DEVELOPMENT OF AN AUTONOMOUS MOBILE ROBOT FOR RADIATION SOURCE DETECTION USING NEURAL NETWORKS

MANASH BURAGOHAIN
Department of Mechanical and Aerospace Engineering, University of Missouri – Rolla, USA

GANESH K VENAYAGAMOORTHY
Department of Electrical and Computer Engineering, University of Missouri – Rolla, USA

AKIRA TOKUHIRO
Department of Mining and Nuclear Engineering, University of Missouri – Rolla, USA

ABSTRACT
This paper presents the design of an autonomous mobile robot to map out the radiation sources on a contaminated surface. This involves simulation of a mobile robot with sensors and the radiation sources on a surface. The basic search criteria are dependent on the strength of the source and the distance it is from the robot. A neural network is developed to navigate the mobile robot to the radiation sources. This paper provides an alternative to human involvement in detection and identification of radiation contamination. Preliminary simulation results are promising and are presented in the paper.

INTRODUCTION
Considering a hypothetical situation such as an accident at a nuclear plant, a site of dirty bomb or Radiological Dispersal Device (RDD) [1] attack. There is a need for immediate identification and isolation of the radiation sources. It is a very hazardous task, at the same time neither it be neglected nor delayed. Traditionally humans did the task. There have been attempts to develop technologies which will reduce human involvement. One of the prominent among the many technologies proposed and developed consists of the class of remotely operated systems. Though remotely operated systems reduce the human involvement, it is seen by the industry as a very complicated and cost intensive technique. Also it is widely accepted that the factor of time and human exposure will be the critical parameters in developing any system for identification and the isolation of the radioactive sources in a situation of nuclear emergency. Because more swiftly a radiation source is identified the lesser time it will take to isolate it and thus reduces the chance of contaminating more areas. In a situation of nuclear emergency the amount of radiation dispersed cannot be determined or projected accurately [2] as during experiments performed under controlled conditions.

There have been efforts for radiation detection in an unstructured environment [3] and some using distributed system for surveillance in unstructured environments [4]. In the past decade, there has been considerable effort to develop autonomous robotic vehicles for random patrols, barrier assessment, intruder detection, reconnaissance and surveillance, building entry, target detection, building or terrain mapping, and explosives neutralization.

Mobile robotic platforms with the above capabilities will improve the ability to counter threats, limit risks to personnel, and reduce manpower requirements in hazardous environments. By increasing sensory "reach", giving the robots a significant degree of autonomy and it seeks to augment human capabilities reduce exposure to risk, and present timely, relevant information to the user.

Similar initiatives to develop Unmanned Ground Vehicles for remote reconnaissance and surveillance have been reported in the literature. Sandia National Laboratories developed the Surveillance And Reconnaissance Ground Equipment (SARGE) [5] robotic vehicle for the US DoD. SARGE is a teleoperated robot for battlefield surveillance applications without computing power to support autonomous navigation or vision processing. SARGE was built around a Yamaha Breeze 4-wheel all-terrain vehicle.

In [6] an Autonomous Robot for Surveillance Key Applications (ARSKA) is presented. This UGV is built around a Honda TRX 350 all-terrain vehicle. ARSKA is equipped with ultrasonic sensors for contour following and obstacle avoidance. Two positioning systems have been used with the vehicle: an external optical measurement device called a tachymeter, and differential GPS (DGPS). ARSKA can be controlled using a ground station. The basic functions of the ground station are task preparation and monitoring and on-line telecontrol of the vehicle. ARSKA has been used to guard an Army storage area.

The focus of the above autonomous robotic surveillance and reconnaissance systems is the use of real time computing based on conventional algorithms to accomplish the task at hand. In this type of autonomous surveillance system, minimal supervised autonomy is achieved at the expense of costly and power-intensive sensors and high-bandwidth, bulky tele-operated command and control ground stations. In general, a high degree of autonomy requires considerable computing power. The path planning algorithms used generally require prior knowledge of free paths and obstacles in the environment, which are not always available. These deficiencies pose considerable challenges when such autonomous platforms are to be employed in applications or environments that they were not initially designed for.

In these single-platform surveillance systems, the principal cost is that of the computing and payload. However, if a intelligent computing technique such as neural network is employed, and limit the payload according to the specifics of the task, cheap intelligent autonomous mobile agents can be developed.

In this paper, the use of a feedforward neural network navigator for a robot for radiation source mapping is presented. The feedforward neural network structure is favourable for real time implementation on a field programmable gate array with less computational intensity and memory requirements.

MOBILE ROBOT AND SENSORS

The design of the robot is such that it is equipped with four radiation intensity sensors (1-4) in four cardinal directions as shown in figure 1. The sensors have a resolution of 180 degrees, which makes them effective towards radiation in front and not influenced by radiations behind them. The intensity of a radiation source measured by a sensor depends on its orientation with the sensor and also on the Euclidean distance between them.

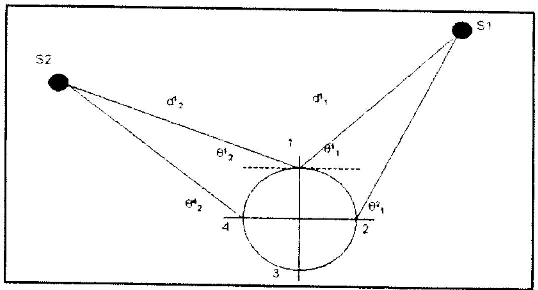

Figure 1: Schematic of the radiation sensor positions (1-4) and the orientations with two radiation sources (S1 and S2).

For the simulation of these radiation intensity sensors, they are modeled based on the formula given in (1a) and (1b) for sensor 1 and 2 respectively.

$$I_1 = \frac{S1}{(d_1^1)^2}\sin(\theta_1^1) + \frac{S2}{(d_2^1)^2}\sin(\theta_2^1) \tag{1a}$$

$$I_2 = \frac{S1}{(d_1^2)^2}\cos(\theta_1^2) \tag{1b}$$

Hence, (1a) and (1b) can be generalized as:

$$I_j = \sum_{i=1}^{n} \frac{Si}{(d_i^j)^2}\sin(\theta_i^j) \tag{2a}$$

for, $j = 1$ and 3.

$$I_j = \sum_{i=1}^{n} \frac{Si}{(d_i^j)^2}\cos(\theta_i^j) \tag{2b}$$

for, $j = 2$ and 4.

Where:
j is sensor number.
i is number of active sensor w.r.t. sensor j
I is the intensity measured at the individual sensors
Si is the absolute strength of the radiation source
d is the Euclidean distance between the source and the sensor
θ is the angle between the source beam and the sensor.

Random radiation sources are initialized in the field of activity. The robot with the four sensors starts with a initial step, gets the intensity feedback for all its sensors and orients itself and moves another step. The basic criteria for reorientation is such that the the robot moves towards the source, which emits the strongest signal. During the search process, the cardinality of the sensors remains intact, only the orientation with respect to the movement of the robots keeps updating according to the changes in the intensity fields. This approach is explained below.

As a convention, the numerals – 1, 2, 3 and 4 are replaced with the cardinal directions North, South, East and West respectively for denoting the sensors. The sensor strengths are recorded for the first step as N_1, S_1, E_1 and W_1 and for the nth step the strengths are N_n, S_n, E_n, W_n. The algorithm then proceeds towards calculating the potential gradient in the sensors on the basis of the strengths in two consecutives steps. This is illustrated in (3) below.

$$N_{grad} = \frac{N_{n+1} - N_n}{k},\ S_{grad} = \frac{S_{n+1} - S_n}{k},\ E_{grad} = \frac{E_{n+1} - E_n}{k},\ W_{grad} = \frac{W_{n+1} - W_n}{k} \qquad (3)$$

Where 'k' is the distance moved by the robot in a single step.

Based on the gradients and the actual strengths a "Decision Matrix" is generated for deciding the course of direction of the robot (Table 1).

Table 1: Decision matrix

	N_{grad}	S_{grad}	E_{grad}	W_{grad}
N_{grad}	0	*NS*	*NE*	*NW*
S_{grad}	*SN*	0	*SE*	*SW*
E_{grad}	*EN*	*ES*	0	*EW*
W_{grad}	*WN*	*WS*	*WE*	0

Where: $NS=SN= N_{grad}-S_{grad}$, $NE=EN= N_{grad}-E_{grad}$, and so on.

The decision on the direction of motion is based on a set of rules illustrated for the case where N_{grad} is the highest. In the matrix the values of *NS*, *NE*, *NW* are considered and the rules below are applied.

a. If *NE* is the lowest then move in the *N-E*
b. If *NW* is the lowest then move in the *N-W*
c. If *NE*=*NW* and are the lowest then move in the *N*
d. If *NS* is the lowest AND $NE < NW$ OR $NE = SE$ then move in the *E*
e. If *NS* is the lowest AND $NE > NW$ OR $NW = SW$ then move in the *W*
f. If $NE = NW = SE = SW$ move in the direction highest of among $N_{n+1}=E_{n+1}=S_{n+1}=W_{n+1}$.

Similarly, a set of rules exist for cases where S_{grad}, W_{grad}, and S_{grad} are the highest.

As can be seen, the method described above for locating the sources involves a great deal of compuation. And to incorporate it into a real unit, and embedding the whole program into a hardware is not viable when we need to develop a low cost, miniature autonomous mobile radiation detection unit. Therefore, in this paper the alternative design based on a neural network to overcome the computational burden and provide a nonlinear path for the detection unit is presented.

NEURAL NETWORK NAVIGATOR

A feedfoward neural network [7] shown in figure 2 is trained with backpropagation for the mobile robot navigation.

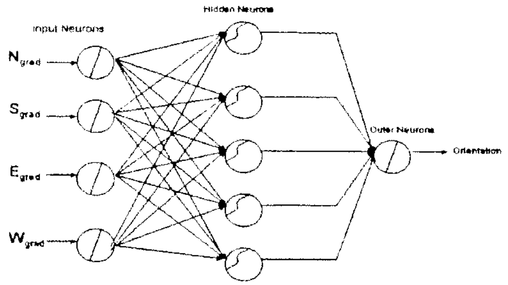

Figure 2: The feedforward neural network architecture implemented for estimating the orientation of the robot.

The inputs to the neural network are the intensity gradients recorded by the four radiation intensity sensors, and the output is the orientation of the robot corresponding to input set of intensity gradients. The feedforward neural network has linear neurons in the input and output layer, and five sigmoidal neurons in the hidden layer. A trained network having a sufficient accuracy can predict the path of the robot that was obtained using the conventional method (non-neural network). For training the neural network, data is generated using the conventional algorithm at this stage.

RESULTS

The results obtained with the conventional algorithm is denoted in the diagrams below as 'Actual'. The results obtained with the neural network is denoted as 'NN based'. Figure 3 shows the path of the robot taken to locate the five radiation sources of equal intensity when they are both located in a single quadrant.

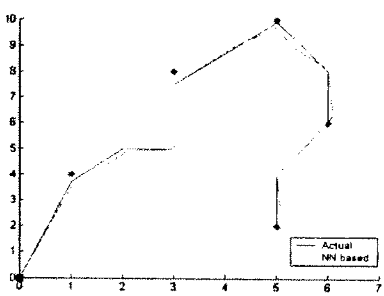

Figure 3: This shows the path obtained using the conventional method and with the neural network method.

Figure 4 shows the path taken by the robot for locating the same five radiation sources but now placed in all the four quadrants. In both the cases , it is clear the neural network has learned the conventional algorithm but can loc the sources much faster than the conventional algorithm which requires m time to calculate the orientation at each instant.

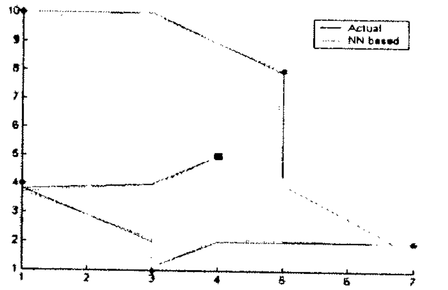

Figure 4: This shows the path obtained using the conventional method and wi the neural network method when the sources in the adjacent quadrants.

CONCLUSIONS

It have been shown that a feedfoward neural network can be successful trained to locate radiation sources randomly spread out in a field or buildir The accuracy achieved is comparable to the conventional method but at t same time the computation involved using the neural network (4×5×1) noticeably small compared to that taken by the conventional algorithm.

Future work involves the development of the above system for radiati sources of varying intensity and an environment with obstacles. It is anticipat that some form of reinforcement learning will be used. The next step implementing the simulated system into an actual robotic system with actu radiation intensity sensors using a digital programmable platform.

REFERENCES

[1] U.S. Nuclear Regulatory Commission, "Fact Sheet on Dirty Bomb http://www.nrc.gov/reading-rm/doc-collections/fact-sheets/dirty-bombs.html , 04/30/2004.

[2] Center for Disease Control and Prevention, "Dirty Bombs - Dangers of a dirty bomb http://www.bt.cdc.gov/radiation/dirtybombs.asp , 04/30/2004.

[3] Ron Fulbright and Larry M. Stephens, "SWAMI: An Autonomous Mobile Robot for Inspecti of Nuclear Waste Storage Facilities". Autonomous Robots, vol. 2., 1995, pp. 225-235.

[4] John M. Dolan, Ashitey Trebi-Ollennu, Alvaro Soto and Pradeep Khosla, "Distributed Tactic Surveillance with ATVs". SPIE (the International Society for Optical Engineerin Proceedings on Unmanned Ground Vehicle Technology (AeroSense '99), Vol. 3693, Apr 1999, pp. 192-199

[5] J. Bryan Pletta and John Sackos, "An Advanced Unmanned Vehicle for Remo Applications" Sandia National Laboratories Report, 1998.

[6] Schönberg, T., Ojala, M., Koskimäki, E., Suomela, J. & Halme, A., "A small Scal Autonomous Test Vehicle for Developing Autonomous Off-Road Applications", Internation Conference on Machine Automation, Tampere, Finalnd, 1994, pp. 143-157

[7] Andries P. Engelbrecht, "Computational Intelligence: An Introduction", John Wiley, 200 ISBN: 0-470-84870-7