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Principal component analysis for unsupervised calibration of bio-inspired airflow array sensors

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Abstract. This paper describes the automatic calibration of a set of air flow sensitive sensors on a robot exposed to unknown random air flow stimuli. This might support the idea that the cricket cercus neural system in the terminal abdominal ganglion is evolved by learning. The algorithm makes use of the singular value decomposition (SVD) and the known reduced model dimension of the system for learning the sensor array setup. The absolute orientation of the array can only be found in function of a reference flow or reference sensor which must be calibrated manually. When only a change in airflow measure is needed, the reference sensor can be left uncalibrated.

1 Introduction

Inspired by the ontogenetic development of a cricket cercus flow-sensing system, a self-calibrating robot was constructed. [3] The robot is equipped with a set of flow sensors which each measure the flow velocity in a particular direction, similar to the way a cricket is equipped with a set of filiform hairs on its cerci at the back of its abdomen. These hairs move with the air flow. The cricket has neurons that encode the rotation angle of each individual hair. Given this rotation an estimate of the air flow can be generated [6]. The hairs are able to move only in a plane [5]. This way, each hair encodes for the airflow component along a particular direction. When this preferred direction is known multiple methods can be proposed to reconstruct the air flow and estimate the direction of the air flow [9]. This way a cricket is able to detect an approaching predator by the predator generated air distortion and jump away in the most favorable direction [1]. In the terminal abdominal ganglion a neural map was found which encodes for the direction of the approaching air flow [7]. We derive an algorithm to automatically and precisely combine the output of the multiple uncalibrated sensors and generate a direction estimate of the airflow direction. The algorithm is able to automatically calibrate a set of sensors assuming that all the sensors are stimulated by a common airflow stimulus. The stimulus ensemble can be completely arbitrary. The only conditions that have to be fulfilled are that the stimulus is the same for all the hairs and that the stimulus ensemble is sufficiently diverse so that stimulus variation in all 3 spatial dimensions is present in the trainings-data. Conditioning of the problem is improved by adding more stimuli from more diverse directions. The theoretical claims were verified in practice by automatically calibrating the sensors on a robot equipped with an array of 11 direction sensitive air flow sensors.

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2 Array of airflow sensors

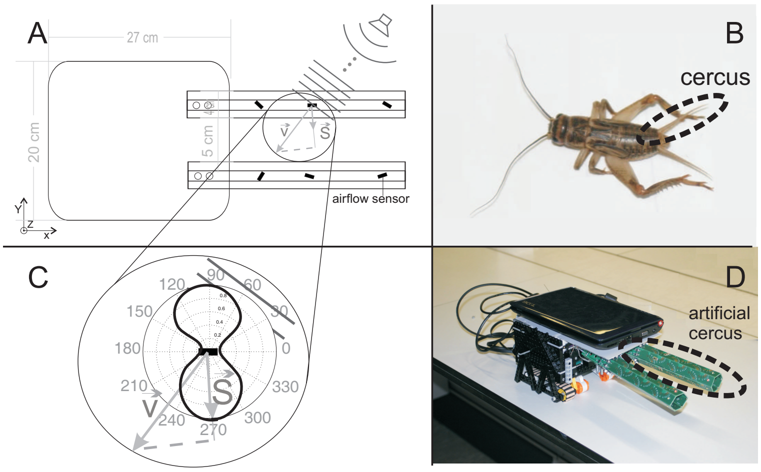

Figure 1: A: top view drawing of the robot hardware setup, B: cricket (Acheta Domesticus), C: magnification of the airflow sensor with directivity pattern in polar plot and vector drawing of model parameters. D: photo of robot

The robot is equipped with 11 Micro-flown sensors [4] distributed over the two artificial cerci (see figure 1). This sensor is capable of measuring very small (70 nm/s) [6] air flow perturbations. The sensor is based on differential hot wire anemometry resulting in a figure of eight directivity response of the sensor as a function of the azimuth and elevation angle. The output y_i of the sensor i can be well approximated as a cosine function. i.e. the dot product of the sensor configuration vector $\vec{S}$ and the wind stimulus vector $\vec{V}$.

$$y_i = \vec{S_i} \cdot \vec{V} \tag{1}$$

in which $\vec{S_i} = [S_{xi} S_{yi} S_{zi}]$ is the unity vector pointing in the direction of the sensor's preferred airflow direction and $\vec{V} = [V_x V_y V_z]^T = \left|\vec{V}\right| \cdot \vec{e_v}$, is the vector representing the wind direction $\vec{e}_V$ and amplitude $\left|\vec{V}\right|$.

When multiple samples are collected at different time-steps 1...J, these samples can be written down in a matrix as :

$$Y = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1J} \\ y_{21} & y_{22} & & y_{2J} \\ \vdots & & y_{ij} & \\ y_{I1} & y_{I2} & & y_{IJ} \end{bmatrix} \tag{2}$$

and the array-output modeled as:

$$Y = S \cdot V \tag{3}$$

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with S= $\begin{bmatrix} \vec{S_1} & \dots & \vec{S_I} \end{bmatrix}^T$ and V= $\begin{bmatrix} \vec{V_1} & \dots & \vec{V_J} \end{bmatrix}$.

3 Algorithm description

Given matrix equation **??** the problem to solve is: given the data matrix Y, find both S and V. For this problem there are of course multiple solutions, but surprisingly, only a few extra constraints have to be given to make the solution unique.

These extra constraints are:

- S is a Ix3 matrix with I the total number of individual airflow sensors. (and 3 the number of dimensions to describe the sensor preferred direction, when all the sensors preferred directions would be placed in a plane, S would have dimension Ix2)
- V is a $3 \times J$ matrix with J the total number of sample-points per sensor.
- $S_{ix}^2 + S_{iy}^2 + S_{ix}^2 = S_{gain}^2$, for now we assume the gain of the sensors to be $S_{gain} = 1$,

These constraints give already a unique solution up to an orthogonal transformation, this is enough to find a unique wind-vector change $\triangle V$. In other words, the absolute airflow direction can not be given, but the relative airflow direction, the difference in direction between two measurements can be given. When the absolute direction of the airflow is required, this last unknown orthogonal transformation has to be found, by fixing the array coordinate system to the world reference system for which multiple procedures exist.

3.1 Algorithm

The main procedure for calculating the sensor-configuration of a set of sensors is as follows:

- Acquire samples in the data matrix: Y
- remove mean: Y=Y-E(Y), with E(Y) the DC voltage offset of the sensor.
- calculate covariance matrix: $R = \frac{1}{(J-1)} Y \cdot Y^T$ with J the number of samples per sensor.
- calculate eigenvectors K from the eigenvector decomposition of this covariance matrix: R so that $R \cdot K = K \cdot D$
- Take the three eigenvectors who accompany the three highest eigenvalues E_1, E_2, E_3 and multiply by their square root.

$$K_1 = K(:, 1:3) \cdot \begin{bmatrix} \sqrt{E_1} & 0 & 0 \\ 0 & \sqrt{E_2} & 0 \\ 0 & 0 & \sqrt{E_3} \end{bmatrix} \text{ so } K_1 \text{ is a } I \times 3 \text{ matrix}$$

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- find K_2 with $K_2 = K_1 \cdot C$, so that $\forall i : norm(K_2^i) == 1$ with K_2^i the i th row vector of K_2 and C a 3×3 matrix. Local minima are present in this 9 dimensional search space. Numerical experiments showed that the Nelder-Mead simplex method reliably converges when a few (4) searches are started from different random initialization values.

It can be shown that $K_2 = S \cdot T$ with T an arbitrary orthogonal transformation [8].

3.2 Efficient implementation

Please note that there is no explicit singular value decomposition calculated in the algorithm as is done with most principal component algorithms. Instead, for the sake of memory efficiency, the implementation is based on the eigenvector decomposition of the covariance matrix. The advantage is that during learning, not the entire data matrix has to be stored, but only the much smaller covariance matrix, i.e., a covariance matrix of size 11×11 instead of a data matrix of size $11 \times 1.500.000$ for a typical calibration experiment. The covariance estimation $R_{(n-1)}$ can be easily updated by the new measured covariance matrix R by the following recursive average update rule.

$$R_n = \frac{(n-1)}{n} R_{(n-1)} + \frac{1}{n} R \tag{4}$$

with n the iteration number. The covariance matrix R can be updated per sample $n = 1..J$ or after a specific set of data (length L) is acquired $n = 1.. \lfloor J/L \rfloor$, depending on the targeted hardware this set size can be optimized for efficient data throughput. Here 15 seconds of data acquisition were used between each update.

4 Experimental results

An unsupervised learning experiment was conducted to verify the validity of the model. The robot was placed on the edge of a table so that the cerci could be stimulated from all directions. A sub-woofer producing a sound-/flow-field of 40 Hz was used as stimulus. The sub-woofer was moved in a random fashion trough space so that the robot gets stimulated from different directions. The robot acquires the data from the 11 sensors at 5000 samples/sec; 12 bit resolution. This data is processed as described above. Filtering was performed to extract the 40Hz sound-channel thereby maximizing the signal/noise ratio. This is not necessary but reduces the amount of iteration steps required for convergence.

A first indication of model validity can be obtained by analyzing the singular values from the SVD. It is assumed that only three nonzero singular values can be found according to the model. In a typical experiment we find singular values: 50.79, 32.06, 16.23, 0.477, 0.3238, 0.0662, 0.0282, 0.0140, 0.011, 0.0012. The three first singular values explain almost 98.9% of the collected data, so it can be assumed that the model explains the real measurements to a high degree

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of accuracy. Then, given this data decomposition, a model was extracted to find the sensor configuration matrix via the Nelder-mead simplex search. In figure 2, it can be seen how the random initialized sensor sensitivity vectors converge towards a previously learned setup. Every step is the accumulation of 15 seconds of new data with a randomly moved sub-woofer. After 6 steps, 6×15 sec, convergence of the algorithm was found (see figure 3A).

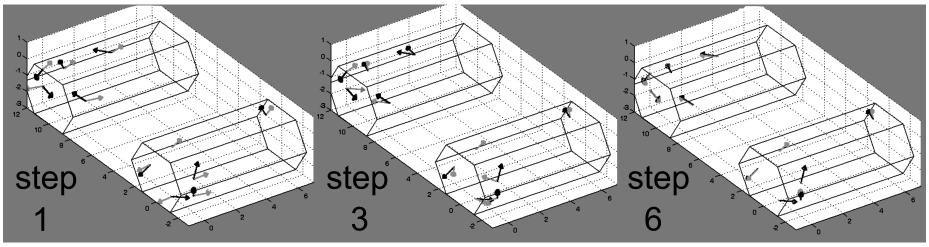

Figure 2: 3D representation of the converging of the sensor configuration vectors in function of their different convergence steps.

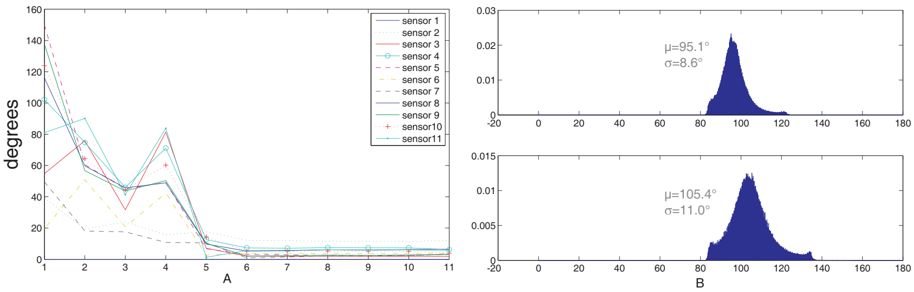

Figure 3: A: Error (degrees) per sensor as a function of iteration index for the unsupervised learning algorithm. B: Airflow direction estimate histogram, (top) manual configuration, (bottom) learned configuration

When convergence was reached, a verification of the sensor configuration file was done by estimating the position of a stationary sub-woofer with both a manually configured sensor-configuration and with a learned sensor-configuration. The least mean square direction estimate was calculated [9], as shown in figure 3B. We observe that the histogram of the estimates based on the learned configuration resembles the one based on the manually determined configuration quite well. The slightly increased variance is most likely due to biases in the learned preferred directions caused by small non-uniformities of the airflow over the cercus.

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5 Conclusion

We have shown that a mechanosensor array can be automatically calibrated by applying random airflow stimuli, given that the stimulus ensemble covers all three spatial dimensions. Because of the considerable changes to the cerci in the course of ontogenetic development of the cricket we conjecture that crickets might use a similar learning scheme to determine the preferred directions of the hairs on their cerci based on the randomness of natural airflow stimuli. Interestingly, it was shown recently [2] that a calculation equivalent to principal component analysis can be executed on spiking neural networks driven by a biologically plausible learning mechanism.

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