A Simple Local Navigation System Inspired by Hippocampal Function and Its Autonomous Mobile Robot Implementation

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Abstract:

We propose a practical simple local navigation system inspired by the sequence learning mechanism of the entorhino-hippocampal system. The proposed system memorizes a route as sequences of landmarks in the same way humans do. The proposed local navigation system includes a local route memory unit, landmark extraction unit, and learning-type matching unit. In the local route memory unit, the concept of the sequence learning mechanism of the entorhino-hippocampal system is implemented using a fully connected network, while a sequence of landmarks is embedded in the connection matrix as the local route memory. This system has two operation modes: learning and recall modes. In learning mode, a sequence of landmarks, i.e. a local route, is represented by enhanced loop connections in the connection matrix. In recall mode, the system traces the stored route comparing current landmarks with the stored landmarks using the landmark extraction and learning-type matching units. The system uses a prospective sequence to match the current landmark sequence with the recalled one. Using a prospective sequence in the route comparison allows confirmation of the correct route and deals with any slight change in the current sequence of landmarks. A certainty index is also introduced for judging the validity of the route selection. We describe a basic update mechanism for the stored landmark sequence in the case of a small change in the local route memory. The validity of the proposed system is confirmed using an autonomous mobile robot with the proposed navigation system.

Keywords: *human-like local navigation, sequence learning, entorhino-hippocampal system, autonomous mobile robot.*

1. Introduction

Recently, due to the rapid growth in digital technology, there has been accelerated development of highly intelligent machines. Intelligent machines have made our daily lives far more convenient. Huge quantities of data are easily handled electronically at high speed and many electrical devices have been provided with powerful functionality. In particular, the latest vehicles come equipped with very sophisticated information devices [1]. One of the most remarkable technologies is the navigation system, which guides us to our destinations in unfamiliar territory. The guidance is supported by a GPS system and an accurate digital map. In other words, the system is highly dependent on data and therefore, has a weakness with respect to recent changes and mistakes in the data. Humans on the other hand, can handle such changes flexibly. Introducing such human-like information processing would be vital in compensating for the weakness in digital equipment. Our aim is to develop an effective human-like system, which compensates for this weakness and is able to suggest a plausible route even when conventional navigation systems fail due to insufficient information.

Recently, many researchers have focused on the function of spatio-temporal representation in the hippocampus [2], [3]. Yoshida and Hayashi proposed a computational model of the sequence learning in the hippocampus; that is, neurons that learn a sequence of signals can be characterized, in the hippocampal CA1, by using propagation of neuronal activity in the hippocampal CA3 [5]. A network model of the entorhinal cortex layer II (ECII) with entorhino-hippocampal loop circuitry was proposed by Igarashi *et al.* [6]. Loop connections between stellate cells in the ECII are selectively potentiated by afferent signals to the ECII, and consequently stellate cells connected by potentiated loop connections fire successively in each theta cycle. The mechanism has also been investigated from a neurobiology viewpoint [7]. We focus on the attractive abilities of sequential learning and apply them to a local navigation system.

Several navigation mechanisms, inspired by crucial brain functions especially in the hippocampus and its surroundings, have been proposed [4], [8], [9]. Most of these mechanisms, however, tend to become very intricate as a result of faithfully mimicking the brain mechanism. On the other hand, simplicity of the model is an important factor for practical embedded systems. We aim to develop a simple local navigation system introducing the essence of the remarkable brain functions. We have proposed a practical simple local navigation system inspired by the sequence learning mechanism of the ECII with entorhino-hippocampal loop circuitry [10]. In the system, a route is represented as a sequence of landmarks as is the case in humans. The proposed local navigation system consists of a simple local route memory unit, a landmark extraction unit, and a learning-type matching unit. In the local route memory unit, the sequence learning mechanism of the entorhino-hippocampal system is implemented using a fully connected network, while a sequence of landmarks is embedded in the connection matrix as the local route memory. This system has two operation modes: learning and recall modes. In the learning mode, a sequence of landmarks is represented by enhanced loop connections in the connection matrix. In the system, a certainty index is introduced to evaluate the validity of the route selection. We have realized a flexible local navigation system in a simple architecture using the prospective landmark sequence and certainty index. In this paper, we describe the mechanisms for storing and recall the landmark sequence and present a basic update mechanism for the stored landmark sequence. We confirm the validity of the proposed system and investigate its adaptability to changes in circumstance through experiments using an autonomous mobile robot with the proposed mechanism.

2. Sequence learning mechanism of the entorhinal-hippocampal system

Igarashi *et al.* proposed a computational model of the ECII network with entorhino-hippocampal loop connections [6]. In their model, a pair of afferent pulse trains to the ECII, with clearly different frequencies, is selected by virtue of loop connections that are selectively potentiated by the pairs of afferent signals. The frequency depends on the strength of sensory input. The signal transmission delay through the loop connections produces the order of places. Here a "place" means a place in the real world corresponding to a landmark. We assume that the observer moves at a constant speed.

Here, let us assume that a route is coordinated by a sequence of places, A, B, C, D, and E. The signal for each place is represented by a frequency depending on the distance between the observer and the place, where a high frequency corresponds to a shorter distance. A higher frequency signal makes a so-called "place cell" fire in a shorter period of time. When a signal observed at place A is fed into the ECII, the signal of the place cell A is transmitted from the ECII to the ECV through the DG-CA3-CA1 in the entorhino-hippocampal loop circuit as shown in Fig. 1. If signal B observed at place B fires another place cell B in the ECII at the time the transmitted signal A arrives at the ECV cell A, the connection between the ECV cell A and ECII cell B is enhanced by learning mechanisms in the brain. This means that a relationship between place A and place B is established. The relationships for the following signals are established in the same manner. As a result, the order of places is embedded in the loop connection weights from the ECV to ECII neurons.

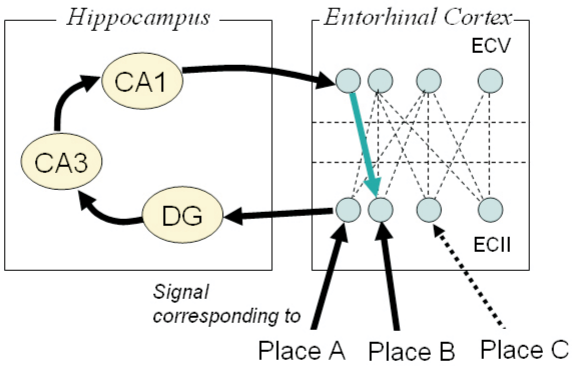


Fig. 1. Entorhino-hippocampal loop circuit. Here "place" means a place in the real world, and ◯ represents "a place cell" which is a neuron in EC corresponding to a place in the real world.

In this paper, we develop a practical simple local navigation system inspired by the sequence learning mechanism in the hippocampus and the entorhinal cortex. The system uses signals obtained from images of landmarks specifying places and the route is stored as a chain connection of landmarks.

3. Simple local navigation system inspired by the sequence learning mechanism in the entorhino-hippocampal loop circuit

We propose a dedicated navigation system inspired by the structure of the entorhino-hippocampal loop circuitry. In the proposed system, the sequence learning mechanism is implemented using a fully connected network (as shown in Fig. 2), while the order of landmarks is embedded in the matrix of loop connections as a local route memory unit. Here each landmark corresponds to a place in the real world. The entorhino-hippocampal loop circuitry illustrated in Fig. 1 is represented by neurons corresponding to place cells in the ECII and connecting loops with connection weights. A connection weight represents an established connection between the corresponding place cells in the ECV and ECII. The navigation system also includes a landmark extraction unit and a learning-type matching unit as shown in Fig. 3. The landmark extraction unit extracts landmarks from an image obtained with a camera, and the learning-type matching unit evaluates the degree of matching with the current tracing route.

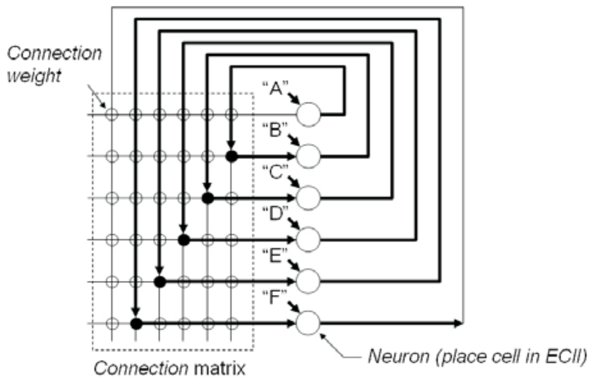


Fig. 2. Local route memory unit: the route is coordinated by a sequence of observed landmarks. Landmark sequence: A→B→C→D→E→F→. Each landmark corresponds to a place in the real world. The loop circuit illustrated in Fig. 1 is represented by neurons corresponding to place cells in ECII and a loop connected with a connection weight. The connection weight represents an established connection between place cells in ECV and ECII.

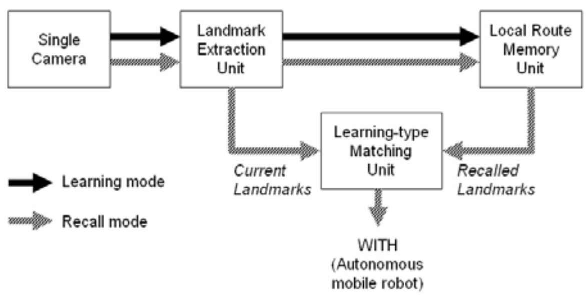
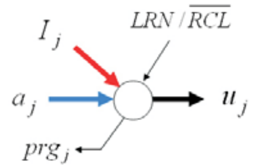


Fig. 3. Proposed navigation system includes a landmark extraction unit, a learning-type matching unit, and a local route memory unit.

The system has two operation modes, learning mode and recall mode. In learning mode, the order of the obtained landmarks is stored in the local route memory unit. In recall mode, the local route memory unit recalls the prospective landmark sequence and the learning-type matching unit evaluates the selected current route by comparing the observed landmark sequence with the recalled prospective landmark sequence. Here, we assume the following procedure. 1) First, in learning mode, the system memorizes a route by moving along the route or storing the data of the route. 2) Thereafter, in recall mode, the system traces the route automatically according to the stored one.

Fig. 4 shows the basic elements of the local route memory unit. Fig. 4a) depicts a neuron unit corresponding to a place cell in the ECII. Here I_j, a_j, u_j and prg_j are the landmark input, activation input, output of the neuron, and a program signal, respectively. A $LRN / \overline{RCL}$ is a mode select signal equal to "1" in learning mode and "0" in recall mode. Once the neuron has been activated, output u_j retains the activated state until another neuron is activated. Fig. 4b) depicts the connection weight unit, where w_{ij} is a connection weight. The connection weight unit stores the ordering relationship between the *i-th* and *j-th* neurons. When I_j is fed into the *j-th* neuron, u_j is activated in learning mode, prg_j becomes "1" and the connection weight w_{ij} is set to "1".

(a) j-th neuron unit



(b) Connection weight unit

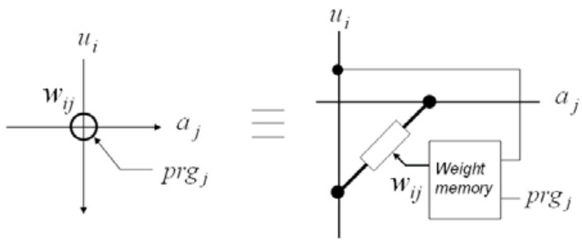


Fig. 4. (a) Neuron unit and (b) connection weight unit. The neuron corresponds to a place cell in ECII. Here I_j, a_j, u_j and prg_j are the landmark input, activation input, output of the neuron, and a program signal, respectively. A $LRN / \overline{RCL}$ is a mode select signal equal to "1" in learning mode and "0" in recall mode. Once the neuron has been activated, u_j retains an activated state until another neuron is activated. The connection weight unit memorizes the ordering relationship between the i-th and j-th neurons. When I_j is fed into the j-th neuron, u_j is activated in learning mode, prg_j changes to "1" and the connection weight w_{ij} is set to "1".

In the neurobiological computational model, the loop delay corresponds to the sampling period of capturing the landmark. Conversely, in the proposed system, the landmark is captured every time it is observed and the activation state of the neuron is kept with a latching mechanism until the next landmark appears.

3.1. Learning mode

In learning mode (Fig. 5), the system coordinates the route as a sequence of observed landmarks. A signal corresponding to the landmark is fed into the local route memory unit and a connection is made between the current landmark and the one immediately before. Here, let us assume that a signal of the *j-th* landmark I_j is observed after a signal of the *i-th* landmark I_i. The relationship between the landmarks is represented by enhanced loop connections in the connection matrix as follows:

1) u_i is activated by signal I_i and the activation state is retained until the next neuron is activated.
2) Then, the landmark signal I_j is fed into the *j-th* neuron, and a program signal prg_j is set to "1".
3) The connection weight w_{ij} is assigned by the following equation.

$$w_{ij} = \begin{cases} 1 & if \quad u_i = 1 \quad and \quad prg_j = 1 \\ 0 & others \end{cases} \tag{1}$$

4) Moreover, an activation signal a_j is assigned by the following equation.

$$a_j = \begin{cases} 1 & if \quad u_i = 1 \quad and \quad w_{ij} = 1 \\ 0 & others \end{cases} \tag{2}$$

5) a_j activates u_j in preparation of the next landmark signal.

By repeating the above steps, the local route is stored in the local route memory unit.

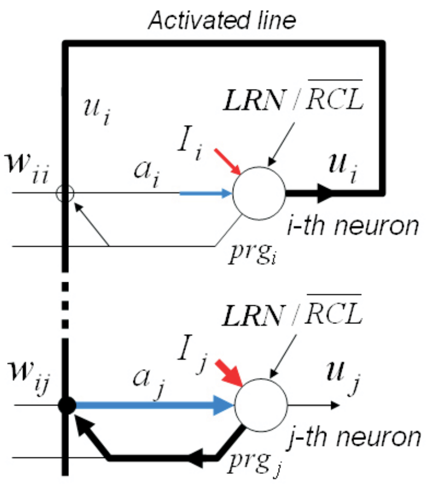


Fig. 5. Assignment of the connection weight in learning mode.

3.2. Recall mode

In recall mode (Fig. 6), $LRN / \overline{RCL}$ = "0", the system traces the stored route in the local route memory unit as follows:

1) When the landmark signal I_i is observed and fed into the *i-th* neuron, I_i activates u_i.
2) If the connection weight w_{ij} on the activated line u_i is "1", then a_i is set to "1".
3) The neuron output signal u_j is activated by a_j.
4) One recall leads to another, until the *(i+k)-th* landmark signal I_{i+k} is recalled in the same manner. Here, the observed and prospective sequences consist of K landmarks.

5) The recalled sequence consists of K landmarks is fed into the matching unit and compared with the current sequence of observed landmarks.

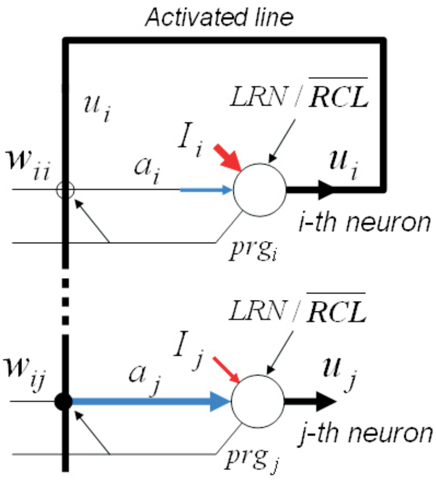


Fig. 6. Landmark sequence activation in recall mode.

3.3. Certainty index CI for judging the validity of the selected current route

In recall mode, the matching unit matches the current sequence of landmarks and the corresponding recalled sequence (where both sequences consist of K landmarks). The certainty index CI is introduced to verify the correctness of the current selected route.

The certainty index CI represents the validity of the route currently selected and is defined as

$$CI_i = \frac{1}{K}\sum_{k=1}^{K} m_{i+k} \; , \tag{3}$$

$$m_{i+k} = \begin{cases} 1 & for \;\; I^R_{i+k} = I^O_{i+k} \\ 0 & others \end{cases} , \tag{4}$$

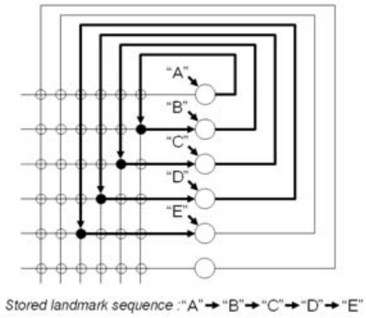
where K is the length of the recalled sequence used for route matching, and I^R_{i+k} and I^O_{i+k} represent the $(i+k)$-*th* recalled landmark and currently observed landmark, respectively.

A slight change in the circumstances can be represented by a change in the CI. For example, a crossing can be detected by a change in the certainty index CI_i. As the observer reaches the crossing, the certainty index CI_i decreases to $1/K$. It is because that the number of the matched landmarks decreases as closing to a crossing.

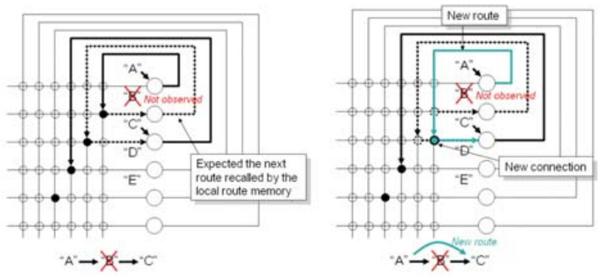
3.4. Update mechanism of the stored route in the local route memory

In the proposed method, the order of landmarks is embedded in a matrix of loop connections as the local route memory. The stored route in the local route memory unit can easily be updated by rearranging the loop connections. In this section, we describe the procedure for updating the connections in two different cases: a missing or added landmark observed in the selected route. When the mismatched landmark is detected, the system investigates the subsequent sequence after a change point. If the subsequent landmarks match the stored landmarks, the system accepts that the selected route is correct and that an environmental change has occurred in the stored landmark sequence. If an update of memory is required, the connections are updated as described below.

(a) Stored route



(b) Adaptability to a missing landmark in the real world: the case in which landmark "B" disappears in the real world.



(c) Adaptability to an additional landmark in the real world: the case in which landmark "b" appears between landmarks "A" and "B".

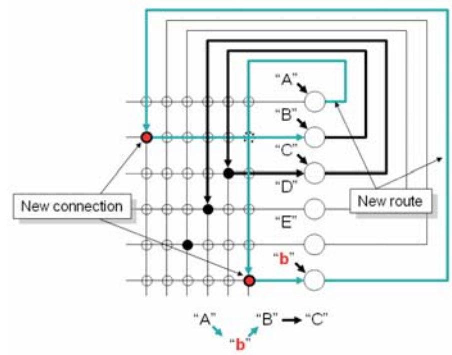


Fig. 7. Proposed system can adapt to stored route changes caused by a slight change in landmarks. The stored route in the local route memory can be updated by rearranging the loop connections.

Let us assume that the route depicted in Fig. 7a) is stored in learning mode. Fig. 7b) illustrates the case where landmark "B" disappears in the real world. In this case, first, the landmark of place A is observed. The system recalls the prospective landmark sequence and expects the landmark of place B as shown on the left in Fig. 7b). If "C" is observed instead of "B", the system confirms that landmark "B" is missing and generates a new connection-node between "A" and "C" as shown on the right in Fig. 7b). As a result, the stored route is updated. On the other hand, Fig. 7c) illustrates the case where landmark "b" appears between landmarks "A" and "B". In this case, a new route is created by generating two new connections instead of the old one as shown in Fig. 7c).

4. Experimental results

To confirm the validity of the proposed local navigation system for practical engineering applications, we made use of an autonomous mobile robot "WITH" [11], which is a basic omni-directional mobile robot platform developed as a result of the Kyutech 21st COE program. We confirm that the proposed system can extract landmarks and store a route in the form of a sequence of landmarks and that the robot with the proposed mechanism can trace the route corresponding to the stored landmark sequence in the local route memory unit. Moreover, we show that the robot behaves like a human when circumstances change slightly.

Fig. 8 shows the autonomous mobile robot consisting of the robot base WITH, a USB camera, and palmtop computer VAIO type-U in which the proposed navigation system is embedded. The setting signal of the operation modes and the cruise control signal in learning mode are given wirelessly by an external computer.

The experiments were designed to investigate the following behavior: 1) route tracing according to the stored route memorized in learning mode; and 2) selecting a plausible route when a slightly altered sequence of landmarks is encountered as a result of either a missing landmark or the addition of an unknown landmark in the stored route sequence.

Fig. 8. Autonomous mobile robot consisting of the mobile robot base WITH, a USB camera, and a palmtop computer VAIO type-U in which the proposed navigation system is embedded.

4.1. Route tracing according to the route stored in the local route memory unit

Landmarks are set along the path on an experimental field as shown in Fig. 9. A path, of width 24 cm, is drawn using two black lines. Each landmark is about 10 cm x 10 cm and labeled with one of the colors, red (R), blue (B), light-green (G), yellow (Y), or orange (O). Fig. 10 shows the arrangement of the landmarks and the route stored in learning mode in this experiment. In general, a change in lighting has an effect on the appearance of landmarks obtained with a camera. Different color images can therefore be obtained for the same landmark. Here, we avoid the problem by using a standard three-layer-perceptron trained in advance with all the landmarks used in the experiments. In this experiment, the MLP is trained using the hue data of an HSV image set for each landmark. The trained MLP works as a classifier of the landmark obtained with a camera.

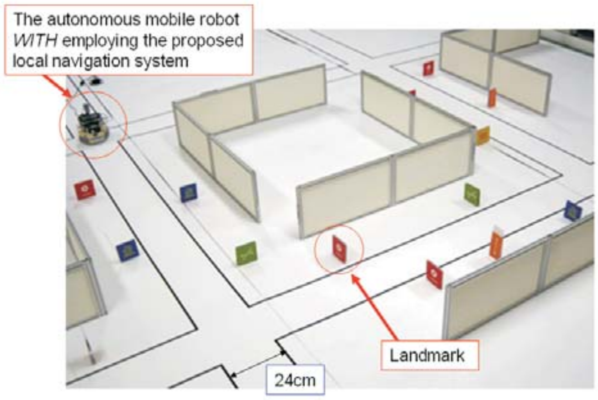


Fig. 9. Experimental field: field size is 5.5m x 5.5m, path is drawn using two black lines, and width of the path is 24cm. Each landmark is about 10cm x 10cm and labeled with a color: red, blue, light green, yellow, or orange.

Fig. 10. Arrangement of landmarks and the stored route in the experiments.

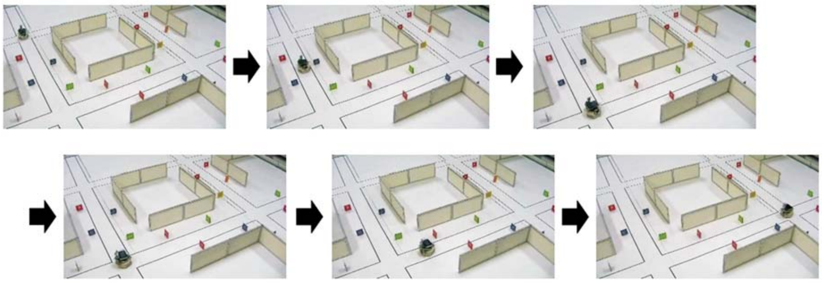
First, in learning mode, an operator controls the robot navigating through the planned route. The system obtains landmarks beside the path along the route traversed and stores the route as a sequence of these landmarks. Once this has been completed, we make the robot trace the stored route autonomously.

Fig. 11a) shows the camera view in which landmarks obtained by the landmark-extracting unit are displayed. The robot traces the correct route as shown in Fig. 11b). Fig 11c) shows the prospective sequence recalled by the local route memory unit and a change in the certainty index as defined in Eq. (3). As shown in Fig.11c), by monitoring the change in the CI, it is known when the robot reaches a crossing. The CI returns to "1" after the robot turns at the crossing. This means that the correct route has been selected.

4.2. Route tracing with a slight route change

Two situations are assumed: a missing landmark and the addition of an unknown one in the current route. The *(a) Camera view: landmarks are extracted from an image obtained with a single camera*

(b) Autonomous mobile robot traces the stored route automatically



(c) Prospective sequence recalled by the local route memory unit and a change in the certainty index

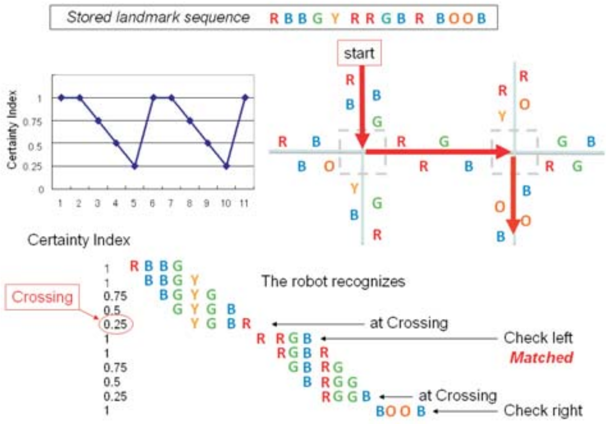
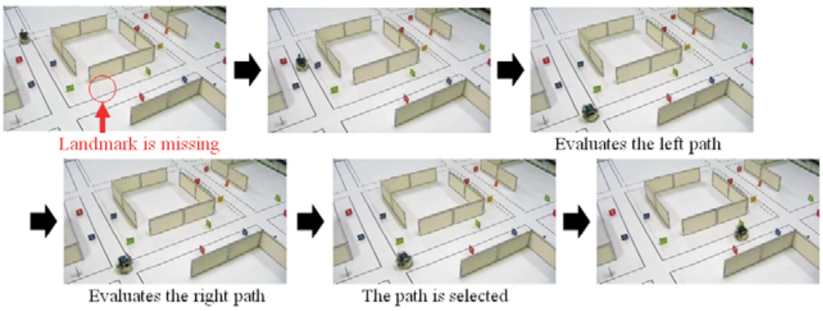


Fig. 11. Result of route tracing according to the route memorized in learning mode.

(a) Missing landmark in the current route



(b) Change in the certainty index CI

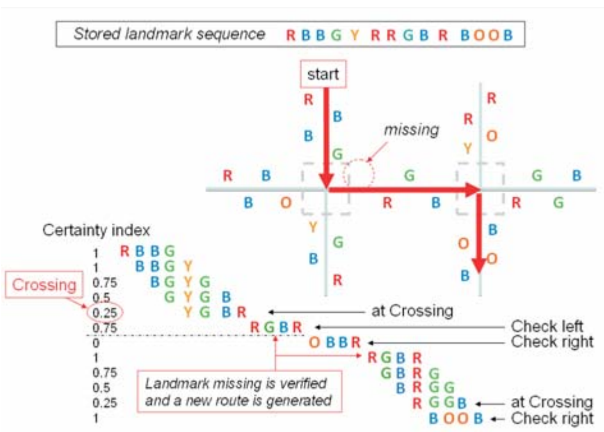
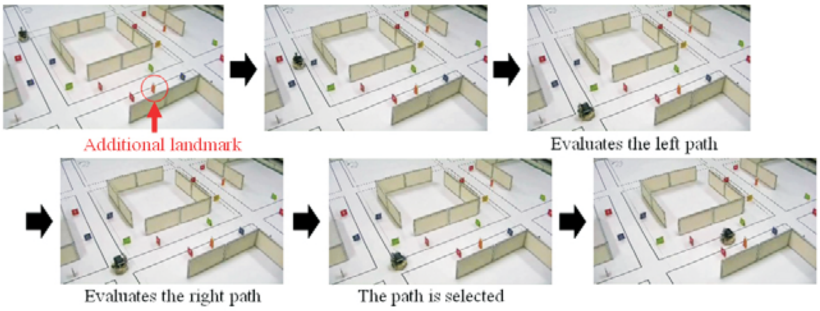


Fig. 12. Behavior of route tracing in the case of a slight change in the route stored in the local route memory. (a) At a crossing, the system evaluates all possible routes and chooses the route with the highest matching degree as the correct direction. (b) The robot recognizes a missing landmark from a change in the CI and by comparing the current route with a shifted memory route.

(a) Additional landmark



(b) Change in the certainty index CI

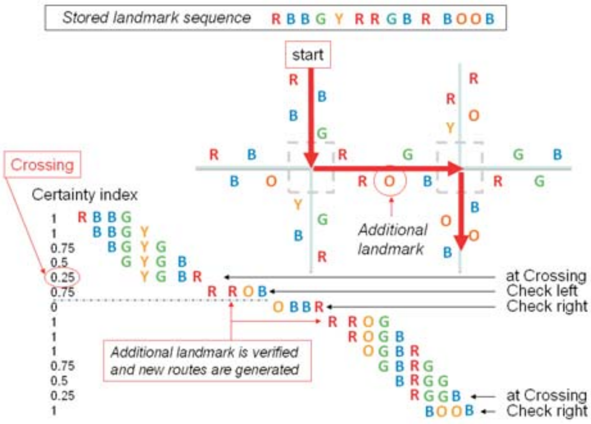


Fig. 13. Behavior of route tracing in the case of a slight change in the route stored in the local route memory. (a) At a crossing, the system evaluates all possible routes and chooses the route with the highest matching degree as the correct direction. (b) The robot recognizes an additional landmark from a change in the CI and by comparing the current route with a shifted memory route.

behavior in the case of a missing landmark or an additional one is shown in Figs. 12 and 13, respectively. Fig. 12. shows the case that landmark is missing. The robot recognizes a missing landmark from a change in the CI and by comparing the current route with a shifted memory route. Then the system generates a new route by update mechanism described in 3.4. Conversely, in the case that an additional landmark is appeared in the real world (Fig. 13), the robot recognizes the additional landmark from a change in the CI and by comparing the current route with a shifted memory route. Consequently, the system generates new routes by update mechanism described in 3.4. At a crossing, the robot decides which way to move by comparing the matching degree (CI) of the local landmark sequence for all possible paths. Despite checking all possible paths at the crossing, perfectly matching paths are not detected in these cases. Therefore, the robot selects the path with the highest matching degree (CI) as the plausible direction. When a local route stored in memory is found in the selected route, the system concludes that its decision was correct and that the route had changed slightly.

5. Conclusions

A practical simple human-like navigation system inspired by the entorhino-hippocampal loop mechanism was proposed and the validity confirmed through experiments using an autonomous mobile robot. The system navigates using landmarks stored in the memory unit. By using a prospective landmark sequence, the system is able to adapt to slight changes in the local route stored in the route memory unit. In this paper, we confirmed that the correct action is taken when there is either a missing or an additional landmark in a local route. This ability makes the navigation system flexible. In addition, we introduced the certainty index as a measure of recognizing the present situation in a route tracing. We also presented the basic idea for updating the route stored in the local route memory unit in the case of a slight change in circumstances by changing the connection weight of "the fully-connected network". The authors emphasize that the proposed system implementing the sequence learning mechanism can be completed even by a small palmtop computer. This feature is very important from an engineering viewpoint.

The system compensates for the latest digital navigation systems requiring a GPS and up-to-date map for accurate navigation. In particular, the system is promising as a low-cost and effective navigation system. It can be used in places where GPS signals are unavailable and in shopping malls where costly dedicated equipment such as RFID-tag is not employed.

In our future work, we aim to develop a decision mechanism for updating the timing and to investigate the adaptability of the proposed method. Improvement of the representation ability of the certainty index is necessary for recognizing more complex situations. A robust landmark extraction technique that can operate in real scenes is also important to use the proposed method in practical applications.

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