A DEEP REINFORCEMENT LEARNING APPROACH TO AUDIO-BASED NAVIGATION IN A MULTI-SPEAKER ENVIRONMENT

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ABSTRACT
In this work we use deep reinforcement learning to create an autonomous agent that can navigate in a two-dimensional space using only raw auditory sensory information from the environment, a problem that has received very little attention in the reinforcement learning literature. Our experiments show that the agent can successfully identify a particular target speaker among a set of \( N \) predefined speakers in a room and move itself towards that speaker, while avoiding collision with other speakers or going outside the room boundaries. The agent is shown to be robust to speaker pitch shifting and it can learn to navigate the environment, even when a limited number of training utterances are available for each speaker.

Index Terms— deep reinforcement learning, autonomous navigation, raw audio sensory data

1. INTRODUCTION

We address the problem of environment navigation by an autonomous agent in a two-dimensional space, for the case where the sound sources are human speakers, using a Reinforcement Learning (RL) approach for training the agent. Our objective is to investigate whether an agent can learn to navigate autonomously in a two-dimensional space, towards a target sound source (speaker) while simultaneously avoiding other sound sources (other speakers). An important constraint is that the agent is only allowed to use raw audio data in the form of a two-channel audio signal, in an attempt to simulate what a human listener would hear. For this purpose we created an environment in the Unity game engine [1] which simulates a player, controlled by the agent, moving in a room where there also exist a number of speakers. The objective of the player is to move towards and eventually reach a specified target speaker, while at the same time avoiding coming into contact with the other speakers or going outside the room. The player receives stereo audio from the environment, processed by the Unity game engine to have pseudo-spatial two-dimensional information. Our experiments show that an agent trained with deep reinforcement learning, rewarded when reaching the target speaker and punished when bumping into other speakers or going outside the room, is able to solve the aforementioned episodic problem with a high degree of success.

2. RELATED WORK

So far, limited work has been published on audio-based virtual environment navigation for autonomous agents. An overview of the most related research efforts indicates that audio is usually treated as an additional modality to image sensing. More specifically, [2] proposed an agent that uses audio information, in addition to visual information, to navigate a maze environment created in ViZDoom [3] and reach a goal. They found that the agent was able to reach the goal significantly faster and more reliably when using raw audio information from the environment in addition to visual information, compared to the case when only visual information was processed by the agent. [4] developed a framework for sound localization and tracking of sound sources, along with visual information, for navigation of an autonomous agent in a virtual environment. Their system consists of a sound propagation model and sound localization model based on classical (non-DNN) algorithms. They show that an agent based on their system is successful in navigation, localization and collision avoidance in an environment with multiple sound sources. In [5], the authors used Deep Reinforcement Learning for controlling the gaze of a robotic head based on audio and visual data from the virtual environment.

For the sake of completeness, we also provide a brief overview of related work in the neighboring disciplines of speaker localisation and speaker detection. This is because our agent is implicitly performing speaker detection while navigating and also because, even though it is not performing speaker localization, it can be considered as trying to move to the direction of the target speaker while avoiding obstacles, i.e., other speaker locations on the way. Speaker Identification [6] is a well studied field and in recent years, methods based on dynamic programming [7] and Machine Learning methods, particularly those based on Deep Neural Networks, have enjoyed success over classical methods [8]. Speaker localization from multiple audio sources in two and three-dimensional space is also a topic which has attracted a significant body of published work. Again, recent efforts focus on
supervised Deep Learning methods for multiple speaker detection and localization problems ([9], [10], [11]), as well as more general audio-source localization tasks ([12], [5]) and performance improvement over classic algorithms has been reported along with more flexible setups where fewer assumptions about the environment need to be made.

Our approach is offering a simultaneous solution to the tasks of audio-based navigation and speaker detection and it is therefore different from the aforementioned efforts, i.e., audio is the only available modality for training an autonomous agent with deep reinforcement learning (and not an auxiliary one as in [2, 3, 4, 5]) and, in addition, due to the need for controlling an avatar that navigates to and reaches a target speaker, algorithms that perform simultaneous speaker localization and detection are not readily applicable in our case.

3. AGENT AND ENVIRONMENT OVERVIEW

We now provide a description of our method and the virtual environment that we set up to apply and test the proposed approach.

3.1. Agent Architecture

Our agent is based on a combination of the Proximal Policy Optimization (PPO) reinforcement learning algorithm [13] with a small neural network consisting of two fully connected hidden layers. Our choice of reinforcement learning algorithm is not restrictive and other policy gradient optimization algorithms can be potentially suitable as well. Each hidden layer of the network has 256 neurons and the output of the network is a fully connected layer consisting of 2 neurons that estimate the velocity of the agent in the x and y directions, respectively. The input to the neural network is the the x and y axis, respectively.

3.2. Environment

For our experimental study, we used the Unity editor to create a custom virtual environment that runs on the Unity game engine. We chose to create the environment in Unity after

![Fig. 1. Agent’s neural network architecture. The left and right channel of a stereo audio signal from the Unity environment are concatenated into a single vector. This vector is then fed into two fully connected hidden layers. The outputs of the network are the velocity of the agent-controlled player in the x and y axis, respectively.](image)

Our test environment (Figure 2) consists of key components: 1) A rectangular room, 2) speakers (S1, S2 and TS) inside the room, one of which is the target speaker (denoted TS) and 3) The agent (A) inside the room. Each speaker is a stationary Unity audio source which plays back an audio file containing an utterance for that speaker, randomly selected from a pool of utterances. When an utterance finishes, another one is randomly selected from the pool and played back. All audio sources share the same properties and are accordingly configured in the Unity editor. Specifically, the signal intensity (volume) of the audio source decreases linearly with the distance from the source (linear volume roll-off). The maximum distance from which an audio source can still be heard is set so that all sources are audible across the entire room. The agent (A) can move inside the room along the x and y axes by adjusting its velocity vectors $v_x$ and $v_y$ over each axis. Each training episode begins with the agent appearing in a random location on the lower edge of the room and the speakers show up in random locations inside the room. The agent receives a positive reward of +1.0 when it reaches TS and a negative reward of −1.0 when it crashes onto another speaker, i.e., S1 or S2 or when it moves outside the room boundaries. It also receives a small negative reward of −0.001 for every step it
The environment can be formalized as a Markov Decision Process (MDP) with the following characteristics: 1) The state $s_t$ at time $t$ (denoted $s_t$) consists of the two 1-D vectors, each representing the raw audio waveform from left and right channels of the stereo audio input from the environment, concatenated into a single 1-D vector, 2) Given $s_t$, the agent takes an action $a_t$, which consists of the normalized velocity vectors $v_x, v_y$, with $v_x \in [-1, 1]$ and $v_y \in [-1, 1]$, each applied to the respective axis of the agent-controlled player, 3) As a result of action $a_t$, the agent transitions to the next state $s_{t+1}$ and receives a reward $r \in [-1, 1]$.

We assume that there exists an optimal policy $\pi^*$, which, when followed by the agent, maximizes the cumulative reward $r$ achieved for a horizon of $T$ timesteps, where each timestep is an interaction with the environment. The agent’s training objective is to find an as close as possible approximation $\pi_\theta$ to the optimal policy, such as $\pi_\theta \approx \pi^*$, where $\theta$ are the parameters of a neural network. To train the network parameters, the policy runs for $T$ timesteps and the collected samples are used for updating the policy gradient. In order to do this we first need to estimate the advantage at timestep $t$ of action $a_t$ in state $s_t$, as it was formulated in [14]:

$$A_t(a_t, s_t) = \delta_t + \gamma \delta_{t+1} + \cdots + \gamma^{T-t+1} \delta_{T-1},$$  \hspace{1cm} (1)

with

$$\delta_t = r_t + \gamma V^\pi(s_{t+1}) - V^\pi(s_t),$$  \hspace{1cm} (2)

where

$$V^\pi(s) = \mathbb{E}_{k=0}^{\infty} \gamma^k r_{t+k}$$  \hspace{1cm} (3)

is the value estimate of state $s$ under policy $\pi$ and it is the mean expected reward, over $k$ timesteps, for following policy $\pi$ from state $s$. In the above, $t \in [0, T]$ is the timestep index, $r_t$ is the reward at timestep $t$ and $\gamma \in (0, 1)$ is the future reward discount factor. The objective minimized by PPO is, according to [13]:

$$L_t(\theta) = \mathbb{E}_t [L_t^C(\theta) - c_1 L_t^{VF}(\theta)] + c_2 S^2[\pi_\theta](s_t),$$  \hspace{1cm} (4)

where

$$L_t^C(\theta) = \mathbb{E}_t \left[ \min(r_t(\theta) A_t, \text{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon) A_t) \right]$$  \hspace{1cm} (5)

and

$$L_t^{VF}(\theta) = (V^\theta(s_t) - V^\pi_{target})^2$$  \hspace{1cm} (6)

c_1, c_2$ are coefficients, $S$ is an entropy bonus added to policy estimation, which incentivizes exploration, and $\epsilon$ is a hyperparameter. In our experiments we set $\gamma = 0.99$, $c_1 = 0.95$, $c_2 = 0.001$ and $\epsilon = 0.2$.  

3.3. Training the Agent

Fig. 2. Top-down views of the environment used for the experiments. The views show two example state snapshots, one where agent $A$ has direct “line-of-sight” to $TS$ (left) and one where it does not (right). Agent $A$ can move along the $x$ and $y$ axes, while speakers $S1$, $S2$ and $TS$ are stationary. $TS$ is the target speaker and $S1$, $S2$ are other speakers in the room whose signals interfere with the signal produced by speaker $TS$. The agent $A$ must reach speaker $TS$ without bumping into (coming into contact) with speakers $S1$ and $S2$.

takes to discourage the agent from procrastinating. A training episode ends when the agent either reaches the target speaker or one of the other speakers or moves outside the room boundaries.

To facilitate reproducibility, we provide the Unity project files\footnote{https://github.com/petrosk/AudioRL}. The Unity project includes all the required components for running the experiments: the Unity environment, a pre-trained agent and the dataset.

4. EXPERIMENTS

4.1. Testing Methodology

The dataset used for the experiments was created from three publicly available audiobooks, each read by one of the speakers (two male speakers and a female one). We first split each audiobook automatically in utterances, using a Voice Activity Detector (VAD) which labels the boundaries of each utterance. We then manually verify the VAD results and correct the boundaries of detected utterances where needed. We assume that the definition of an utterance is the linguistic one: "An uninterrupted chain of spoken or written language." [15]. This procedure resulted into a dataset of approximately 600 utterances for each one of the three speakers.

At a next step, the pool of utterances of each speaker is split into a training partition and a testing partition. The overall training and testing sets are the union of these three training and testing partitions, respectively. The resulting training set consists of approximately 500 utterances for each speaker, while the test set consists of around 100 utterances per speaker. We then set one speaker as the target and train the agent for a total of 6 million steps in the created environment. Upon completion of the training stage, we evaluate the
agent’s performance by switching to the test set and letting the trained agent play 100 episodes in the environment. For each episode we keep a record of success or failure. Success means that the agent reached the target speaker, while failure means that it reached another speaker or went outside the room boundaries. After the 100 testing episodes are completed, we compute the agent’s success rate and compare it with the corresponding success rate of a baseline agent performing a random action policy. This training-testing experiment is repeated three times by setting each time one of the three speakers as the Target Speaker. In the end, we average the success rates over all Target Speakers.

Furthermore, we evaluate the limits of generalization of our agent by training on only 1 utterance per speaker and testing again on the full test set of 100 utterances per speaker. In this way we can observe if our agent can still learn when very few training data are available for each speaker.

As a final test regarding the agent’s generalization capabilities, we randomly shift the pitch frequency of each speaker by 4 to 8 percent for each test utterance and compute again the success rate. Note that the agent is only trained on the training set of 500 utterances per speaker without pitch shifting (i.e., without data augmentation).

4.2. Results

Our findings are summarised in Figure 3. Specifically:

a) The success rate of our reinforcement learning agent (based on PPO) on 100 test episodes, along with the success rate of an agent that moves randomly in the environment. Our agent is able to successfully reach the target speaker in 98 out of 100 played episodes (98% success rate). In contrast, the success rate of the random agent is 15%. This result can be interpreted as an indication that the proposed RL agent is capable of learning a representation of the environment that leads it to identify the target speaker and its position, based only on raw audio data.

b) The success rate of the PPO agent when trained on the training set of 500 utterances per speaker and when it is only trained on 1 utterance per speaker. Like before, the agent is again evaluated on the same test set of 100 utterances per speaker. We saw that, when trained on the full training set, the agent has a 98% success rate on the test set. This time, i.e., when trained on the minimal training set of just 1 utterance per speaker it has a 78% success rate on the test set. This result can be interpreted as an indication that the agent can generalize satisfactorily from very little training data.

c) The success rate of the PPO agent when the pitch of every speaker is randomly shifted between 4 and 8 percent during testing. It can be seen that, even though the agent was trained on the original pitch of the speakers, the success rate only exhibits a modest drop from 98% to 93%, which leads us to believe the agent is also invariant, to a certain extent, to mild pitch shifting of the speakers.

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5. CONCLUSIONS

In this work we investigated the performance of deep reinforcement learning in audio-based only navigation in a two-dimensional space containing speakers as audio sources. An autonomous agent based on deep reinforcement learning was tasked with continuous control of a virtual entity moving in a room. The agent had to move the entity in the room in order to find and reach a particular speaker while not colliding with other speakers in the room. After the agent was trained in this task, its performance was evaluated using a test set of utterances not seen during training for each speaker. Our experiments showed that the agent was able to successfully learn this task from a state space consisting of time slices of each channel in the stereophonic raw environmental audio input. The agent was shown to generalize well to the unseen test set as it was able to complete the task with relatively high degree of success even when trained on a single utterance from each speaker. It was also shown to be robust to speaker pitch shifting not seen during training. As future work, we would like to examine scaling the experiments in larger and more complex environments with a larger number of different speakers and possibly other types of sound sources, e.g., environmental sounds.

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