $a_1 = 2\exp(-\beta\tau)\cos(2\pi f\tau)$

and $$b_0 = \bar{\rho}\sqrt{1 - a_2^2 - a_1^2 - 2\frac{a_2 a_1^2}{1-a_2}}$$

These parameter need to be tuned appropriately for expected motion in order to obtain best tracking results. In this paper the features of the road boundaries are modeled using the constant velocity model. According to the theory of control system β and f must set zero for constant velocity model, so the coefficient of the dynamic model are defined as:

$$A_1 = \begin{pmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 2 \end{pmatrix} \; A_2 = \begin{pmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & -1 \end{pmatrix} \; B_0 = \begin{pmatrix} 3 & 0 & 0 \\ 0 & 3 & 0 \\ 0 & 0 & 3 \end{pmatrix}$$

These coefficients can also be obtained by learning from the training data, thought this is not required in this application.

The Kalman filter is update the estimate of $\mathbf{X}(t)$ by merging the information from the predicted state and the visual measurement obtained in (16). The prediction phase is based on the dynamic model defined in (17). A single time step of the dynamical model has been applied to $\mathbf{X}(t_{k-1})$ to obtain a predicted state $\mathbf{X}(t_k)$ [16]:

$$\tilde{\mathbf{X}}(t_k) = A_2\mathbf{X}(t_{k-2}) + A_1\mathbf{X}(t_{k-1}) + (I - A_2 - A_1)\bar{\mathbf{X}} \qquad (18)$$

and

$$\begin{aligned}\tilde{P}(t_k) = {} & A_2 P(t_{k-2}) A_2^T + A_1 P(t_{k-1}) A_2^T + A_2 P^T(t_{k-2}) A_1^T \\ & + A_1 P(t_{k-1}) A_1^T + B_0 B_0^T\end{aligned} \qquad (19)$$

where $\bar{\mathbf{X}}$ is the mean shape. Following the prediction step from a given time step, a state of the road boundary is measured using (11). These measurements must be used to influence the predicted position and variance. For each measurement the curve estimate has been updated as follows:

$$\hat{\mathbf{X}}(t_k) = \tilde{\mathbf{X}}(t_k) + K(t_k)\mathbf{Z}(t_k) \tag{20}$$

and

$$P(t_k) = \left(I - K(t_k)S(t_k)\right)\tilde{P}(t_k) \tag{21}$$

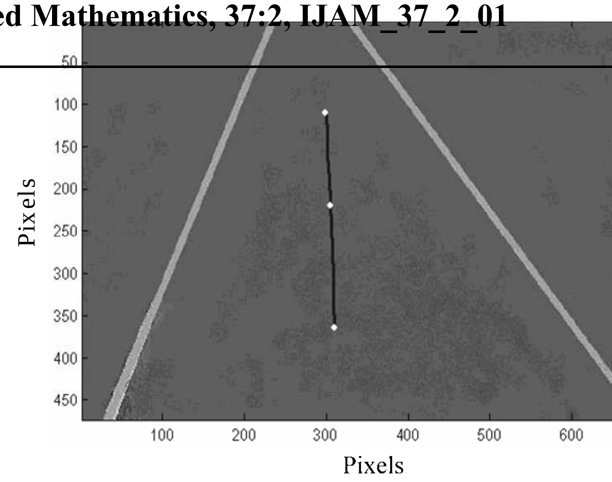
where *K(s)* is the Kalman gain and defined as:

$$K(t_k) = \tilde{P}(t_k)\left(S(t_k)\tilde{P}(t_k) + I\right)^{-1} \tag{22}$$

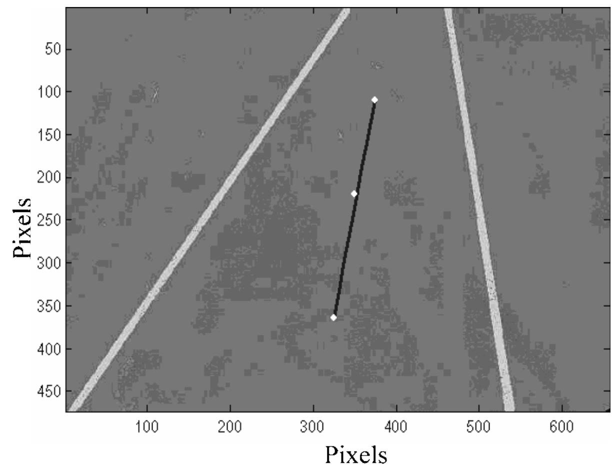
The term $\mathbf{Z}(t_k)$ and $S(t_k)$ are aggregated observation vector and associated statistical information respectively. If the measurement failed along the normal due to obstructions or multiple features so that $\mathbf{Z}(t_k) = 0$ and $S(t_k) = 0$, and the state of road boundary is predicted without modification.

V. Results and Discussion

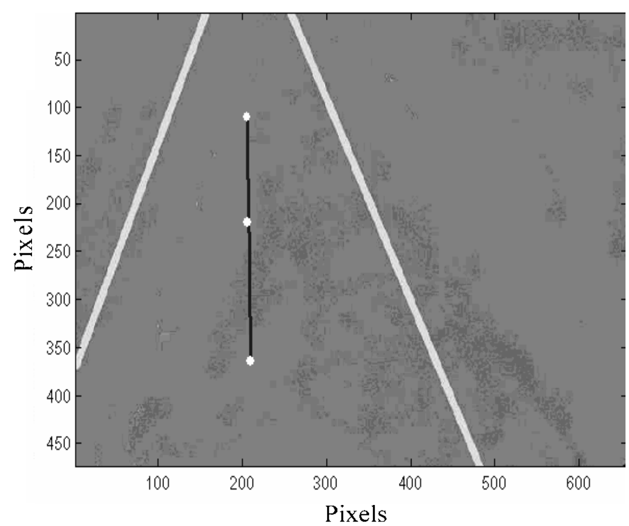
This section presents the results obtained from the implementation of the purposed road tracking algorithm on flat and painted boundaries. The algorithm is implemented on Matlab version 7.0 without code optimization, and executed on a Pentium IV 1.70 GHz standard desktop computer. The implementation on Matlab shows the developed tracking system effectively track a range of road models, such as straight road model as shown in Fig. 4, and parabolic models as depicted in Fig. 5. An active contour deform into the shape of road boundary in few iterations. The pose and orientation of the current road boundaries is calculated by comparing the updated active contour and the reference B-spline template. In general, the accuracy and the performance of the tracking system improve as the number of feature points, used in curve fitting stage increase. However, as the number of features increases, the computational load become heavier. There is an obvious trade-off between accuracy of the tracking algorithm and the computational time. To achieve the balance between performance and accuracy, 10 feature points were used. It was observed from the implementation, that at least five feature points are required for successful deformation of template contour to the image feature. The curve fitting algorithm fits the B-spline contour on image features which represents the right side boundary of the road, and after that offset D is added to get the middle of the road. The Kalman filter is used to track the road boundaries using the B-spline contour over the image sequence. Every 10th frame of 4500 frames sequence was used to check the robustness and the accuracy of the purposed tracking system. Fig. 6 shows the graphs of actual, predicted and updated position of road boundaries. It can be observed that the maximum error is approximately 15 pixels. It can be



(a)

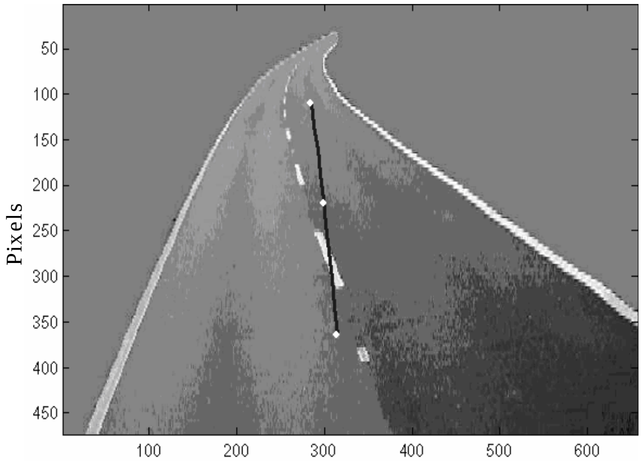


(b)

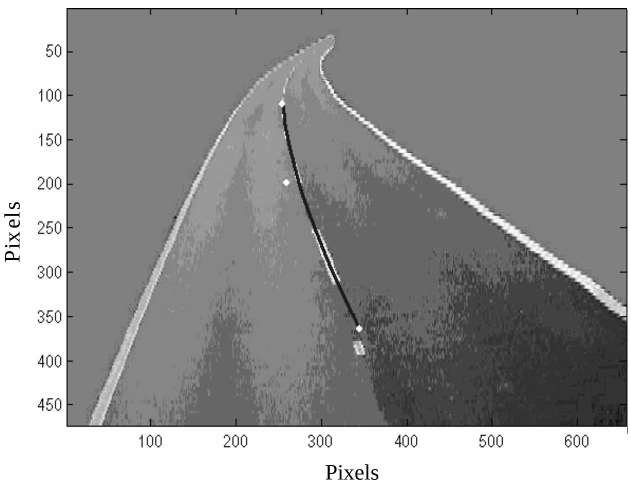


(c)

Fig. 4 Shows the simulation result of the tracking algorithm for straight road boundaries



(a) Initial shape



(b) Final shape after N iteration

Fig. 5 Shows the simulation result of the tracking algorithm for parabolic road boundaries

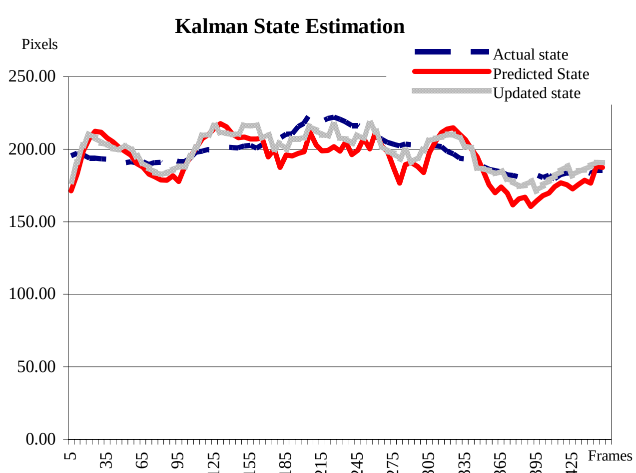


Fig. 6 Comparison of actual, predicted and updated position of road boundaries using the Kalman filter.

seen that the tracking algorithm recovers the actual position of the road boundaries within few frames which shows the robustness of the tracking algorithm. In this work, it is assume that the road boundaries are well painted, and one feature is found on each normal, are utilized. This undeniably will influence the robustness of the guidance system.

VI. Conclusion and Future Work

In this paper, a vision system for outdoor AGV navigation was presented. The developed vision system successfully tracks a range of road models in an image sequence. However, it required more efforts to refine this approach for actual navigation requirement. The edge features extracted for measuring the pose and orientation of road boundaries is statistically independent. The robustness of the tracking algorithm can be increased by defining the statistical relation between feature points, as false features points can be avoided. The relationship between feature points can be obtained by using the neural network or any statistical model like Markov model. Moreover, further studies on improving the algorithm structure and calculation steps to achieve better computation time need to be explored. In order to improve tracking and to make the algorithm more robust in case of unpainted road line and real traffic conditions, condensation algorithm technique will be explored.

Acknowledgment

The work described in this paper was supported by the Yayasan FELDA of Malaysia and authors would like to thanks them for the research grant provided.

References

[1] Y. Wang, E.K. Teoh, and D. Shen. "Lane detection and tracking using B-Snake" *Image and Vision Computing*, vol. 22, 2004, pp. 269-280.

[2] A. Broggi. "Robust real time land and road detection in critical shadow conditions", *Proceeding IEEE International Symposium on Computer vision,* 1995, pp. 19 – 21.

[3] A Broggi and S. Berte. "Vision-based road detection in automotive systems: a real time expectation-driven approach" *J. Artificial Intell. Research,* vol. 3, 1995, pp. 325 – 348.

[4] A. Broggi. "A massively parallel approach to real-time vision based road marking detection" *Proceeding IEEE Intelligent Vehicles '95,* 1996, pp. 84 – 89.

[5] H. Andrew, S. Lai, H. Nelson, and C. Yung. "Lane detection by orientation and length discrimination" *IEEE Transaction on Systems, Man and Cybernetics,* 2000, pp. 539 – 548.

[6] A. Broggi. "An Image Reorganization Procedure for Automotive Road Following Systems" *Proc. 2nd IEEE Intl Conf. on Image Processing,* vol. 3, 1995.

[7] A. Broggi. "Parallel and Local Feature Extraction: a Real-Time Approach to Road Boundary Detection" *IEEE Trans. On Image Processing,* 4, 1995, pp. 217-223.

[8] S.K. Kenue and S. Bajpayee. "LANELOK: robust line and curvature fitting of lane boundries", *In Proc/ of SPIE- Mobile Robots VII,* 1831, 1993, pp 491 – 503.

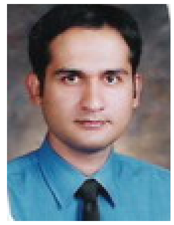
[9] R. M. Haralick, S.R. Sternberg, X. Zhuang. "Image analysis using mathematical morphology", *IEEE Transaction on PAMI,* 9, 1987, pp. 532 – 550.

[10] A. Broggi, S. Berte. "A morphological model-driven approach to real time road boundary detection for vision based automotive systems", *In Pro. 2nd IEEE Workshop on Application of Computer vision,* 1994, pp. 73 – 90.
[11] A. Broggi, G. Conte, F. Gregoretti, C. Sansoe, L. M. Reyneri. "The PAPRICA massively parallel processor", *In Proc. IEEE Intl Conf. on Massively Parallel Computing Systems,* 1994, pp. 16 – 30.
[12] J. MacCormick, *Stochastic algorithms for visual tracking*, Springer-Verlag London Limited, Cambridge, England. ISBN 1-85233-601-3, 2002
[13] A. Blake, M. Isard, *Active contour*, Springer-Verlag London Limited, Cambridge, England. ISBN 3-540-76217-5, 1998.
[14] M.S. Grewal, A.P. Andrews *Kalman filtering: Theory and Practice with MATLAB*, 2nd Edition, *John Willy & Sons*, Singapore 2001.
[15] J. MacCormick, A. Blake. "A Probabilistic Contour Discriminant for Object Localisation", *In Proc. of sixth Intl. Conf. on Computer Vision*, 1998, pp. 390 – 395.
[16] J.C. Tai, S.T. Tseng, C.P. Lin, and K.T. Song. "Real-time image tracking for automatic traffic monitoring and enforcement applications. *Image and Vision Computing,* vol. 22, 2004, pp 485 – 501.

Muhammad Asif received B.S. degree in biomedical engineering from the Sir Syed University of Engineering and Technology, Karachi, Pakistan in 2002, and M.S. degree in electrical and electronic engineering from the Universiti Sains Malaysia (USM) Malaysia, in 2007. He is working as Lecturer and Researcher in the Department of Telecommunication and Computer Engineering at the National University of Computer and Emerging Sciences, Karachi, Pakistan. His research addresses the issues and problems of navigation, mapping and design and implementation of statistical control algorithm for autonomous ground and underwater vehicles. From 2004 to 2006, he was a Research Engineer in USM Robotic Research Laboratory (URRG) at the Universiti Sains Malaysia (USM), Malaysia.

Dr. Mohd Rizal Arshad graduated from the University of Liverpool, in 1994 with a B.Eng. in Medical Electronics and Instrumentation. He then pursues his MSc. in Electronic Control Engineering at the University of Salford, graduating in Dec. 1995. Following from this, in early 1999, he continues with a PhD degree in Electrical Engineering, with specialisation in robotic vision system,. Since then, he has been working at the Universiti Sains Malaysia (USM), Malaysia as Associate Professor and researcher. He has supervised a number of postgraduates students at the MSc. and PhD. levels. He has also published actively in local and international publications. Dr. Mohd Rizal Arshad is currently the deputy dean of the School of Electrical and Electronic Engineering, and with his team of researcher, is also the pioneer of underwater system research efforts in Malaysia.

Muhammad Yousuf Irfan Zia received B.S. degree in Electronic Engineering from Sir Syed University of Engineering & Technology, Karachi, Pakistan in 1998 and M.S. degree in Computer Systems Engineering from N.E.D. University of Engineering & Technology, Karachi, Pakistan in 2002. He has more than nine years of teaching and research experience and have taught undergraduate and graduate level courses and supervised projects in top ranking universities in Pakistan. Currently he is associated with National University of Computer & Emerging Sciences as Assistant Professor in the department of Telecommunication & Computer Engineering. His areas of interests include Industrial Automation, Instrumentation and Embedded Systems.



Abid Yahya was born in Pakistan. He received the B.Sc degree from University of Engineering and Technology Peshawar Pakistan in Electrical and Electronic Engineering. While at the Universiti of Sains Malaysia , he received a graduate fellowship from the school of Electrical and Electronic Engineering. While completing his M.Sc thesis, he conducted research in the area of interference and jamming rejection. His research interests include Forward Error Correction for Frequency Hopping Spread Spectrum and Multiple Description Coding For Interference In Wireless Communication.