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Range estimation on a robot using neuromorphic motion sensors

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Abstract

Neuromorphic motion sensors using analog very large scale integrated technology are attractive for use on battery powered robots which require a low payload. Their features include low power consumption, continuous computation, light-weight, and robustness to different light and contrast conditions. Their outputs are not compatible with controllers that require precise measurements from their sensors. We describe a preliminary investigation into neural architectures that can translate information from these type of sensors into an output suitable for controlling the motor outputs of a robot. In this work, we use a neural network to produce an output that is similar to the range measurements of infrared range sensors, and we use this output to guide the behavior of the robot in a collision-avoidance task.

Keywords: Neuromorphic motion sensors; Range information from aVLSI sensors; Bio-inspired motion chips; Low-power motion chips; Neural network; aVLSI vision sensors

1. Motivation

Neuromorphic motion sensors based on different motion algorithms, for example, correlation-based motion, time-to-travel, energy models, and optical flow [1–10], are being incorporated as an on-flight or robotic sensor to replace CCD cameras and digital processors. The characteristics of the sensors; low-power consumption (μW), light-weight (several grams), analog collective computation, and robustness to different light and contrast conditions [11], make them attractive for mobile, battery powered robots [12].

The use of the motion signals from the neuromorphic sensors in generating fly or bee-like behaviors on a robot [13–15] or additional use of position and contrast information from these sensors in visual tasks like line tracking [16] show the viability of these sensors for guiding the movement of a robot. However, the sensori-motor controller in most of these cases works well only under a restricted set of conditions. The goal in this work is to look at neural architectures that can act as sensori-motor controllers on an autonomous robot. On-line learning can also be incorporated into these architectures so that the system can learn to adapt to output signal statistics of the bio-inspired sensors and to changing conditions in the environment. Floreano and Mattiuisi [17] have shown that spiking neural systems can be used successfully

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as sensori-motor controllers using inputs from a CCD imager.

A frequently used signal for robot navigation is range information. This information represents a physical property of the external world and is typically provided by infrared-red range and laser-range sensors. In this work, we trained a neural network to predict the information provided by IR range sensors from the neuromorphic motion sensors under different operating conditions. Other input information, like ambient light information and the outputs of the wheel sensors, are also provided to the network. We use this trained network to guide the robot in a collision-avoidance task. The fact that we trained the network in this work to predict the output of the range sensors is an arbitrary choice. We could have also chosen the output of the network to be the direct signal that controls the wheels of the robot.

2. Experimental setup

We developed a system which allowed us to control the movement of a robot from a computer and to record the sensory data. Our experimental setup, as shown in Fig. 1, consists of a commercially available Koala robot (from K-team SA), on which the aVLSI motion sensors as well as conventional range and light sensors, and a video camera were mounted. The sensors were interfaced to an ATMEL microcontroller which sampled the signals at 30 Hz with a resolution of 12 bits. The data from the microcontroller was recorded on the computer and subsequently analyzed under Matlab. This setup is described in [18].

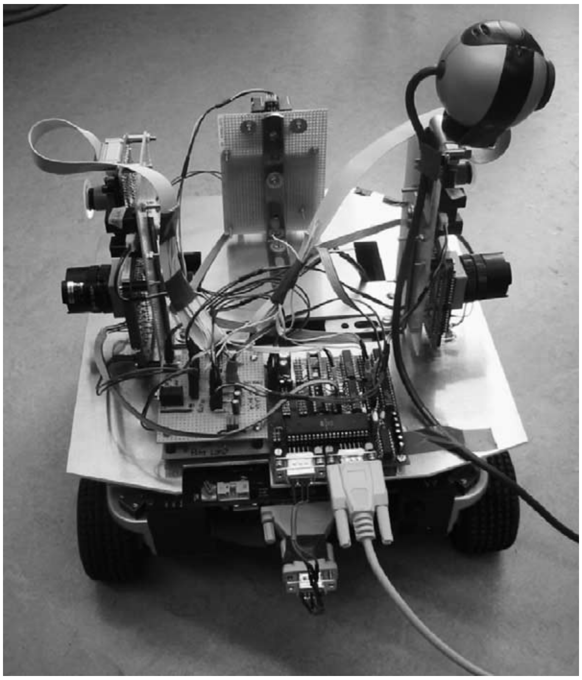

Fig. 1. Robot with the different sensors and the controller board. The neuromorphic motion sensors are mounted on the front and the left and right sides of the robot.

2.1. The aVLSI sensors

Each motion sensor board (Fig. 2) carries a chip, a lens, and some electronics to generate the operating

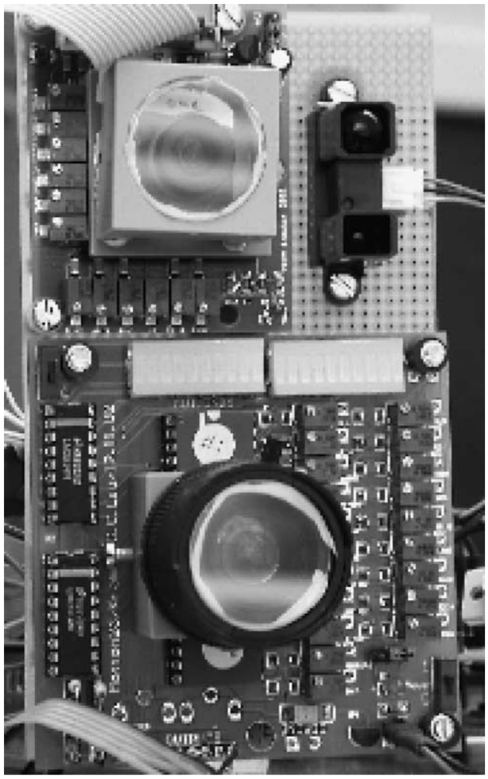

Fig. 2. Two motion sensor boards and the IR range sensor. The bottom motion sensor board carries a chip, a lens, two LED display bars to show the direction and speed of motion, and potentiometers that control biases to the chip. The outputs of this chip and the IR range sensor are used for the network training. The top motion sensor board (to the left of the IR range sensor) carries a chip which measures motion based on optical flow and is not used in the work described here.

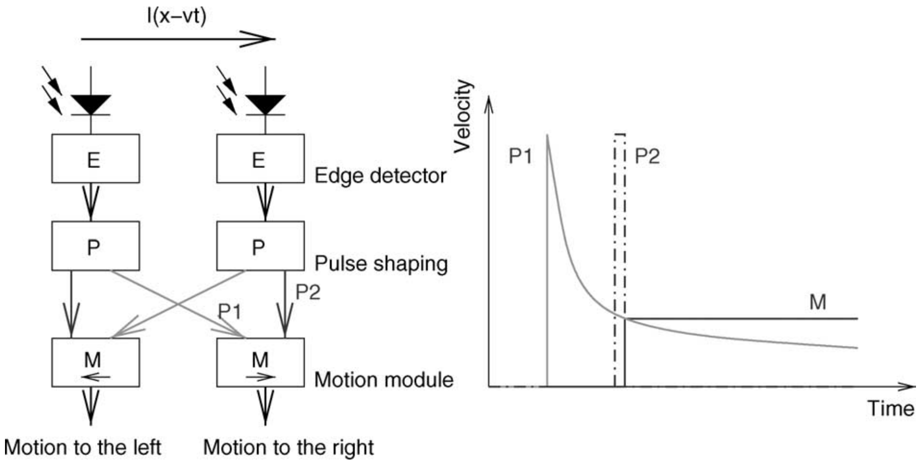

Fig. 3. Architecture of the motion sensor. The sensor produces logarithmic compressed global motion output based on a time-to-travel algorithm. Figure is adapted from [19]. The edge detector block generates a non-linear amplified output of temporal contrast changes. The output of this detector is used by the pulse shaping block to generate a sampling pulse (P2) and a signal (P1) that is charged initially to a high value and decays with a $1/t$ function. The P2 pulse samples the P1 signal of its neighboring pixel when the stimulus arrives at a pixel. The signal level (M) is inversely proportional to the time taken to travel between two pixels.

voltages for the chip. The chips were fabricated in a 1.2 μm CMOS technology. Although they do not attain the precision levels of an equivalent system consisting of a CCD camera and a digital processor, the chips are much smaller than the latter system.

The motion sensors used in this work compute a log compressed velocity signal from the image motion. These sensors were designed by Jörg Kramer and are based on a time-to-travel algorithm [19] (see Fig. 3). We are presently running experiments which include the addition of other motion sensors [9,10]. Three of these sensors were mounted on the robot; two sensors on the sides with 4 mm lenses, and one sensor in front with an 8 mm lens. Each chip is one-dimensional and outputs the global motion, and the velocity and position of the pixel with the fastest local motion. The motion computation on this chip is loosely based on the correlation-based model proposed by Hassenstein and Reichardt to describe the optomotor response in the *Chlorophanus* beetle [20].

2.2. Conventional sensors on setup

We also mounted a USB camera, infrared (IR) distance sensors to record the distances of obstacles, and an ambient light sensor to record the background lighting. The infrared distance sensor (GP2Y0A02YK from Sharp) has a detecting distance range from about 15 to 150 cm. The ambient light sensor consists of a photodiode and some digital circuits. The wheel speeds of the robot were also recorded. We use the wheel sensor readings to reconstruct the path of the robot, the range sensor outputs to reconstruct its physical environment (see Fig. 6), and the outputs of other sensors (for example, the ambient light sensor and the USB camera) to reconstruct its operating conditions.

3. Data collection

We first recorded the data from all sensors while the robot operated in different environments. These data were subsequently used in the training and evaluation of the performance of a two-layered network in estimating the range information from the IR sensors. The physical environment of the robot consisted of vertical striped walls as shown in Fig. 4. The stripes were 20 mm wide stripes and the wall was around 20–75 cm from the sensors, that is, the spatial frequency of the striped stimulus varied between 0.7 and 2.7 Hz.

An example of the recorded sensor data when the robot rotated at a constant speed in an oval-shaped environment consisting of a high contrast, black and white striped wall is shown in Fig. 5. Whenever the robot was closer to the wall, a higher image flow was recorded in the field of view of the motion sensor. Hence, the mo-

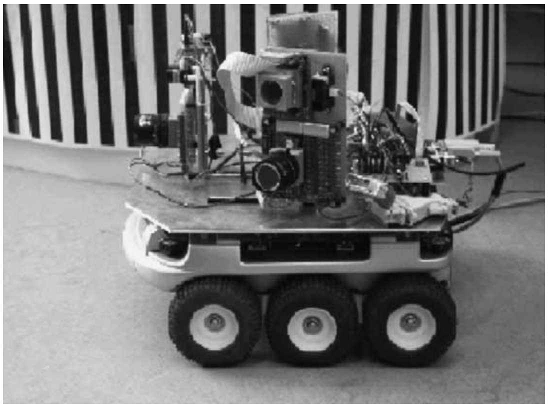

Fig. 4. Picture of the Koala next to a wall with vertical striped gratings. This texture is used in all the experimental runs described in Section 3.

tion signal oscillated at the turning frequency of the robot. We see a phase delay between the outputs of the different motion sensors because of the different physical locations of the sensors; on the right side, left side, and front of the robot. The output of the front motion sensor has a constantly higher value for the same object speed when compared to the other motion sensors because it has a smaller focal length lens. Data was also recorded for different robot speeds in this environment. The environment and path of the robot during the experiment can be reconstructed from the wheel and IR sensors (see Fig. 6).

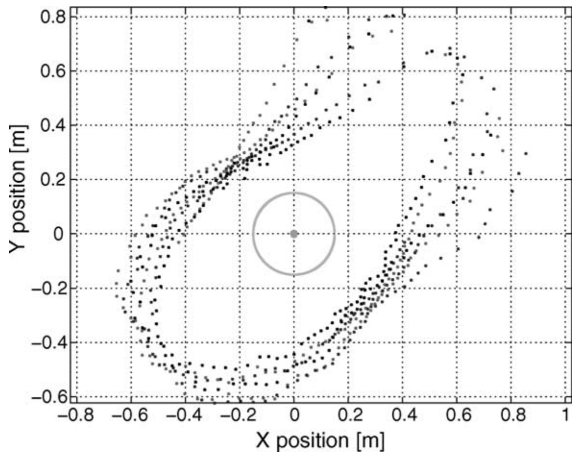

Fig. 6. The oval-shaped environment seen from above. Each dot represents the possible location of the oval-shaped environment based on the outputs of the IR range sensors and the wheel sensors. Errors from measurements in the wheel sensors lead to different possible locations of the environment for each complete rotation of the robot.

Fig. 7 shows another example of the responses of one of the motion sensors and IR sensors during an experiment when the robot did a straight run along a curved wall with the high contrast stripes. The sensors were normal to the wall. The plot shows that there is

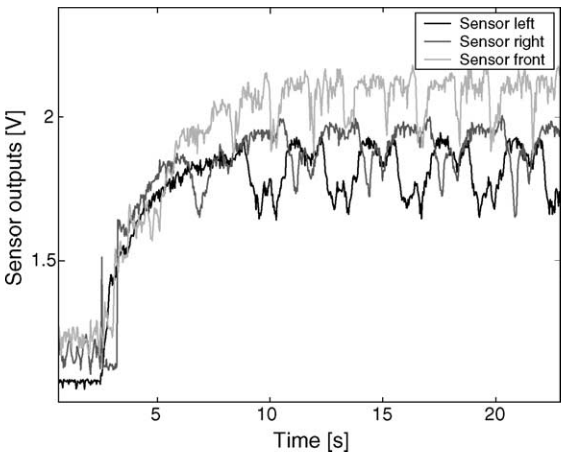

Fig. 5. Outputs of the three aVLSI motion sensors when the robot was rotating in place in an oval-shaped environment. Each motion sensor registered a higher reading when it was closer to the wall. Each oscillation in the output represented a complete 360° turn of the robot.

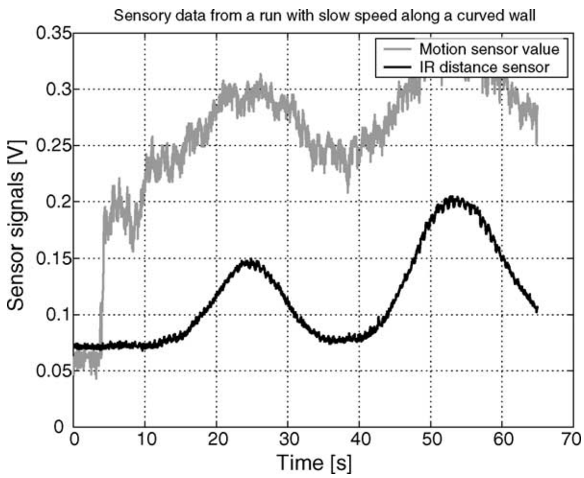

Fig. 7. Global motion output of an aVLSI motion sensor and output of the IR range sensor when the robot travelled along a curved striped wall at a constant speed. A higher IR range sensor signal corresponds to a closer wall.

a correlation between the output of the range sensor and the global motion computed by the motion sensor. Also note the relatively lower signal-to-noise ratio of the motion sensor signal compared to the IR range sensor signal. We also collected a large set of data in more complex experimental setups for training the neural network. In these instances, we varied both the speed and orientation of the robot in different environments (curved and straight walls) under different lighting conditions.

4. Network for distance estimation

We trained a neural network to predict the range output of the infrared red sensors from the outputs of the neuromorphic motion sensors, wheel sensors, and ambient light sensors. The range output is one measure of the physical property of the world which is invariant to the background illumination. This output can then be used to control the wheels of the robot.

We used the backpropagation algorithm in training the network. Different network architectures were also considered for their performance. The neurons have a sigmoidal activation function. The plots in Fig. 8 show an example where the trained network with two hidden layers and six neurons per layer is able to predict the range output of the IR sensor in an experimental setup shown in Fig. 4. (straight run along a curved wall) with different speeds of the robot. The top plot shows the outputs of the network during the training stage and the bottom plot shows both outputs during the evaluation stage. The mean-squared error (MSE) during training is 0.0078 and the MSE during validation is 0.1032.

We also used input data from a more complex situation where the robot travelled at different speeds along a curved path next to a straight wall. The motion sensor outputs, wheel sensor readings, and ambient sensor output recorded for a large number of different combinations of the left and right wheel speeds were presented as input to the network.

In this case, the output of the trained network was not as accurate during the validation stage as shown in Fig. 9, but the average value of the output still agrees reasonably well with the output of the range sensor. When the output of the trained network is somewhat inaccurate during evaluation, it can be caused by the lack of motion information from the sensors when the robot was changing its direction of motion, and therefore, drove at a very slow speed for a moment. The network might not have been sufficiently trained under conditions of decceleration and acceleration for it to make a more accurate prediction of the IR range output. However, overall, the network is able to used the inputs from the neuromorphic sensors.

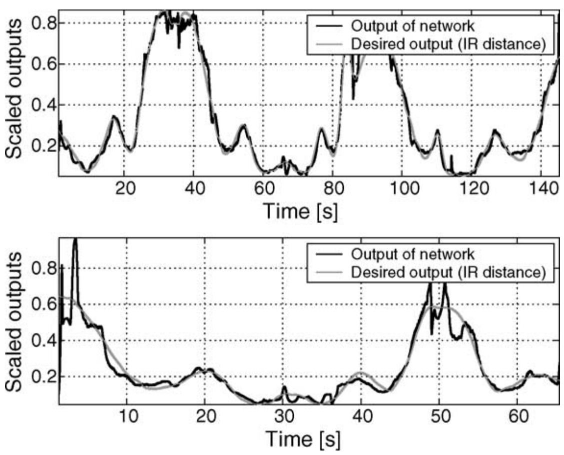

Fig. 8. Data from training set obtained under conditions when the robot travelled alongside a curved wall at different speeds. Training (top plot) and evaluation (bottom plot) of the network.

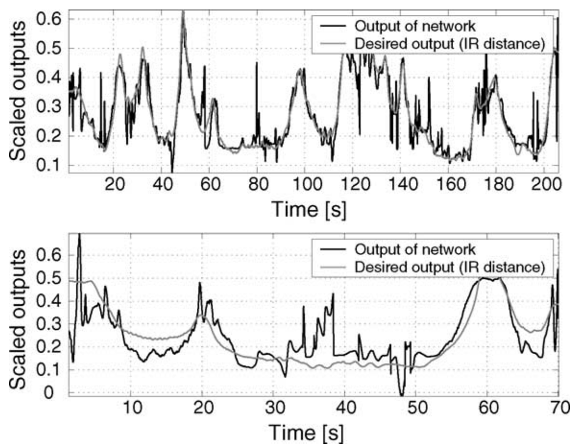

Fig. 9. Output of network and the IR sensor readings in the situation when the robot travelled along a curved path at different speeds next to a straight wall. Output of the network (top plot) after training and during evaluation (bottom plot) using the test data set.

5. Collision avoidance

We tested the use of the output of the trained network in a collision-avoidance task. Because of the differences in the output voltages and gain responses of the motion sensors on the left and right side of the robot, we trained separate networks for these two sets of sensors before downloading these networks to the on-board microcontroller. The network used in this case had two hidden layers with six neurons and four neurons each. In order to be able to meet the memory and computational specifications of the microcontroller, we replaced the sigmoidal activation function of the neuron with a simple linear-threshold function. We used the outputs of the networks in a collision-avoidance task while the robot moved in a rectangular arena with vertical striped walls as mapped in Fig. 10. The robot travelled in a straight path unless the outputs of the networks indicated that the robot was too close to the wall, that is, when the output of the network exceeds a preset threshold. This path taken by robot as shown in Fig. 10 showed that the range information as inferred from the motion sensors enabled the robot to perform this collision-avoidance task.

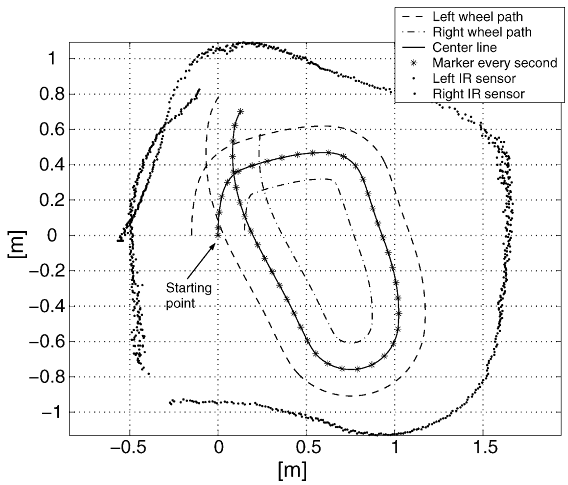

Fig. 10. Path of the robot in a rectangular arena with vertical striped walls. We used the outputs of two networks trained separately on the sensors on the left side and right side of the robot. The robot was programmed to travel in a straight line unless the output of the network indicated that the robot was too close to the wall. The dotted outline is a reconstruction of the rectangular area from the left IR sensor. The position of the robot (marked with asterisks) was inferred from the wheel speeds which were sampled at 30 Hz. The left and right wheel paths are marked by dashed lines and dashed-dotted lines, respectively.

6. Conclusion

Certain characteristics of neuromorphic motion sensors make them attractive for battery powered robots. These characteristics include processing speed, weight, size, and robustness to different lighting and speed conditions. However, their outputs cannot be used for direct mapping to the motors because the state of the system adapts to signal contrast and background intensities. This work is a preliminary investigation into neural architectures that can act as sensori-motor controllers for these types of sensors.

The trained neural network can produce a range output that is similar to the output from the IR range sensors, and this output can be used to guide the robot's movement around its environment. While we have used the network to predict the range output of the IR sensors in this work, this is not a necessary output of the network. The output could be the signal that drives the wheels of the robot. We would then use another input signal like a collision signal to teach the system to produce the right motor outputs.

In the future, we will describe the outcome of experiments which include the different types of motion sensors because these sensors can perform differently from each other based on their design. We will also investigate the performance of spiking neural architectures as a sensori-motor controller using inputs from neuromorphic sensors.

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