Moving Object Trajectory based on Kohenen Network for Efficient Navigation of Mobile Robot

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Abstract**—**In this paper, we propose a novel approach to estimating the real-time moving trajectory of an object is proposed in this paper. The object's 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 Extended Kalman Filter(EKF) and neural networks are utilized cooperatively. Since the EKF needs to approximate a nonlinear system into a linear model in order to estimate the states, there still exist errors as well as uncertainties. To resolve this problem, in this approach the Kohonen networks, which have a high adaptability to the memory of the input-output relationship, are utilized for the nonlinear region. In addition to this, the Kohonen network, as a sort of neural network, can effectively adapt to the dynamic variations and become robust against noises. This approach is derived from the observation that the Kohonen network is a type of self-organized map and is spatially oriented, which makes it suitable for determining the trajectories of moving objects. The superiority of the proposed algorithm compared with the EKF is demonstrated through real experiments.

Index Terms**—**Object Tracking, Detection, CCD camera, Image processing, Kohenen Network.

I. INTRODUCTION

DETECTION of moving objects has been utilized in industrial robotic systems, for example, in the recognition and monitoring of unmanned systems that also require compression of moving images [1-2]. Trajectory prediction of moving objects is required for a mobile manipulator that aims at the control and observation of motion information such as object position, velocity, and acceleration. Prediction and estimation algorithms have generally been required for industrial robots. For a simple example, in a pick-and-place operation with a manipulator, the precise motion estimation of the object on the conveyor belt is a critical factor in stable grasping. A well-structured environment, such as the moving-jig that carries the object on the conveyor belt and stops when the manipulator grasps the object, might obviate the motion estimation requirement. However, a well-structured environment limits the flexibility of the production system, requires skillful designers for the jig, and incurs a high maintenance expense; eventually it will disappear from automated production lines. 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 most accurate position, velocity, and acceleration at any instance to capture the moving object safely without collision and to pick up the object stably without slippage. When the motion trajectory is not highly random and continuous, it can be modeled analytically to predict the near-future values based on previously measured data [2].

In this paper, a novel approach for the real-time trajectory estimation of a moving object is proposed. For image-data capturing, a CCD camera was utilized. Through a geometrical analysis of the camera and the object, the position of the object could be estimated [3]. There are several approaches in which the state estimator is used to predict the linear and angular velocities of a moving object. The most general approach known so far is the Kalman filter, the performance of which is well verified by numerous studies [4-8]. However, the Kalman filter is not properly applicable to the unstructured environment, even though the adaptive or extended Kalman filter has been proposed to improve prediction accuracy [9]. To make the system robust against noises in the input data and uncertainties, in this approach, artificial neural networks are incorporated into the Kalman filter. Since the artificial neural networks are trained by only the relationship between the input and output, this approach is expected to have higher flexibility than the adaptive or extended Kalman filter. Among the several advantages of the neural networks, the

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adaptability to variations is well matched to this problem. That is, it has robust characteristics against measurement noises. Fig. 1 summarizes the trajectory estimation system for this research. The input for the dynamic model comes from either the Kalman filter or SOM according to the following decision equation:

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

where k=1 for $error \le threshold$ and k=0 for $error > threshold$.

The threshold value is empirically determined based on the size of the estimated position error.

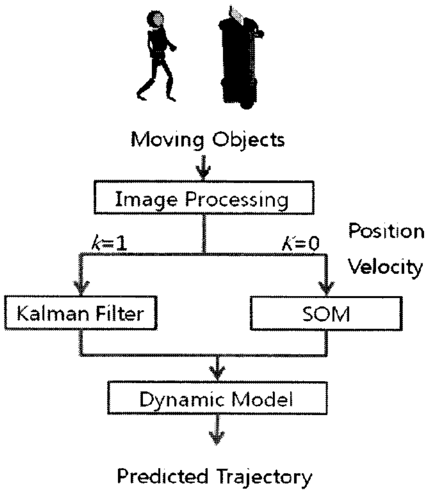


Fig. 1. Trajectory estimation system

II. PARAMETER LEARNING

A. System Architecture

Fig. 1 shows a scene of objects through the corridor outside the building. There are incoming and outgoing individuals in the scene. Multiple cameras unit is hung from the ceiling of the laboratory so that the moving objects can be observed and tracked in a tracking area in front of the door. The images captured by the cameras are processed and the number of the moving object is calculated.

To cope with inherently dynamic phenomena (objects enter the scene, move across the field of view of the camera, and finally cross the counting line), the object recognizing and tracking problem has been decomposed into the following three steps: [3][6]

- Determine whether any potentially interesting objects have entered into the scene (Alerting phase);
- Track their motion until the counting line is reached (Tracking phase);
- Establish how many objects correspond to tracked objects (Interpretation phase).

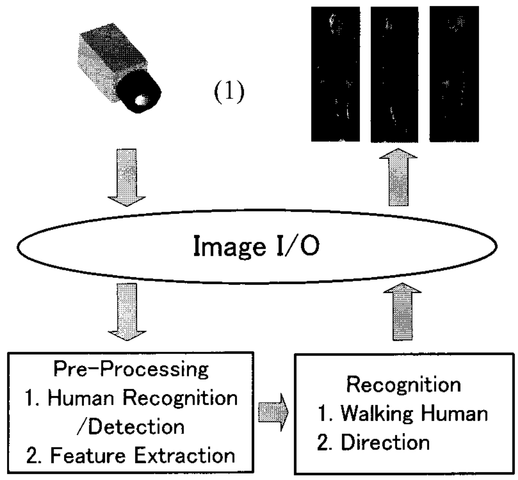


Fig. 2. Object Finding Process.

B. Pre-Processing

Classifying the moving-object pattern in the dynamically changing unstructured environment has not yet been tackled successfully [13]. Therefore, in this research, the camera was fixed on a stable platform in order to capture static environment images. To estimate the states of the motion characteristics, the trajectory of the moving object was pre-recorded and analyzed. Figures 3(a) and (b) represent the object images at (t-1) instance and (t) instance, respectively.

(a) (b)

Fig. 3. Image at the each instance: (a) Image at (t-1) instance, (b) Image at (t) instance

As recognized in the images, most parts of the CCD image correspond to the background. After eliminating the background, the difference between the two consecutive image 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 assigned values can be used. The difference method is popular in image pre-processing for extracting desired information from the whole image frame [14], which can be expressed as

$$\mathrm{Output}(x, y) = \mathrm{Image1}(x, y) - \mathrm{Image2}(x, y) \quad (2)$$

The difference image between Figs. 2(a) and (b) is represented in Fig. 4. When the difference image for the whole time interval can be obtained, the trajectory of the moving object can be calculated precisely.

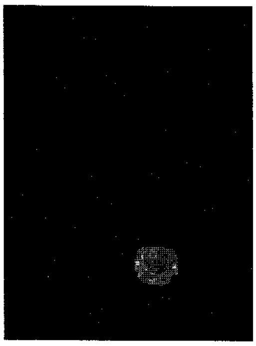


Fig. 4. Difference image between (t) and (t-1) instance images

III. STATE ESTIMATION BY KALMAN FILTER

The input-image data include uncertainties and noises that occur during pre-processing. Therefore, the Kalman filter is suitable for the observer that estimates the states under a noisy environment, since the state transition matrix itself has irregular components [4-5]. Note that the Kalman filter is a recursive process to minimize the estimation error by multiplying a suitable filter gain by the error between estimated and measured values. In the problem of state estimation of a moving object, the measurement vector for the Kalman filter is derived from the position of the moving object on the xy-plane, which position is obtained from the image frames. Using the measurement vector, the state variables -- (x, y) position, direction, and linear/angular velocities -- are estimated.

In obtaining the filter gain, a zero-mean variance matrix for the estimation error is included, which can be estimated by the terms of the zero-mean variance matrix, state transition matrix, and zero-mean measurement noise matrix, $\mathbf{Q}_{k-1}$, of the previous instance, as

$$\mathbf{P}'_k = \mathbf{A}_{k,k-1}\mathbf{P}_{k-1}\mathbf{A}^T_{k,k-1} + \mathbf{Q}_{k-1} \quad (3)$$

Now the optimal filter gain, $\mathbf{K}_k$, to minimize the state estimation error can be obtained as

$$\mathbf{K}_k = \mathbf{P}'_k\mathbf{C}^T_k[\mathbf{C}_k\mathbf{P}'_k\mathbf{C}^T_k + \mathbf{R}_k]^{-1} \quad (4)$$

(2)

where $\mathbf{P}'_k$ is the zero-mean variance matrix for the estimation error, $\mathbf{C}_k$ is the observation matrix, and $\mathbf{R}_k$ represents the zero-mean variance matrix for the measurement noises.

The states are estimated by the following state transition equation, in which an innovation term is added as an input and multiplied by the Kalman filter gain, K_k, which is the difference between the measurement vector, $\mathbf{y}_k$, and the estimated output using the data from the previous step:

$$\hat{x}_k = \mathbf{A}_{k,k-1}\hat{x}_{k-1} + \mathbf{K}_k[\mathbf{y}_k - \mathbf{C}_k\mathbf{A}_{k,k-1}\hat{x}_{k-1}] \quad (5)$$

where $\mathbf{C}_k\mathbf{A}_{k,k-1}\hat{x}_{k-1}$ represents the estimated output, $\hat{y}_k$.

Before going back to Eq. (12) for the next step, the zero-mean variance matrix of the estimated error needs to be modified as [6-7].

$$\mathbf{P}_k = \mathbf{P}'_k - \mathbf{K}_k\mathbf{C}_k\mathbf{P}'_k \quad (6)$$

IV. SELF-ORANIZED MAP

For a nonlinear system, the Kalman filter requires a process to approximate to a quasi-linear model to derive the filtering equations, which approximation leads to many estimation errors. For the linear model derivation, the Taylor series expansion is usually adopted to select the number of 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 estimating the state variable, x_k. Especially since Kalman filtering is based on the first-order approximation, it neither estimates the states properly all of the time nor guarantees the convergence of the states. The adaptive or extended Kalman filter proposed in order to overcome this difficulty, but again, the adaptive Kalman filter suffers from a too-high computational complexity for real-time control. To avoid all of these difficult calculations, there are several ideas for estimating the states using artificial neural networks [10-12]. In these approaches, the supervised learning schemes that require data on the input and output pair are used. When the experimental environments are dynamically changing, the supervised learning scheme is no longer suitable, since the input and output data sets cannot be utilized efficiently. Therefore, in this approach, SOM as a type of unsupervised learning scheme is adopted to estimate the trajectory of a moving object.

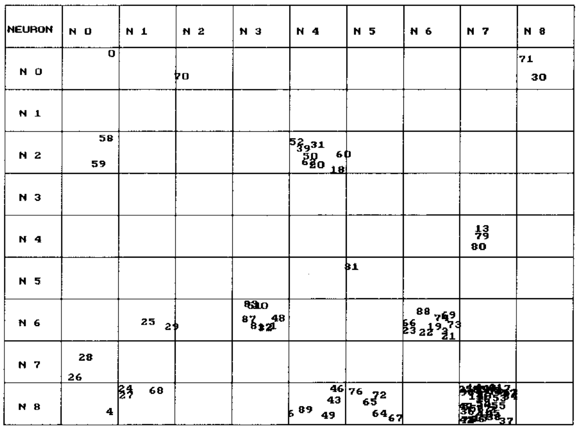
Each neuron in SOM calculates and maintains the Euclidian distance that represents the closeness of the connection intensity vector and the input vector. Each neuron, which belongs to a group that is formed by the winner through competition, can have only the output. This winner neuron and neighboring neurons are allowed to learn from a specific input vector. The connection intensity between the winner neuron j and the neighboring neurons is adaptively changed by

$$w_{ij}(t+1) = w_{ij}(t) + \alpha(x_i(t) - w_{ij}(t)) \qquad (7)$$

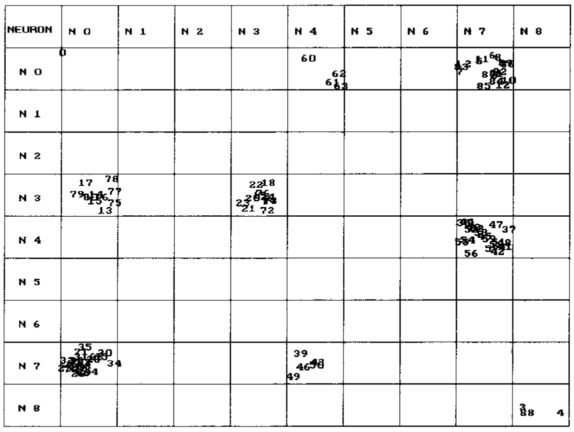
where the parameter, α, is pre-determined for SOM.

Before the main experiments, the Kohonen networks were trained for the moving object, an autonomous micro-mouse designed for this research. The pattern classifications of learning results for the velocity and orientation, respectively, are illustrated in Fig. 5.

The velocity and orientation of the moving object can be grouped into several regions, and inside each region, a specific neuron can be selected by real-time learning. The hybrid neural networks formed by the velocity and orientation networks are implemented to achieve more efficient learning and to clearly show that the motion characteristics of the moving object can be classified into several patterns. Since Kohonen networks have learning abilities as neural networks, the un-experienced input coming from the estimation process can be classified into one of the groups, and inside the group region it can be learned for a specific state value. For supervised learning, the input patterns are artificially provided, by humans *a priori*, and the neural networks learn only the direction to the object patterns from the given input patterns. However, unsupervised learning such as SOM can determine the intrinsic features from the arbitrary input patterns, and can compete with different neurons for the different features. SOM can be efficiently utilized for the trajectory estimation of a moving object when the nonlinearity of the moving object is too high to be estimated by the Kalman filter. Limiting the application of SOM to the nonlinear region is proposed in order to save learning patterns. Many precise learning patterns are required for learning both the linear and nonlinear regions. An insufficient number of learning patterns might lead to erroneous learning results [13]. Since SOM utilizes the dynamic model for trajectory estimation described in Eq. (7), the stochastic characteristics are not essential for SOM, but are definitely required for the Kalman filter.



(a) Learning results for velocity



(b) Learning results for orientation

Fig. 5. Pattern classifications for velocity and orientation

V. EXPERIMENTS

In the present study, a micro-mouse was designed for a moving object using the microprocessor, ATmega128, which generates a non-programmed trace with the maximum speed of 15 Cm/sec. To show the effectiveness of the SOM, three experiments were performed to show the following: 1. A relatively linear motion can be estimated properly by the Kalman filter, 2. The extended Kalman filter is somewhat effective for reducing the estimation error in the nonlinear region, and 3. The SOM improves the estimation performance significantly compared with the extended Kalman filter.

A. Comparison between the EKF and SOM

Before comparing the extended Kalman filter with SOM, some experiments were performed to confirm the superiority of the unsupervised learning method over the supervised learning method [11-12], and the results are summarized in Table 1.

As shown in Table 1, even though supervised learning also has outstanding performance, the performance degradation becomes severe and becomes unsuitable for the dynamically changing environment, whereas unsupervised learning remains consistent. Based on this observation, SOM is selected as the best alternative to the extended Kalman filter for the nonlinear region. To reduce the estimation error, the extended Kalman filter and SOM [10-11] was applied for the nonlinear region, and the results are shown in Fig. 5. The estimation error for the nonlinear region is reduced by 48 % by the extended Kalman filter. However, the maximum error is still larger than 1 Cm. Another experiment was performed with SOM instead of the extended Kalman filter in the nonlinear region to show the superiority of the unsupervised learning scheme, SOM. Figure 6 shows the experimental results of state estimation by the Kalman filter for the linear region and by SOM for the nonlinear region (from S to T). We need to focus on the nonlinear region where SOM is applied for the estimation instead of the extended Kalman filter. By comparison of Figs. 6(a) and 6(b), it is recognized that SOM is much better than the extended Kalman filter for estimating the nonlinear region. The maximum estimation error by the SOM is 1.2 Cm, which is about 67% of that by the extended Kalman filter.

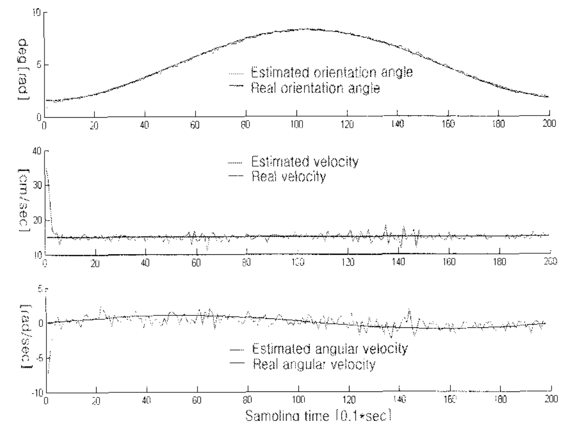
Table 1. Performance comparison of two different neural networks

Classification / Class	Number of trials	Number of success*
Supervised Learning	100	75
Unsupervised Learning	100	88

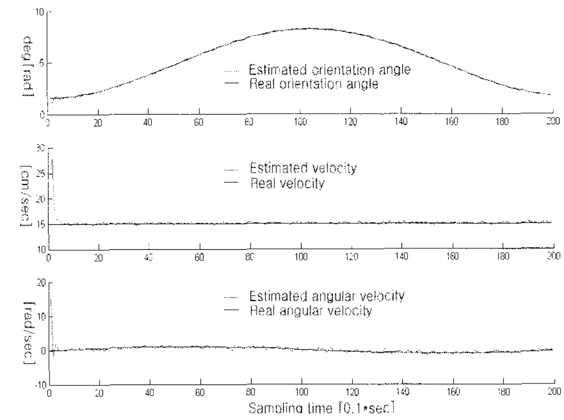
* A success is tallied when the estimation error is less than 3 Cm.

B. Tracking Experiment

To compare the tracking performance of a mobile robot using the algorithms of the extended Kalman filter, and SOM, experiments of capturing a micro mouse with random motion by the mobile robot were performed. As can be recognized from Fig. 6, SOM provided better performance to the mobile robot in capturing the random motion object than the other algorithms. Figure 6 shows the orientation, the linear and angular velocities of the mobile robot with each of the algorithms, which comparison concludes that SOM provides a smooth and stable trajectory to the mobile robot to capture a random motion object.



(a) Extended Kalman Filter



(b) SOM

Fig. 6. A comparison between orientation, linear velocity and angular velocity of estimated moving object.

V. CONCLUSION

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

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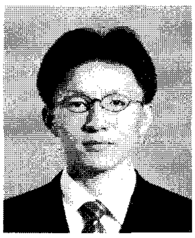

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