Discovering Motion Flow by Temporal-Informational Correlations in Sensors

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Abstract

A method is presented for adapting the sensors of a robot to its current environment and to learn motion flow detection by observing the informational relations between sensors and actuators. Experiments are performed where the robot learns to detect motion flow and perform simple motion flow tracking starting from unstructured sensory input.

1. Introduction

One of the amazing capabilities of many sensory systems is the ability to adapt to the current environment. For example, consider reading this paper outside, where the black print reflects considerably more light to the eye than the white paper does indoors. Still, the print looks black both indoors and outside and the white paper looks white both outside and indoors. This adaptation to the light conditions of different environments is believed to be realized partly by the lateral connections of horizontal cells in the retina (Purves et al., 2001), and enables the visual processing system to perceive relative differences in light intensity instead of just absolute differences.

This paper presents a similar sensor adaptation mechanism which enables a robot to adapt its sensors to its current environment by on-line estimation of the statistical structure of the robot's sensory environment. This is similar to adaptation in the fly's visual system (Laughlin, 1981) and is discussed in more detail in (Olsson et al., 2005b). Based on this adaption we present a method which enables a robot to "discover" and learn sensorimotor grounded motion flow detection from unstructured sensor data. The method for learning motion flow detection is based on body babbling cf. (Meltzoff and Moore, 1997) whereby the robot discovers relations between its motors and temporal correlations in its sensory input, based on the method presented in (Olsson et al., 2005a). But, while (Olsson et al., 2005a) use the optical flow algorithm of (Lucas and Kanade, 1981) to detect motion flow, we here present a method to detect motion flow based on the sensory reconstruction method (Olsson et al., 2004), extended by considering temporal correlations between sensors. This is loosely inspired by the way motion detection seems to work in the fly, where sensors are connected to correlators using temporal delays (Harris et al., 1999). The method is exemplified by experiments performed with a real robot where the robot starts by learning the structure of its sensors, then learns to detect motion flow, and finally manages to perform simple object tracking based on motion flow detection.

The rest of this paper is structured as follows. Section 2 presents the proposed methods of sensor adaptation, learning of motion flow detection, and object tracking based on these methods. In section 3 results from experiments with a real robot learning to detect motion flow and performing simple object tracking is presented. Finally section 4 concludes and points out some ideas for future work.

2. Method

In our experiments a visual sensor is modeled as discrete random variable S_i and the possible input values to each sensor is in the alphabet $\mathcal{S} = \{0, 1, \ldots, 255\}$. Each sensor reads one value, $s_{i,t}$, at each time step t. The visual layout of the sensors is unknown and the sensory reconstruction method (Olsson et al., 2004) is used to reconstruct the layout of the sensors. It is important to note this method cannot find the orientation of the visual field, only the spatial relations between sensors. An example of this is shown in figure 1, where the the real orientation had sensor 1 in the upper left corner and 64 in the bottom left corner.

2.1 Sensor Adaptation

In (Olsson et al., 2005b) entropy maximization is discussed as a method for compressing sensor data while maintaining correlations between sensors. To compress a sensor S_i, one method is binning, whereby the space of possible inputs is divided into a number N of equidistributed bins, and the input is mapped to a smaller alphabet $\mathcal{T}$. The problem with this method is that the distribution of sensory input of natural scenes rarely is uniform, which means that this is a non-optimal encoding. Instead, Laughlin found in 1981 (Laughlin, 1981) that the fly seem to encode contrast using the principle of entropy maximization. Entropy maximization means that the bins are selected in such a way that each bin is likely to contain the same number of possible sensor readings, or more formally

$$\forall c \in \mathcal{T},\ P(s_{i,t} = c) \approx \frac{1}{|\mathcal{T}|} \qquad (1)$$

In (Olsson et al., 2005b) each sensor adapts its bins to the current environment by constantly estimating the distribution of its most recent inputs. This enables the robot to find correlations not found by normal binning, which is utilized in the motion flow detection described below.

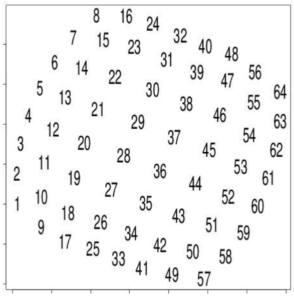
2.2 Learning Motion Flow Detection

In the sensory reconstruction method (Olsson et al., 2004) each sensor is seen as a time series and treated as a random variable. When the joint entropy,

$$H(X,Y) = -\sum_{x\in\mathcal{X}}\sum_{y\in\mathcal{Y}} p(x,y)\log_2 p(x,y), \qquad (2)$$

is computed between two sensors S_1 and S_2 to compute the *information distance* (Crutchfield, 1990), $d(X,Y) = H(X|Y) + H(Y|X)$, the value at time t in sensor S_1 is usually compared to the value at the same time t in sensor S_2. Now, consider shifting the values of sensor S_2 in time, where the value at time t in sensor S_1 is compared to the value at time $t+n$, where n is a constant, in sensor S_2. This enables us to find temporal correlations between sensors, which can be used to discover motion flow in the sensors.

To learn how motion flow causes temporal correlations in sensors we use the following method illustrated by an example. Given that the visual layout has been found, select a sensor in the center of the map, for example sensor 29 in the discretized map in figure 1. Now the robot can perform movements in different directions and save the sensor data associated with each motor setting. Sensoritopic maps are created for the data of each direction with different values of the shifting constant n, where n always is 0 for the center sensor, in this case sensor 29. For each direction there will now be a map where the informational distance between the center sensor and one other sensor is 0 or close to 0 if there is motion flow. The spatial relation between this sensor and the center sensor describes the direction of that particular flow. For example, if the distance between the center sensor, 29, and 30 is 0, this signifies that the flow is moving upwards, since sensor 29 at time t is correlated with sensor 30 at time $t+n$.



(a) Sensoritopic map

8	16	24	32	40	48	56	64
7	15	23	31	39	47	55	63
6	14	22	30	38	46	54	62
5	13	21	29	37	45	53	61
4	12	20	28	36	44	52	60
3	11	19	27	35	43	51	59
2	10	18	26	34	42	50	58
1	9	17	25	33	41	49	57

(b) Reconstructed discrete map

Figure 1: Figure 1(a) shows the sensoritopic map of the visual field found by the sensory reconstruction method and 1(b) the discretized sensor map.

2.3 Object Tracking

Given that the robot now knows what direction of movement that causes a certain motion flow in its visual sensors, it can now use this knowledge combined with the learned sensorimotor laws (Olsson et al., 2005a) to perform simple motion tracking. For example, if the robot detects a motion flow which is similar to the flow generated by moving its head down, it can track this flow by performing the inverse of that movement. The tracking can either be performed after waiting a number of frames and averaging the motion flow, or by computing the flow between each frame. This adds the problem of motion flow that comes from the movement of the robot itself, which might be solved by subtracting the known motion flow of a certain movement from the motion flow experienced by the robot.

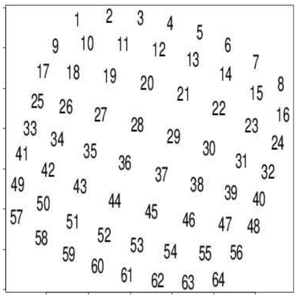
3. Experiments

In the experiments we have used a SONY AIBO[1] robot. The robot was sitting on a bench in the lab, see figure 2, connected to a computer using a dedicated wireless network transmitting 30 frames of sensor data per second. The camera of the AIBO captures 88 by 72 pixels. This image was pixelated to an

[1]AIBO is a registered trademark of SONY Corporation.

Figure 2: The SONY AIBO sitting in the experimental set-up trying out various actuator settings.

8 by 8 image of the intensity which gives a total of 64 sensors. The first step was to reconstruct the visual field using the sensory reconstruction method like in (Olsson et al., 2005a) by only moving the head. Figure 3(a) shows the reconstructed visual field and figure 3(b) a discretized version.



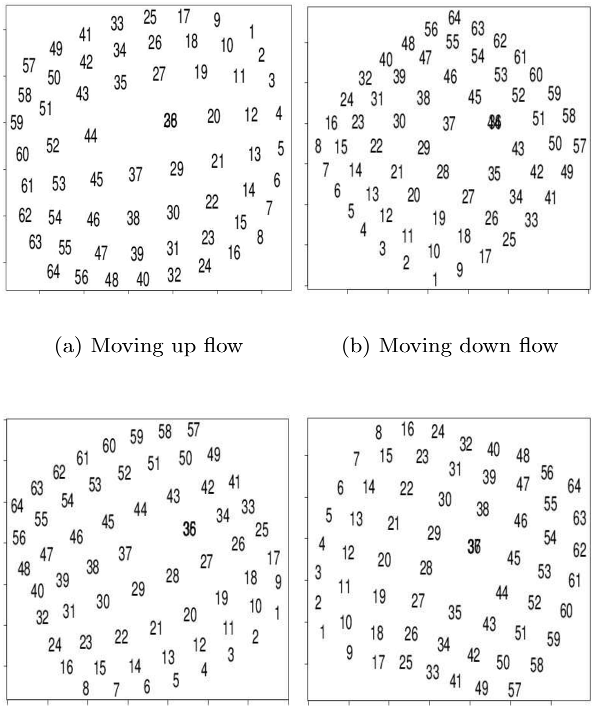
(a) Reconstructed map

1	2	3	4	5	6	7	8
9	10	11	12	13	14	15	16
17	18	19	20	21	22	23	24
25	26	27	28	29	30	31	32
33	34	35	36	37	38	39	40
41	42	43	44	45	46	47	48
49	50	51	52	53	54	55	56
57	58	59	60	61	62	63	64

(b) Discrete map

Figure 3: Figure 3(a) shows the reconstructed visual field and 3(b) the discretized version used for the motion flow detection.

The next step was to discover motion flows as described above. In order to simplify the experiment and results only four possible movements were allowed by the head: up, down, left, and right, using only one speed. Each possible movement was performed 30 times and all the data from each movement saved to one file per movement. Then sensoritopic maps for each movement were created where all sensors, apart from sensor 36, were shifted in time one or two time steps to find what motion flow in the sensors that each movement induced. Figure 4 shows examples of the created maps for all four movements. In each of these figures we find that sensor 1 is located in different corners of the sensory layout, while the ordering of the sensors is the same. This is due to the fact that the sensory reconstruction method does not find the real physical order of sensors, just their positional relations. We also find that for each map, the non-shifted sensor, 36, is in exactly the same position as another sensor, which means that these two sensors are completely correlated. For example, in figure 4(c) we find that sensor 36 is completely correlated with 35. Looking at figure 3(b) sensor 35 is positioned to the left of sensor 36, which means the flow is from the right to the left. Similarly, if we look at for example figure 4(b), sensor 36 is completely correlated with sensor 44, which indicates a downward flow, which is the case since this flow was in fact induced by downward movements by the robot. Given the knowledge what motor action that causes a particular flow, basic motion flow tracking can now be performed. Simple experiments verifying the method were performed that showed tracking of a moving red ball and hand in an otherwise static environment.



(a) Moving up flow

(b) Moving down flow

(c) Moving left flow

(d) Moving right flow

Figure 4: Figure 4(a) to 4(d) shows the sensoritopic maps with a time-shift of 1 for all sensors but sensor 36. The direction is found by finding which sensor the center sensor 36 is completely correlated with. For example, in 4(b) sensor 36 is complete correlated with sensor 44. Looking at the discretized map in 3(b) we find that this corresponds to moving down.

4. Conclusions

This paper has presented a method for sensor adaptation that compresses the information in individual sensors while maintaining correlations between sensors. The adaptation makes the motion flow discovery algorithm more robust to noise and perform better in changing conditions. From the compressed sensor data motion flow detection is learned by shifting the compressed sensory channels in time while the robot performs various actuator settings similar to body babbling found in infants. This allows the robot to learn how correlations over time in the sensors are related to the actuators, and as a by-product, the direction of motion flow given a certain movement. Using this method a robot can develop from unknown sensors and actuators to being able to perceive motion flow. Using this skill simple motion flow tracking is possible, as was verified in the presented experiments.

In our view, the presented method should not be seen as a replacement for traditional motion flow detection techniques. It is rather the principles of discovering motion flow and the relation between sensors and actuators by information theoretic means which are important. The robot develops from a state with unknown sensors and actuators by experimenting with its actuators and their effect on the sensors to being able to perform simple tasks. This makes the robot robust to various changes in the environment and sensors, as it can re-adjust its model of sensors and actuators at anytime by once again performing the same algorithm. Another useful area for the presented method is detecting and adjusting to morphological changes, for example changes in effector capacity and the loss or gain of sensors. For example, if extra visual sensors are added to the robot, they can be added to the visual field automatically, based purely on their informational relations with other sensors. Conversely, if the robot experience sensor failures it can detect that by the new relations between the broken sensors and the functional ones. Thus sensory adaptation and sensorimotor control can be responsive to ontogeny and experience of the robot.

There are plenty of issues to consider for future work. One interesting area of research is to look at motion flows in different sensory channels, e.g. the green, red, blue sensors found in cameras. Depending on the statistics of a certain environment one channel might be more efficient than another one to detect motion flow in that particular environment. One question is how to find the best channel for a certain environment. There is also more work to be done in the area of morphological and sensor changes as discussed above. Finally it should also be noted that the presented method not only can be applied to visual sensors, but also to other modalities where motion flow is possible - for example infrared sensors and haptic sensors. This is also something that will be considered in future work.

Acknowledgments

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