An Adaptive Neural Mechanism with a Lizard Ear Model for Binaural Acoustic Tracking

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Abstract. Acoustic tracking of a moving sound source is relevant in many domains including robotic phonotaxis and human-robot interaction. Typical approaches rely on processing time-difference-of-arrival cues obtained via multi-microphone arrays with Kalman or particle filters, or other computationally expensive algorithms. We present a novel bio-inspired solution to acoustic tracking that uses only two microphones. The system is based on a neural mechanism coupled with a model of the peripheral auditory system of lizards. The peripheral auditory model provides sound direction information which the neural mechanism uses to learn the target's velocity via fast correlation-based unsupervised learning. Simulation results for tracking a pure tone acoustic target moving along a semi-circular trajectory validate our approach. Three different angular velocities in three separate trials were employed for the validation. A comparison with a Braitenberg vehicle-like steering strategy shows the improved performance of our learning-based approach.

Keywords: Binaural acoustic tracking, correlation learning, lizard peripheral auditory system

1 Introduction

There are several applications where acoustic target tracking can be useful. Human-robot interaction in social robots is deemed to be richer if the robot's acoustomotor response maintains its auditory focus on a subject of interest [16,19]. During phonotaxis a robot can localise acoustic sources and navigate towards them [22].

Acoustically tracking a sound source moving with fixed but unknown speed along a fixed but unknown trajectory requires that the relevant sound source must first be successfully localised in space and then this localisation must be repeated sufficiently fast to minimise the static tracking error. Localising a sound can be done using both interaural intensity difference (IID) and interaural time difference (ITD) cues, requiring a multi-microphone setup with at least two microphones. Generating IID cues requires a sufficiently large solid obstruction between the individual microphones to create sound shadows, while ITD cues can be generated without the need of such obstructions. Here we focus on acoustic tracking of a moving sound source using only ITD cues. A sound source moving with a given velocity in a given direction with respect to the microphones generates dynamic ITD cues. The instantaneous values of these cues vary with the relative position of the sound source and the speed with which they vary depends on the relative speed of the sound source. Tracking a moving sound source thus requires transforming these relative position- and velocity-dependent cues into a desired behaviour such as robotic orientation or phonotaxis.

Acoustic target tracking has been approached via a number of techniques [17,7,18,8,11,24,12,13,25]. All techniques use multi-microphone arrays in various geometric configurations such as linear, square, circular or distributed arrays to extract ITD cues for localisation. Computationally intensive algorithms are also a common feature among these techniques.

We present a acoustic tracking system using two microphones that implements a neural learning mechanism. The mechanism is adapted from Input Correlation (ICO) learning [21] which is derived from a class of differential Hebbian learning rules [10]. The ICO learning architecture is characterised by its stability, fast convergence and adaptability via synaptic plasticity all of which are desirable qualities in an acoustic tracking system. The proposed learning mechanism is coupled with a model of the lizard peripheral auditory system [26] which provides sound direction information. The peripheral auditory model has been extensively studied via various robotic implementations as reviewed in [23].

The paper is organised in the following manner. Section 2 describes the lizard ear model, its directional response and its role in sound localisation. It also briefly describes ICO learning, which is the basis for the learning mechanism presented in Sec. 3. The experimental setup is also described in Sec. 3. Section 4 presents the results of the proposed approach in tracking a moving sound source. Section 5 summarises the research and discusses future directions.

2 Background

2.1 Lizard Peripheral Auditory System Model

Lizards such as the bronze grass skink or *Mabuya macularia*, and the tokay gecko or *Gekko gecko* as depicted in Fig. 1(a), are known for their remarkably directional peripheral auditory system [3,4]. Thanks to an internal acoustical coupling of the two eardrums of the animal, formed by efficient transmission of sound through internal pathways in the head as shown in Fig. 1(b), the lizard ear achieves a directionality higher than that of any known vertebrate [3].

The lizard peripheral auditory system is small in size (the distance between the eardrums for most lizard species is 10-20 mm) with respect to the sound wavelengths (340-85 mm, corresponding to 1–4 kHz) for which it exhibits strong directionality [4]. For these wavelengths the sound pressure difference between the ears is negligible due to acoustic diffraction around the animals head, thus generating negligible (1–2 dB) IID cues. The system thus converts μs-scale interaural phase differences (corresponding to ITDs) between incoming sound waves

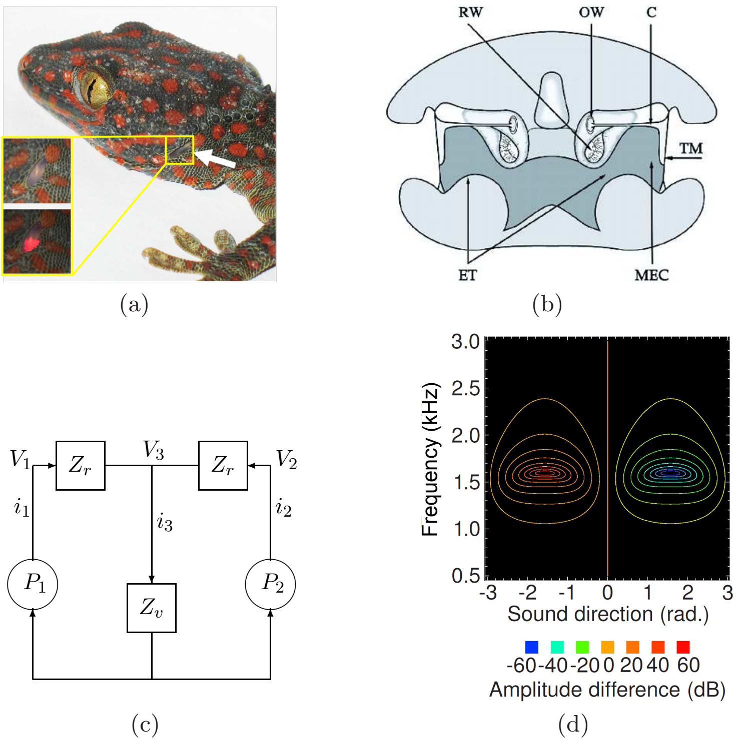

Fig. 1. (a) An eardrum visible on the side of the gecko head (redrawn from [4]). (b) Early cross-sectional diagram of the lizard (*Sceloporus*) auditory system (taken from [3]). (c) Ideal lumped-parameter circuit model (based on [6,5] and taken from [28]). (d) Contour plot modelling binaural subtraction (refer to Eqn. (2)) of the ipsilateral and contralateral responses (redrawn from [28]).

at the two ears due to the physical separation, into relatively larger (up to 40 dB) interaural vibrational amplitude differences [3] which encode information about sound direction relative to the animal. Each eardrum's vibrations are the result of the superposition of two components – an external sound pressure acting on its outer side and the equivalent internal sound pressure acting on its inner side, generated due to sound interference in the internal pathways. This process leads to contralateral (away from the sound source) cancellation and ipsilateral (towards the sound source) amplification of eardrum vibrations. In other words, the ear closer to the sound source vibrates more strongly than the ear further away from the sound source. The strengths of the vibrations depend on the relative phase difference between the incoming sound waves at the two ears.

An equivalent electrical circuit model as shown in Fig. 1(c) of the peripheral auditory system [6,5] allows one to visualise the directionality as shown in Fig. 1(d) as a difference signal obtained by subtracting the two vibrational amplitudes. The difference signal can be formulated as

$$\left|\frac{i_1}{i_2}\right| = \left|\frac{G_\mathrm{I} \cdot V_1 + G_\mathrm{C} \cdot V_2}{G_\mathrm{C} \cdot V_1 + G_\mathrm{I} \cdot V_2}\right| \ , \tag{1}$$

where frequency-dependent gains G_I and G_C model the effect of sound pressure on the motion of the ipsilateral and contralateral eardrum respectively. These gains are analogue filters in signal processing terminology with coefficients determined experimentally by measuring the eardrum vibrations of individual lizards via laser vibrometry [3]. Expressing i_1 and i_2 in decibels,

$$i_\mathrm{ratio} = 20\left(\log|i_1| - \log|i_2|\right) \ \mathrm{dB} \ . \tag{2}$$

The model responds well for frequencies between 1-2.2 kHz, with a peak response at approximately 1.6 kHz. i_ratio is positive for $|i_1| > |i_2|$ and negative for $|i_2| > |i_1|$. The model's symmetry implies that $|i_\mathrm{ratio}|$ is the same on either side of the centre point $\theta = 0°$ and is locally symmetrical within the range $[-90°, +90°]$ (considered henceforth as the relevant range of sound direction). The difference signal given by Eqn. (2) provides sound direction information in that its sign indicates whether the sound is coming from the left (positive sign) or from the right (negative sign), while its magnitude corresponds to the relative angular displacement of the sound source with respect to the median.

2.2 Input Correlation (ICO) Learning

ICO learning [21] is online unsupervised learning in which synaptic weight update is driven by cross-correlation of two types of input signals – "predictive" signal(s) which are earlier occurring stimuli and a "reflex" signal which is a later occuring stimulus arriving after a finite delay and drives a reflex (Fig. 2). The output of the ICO learning mechanism is a linear combination of the reflex input and the predictive input(s). The synaptic weight of the reflex input is set to a constant positive value such as 1, representing an unchanging reflex signal. The learning goal of ICO learning is to predict the occurrence of the reflex signal by using the predictive signal, thereby allowing an agent to react earlier. Essentially, the agent learns to execute an anticipatory action to avoid the reflex. During learning, the synaptic weight(s) of the predictive signal(s) are updated through differential Hebbian learning [9,10] using the cross-correlation between the predictive and reflex inputs. The synaptic weights tend to stabilise when the reflex signal is nullified [21], which implies that the reflex signal has been successfully avoided. ICO learning is characterised by its speed and stability and has been successfully applied to generate adaptive behaviour in real robots [14,15,20].

3 Materials and Methods

The task of acoustic tracking is defined as follows – a robotic agent must learn the correct angular turning velocity which allows it to rotate sufficiently fast along a fixed axis so as to point in the direction of the instantaneous position of a sound source moving with an unknown velocity in a given direction along a pre-defined semi-circular arc-shaped trajectory. To solve this task we employ an adaptive neural architecture that combines the auditory preprocessing of the lizard peripheral auditory model and the neural ICO learning mechanism as described next.

3.1 The Adaptive Neural Architecture

Figure 2 shows the neural mechanism embedded as a closed-loop circuit in the task environment. The central idea is for the robotic agent to learn the temporal relationship between the perceived sound direction *before* turning and *after* turning. The temporal relationship is encoded in the synaptic weights of the neural mechanism, which are used to calculate the correct angular turning velocity.

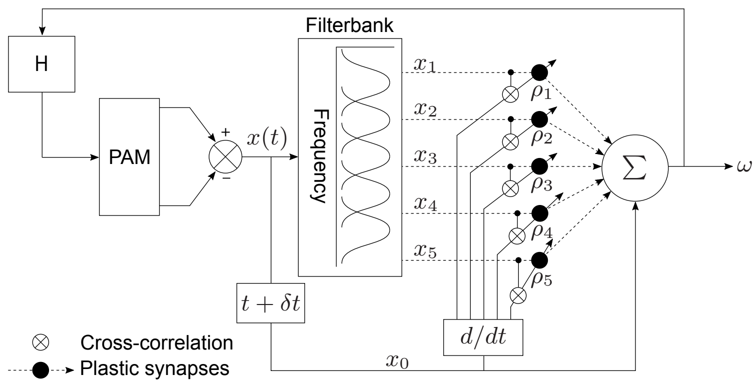

Fig. 2. Neural mechanism for acoustic tracking as a closed-loop system.

The output of the neural mechanism ω is the angular velocity, defined as the angular deviation per time step, required to turn the robot fast enough to point at the appropriate loudspeaker in one time step. ω is transformed into corresponding ITD cues via the environmental transfer function H. The peripheral auditory model (PAM) translates these cues to a difference signal $x(t)$ (given by Eqn. (2)) which encodes information regarding sound direction. A filter bank decomposes $x(t)$ into frequency components $x_k(t)$, where $k = 1, \ldots, N$, to extract frequency information. The filter bank comprises 5 bandpass filters, each with a 3 dB cut-off frequency of 200 Hz and center frequencies at 1.2 kHz, 1.4 kHz, 1.6 kHz, 1.8 kHz and 2.0 kHz. This results in $N = 5$ filtered signals outputs of the filter bank. This step is necessary beacause in the absence of sound frequency information the peripheral auditory model provides ambiguous information regarding the sound direction. This is because the output of the peripheral auditory model is non-linearly dependent on the sound frequency. The magnitude responses of the filters in the filter bank represent the receptive fields of individual auditory neurons. These recpetive fields, better known as spectro-temporal receptive fields [1], are the range of sound frequencies that most optimally stimulate the neuron. The filtered signals $x_k(t)$ are used as inputs which are then correlated with the derivative of the unfiltered difference signal $x_0(t)$. The input signals $x_k(t)$ can be viewed as the predictive signals used to predict the instantaneous sound direction before turning, while the unfiltered difference signal $x_0(t)$ can be viewed as the "reflex" or the retrospective signal generated after turning.

In ICO learning, once the reflex signal is nullified, the synaptic weights are stabilised; thereby generating a behavioural response that prevents future occurrences of the reflex signal. Here, as soon as the sound moves to a new position along its trajectory, a new and finite retrospective signal x_0 is generated. This signal is then nullified after turning, before the sound moves to a new position along its trajectory. Our approach can therefore be viewed as one successful iteration of ICO learning being repeated for each new position of the sound source as it moves along its trajectory. This implies that the synaptic weights can grow uncontrollably if the learning is allowed to continue indefinitely. To avoid this condition, we introduce a stopping criterion for the learning – the learning stops when the tracking error θ_e becomes less than $0.5°$. θ_e is defined as the difference between the angular deviation of the robot and the angular deviation of the sound source in *one* time step. In other words, the learning stops when the robot is able to point to within $0.5°$ from the position of the sound source within *one* time step.

3.2 The Experimental Setup

The experimental setup in simulation, as illustrated in Fig. 3, comprises a virtual loudspeaker array which generates relevant tones. The array comprises 37 loudspeakers arranged in a semi-circle in the azimuth plane. The angular displacement between consecutive loudspeakers is $5°$. To simulate motion of a single sound source, the loudspeakers are turned on sequentially starting from the loudspeaker at one of the ends of the array. To maintain sound continuity and simulate a continuously moving sound source (albeit in discrete steps), the next loudspeaker plays immediately after the previous loudspeaker has stopped. A given tone can thus be moved across the array along a semi-circular trajectory from either the left or the right with a given angular velocity. The angular velocity is defined as the angular displacement in radians every 10 time steps. When a given loudspeaker is turned on, it plays a tone for 10 time steps before it is turned off and the next consecutive loudspeaker is turned on immediately afterwards. This process is repeated until the last loudspeaker in the array is reached. In the current setup, the direction of movement of sound is chosen to be from the left to the right of the array. The movement of sound from loudspeaker #1 to loudspeaker #37 is defined as one complete iteration. Since one iteration may be insufficient to learn the correct angular velocity, the process is repeated from the first to the last loundspeaker until the synaptic weights converge.

The robot that must track the moving sound source is located at the midpoint of the diameter of the semi-circle and is only allowed to rotate on a fixed axis. To track the sound source by rotational movements, the robot must turn

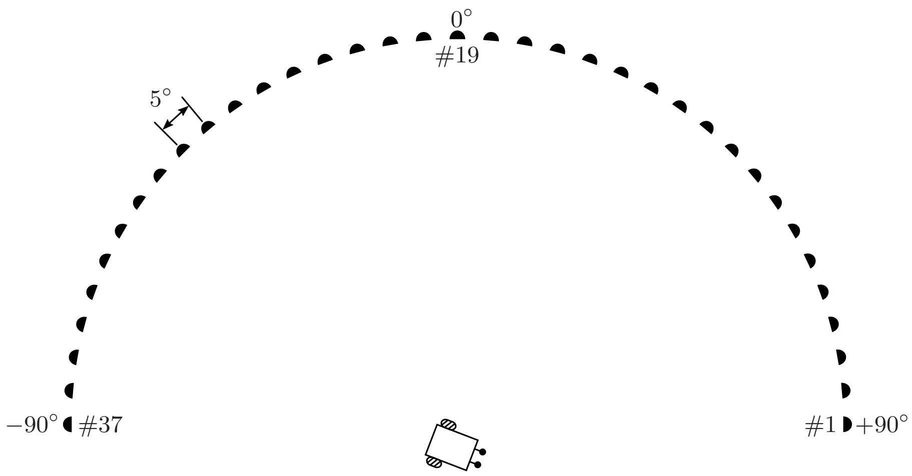

Fig. 3. The simulation setup.

with a sufficiently large angular velocity in order to point towards the instantaneous position of sound source before the sound moves to a different position along its trajectory. The angular velocity of the robot is defined as the angular rotation per time step. The goal of the learning algorithm is to learn the correct angular velocity that would allow the robot to turn and point towards the current loudspeaker in *one* time step, starting from the time step at which the given loudspeaker started playing the tone.

The learning takes place as follows. The robot initially points in a random direction (chosen as 97°). Loudspeaker #1 emits a 2.2 kHz tone, chosen because sufficient directional information from the peripheral auditory model is available at this frequency. The robot uses the extracted sound direction information to turn towards the current loudspeaker with an angular velocity given by

$$\omega = \rho_0 x_0 + \sum_{k=1}^{N} \rho_k x_k, \text{ where } N = 5. \tag{3}$$

After the turn is complete, the robot again extracts sound direction information via the peripheral auditory model and determines $x_0(t+\delta t)$. Finally, the synaptic weights ρ_k are updated according to the learning rule

$$\frac{d\rho_k(t)}{dt} = \mu x_k(t) \frac{dx_0(t)}{dt}, \text{ where } k = 1, \ldots, N. \tag{4}$$

After this step, loudspeaker #1 is turned off and the next loudspeaker in the array (loudspeaker #2) emits a tone of the same frequency as earlier and the learning procedure described above is repeated.

The acoustic tracking performance is individually evaluated for three different angular velocities of the sound source – 0.5°/ time step, 1.0°/ time step and 1.5°/ time step. For all trials, the neural parameters are set to the following values – the learning rate $\mu = 0.0001$ and synaptic weight $\rho_0 = 0.00001$. All plastic synaptic weights ρ_k are initially set to zero and updated according to Eqn. (4). The neural mechanism's performance is also compared with a Braitenberg vehicle-like [2] sensorimotor mechanism that generates rotational motion. The Braitenberg mechanism is simulated by turning off the learning and setting the weights ρ_k to constant values. Two sets of randomly-chosen weights are used – one ($\rho_k = [0.035, 0.0197, 0.0251, 0.0616, 0.0473]$) resulting in a relatively small angular turning velocity and another ($\rho_k = [0.0352, 0.0831, 0.0585, 0.055, 0.0917]$) resulting in a relatively large angular turning velocity.

4 Results and Discussion

Figure 4 shows the tracking error θ_e which reduces exponentially over time for the three trials. The insets reveal the evolution of θ_e for the last iteration of the movement of the sound source. The spikes in θ_e represents a mismatch between the position at which the robot was pointing last and the new position of the sound source. This creates finite ITD cues from which the robot extracts sound direction information via the peripheral auditory model. The robot then turns towards the sound source with the last learned angular turning velocity, reducing the tracking error. This process repeats over each subsequent time step, exponentially reducing the tracking error, until the stopping criterion is met.

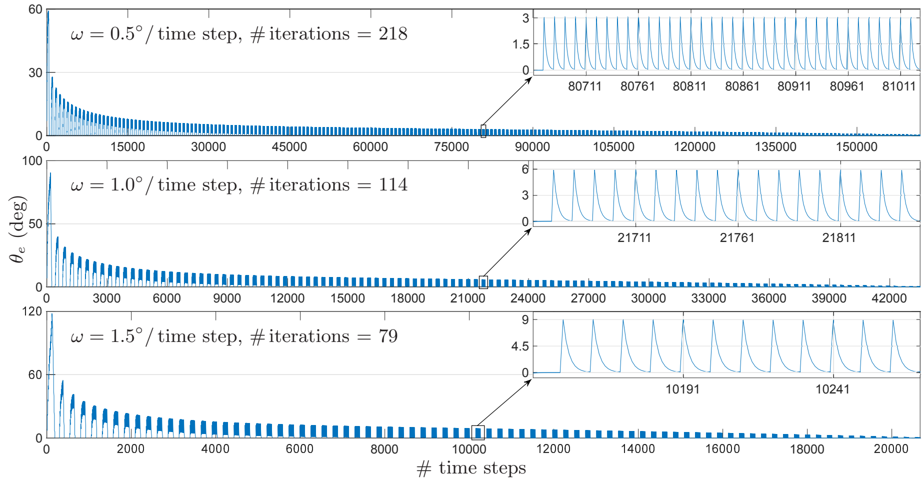

Fig. 4. Evolution of tracking error θ_e over time for the three separate trials in which the sound source is moving with three separate angular velocities – 0.5°/ time step (top panel), 1.0°/ time step (middle panel) and 1.5°/ time step (bottom panel). The insets show θ_e for a single iteration as an example.

The number of iterations required to reach the stopping criterion, where the weights stabilise, decreases for increasing angular velocity of the sound source. This is because the mismatch between the direction at which the robot was pointing last and the current position of the sound source is relatively greater for greater angular velocity of the sound source. This results in relatively larger predictive signals, and consequently a relatively larger correlation term $x_k(t)\frac{dx_0(t)}{dt}$ per time step in Eqn. (4). This consequently results in relatively faster weight updates, reducing the overall time taken to learn the correct angular velocity.

An example of the predictive signal x_5 and the derivative $\frac{dx_0(t)}{dt}$ of the retrospective signal x_0, for three separate iterations for the sound source moving with an angular velocity of $1.5°/$ time step, is shown in Fig. 5. The learning results in faster turns by the robot as indicated by the decreasing slope of $x_5(t)$ as shown.

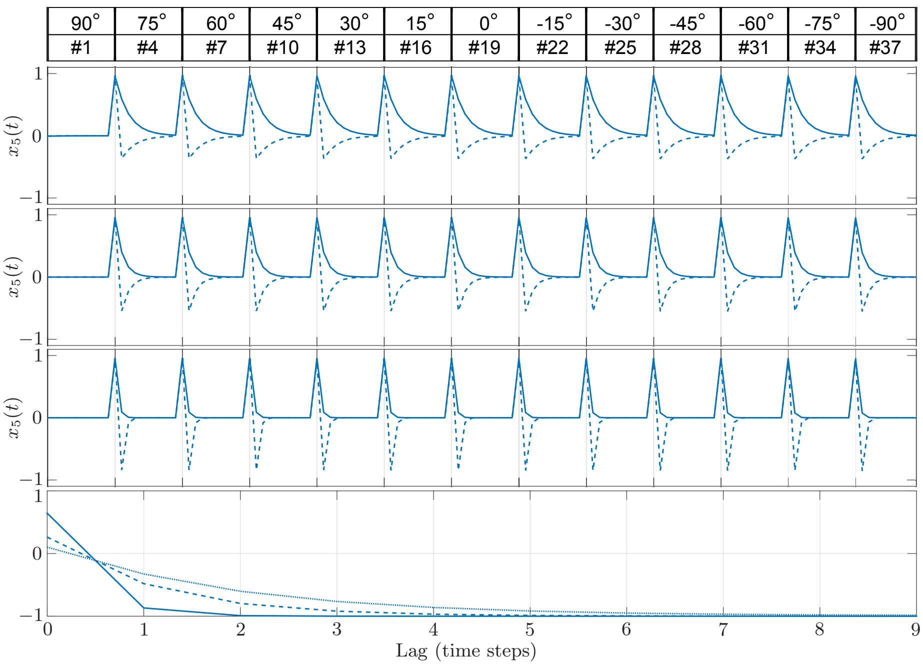

Fig. 5. Snapshots of the evolution of the predictive signal $x_5(t)$ (solid line) and the derivative of retrospective signal $\frac{dx_0(t)}{dt}$ (dashed line) for a sound source moving with angular velocity of $1.5°/$ time step. **Top panel**. The instantaneous position of the sound and the corresponding loudspeaker designation. **Second − fourth panels**. Example snapshots for iteration #38 (second panel), #54 (third panel) and the last iteration (#79, fourth panel). **Bottom panel**. The positive-lag cross-correlation of $x_5(t)$ and $\frac{dx_0(t)}{dt}$ for iteration #38 (dotted line), #54 (dashed line) and #79 (solid line).

The maximum correlation as shown in the bottom panel in Fig. 5 between the predictive and retrospective signals increases as the number of iterations increases. This confirms that as the synaptic weights increase, consequently increasing the learned angular turning velocity as learning progresses, the correlation between the predictive and retrospective signals also increases, resulting in an increasing correlation term in Eqn. (4).

Figure 6 shows a comparison of the correlation learning mechanism to the Braitenberg vehicle-like sensorimotor mechanism for rotational turning. Depending on the synaptic weights chosen, the angular turning velocity of the robot may be either less or greater than the angular velocity of the sound source. Thus the robot either takes a relatively long time to reach the target's position or overshoots the target's position, resulting in a relatively greater tracking error in both cases. On the other hand, the learning mechanism allows the robot to learn a relatively accurate angular turning velocity that closely matches that of the sound source, resulting in a relatively smaller tracking error.

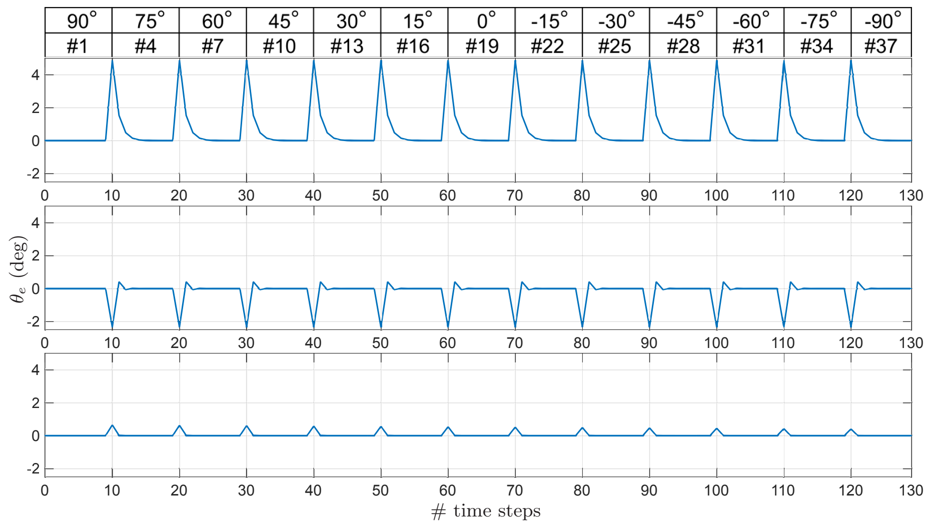

Fig. 6. Braitenberg vehicle-like mechanism for rotational turning versus the correlation learning mechanism. The panels show the evolution of tracking error θ_e over time in the last iteration for the sound source moving with an angular velocity of 1.5°/ time step. **Top panel**. The instantaneous position of the sound and the corresponding loudspeaker designation. **Second and third panels**. θ_e for the Braitenberg approach where the angular turning velocity is less (second panel) and greater (third panel) than 1.5°/ time step. **Bottom panel**. θ_e with correlation learning where the learned angular turning velocity closely matches with 1.5°/ time step.

5 Conclusions and Future Directions

A neural mechanism for acoustic tracking is presented which allows a simulated robotic agent to learn the correct angular velocity necessary to turn and align itself towards the instantaneous position of a virtual sound source moving along a semi-circular arc-shaped trajectory. The learning rule correlates the perceived sound direction information, obtained via a peripheral auditory model of lizard hearing, before and after turning to update the synaptic weights. The learned synaptic weights thus correspond to the angular velocity of the sound source. The mechanism successfully learned three different angular velocities. We aim to validate the approach as a next step in an identical experimental setup by implementing the neural mechanism on a real mobile robot.

In the presented approach the robot only turns after the sound source has moved to a new location along its trajectory. There is a finite and unavoidable delay between the sound source moving to a new location and the robot completing its turn. The same mechanism may be used to predict this time delay, so that after learning the robot would turn fast enough to point at the next position of the sound source at the same instant as the sound source itself. Such a system could be viewed as an internal forward model [27] for acoustic tracking.

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