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Silicon Retina Sensing guided by Omni-directional Vision

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Abstract
In the RoboCup mid-sized league autonomous robots perform at high speed and there is a general need to increase the update rate of the overall optical sensory system. A way of combining a relatively new sensor-technology, that is optical analog VLSI devices, with a standard digital omni-directional vision system is investigated. The sensor used is a neuromorphic analog VLSI sensor that estimates the global visual image motion. The sensor provides two analog output voltages that represent the components of the global optical flow vector. The readout is guided by an omni-directional mirror that maps the location of the ball and directs the robot to align its position so that a sensor-actuator module that includes the analog VLSI optical flow sensor can be activated. The purpose of the sensor-actuator module is to operate with a higher update rate than the standard vision system and thus increase the reactivity of the robot for very specific situations. This paper will demonstrate an application example where the robot is a goalkeeper with the task of defending the goal during a penalty kick.

Keywords: neuromorphic, analog VLSI, optical flow, omni-directional vision, RoboCup.

1. Introduction

In our lab we exploit analog VLSI (aVLSI) technology in fast-wheeled mobile robotics applications, such as the RoboCup domain, where soccer-playing robots perform at high speed, i.e. in the order of 1 m/s. Our robots use a differential drive

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for movement, a pneumatic kicker for shooting, two small movable helper arms to prevent the ball from rolling away and a camera based vision system. The update rate of the overall optical sensory system is increased by the use of neuromorphic aVLSI sensors that have a continuous time mode of operation. Aspects such as speed, low weight, low power consumption and small size contribute to a more streamlined design and increase robot performance.

The output from aVLSI sensors is usually a low-dimensional analog signal. Sensors with a higher level of complexity typically operate in the kHz range and sensors with more elementary circuits in the MHz range depending on their internal time constants. The output signal of the sensors gives no information of what hypothetical object is tracked in the scene. Different objects can trigger the output from multiple aVLSI sensors by coinciding with their respective activity regions. In principle reading out a few analog signals is equivalent to the calculation of certain motion properties such as relative position or velocity for that particular object. By choosing different lenses the field of view of a particular sensor can be modified (cf. fig. 1). Multiple data streams can be collected from different sensors to achieve a more robust representation of the visual scene with sensor fusion. Active mechanics, e.g. movable mechanical parts on the robot, that need to be controlled by a very rapid "reflex like" mechanism are implemented as sensor-actuator modules, that is aVLSI sensors embedded with a micro controller as a module. This reduces the over-all reaction time for the active mechanics (cf. fig. 2).

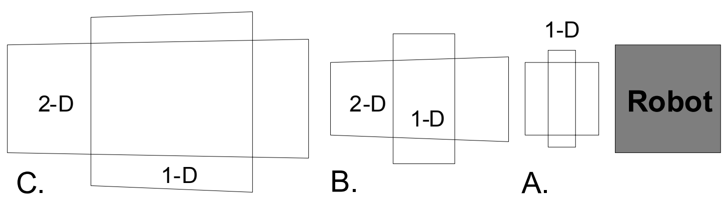

Fig 1. Fields of view for two types of silicon retina sensors (1-D and 2-D focal plane arrays). In “A“ a top down view is shown and in “B” and “C” the view angle is incrementally increased.

Experiments performed with a moving ball using aVLSI devices [1] show that those tasks are quite difficult to achieve due to the characteristics of the circuits, which usually have a quite coarse representation (number of pixels) and thus a narrow field of view. The winner-take-all (WTA) function that measures the optical activity of a winning characteristic e.g. contrast or visual motion on the contrary simplifies the processing task. To investigate the possibility to fuse the information from multiple aVLSI sensors by using an external arbiter, that in our case is a digital vision system equipped with an omni directional camera, could be a possible solution to robustify the sensory information. The omni directional arbitration system divides the surrounding scene into speciality areas corresponding to the field of view of particular silicon retina sensors. The arbitration system does object tracking in order to identify novel targets. The object tracking uses a colour threshold and region merging technique in order to determine the centroid of the particular colour marked objects used in the RoboCup environment. Object position prediction is achieved with a statistical approach where certainty of sensory cues is integrated over time. The predicted dynamics of the tracked objects is then in turn used to select the amount of autonomy for each particular sensor-actuator module.

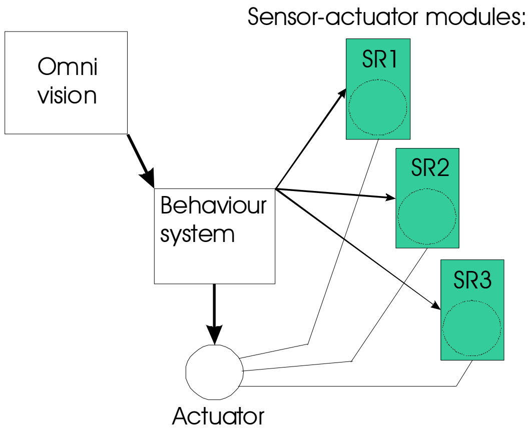

Fig 2. Omni-vision is used to map fields of view of silicon retina driven sensor-actuator modules to the surrounding scene. The behaviour system controls the activation of the modules through interaction with the vision-system.

In this paper we will focus on an example that uses a single aVLSI sensor that calculates global optical flow [2] to predict the motion of a ball during a penalty kick situation. The RoboCup goalie robot of our team will be used to demonstrate the combined use of a digital omni-directional vision system with a silicon retina device.

In sec. 2 our robot platform and the statistical approach that we used for object localization is explained. In sec. 3 the silicon retina device that will be used in our example is described. In sec. 4 the robot dynamics is described for performing the specific task of defending a penalty kick. In sec. 5 the work is summarized.

2. Our robot platform

The robot platform has actuators in the form of motors to drive and turn the robot and a valve to kick the ball pneumatically. Small robot arms attached to the left and right side of the robot to keep the ball in front of the kicker plate. Besides the two optical sensors, camera and retina, the robot has four infrared distance sensors, a contact sensitive bumper strip with rubber shield, and odometry at the actuated robot wheels. This is augmented by a gyroscope for fast turning movements. All of these peripheral devices are controlled by three 16 bit micro controllers manufactured by Infineon. They are interconnected with a bus interface named CAN, which is a standard in German automobile industry. Motor drive (current) control is performed with one of those micro controller modules [3]. A second supervises all of the analog signals in the soccer robot, e.g., distance readings of infrared sensors and also the A/D conversion of the silicon retina signals. The micro controller modules communicate to a small notebook PC via CAN-bus. The operating system can be either Windows or LINUX. The cyclic update rate is either 20 [ms] for Windows with dedicated vision hardware, or 33 [ms] for LINUX without dedicated vision hardware. In the future we will move towards a completely LINUX based platform.

2.1 Vision system

The vision system of our robot consists of a digital camera and a hyperbolical omni-directional mirror manufactured by Accowle. All image analysis is done on-board the notebook PC that also is running the behaviour system. The software package used is a public licensed image-processing package available from the Carnegie Mellon University [4]. This package does colour blob analysis and works well with the colour coded RoboCup environment.

The omni-directional mirror projects the surrounding scene onto a spherical map on the focal plane which is used to estimate the relative distance and orientation of the robot with respect to the goals and the ball. The angle variables are immediately available from the omni-mirror images without the need for any additional processing, while the distance variables only can be estimated after calibrating the system with a quite simple least squares (LS) technique. The mapping between pixel-distances on the image plane and physical distances on the field are reported in the below picture together with the LS estimated model (cf. fig. 3).

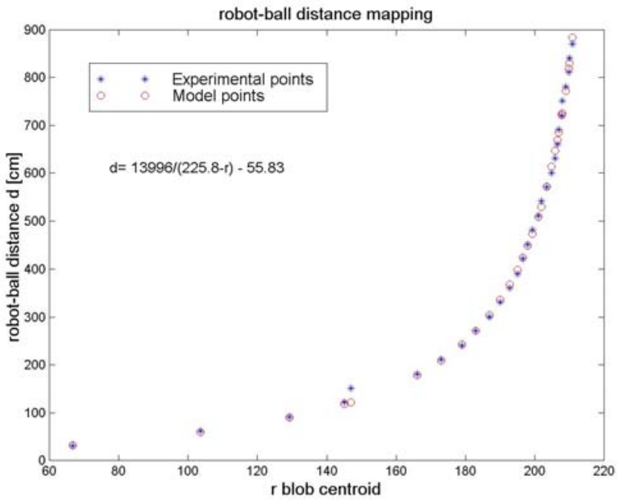

Fig 3. Distance vs. blob centroid fit for the red ball, raw data indicated as '*' and model points as 'o'. A similar fit is made for the goal distance.

2.2 Ball prediction

Predicting the trajectory of a fast moving ball is crucial for a goalie. In our approach we use the vision system to do a rough approximation of the ball trajectory in order to move the robot in a position where the silicon retina can sense the ball. The sensory input of the silicon retina is then used for fast short-term reaction on movements of the ball.

2.2.1 Estimating the current ball position

The position of the ball is estimated by measuring the center of the biggest blob in the camera picture. These measurements are not very reliable because of varying light conditions on the field causing shadows and reflections on the ball. Especially the distance to the ball is noisy as the center of blob is raised/lowered in the camera picture due to these effects. Furthermore coloured blobs not belonging to the ball sometime confuse the vision system; therefore the ball is estimated over time. This is done by computing a Gaussian probability density function for each measured ball prediction. The weight of older measurements is decreased by choosing a standard deviation that increases over time. The Gaussian probability density of the most recent ball position has the smallest standard deviation. By adding the probability densities of recently measured positions (and normalizing the result) one gets the density function for the most probable ball position. The probability of the ball being in a certain region of the field is computed integrating the density function over this region.

2.2.2 Predicting the ball using the probability density function

Using the probability density function, the probability of the ball being in a certain position is measured for a number of grid points located near the currently estimated ball position. The grid points, whose probability increase over time, denote the region where the ball can be expected in the next time steps. This statistical treatment is very robust even when facing various kinds of noise. The performance of the algorithm can be tuned to real-time requirements by choosing an appropriate number of grid points for which these probabilities are computed. It is important to note that this analysis is performed for the standard vision system. For the silicon retina driven sensor-actuator the raw output signal is used and this signal is then compared with a dynamic threshold.

3. Implementation of the sensor-actuator module

3.1 The 2-D optical flow sensor

The applied neuromorphic aVLSI circuit calculates smooth optical flow based on a model of visual motion that includes the intensity constraint, the smoothness constraint and a bias for slow visual motions [2]. The applied prototype chip has a spatial resolution of 10x10 pixels and potentially provides two output signals at each pixel, representing the components of the local optical flow vector. However, external control voltages bias the sensor such that it provides a global estimate of visual motion. That is, the smoothness constraint is assumed to hold faithfully for the complete image space. Using the 2-D optical flow sensor in such global mode of operation has two advantages: firstly, the output signal is low-dimensional because it consists only of two time-continuous analog voltages. This makes expensive scanning operations through the image space unnecessary and reduces significantly the amount of sensory data. Secondly, the collective computation of global optical flow amongst all sensor pixels increases the robustness of the output signal. Neuromorphic analog VLSI sensors are inherently prone with fix-pattern noise due to fabrication mismatch. Since the effect of mismatch results usually in a symmetrical error distribution, the collective operation approximately averages out the mismatch errors [6]. Although the output signal is continuous in time, the internal time-constant of the analog circuit limits the read-out rate for a correct estimate of global optical flow to about 1 kHz.

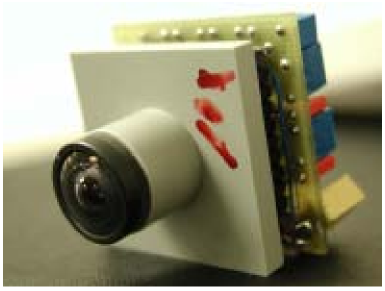

Fig 4. The smooth optical flow silicon retina sensor with three layers: lens, chip and supporting printed circuit board.

The analog output signals of the chip are linear with respect to the visual motion within a range of ±0.5 volt. This output range can be mapped to different ranges of visual motion according to an external control voltage. As shown in fig. 5 the possible detection ranges cover more than three orders of magnitude with a maximal speed detection of ~5000 pixels/sec. Figure 6 demonstrates the global optical flow estimate of the sensor as a function of the visual contrast of the object for a given visual motion. The output remains constant as long as the contrast of the object remains above 30 % [5].

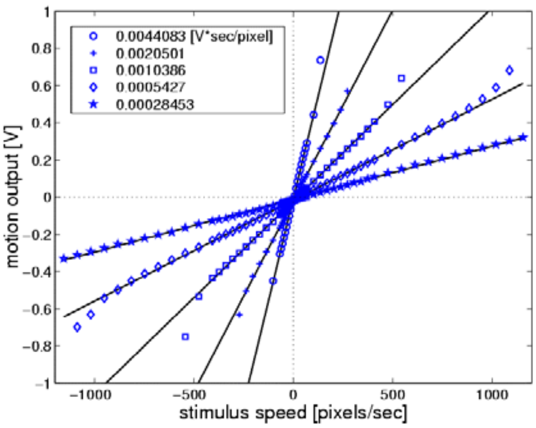

Fig 5. The linear output range of the 2D optical flow sensor can be adjusted to map the range of expected visual motion.

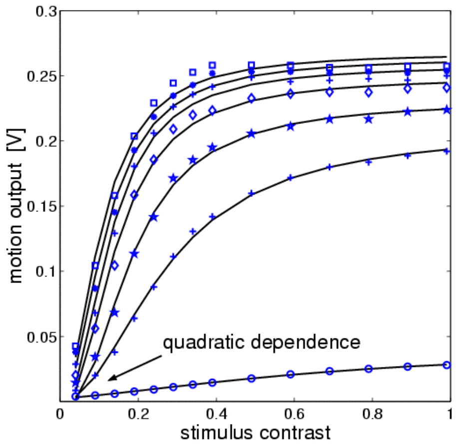

Fig 6. The dependence of the optical flow estimate on the visual contrast of the observed moving object. Above 30% contrast, the output is virtually independent of object contrast.

3.2 The optimal mapping of the output range of the optical flow sensor

For an optimal selection of the linear range the maximum focal plane velocity needs to be measured (cf. fig. 5). For a RoboCup goalie scenario the maximum speed of the ball is hard to estimate. There is no rules constraining the design of the kicking device of a robot, thus the optimal solution is to choose the range that can detect a minimum velocity that is determined not to allow the standard digital system to react in time, that is, a ball that is to fast for the standard vision system is the minimum velocity in the scope of the silicon retina based sensor-actuator module.

3.3 Integration of the optical flow sensor with the motor controller board

The dual output signal of the silicon retina device is sampled by an A/D-converter on the micro-controller board that controls the actuators of the robot wheels. The silicon retina signal is analysed on the micro-controller in order to determine if action needs to be taken.

3.4 The functionality of the sensor-actuator module

The sensor-actuator module is confined to the motor-controller board of the robot and activated or inactivated through a message over the CAN-bus. This message is sent by the top-level behaviour system. This approach scales nicely and several such modules can be integrated and controlled by the top-level behaviour system, although only one such module is described in this paper.

4. A RoboCup goalie example

4.1 Robot Model

Given the fast servomotor loop controlling the wheels speed, the guidance control law is designed on a kinematics level only. With reference to the below figure

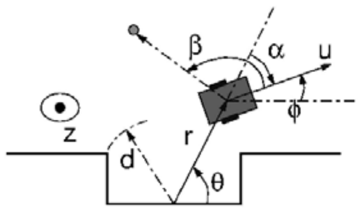

Fig 7. The robot with heading α, ball angle β, velocity *u* relative to the goal at absolute reference angle θ and the minimum robot radius *d* as seen from above.

the kinematics equations of the robot can be written as:

$$\dot{r} = u\cos\alpha$$
$$\dot{\alpha} = \omega - \frac{u}{r}\sin\alpha \qquad (4.1.1\text{-}3)$$
$$\dot{\theta} = \frac{u}{r}\sin\alpha$$

and it can be shown [6] that the guidance law:

$$\omega = \frac{u}{r}\sin\alpha + \gamma\left(\pi/2 - \alpha\right) - hu(d-r)\frac{\cos\alpha}{\pi/2 - \alpha} \qquad (4.1.4\text{-}5)$$
$$u = u_{\max}\cos\beta \quad : \quad \gamma, h, u_{\max} > 0 \ \text{(constants)}$$

guarantees that the robot will be asymptotically driven on a circle of radius d aligned with the ball. The convergence is guaranteed as long as $r>0$ which, in practice, is always the case.

4.2 The sensor-actuator module

When the robot is in place, at the pre-calibrated distance to the ball, the sensor-actuator module is activated. This module will wait for the sensory signal to achieve the limit level determined to be a fast moving ball. Optimally the ball then has a velocity that is faster than the save capability of the goalie with the ordinary vision system.

5. Summary and conclusions

Analog optical VLSI devices could provide an elegant solution for various problems in mobile robotics. The lightweight nature of the sensors, their low power consumption and their substantial on-chip calculation capabilities raises the opportunity to design smaller and faster mobile platforms with advanced scene analysis capabilities. Fast intelligent sensor devices like silicon retina devices are especially advantageous for reactive behaviour based robotics [7], where sensors are influencing actuators in a direct way. The use of an omni-directional vision-system to direct the attention span of the robot could be one possibility to integrate the sensor actuator modules in a more general behaviour pattern such that different sensor-actuator modules are activated according to the relative position, or motion, of visual cues mapped by the omni-directional vision system. The special case treated in this paper that involves our goalie robot suggests that this approach could be well suited for the task of defending a penalty kick in the RoboCup mid-sized league.

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