Trajectory Estimation of a Moving Object using Kohonen Networks

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Abstract: A novel approach to estimate the real time moving trajectory of an object is proposed in this paper. The object position is obtained from the image data of a CCD camera, while a state estimator predicts the linear and angular velocities of the moving object. To overcome the uncertainties and noises residing in the input data, a Kalman filter and neural networks are utilized. Since the Kalman filter needs to approximate a non-linear system into a linear model to estimate the states, there always exist errors as well as uncertainties again. To resolve this problem, the neural networks are adopted in this approach, which have high adaptability with the memory of the input-output relationship. Kohonen Network(Self-Organized Map) is selected to learn the motion trajectory since it is spatially oriented. The superiority of the proposed algorithm is demonstrated through the real experiments.

Keywords: trajectory, Kalman filter, CCD camera, neural networks, Kohonen Network, Self-Organized Map

1. INTRODUCTION

Detection of moving objects is encountered in industrial robotic systems, recognition, monitoring and unmanned systems [1-2]. Prediction of the trajectory of moving objects is required for the servo system that aims at control and observation of motion information such as object position, velocity and acceleration and is required for the industrial robots. For a simple example, in the pick and place operation with a manipulator, the precise motion estimation of the object on the conveyor belt is a critical factor for the successful operation of the stable grasping. The well-structured environment such as the moving-jig that carries the object on the conveyor belt and stops when the manipulator grasps the object may release the motion estimation requirement. However, the well-structured environment limits the flexibility of the production line, requires skillful designers for the jig, costs high maintenance expense and eventually it will be disappeared from the automated production line.

To overcome these problems—to grasp a moving object stably without stopping the motion, the trajectory prediction of the moving object on the conveyor belt is necessary. The manipulator control system needs to estimate the highest accuracy position, velocity, and acceleration at any instance to capture the moving object without collision safely and to lift up the object without slippage stably.

When the motion trajectory is not high random and continuous, the trajectory can be model analytically to predict the near future values based upon the measured previous data [3]. However, this kind of approach requires high computational time for the high degrees of freedom motion and its computational complexity increases rapidly when the modeling errors become high. In addition to these, the performance is highly sensitive to the changes of the environment.

In this paper, a novel approach for the real time trajectory estimation of a moving object is proposed. For the image data capturing, a CCD camera is utilized. Through the geometrical analysis of the camera and the object, the position of the object can be estimated [2]. There are several approaches where the state estimator is used to predict the linear and angular velocities.

The most general approach known so far is the Kalman filter whose performance is well verified by the numerous researches [4-8]. However, the Kalman filter is not properly applied for the noisy environment. The adaptive or extended Kalman filter is proposed to improve the prediction accuracy [9]. To make the system robust against the noises in the input data and uncertainties, in this approach, neural networks are suitably incorporated into the Kalman filter. That is when the Kalman filter cannot predict the highly nonlinear trajectories, the estimation role is passed to the neural networks which are trained previously for the nonlinear properties. Since the neural networks are trained only by the relationship between the input and output, this approach is expected to have higher flexibility than the adaptive or extended Kalman filter.

Neural networks can be classified into two categories: supervised learning and unsupervised learning methods. In most of the previous researches, the supervised learning is adopted to overcome the nonlinear properties [10-12]. Since the supervised learning requires the relation of input and output [9], it is not suitable for the real time trajectory estimation where the input-output relation cannot be obtained in the unstructured environment. Therefore, in this paper, SOM(Self Organizing Map) that is a sort of the unsupervised learning is selected to estimate the highly nonlinear trajectory that cannot be predicted by the Kalman filter properly. Fig. 1 summarizes the trajectory estimation system for this research.

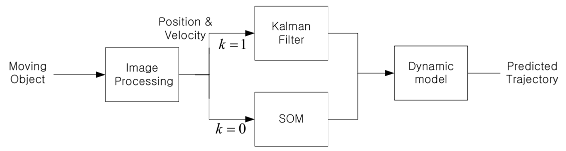


Fig. 1. Trajectory estimation system.

The input for the dynamic model comes from either Kalman filter or SOM according to the following decision equation:

$$predicted\ value = k \cdot Kalman_{out} + (1-k) \cdot SOM_{out} \tag{1}$$

where k=1 for $error \le threshold$ and k=0 for $error > threshold$. The threshold value is determined empirically based on the size of estimated position error.

2. PARAMETER LEARNING

2.1 Preprocessing

To classify the moving object pattern in the dynamically changing unstructured environment is not tackled yet successfully [13]. Therefore, for this research, the camera is fixed on the stable basis. To estimate the states of the motion characteristics, the trajectory of the moving object is pre-recorded and analyzed.

As it is recognized in the images, most parts of the CCD image correspond to the background. After eliminating the background, the difference between the two consecutive images frames can be obtained to estimate the moving object motion. To compute the difference either the absolute values of the two image frames or the signed values can be used. This difference method is popular in the image pre-processing to extract desired information from the whole image frame [14].

2.2 Motion vector estimation

Motion vectors can be defined for the moving object at any instance. To predict the motion trajectory using the Kalman filter and SOM, these motion vectors are the basic inputs that should be obtained from the difference images. The motion vector can be computed based on the data, the difference vector from the consecutive two image frames and the sampling period. When the SOM is utilized for the estimation of the motion vector, motion vectors with high correlation resides close to each other, which will be explained in section 4. The fact that motion vectors of neighboring states have high spatial correlation is utilized for estimating the current motion vector in the motion vector estimation process.

3. Kalman Filter

3.1 Modeling of a moving object

When the velocity and acceleration of a moving object are given for the current instance, the position for the next instance, (P_x, P_y), in the Cartesian space can be estimated as follows [15].

$$\hat{P}_{x+\Delta t} = \hat{P}_x + \hat{V}_x \Delta t + \frac{1}{2}\hat{A}_x \Delta t^2 \tag{2-a}$$

$$\hat{P}_{y+\Delta t} = \hat{P}_y + \hat{V}_y \Delta t + \frac{1}{2}\hat{A}_y \Delta t^2 \tag{2-b}$$

where Δt is the sampling period, and $(\hat{P}_x, \hat{P}_y)$, $(\hat{V}_x, \hat{V}_y)$, and $(\hat{A}_x, \hat{A}_y)$ represent the estimated position, velocity, and acceleration of the moving object, respectively.

An object motion on the xy-plane can be modeled as discrete time varying equations [16] by dividing into linear velocity component, v_k, and angular velocity component, ω_k. The next step position information can be predicted based on the current motion information, v_k and ω_k, as follows:

$$\Delta x_{k+\Delta t,k} = v_k \Delta t \cos(\theta + \frac{1}{2}\omega_k \Delta t) \approx v_k \Delta t \cos\theta_k - \frac{1}{2} v_k \omega_k \Delta t^2 \sin\theta_k \tag{3}$$

$$\Delta y_{k+\Delta t,k} = v_k \Delta t \sin(\theta + \frac{1}{2}\omega_k \Delta t) \approx v_k \Delta t \sin\theta_k - \frac{1}{2} v_k \omega_k \Delta t^2 \cos\theta_k \tag{4}$$

$$\Delta\theta_{k+\Delta t,k} = \omega_k \Delta t \tag{5}$$

where θ_k represents the direction of the moving object *w.r.t* the x-axis on the xy-plane. Also the noises and uncertainties in measuring the velocities, v_k and ω_k, are modeled as follows:

$$\Delta v_{k+\Delta t,k} = \xi_v \tag{6}$$

$$\Delta \omega_{k+\Delta t,k} = \xi_\omega \tag{7}$$

where ξ_v, ξ_ω are zero-mean Gaussian random variables.

To apply a model of the moving object to the Kalman, the previous motion and measurement characteristics need to be converted to a discrete state transition and the observation models that are the followings

$$\begin{aligned} \mathbf{x}_k &= \mathbf{A}_{k,k-1}\mathbf{x}_{k-1} + \boldsymbol{\xi}_{k-1} \\ \mathbf{y}_k &= \mathbf{C}_k x_k + \boldsymbol{\gamma}_k \end{aligned} \tag{8}$$

where $\mathbf{y}_k$ is a measurement vector, $\mathbf{A}_k$ is the state transition matrix, $\mathbf{C}_k$ is the observation matrix, $\boldsymbol{\xi}_k$ represents the irregular components in the state transition, $\boldsymbol{\gamma}_k$ represents measurement noises, and Δt represents the sampling period.

3.2 State estimate by the Kalman filter

The input data, image data, includes uncertainties and noises during the pre-processing. Therefore, the Kalman filter is suitable for the observer that estimates the states under the noisy environment since the state transition matrix itself has irregular components [4-5, 17-18].

In obtaining the filter gain, a covariance matrix for the estimation error is requested.

$$\mathbf{P}'_k = \mathbf{A}_{k,k-1}\mathbf{P}_{k-1}\mathbf{A}^T_{k,k-1} + \mathbf{Q}_{k-1} \tag{9}$$

where $\mathbf{Q}_{k-1}$ is measurement noise covariance matrix. Now the optimal filter gain, $\mathbf{K}_k$, to minimize the state estimation error can be obtained as

$$\mathbf{K}_k = \mathbf{P}'_k\mathbf{C}^T_k[\mathbf{C}_k\mathbf{P}'_k\mathbf{C}^T_k + \mathbf{R}_k]^{-1} \tag{10}$$

where $\mathbf{P}_k'$ is the covariance matrix for the estimation error, $\mathbf{C}_k$ is the observation matrix, and $\mathbf{R}_k$ represents the covariance matrix for the measurement noises. The states are estimated by the following state transition equation where an innovation term is added as an input and multiplied by the Kalman filter gain, $\mathbf{K}_k$, which is the difference between measurement vector, $\mathbf{y}_k$, and the estimated output using the data from the previous step.

$$\hat{x}_k = \mathbf{A}_{k,k-1}\hat{x}_{k-1} + \mathbf{K}_k[\mathbf{y}_k - \mathbf{C}_k\mathbf{A}_{k,k-1}\hat{x}_{k-1}] \tag{13}$$

Before going back to the Eq. (11) for the next step, the covariance matrix of the estimated error needs to be modified as [6-7],

$$\mathbf{P}_k = \mathbf{P}_k' - \mathbf{K}_k\mathbf{C}_k\mathbf{P}_k' \tag{14}$$

4. SELF-ORGANIED MAP

For a non-linear system, the Kalman filter requires a process to approximate to a quasi-linear model to derive the filtering equations, which leads to the high estimation errors. For the linear model derivation, Taylor series expansion is usually adopted to select the number for terms or to select the order of computational complexity that is inversely proportional to the modeling accuracy. Therefore, it suffers from the trade-off between accuracy and complexity in obtaining a linear model and in estimation the state variables. Especially the Kalman filtering is based on the first order approximation, it neither estimates the states properly all the times nor guarantees the convergence of the states. The adaptive or extended Kalman filter is proposed to overcome this difficulty, which again suffers from the computational complexity too high for real time control. To avoid all these difficult mathematics, there are several ideas for estimating the states using the neural networks [10-12]. In these approaches, they are using the supervised learning schemes that require the data on the pair of the input and output for learning. When the experimental environments are changing dynamically, the supervised learning scheme is not suitable any further since the input and output data sets cannot be utilized efficiently. Therefore, in this approach, SOM as a kind of unsupervised learning scheme is adopted to estimate the trajectory of a moving object.

SOM[19] which known also as Kohonen network has high spatial correlation in the two dimensional space where a moving object is randomly changing its trajectory, which provides the rational for the reason why the SOM is selected among the various unsupervised learning schemes. In the optimal solution search problems, to save the time the data sets or regions are divided into several categories before the search process. For the data division process, VQ(Vector Quantization), SOM, LVQ(Learning Vector Quantization) and other algorithms have been proposed. LVQ algorithm is only effective with the supervised learning, while VQ and SOM are useful for unsupervised learning. However, LVQ is limited to the case of 0 neighborhood. Therefore, SOM becomes the only candidate for our purpose to replace the Kalman filter at the high nonlinear region.

SOM is the most popular unsupervised learning algorithm among the numerous networks to classify and estimate the states and it has the winner-take-all strategy through the competitive learning. SOM has been utilized for image segmentation, object recognition, speech recognition, and vector quantization fields widely.

Each neuron in the SOM calculates and keeps the Euclidian distance that represents the closeness of the connection weight vector and the input vector. The connection weight between the winner neuron j and the neighboring neurons is adaptively changed by

$$w_{ij}(t+1) = w_{ij}(t) + \alpha(x_i(t) - w_{ij}(t))$$

where the parameter, α, is pre-determined for the SOM.
SOM is utilized to estimate the position and velocity of the moving object in this paper. During the learning process, SOM determines the optimal states based on the various measurable states. The best estimated set tends sto be selected as a winner neuron. Therefore the stochastic information in Eq. (8) for the Kalman filter is not necessary for the SOM, which enables to use the SOM instead of the Kalman filter for the high nonlinear region where noise distributions and uncertainties are poorly modeled statistically.

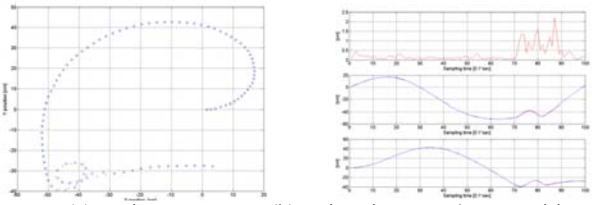
5. EXPERIMENT

A micro-mouse is designed for the moving object using the microprocessor, 80C196KC, which generates a non-programmed trace with the maximum speed of 15Cm/sec.

5.1 Trajectory estimation by Kalman filter

Object direction, velocity, and acceleration are obtained from the image data, and in the measuring process, the Gaussian noise of zero-mean and variance = 2, is added to the data. Even though there exists noises, the Kalman filter estimates the states relatively precisely.

To show the high nonlinear effect of the trajectory, a new experiment has been performed.



(a) Trajectory (b)Estimation error/ x, y position.

Fig. 2 Nonlinear trajectory estimation.

As it is shown in Fig. 2(a), when the trajectory of the moving object is highly nonlinear, the Kalman filter estimation has high positional errors and cannot follow the trajectory efficiently. As it shown in Fig. 2(b), the position estimation error is high at the region "A". Therefore, even the system stability cannot be guaranteed for the high nonlinear region.

5.2 Compensation by neural networks

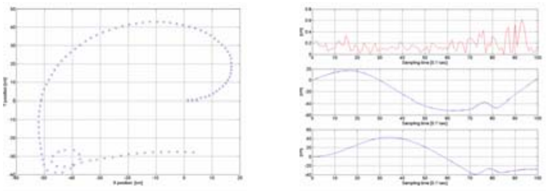
Some experiments are performed to check the superiority of the unsupervised learning to the supervised learning [11-12], and the results are summarized in the table 1.

Table 1 Performance comparison of two different neural networks.

Class \ Classification	Number of trial	Number of success
Supervised Learning	30	22
Unsupervised Learning	30	27

As it is shown in table 1, even though the supervised learning has also outstanding performance, the performance degradation becomes severe and becomes unreliable for the dynamically changing environment while the unsupervised learning is consistent. Based on this observation, the SOM is assumed to be the best alternative of the Kalman filter for the nonlinear region.

Another experiment is performed with the SOM instead of the Kalman filter at the nonlinear region to show the superiority of the unsupervised learning scheme, SOM. For the classification of the nonlinear region, the threshold value is empirically adjusted based on the positional estimation error of the Kalman filter.



(a) Trajectory (b)Estimation error/ position.

Fig. 3 Trajectory estimation by SOM.

Fig. 3 shows the experimental results of state estimation by the Kalman filter and the SOM. We need to focus on the nonlinear region where the SOM is applied for the estimation instead of the Kalman filter. By comparing with Fig. 2, it is recognized that the estimation error at the nonlinear region has been decreased by 60%.

5. CONCLUSION

This research proposes a trajectory estimation scheme for a moving object using the images captured by a CCD camera. In the approach, the state estimator has two algorithms: the Kalman filter estimates the states for the linear approximated region and the SOM for the nonlinear region. The decision for the switch over is made based on the size of the position estimation error that becomes low enough for the linear region and high enough for the nonlinear region. The effectiveness and superiority of the proposed algorithm is verified thorough the experimental data and comparison. The adaptability of the algorithm is also observed during the experiments. For the sake of simplicity, his research is limited to the environment of a fixed camera view. However this can be properly expanded to the moving camera environment where the input data may suffer from high noises and uncertainties. As future research works, selection of a precise learning pattern for the SOM to improve the estimation accuracy and recognition ratio and development of a illumination robust image processing algorithm are left.

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