DISTRIBUTED ROBOTICS
an intelligent system

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Apr. 28, 2007

1 Purpose

In many applications of robotics, it is difficult or impossible for a single robot to complete complex tasks where, for example, a search of a large area or a detailed examination of an object is required. For this reason, systems have been proposed where multiple robots can work together to complete a task [1] [2] [4] [5] [6] [9] [10] [12] [14] [16] [20] [25] [26].

Existing systems, however, are lacking in that they generally use a fixed program, involving simple algorithms [5] [9] [12] [16] [20] [25] [26] to complete the task. This limitation prevents the robots from being useful in many applications; they are unable to learn from and adapt to their environment to achieve better performance and learn new tasks.

Most systems which make use of neural networks typically do so to perform a simple function, such as to define a state [2], to avoid an obstacle [10], or for locomotion [4] [6]. Even systems using neural memory and cognition [14] do not make full use of the huge potential of the adaptive colony available in a distributed robotics system.

In this project, a customizable design is proposed for a neural-based distributed robotics system, capable of learning to complete advanced tasks. Intelligence in the form of programmable-logic based neural networks and input modules (including miniature cameras, accelerometers, GPS sensors, and microphones) corresponding to various abilities are distributed throughout the group. An algorithm for neurally-adaptive communication to allow group feedback, as well as a simple form of societal development, has been designed, allowing each robot to receive feedback from themselves (self-feedback), each other (group-feedback), and an “expert system” (human teacher or ideal algorithm) when necessary.

2 Objectives

The engineering objectives of this project include:

1) To design a software simulation of a distributed robotics system where 2 or more virtual robots work on a simple task. A form of group-feedback is used to allow experimentation on the accuracy of robots learning from other robots.

2) To create an electronic prototype of a robot for use in this system, using FPGA- (Field Programmable Gate Array) based processing with an on-chip stochastic neural network and advanced image processing algorithms.

3) To analyze the development of the software simulation to determine the viability of robot-trained (group-feedback) intelligence and overall system accuracy.

3 Background

Distributed Robotics

Distributed robotics is a new field of artificial intelligence where tasks normally given to a single robot are distributed to a group of robots to achieve better overall performance and a form of redundancy for error-tolerance.

Artificial Neural Networks

Artificial Neural Networks (ANNs) emulate the human brain's ability to learn and recognize patterns. All neural nets consist of neurons as the basic processing nodes, and synapses which store a weight value to connect together the layers of neurons.

Learning can be divided into two categories: supervised and unsupervised. Supervised learning involves use of a feedback-based algorithm such as Backpropagation, where error responsibility is calculated at each node. Unsupervised learning, often using the Hebbian algorithm, finds correlations between input data and divides it into related sets [8].

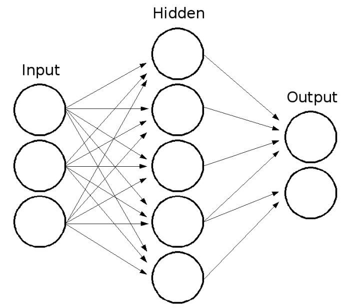

Figure 1: Diagram of a 3-layer neural network

Image Processing

The SIFT (Scale Invariant Feature Transform) algorithm [15] [7] is first used to identify feature points in an image. These points are invariant to scaling and small 3-dimensional rotations. Object recognition may take place from a SIFT-processed image by finding common feature points between the current image and stored objects in a database.

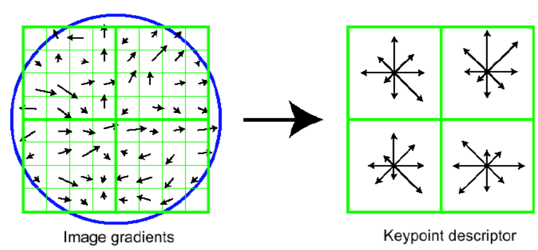

Figure 2: SIFT keypoint generation [15]

Triangulation can be used after each time-step to determine the approximate location of each feature point, assuming the distance moved is known. Navigation takes place based on these positions, using the mapping algorithm.

4 Discussion

System Overview

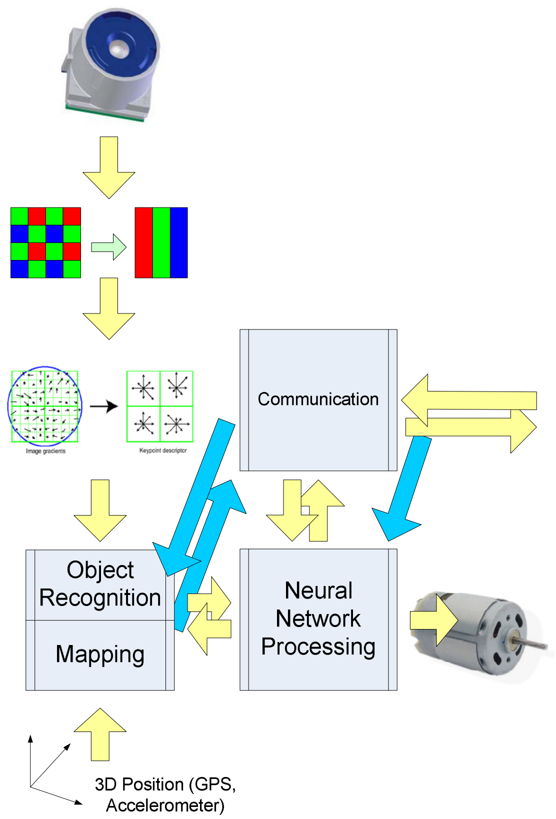

Figure 3: System overview showing:

(1) Camera interface
(2) Bayer format → RGB
(3) SIFT transform
(4) Object recognition
(5) Mapping
(6) 3D position input
(7) Neural networks
(8) Comm. algorithm
(9) Motor output

Camera Interface

The robot receives visual input through a small 9.5 mm^2 SMIA 1MP camera. Custom circuit boards (Fig. 4) for camera interface are created. Due to unavailability of sockets and pad spacing too close to solder (0.1mm), conductive tape is used to attach the cameras.

Images are transmitted serially to the FPGA, where a custom VHDL program reads the data and stores it in a RAM module. It is then processed on-chip using the SIFT algorithm to identify feature points.

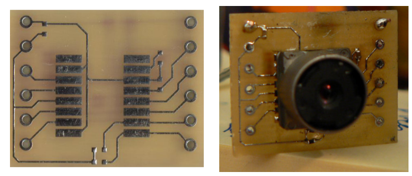

Figure 4: PC board (left) attached camera (right)

Stochastic Neural Network

To create a prototype hardware-based neural network, a new small-scale stochastic-bitstream neural net design was created. Global signals [11] are used for the sigmoid (tanh) and sigmoid derivative ($sech^2$) functions, as well as a pseudo-random binary-weighted bitstream which is multiplexed by the stored synapse values. Arithmetic operations can then take place with simple gate circuits (i.e. XOR will multiply two bitstreams).

Neural Communication Algorithm

A common radio-link is used for communication between robots. In the prototype robot, a Bluetooth module has been used instead to allow simple communication with a computer.

Closed-loop feedback is used in the algorithm to ensure that the neural-generated command is understood correctly. The command may be to provide negative or positive feedback to the other robot, or to share map or object data. Additional commands corresponding to neural defined functions may develop over time.

Mapping Algorithm

Assuming the current position of the robot is known (based on a GPS, accelerometer, and/or known landmarks), identified feature points can be added to the local map as vector lines extending from the camera. Existing vectors can also be confirmed as a 3-dimensional location by triangulation.

A system state is defined when map data is needed. At this point the communication algorithm requests local map data from neighboring robots.

Computer Simulation

A demonstration scenario is created where balls are placed in the center of the screen. Two virtual robots have a simple objective: to navigate to a ball in the center of the screen, pick it up by touching it, and bring it back to the goal at the left side of the screen. After all the balls have been moved, they are replaced to allow training to continue. This simple objective is comparable to a minefield-clearing task, where the balls represent mines.

5 Problem

(Experimentation for **Objective 3**)

In a software demonstration of a distributed robotics application where the robots must work together to complete an object placement task, will one robot be able to be trained from another robot (group-feedback) with similar performance to a robot trained by an ideal algorithm ("expert system") for neurally-controlled navigation?

6 Hypothesis

If complete environment information is available to the neural networks, assuming they consist of at least 4-5 layers and a sequential presentation algorithm is used, then it should be possible for an untrained navigation network to learn from a trained network. This would be an important step to present group-feedback as a viable possibility in distributed robotics.

7 Procedure

A simple environment is designed in C++ with virtual robots and some physics interaction between objects. "Expert-system" feedback rules are created to instruct the robots to complete the objective. Two 5-layer Backpropagation neural networks are created to choose a target object and navigate to this target. The neural networks are implemented in two virtual robots, one which learns from an "expert system", and one which learns from the other robot. Accuracy over time is measured from the software demonstration of 100 observations in 3 trials.

Algorithms for the hardware prototype are designed to implement image processing, a stochastic-bitstream neural network, and adaptive communication between robots. Circuit boards are created and soldered for the camera interface to allow the prototype robot to receive input from the environment.

8 Results

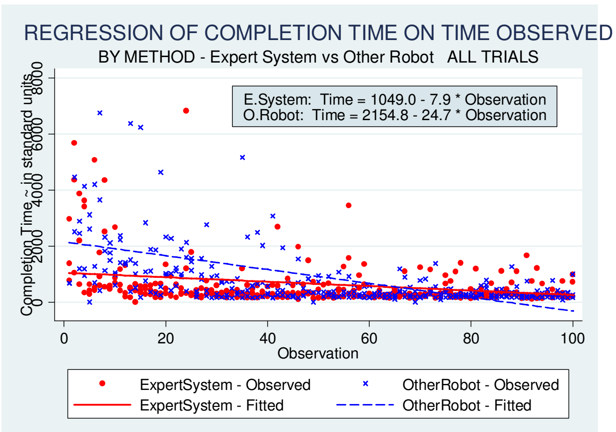

Figure 5: Graph showing accuracy over time of "expert-system" (red) and group-feedback (blue) trained virtual robots

9 Analysis & Conclusion

Data was collected in the demonstration program by allowing one robot to be trained freely by the "expert-system", and one to be trained by the other robot. The amount of time to reach an object and bring it back to the goal is measured for each observation, as well as the rate of correct identification of the target object. This is repeated for 100 observations, and 3 trials. STATA was then used to graph the results and perform regression analysis to find the improvement in accuracy over time.

It was found that there was not a significant difference in performance between the neural networks trained by an "expert-system" and group-feedback. Interestingly, the group-feedback had better accuracy in terms of correctly identifying when to bring an object back to the goal. These results present group-feedback and distributed intelligence as viable possibilities for use in distributed robotics.

10 Previous Work

2005

A 3-dimensional modeling system was created for use with robotics and other applications [23]. This has laid some of the groundwork for the mapping algorithm designed for the current project.

2006

A general purpose analog reconfigurable neural network integrated circuit was designed in this project [22]. The current project also applies neural networks, but this has been extended to creating an entire system capable of working together to achieve specific tasks.

11 Applications

- Minefield Clearing [5]
- Military Surveillance [20]
- Mining & Agriculture
- Exploration & Mapping
- Industrial Inspection

12 Acknowledgements

I thank my mother, Vicki Stagg, for her help and support, as well as my brother, Andrew Stagg, for his support. I would also like to thank Laura Neilsen of Alberta Printed Circuits for providing a discount on circuit boards, and John Carney of Cadence Design Systems for providing a trial license for Cadence Layout.

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