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Robotics Vision-based Heuristic Reasoning for Underwater Target Tracking and Navigation

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1. Introduction

Most of underwater pipeline tracing operations are performed by remote operated vehicles (ROVs) driven by human operators. These tasks often require continued attention and knowledge/experience of human operators to maneuver the robot (Foresti. G.L. and Gentili.,2000). In these operations, human operators does not require an exact measurement from the visual feedback, but based on the reasoning.

For these reasons, it is desirable to develop robotics vision system with the ability to mimic the human mind (human expert's judgement of the terrain traverse) as a translation of human solution. In this way, human operators can be reasonably confident that decisions made by the navigation system are reliable to ensure safety and mission completion. To achieve such confidence, the system can be trained by expert (Howard. A. et al, 2001).

In order to enable robots to make autonomous decision that guide them through the most traversable regions of the terrain, fuzzy logic techniques can be developed for classifying traverse using computer vision-based reasoning. Computing with words is highly recommended either when the available information is too imprecise to use numbers, or when there is a tolerance for imprecision which can be exploited to get tractability and a suitable interface with the real world (Zadeh. L, 1999).

Current position based navigation techniques cannot be used in object tracking because the measurement of the position of the interested object is impossible due to its unknown behavior (Yang Fan and Balasuriya, A, 2000). The current methods available in realizing target tracking and navigation of an AUV, used optical, acoustic and laser sensors. These methods have some problems, mainly, in terms of complicated processing requirement and hardware space limitation on AUVs (Yang Fan and Balasuriya, A, 2000). Other relevant research consists of neural-network terrain-based classifier in Foresti. et.al (2000) and Foresti, G. L. and Gentili (2002). Also, existing method using Hough transform and Kalman filtering for image enhancement has also been very popular (Tascini, G. et al, 1996), (Crovatot, D. et al, 2000), (El-Hawary, F. and Yuyang, Jing, 1993) , (Fairweather, A. J. R. et al, 1997) and (El-Hawary, F. and Yuyang, Jing, 1995).

2. Research Approach

Visible features of underwater structure enable humans to distinguish underwater pipeline from seabed, and to see individual parts of pipeline. A machine vision and image processing

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system capable of extracting and classifying these features is used to initiate target tracking and navigation of an AUV.

The aim of this research is to develop a novel robotics vision system at conceptual level, in order to assist AUV's interpretation of underwater oceanic scenes for the purpose of object tracking and intelligent navigation. Underwater images captured containing object of interest (Pipeline), simulated seabed, water and other unwanted noises. Image processing techniques i.e. morphological filtering, noise removal, edge detection, etc, are performed on the images in order to extract subjective uncertainties of the object of interest. Subjective uncertainties became multiple input of a fuzzy inference system. Fuzzy rules and membership function is determined in this project. The fuzzy output is a crisp value of the direction for navigation or decision on the control action.

2.1 Image processing operations

For this vision system, image analysis is conducted to extract high-level information for computer analysis and manipulation. This high-level information is actually the morphological parameter for the input of a fuzzy inferences system (linguistic representation of terrain features).

When an RGB image is loaded, it is converted into gray scale image. RGB image as shown in Fig. 1. Gray-level thresholding is then performed to extract region of interest (ROI) from the background. The intensity levels of the object of interest are identified. The binary image B[i,j], is obtained using object of interest's intensity values in the range of [T_1, T_2] for the original gray image F[i,j]. That is,

$$B[i,j] = \begin{cases} 1 & T_1 < F[i,j] \le T_2 \\ 0 & otherwise \end{cases} \tag{1}$$

The thresholding process producing a binary image with a large region of connected pixels (object of interest) and large amount of small region of connected pixels (noise). Each region is labeled and the largest connected region is identified as object of interest. In the labeling process, the connected pixels are labeled as either object of interest or unwanted objects by examining their connectivity's (eight-connectivity) to neighboring pixels. Label will be assigned to the largest connected region that represents the object of interest.

At this stage, feature extraction is considered completed. The object of interest is a pipeline laid along the perspective view of the camera. The image is segmented into five segments and processed separately for terrain features as multiple steps of inputs for the fuzzy controller. In order to investigate more closely each specific area within the image segment, each segment is further divided into six predefined sub segments in the image. Each sub segment (as illustrated by Fig. 2) is defined as follows.

- Sub segment 1 = Upper left segment of the image
- Sub segment 2 = Upper right segment of the image
- Sub segment 3 = Lower left segment of the image
- Sub segment 4 = Lower right segment of the image
- Sub segment 5 = Upper segment of the image
- Sub segment 6 = Lower segment of the image.

A mask image with constant intensity is then laid on the image as shown in Fig. 3. This is actually an image addition process whereby it will produce a lighter (highest intensity value) area when intersects the region of interest. The remaining region with highest

intensity value then be calculated its coverage area in the image as shown in Fig. 4. The area, A of the image is determined by.

$$A = \sum_{i=1}^{n} \sum_{j=1}^{m} B[i, j] \tag{2}$$

Sub segment 5-6 are being determined its location relative to the image center. Coverage area and location of object of interest in each sub segment is finally be accumulated as multiple input of the fuzzy inference system.

Fig. 1. Typical input image (RGB).

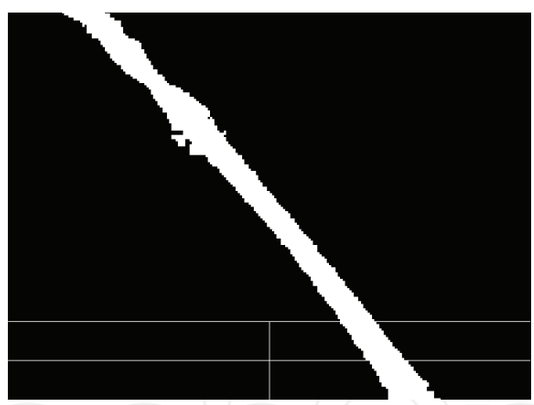

Fig. 2. Show image sub segment.

Fig. 3. Mask on threshold, removed noise image.

Fig. 4. Acquired area information.

2.2 The fuzzy inference system

The fuzzy controller is designed to automate how a human expert, who is successful at this task, would control the system. The multiple inputs to the controller are variables defining the state of the camera with respect to the pipeline, and the single output is the steering command set point. Consider the situation illustrated by Fig. 5. The fuzzy logic is used to interpret this heuristic in order to generate the steering command set point. In this case, the set point of AUV has a certain amount (ΔX) to the right.

Basically, a human operator does not require a crisp / accurate visual input for mission completion. There are total of six inputs based on the image processing algorithm.

- Input variable 1, x_1 = *Pipeline area at upper left segment in the image*
  Input variable 1 fuzzy term set, $T(x_1)$ = {*Small, Medium, Large*}
  Input variable 1 universe of discourse, $U(x_1)$ = [0.1 -1.0]
- Input variable 2, x_2 = *Pipeline area at upper right segment in the image*
  Input variable 2 fuzzy term set, $T(x_2)$ = {*Small, Medium, Large*}
  Input variable 2 universe of discourse, $U(x_2)$ = [0.1 -1.0]
- Input variable 3, x_3 = *Pipeline area at lower left segment in the image*
  Input variable 3 fuzzy term set, $T(x_3)$ = {*Small, Medium, Large*}

Input variable 3 universe of discourse, $U(x_3)$ = [0.1 -1.0]

- Input variable 4, x_4 = *Pipeline area at lower right segment in the image*
  Input variable 4 fuzzy term set, $T(x_4)$ = {*Small, Medium, Large*}
  Input variable 4 universe of discourse, $U(x_4)$ = [0.1 -1.0]
- Input variable 5, x_5 = *End point of pipeline relative to image center point*
  Input variable 5 fuzzy term set, $T(x_5)$ = {*Left, Center, Right*}
  Input variable 5 universe of discourse, $U(x_5)$ = [0.1 -1.0]
- Input variable 6, x_6 = *Beginning point of pipeline relative to image center point*
  Input variable 6 fuzzy term set, $T(x_6)$ = {*Left, Center, Right*}
  Input variable 6 universe of discourse, $U(x_6)$ = [0.1 -1.0]

The only fuzzy output.

- Output variable 1, y_1 = *AUV steering command set point*
  Output variable 1 fuzzy term set, $T(y_1)$ = {*Turn left, Go straight, Turn right*}
  Output variable 1 universe of discourse, $V(y_1)$ = [0 -180]

The input vector, x is.

$$x = (x_1, x_2, x_3, x_4, x_5, x_6)^T \tag{3}$$

The output vector, y is.

$$y = (y_1)^T \tag{4}$$

Gaussian and π-shaped membership functions are selected in this case to map the input to the output. Gaussian curves depend on two parameters σ and c and are represented by.

$$f(x;\sigma,c) = \exp\left[\frac{-(x-c)^2}{2\sigma^2}\right] \tag{5}$$

π-shaped membership function are represented by.

$$f(x;b,c) = \begin{cases} S(x;c-b,c-b/2,c) & for\ x \le c \\ 1-s(x;c,c+b/2,c+b) & for\ x > c \end{cases} \tag{6}$$

where $S(x; a, b, c)$ represents a membership function defined as.

$$S(x;a,b,c) = \begin{cases} 0 & for \quad x < a \\ \dfrac{2(x-a)^2}{(c-a)^2} & for \quad a \le x < b \\ 1-\dfrac{2(x-a)^2}{(c-a)^2} & for \quad b \le x \le c \\ 1 & for \quad x > c \end{cases} \tag{7}$$

In the above equation, σ, a, b and c are the parameters that are adjusted to fit the desired membership data. Typical input variable and output variable membership function plot are shown in Fig. 6 and Fig. 7.

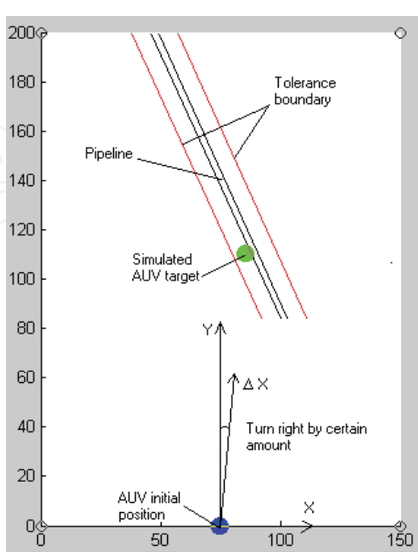

Fig. 5. Illustration of tracking strategy.

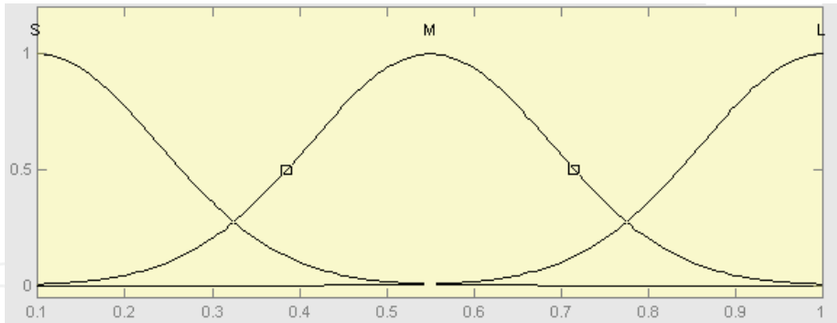

Fig. 6. Typical input variable membership function plot.

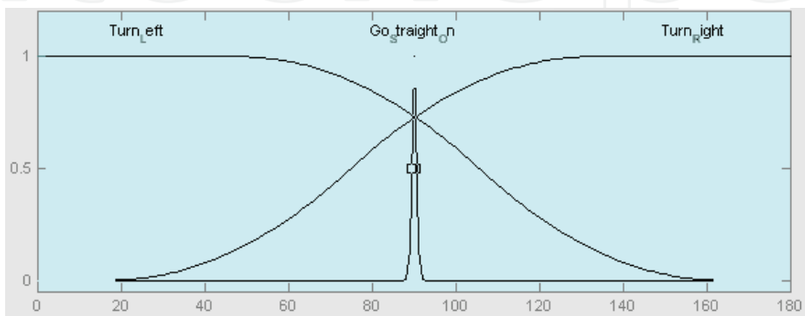

Fig. 7. Typical output variable membership function plot.

There are totally 13 fuzzy control rules. The rule base as shown in Fig. 8.

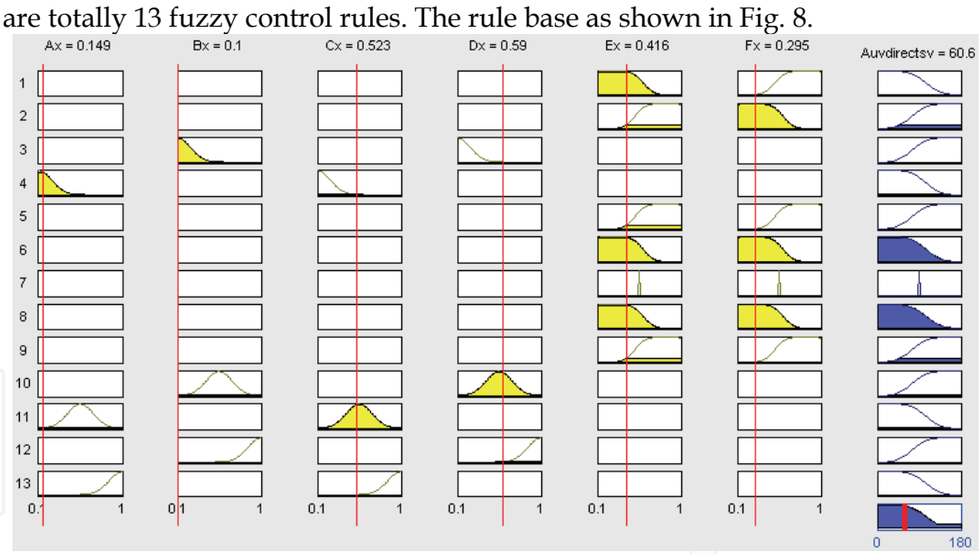

Fig. 8 Rule viewer for fuzzy controller.

In order to obtain a crisp output, the output fuzzy set is then aggregated and fed into a centroid (center of gravity) method defuzzification process. The defuzzifier determines the actual actuating signal, y' as follows.

$$y' = \frac{\sum_{i=1}^{13} y_i \mu_B(y_i)}{\sum_{i=1}^{13} \mu_B(y_i)} \tag{8}$$

3. Simulation and Experimental Results

The simulation procedures are as follows:

a. Define the envelope curve (working area) of prototype.
b. Give the real position and orientation of pipeline defined on a grid of coordinates.
c. Predefine the AUV drift tolerance limit (±8.0cm) away from the actual pipeline location.
d. Initiate the algorithm.
e. AUV navigating paths are recorded and visualized graphically.

The algorithm has been tested on computer and prototype simulations. For comparative pur poses, the results before and after fuzzy tuning are presented. Typical examples of results before fuzzy tuning are shown in Fig. 9 and Table 1.

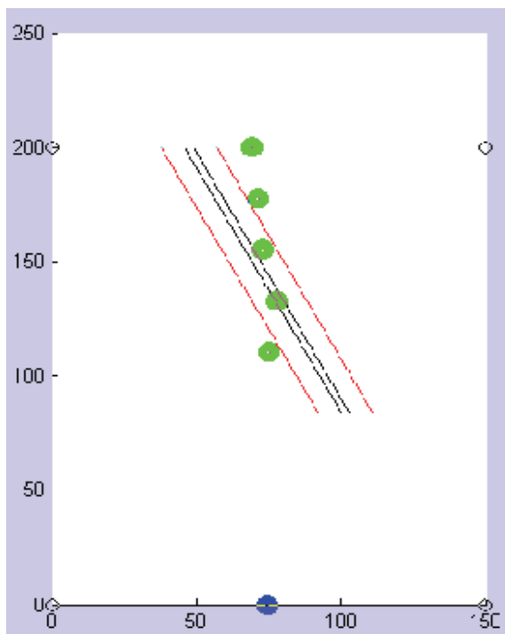

Fig. 9. AUV path (no proper tuning).

AUV path	Actual location x-axis (cm)	Simulated result x-axis (cm)	Drift (cm)	Percentage of Drift (%)
5	47.5	69.5	+22.0	275.0
4	58.5	71.7	+13.2	165.0
3	69.6	73.3	+3.7	46.3
2	80.8	78.3	-2.5	31.3
1	91.9	75.7	-16.2	202.5

Table 1. Data recorded (without proper tuning).

Typical examples of results after fuzzy tuning are shown in Fig. 10 and Table 2.

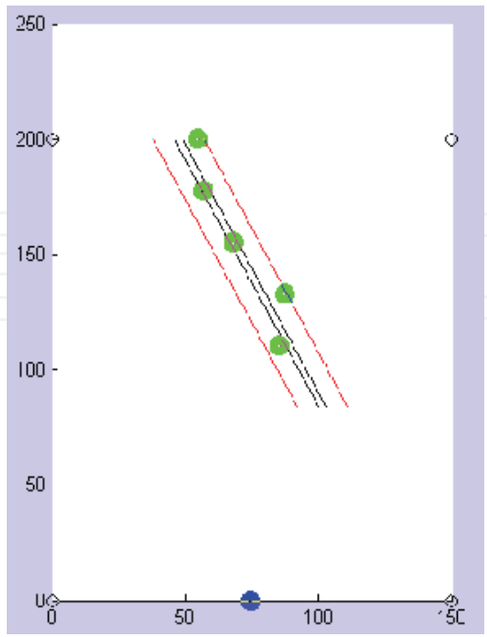

Fig. 10. AUV path (with proper tuning).

AUV path	Actual location x-axis (cm)	Simulated result x-axis (cm)	Drift (cm)	Percentage of Drift (%)
5	47.5	55.2	+7.7	96.3
4	58.5	57.4	-1.1	13.8
3	69.6	68.5	-1.1	13.8
2	80.8	88.1	+7.3	91.3
1	91.9	85.9	-6.0	75.0

Table 2. Data recorded (with proper tuning).

The simulation results show that the drift within tolerance limit is achievable when proper tuning (training) is applied to the fuzzy system. The percentage of drift is considered acceptable , as long as it is less than 100%, since this implies the path is within the boundary. The effectiveness of the system has been further demonstrated with different target orientation and lighting conditions.

4. Conclusions

This paper introduces a new technique for AUV target tracking and navigation. The image processing algorithm developed is capable of extracting qualitative information of the terrain required by human operators to maneuver ROV for pipeline tracking. It is interesting to note

that fuzzy control system developed is able to mimic human operators' inherent ability for deciding on acceptable control actions. This has been verified experimentally and the result is favourable, i.e. within 8.0 cm of drift tolerance limit in a 1.5m x 2.0m working envelope. One of the most interesting parts being the system ability to perform target tracking and navigation from the knowledge of interpreting image grabbed in perspective view from the terrain.

It should also be noted that the system offer another human-like method of representing human experience and knowledge of operating a ROV, rather than being expressed in differential equations in the common PID-controller. Obviously, the system does not require sophisticated image processing algorithm such as Kalman filtering or Hough transform techniques. All input variable required are merely an approximate value for mission completion, just like a human vision system. The simplicity of the system is further recognized when a priori knowledge of the terrain is not necessary as part of the algorithm. Currently a priori knowledge is required by some of the available pipeline tracking techniques such as (Evans, J, et al, 2003) and (Arjuna Balasuriya and Ura, T, 2002). The processing time is therefore reduced.

In general the whole computational process for this prototype is complex and it usually takes about 60 seconds to arrive at its desired output for 5 steps (22.5cm for each step), which is not practical for commercial standard requirement that is at least 4 knot (2m/s) of AUV speed. Commercial standard requirement of a survey AUV can be found in (Bingham, D. ,2002). However, the proposed system would be a workable concept for its capability to look forward and perceive the terrain from perspective view. As illustrated in Fig. 11, the perceived conditions from the second image captured could be processed concurrently while the AUV completing the forth and fifth step based on the previous image information. This will improve the processing time to support high speed AUV application.

In addition, further studies on improving the program structure and calculation steps may help to achieve better computation time. Future development of transputer for parallel processing or higher speed processor can also be expected to bring the system into practical use.

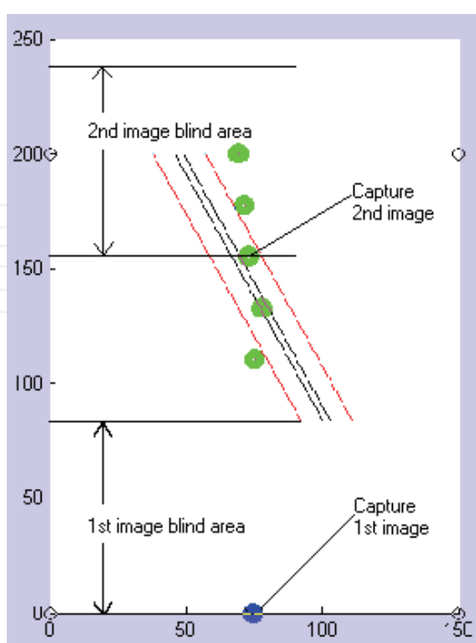

Fig. 11. AUV path and its image capturing procedure.

5. References

Arjuna Balasuriya & Ura, T. (2002). Vision-based underwater cable detection and following using AUVs, *Oceans '02 MTS/IEEE*, 29-31 Oct. 2002, Vol. 3, pp. 1582-1587, 2002

Bingham, D. , Drake, T. , Hill, A. , & Lott, R. (2002). The Application of Autonomous Underwater Vehicle (AUV) Technology in the Oil Industry – Vision and Experiences, *FIG XXII International Congress* Washington, D.C. USA, April 19-26 2002.

Crovatot, D. , Rost, B. , Filippini, M. , Zampatot, M. & Frezza, R. (2000). Segmentation of underwater Images for AUV navigation, *Proceedings of the 2000 IEEE international conference on control applications*, 25-27 September 2000, pp. 566-569, 2000

El-Hawary, F. & Yuyang, Jing. (1993). A robust pre-filtering approach to EKF underwater target tracking, *Proceedings of OCEANS '93*. Engineering in Harmony with Ocean, 18-21 Oct. 1993, Vol.2, pp. 235-240, 1993.

El-Hawary, F. & Yuyang, Jing. (1995). Robust regression-based EKF for tracking underwater targets, *IEEE Journal of Oceanic Engineering*, Vol.20, Issue.1, pp.31-41, Jan. 1995.

Evans, J.; Petillot, Y.; Redmond, P.; Wilson, M. & Lane, D. (2003). AUTOTRACKER: AUV embedded control architecture for autonomous pipeline and cable tracking, *OCEANS 2003. Proceedings*, 22-26 Sept. 2003, Vol 5, pp. 2651-2658, 2003.

Fairweather, A. J. R. , Hodgetts, M. A. & Greig, A. R. (1997). Robust scene interpretation of underwater image sequences, *IPA97 Conference*, 15-17 July 1997, Conference Publication No. 443, pp. 660-664, 1997.

Foresti. G.L. & Gentili. S. (2000). A vision based system for object detection in underwater images, *International journal of pattern recognition and artificial intelligence*, vol. 14, no. 2, pp. 167-188, 2000

Foresti, G. L. & Gentili, S. (2002). A hierarchical classification system for object recognition in underwater environments, *IEEE Journal of Oceanic Engineering*, Vol. 27, No. 1, pp 66-78, 2002.

Howard. A. , Tunstel. E. , Edwards. D. & Carlson. Alan. (2001). Enhancing fuzzy robot navigation systems by mimicking human visual perception of natural terrain traversability, *Joint 9th IFSA World Congress and 20th NAFIPS International Conference, Vancouver*, B.C., Canada, pp. 7-12, July 2001

Tascini, G. , Zingaretti, P. , Conte, G. & Zanoli, S.M. (1996). Perception of an underwater structure for inspection and guidance purpose, *Advanced Mobile Robot, 1996., Proceedings of the First Euromicro Workshop on , 9-11 Oct. 1996*, pp. 24 – 28, 1996.

Yang Fan & Balasuriya, A. (2000). Autonomous target tracking by AUVs using dynamic vision, *Proceedings of the 2000 International Symposium on Underwater Technology*, pp. 187-192, 23-26 May 2000.

Zadeh. L. (1999). From computing with numbers to computing with words –from manipulation of measurements to manipulation of perceptions, *IEEE Transactions on Circuits and Systems*, 45(1), pp. 105-119, 1999.

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The range of potential applications for mobile robots is enormous. It includes agricultural robotics applications, routine material transport in factories, warehouses, office buildings and hospitals, indoor and outdoor security patrols, inventory verification, hazardous material handling, hazardous site cleanup, underwater applications, and numerous military applications. This book is the result of inspirations and contributions from many researchers worldwide. It presents a collection of wide range research results of robotics scientific community. Various aspects of current research in new robotics research areas and disciplines are explored and discussed. It is divided in three main parts covering different research areas: Humanoid Robots, Human-Robot Interaction, and Special Applications. We hope that you will find a lot of useful information in this book, which will help you in performing your research or fire your interests to start performing research in some of the cutting edge research fields mentioned in the book.

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