Towards translating the effect of music into motor using deep learning

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Extended abstract

Towards translating the effect of music into motor using deep learning

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1 Introduction to music, emotion and human motion

For centuries music composers have indicated 120 beats per minute (BPM) as the performance tempo for their marching music compositions. Recent studies [1] confirm that the preferred step frequency for walking is indeed 2Hz (= 120 per minute). The study also shows that runners prefer a step frequency of ~3Hz while listening to music with a tempo of a little less than 3Hz (2.6-2.9Hz or 156BPM to 174BPM). Furthermore, during running brainwaves (EEG Delta waves) of 3Hz were registered.

The relationship between motion and musical rhythm relies on the close connection between their neurological networks, suggesting that musical rhythm might have evolved from rhythmic movement [2]. Moreover, musical rhythm evokes movement because it activates areas in the brainstem and areas of the cerebral cortex [3] which send out signals that make arms and legs move. Next to the relationship between motor and musical rhythm, other neurological studies describe the relationship between music and emotion, revealing the different neurological networks that are activated as a result of an emotional state [4].

Studies applying Russel's [5] two-dimensional Valence-Arousal model for parametric emotion description show how musical composition elements relate to emotion perception [6]. Other studies [7] suggest how emotion can be regarded as one of several subcomponents of musical expression. This means that music holds both a relationship with motor through its rhythmic (tempo) characteristics and a relationship with (perceived) emotion which can be extended through musical expression from music to emotion into movement.

Artificial neural networks can be used to detect emotion from gait [8]. This study also shows that music can act as an agent to influence gait. While the impact of specific musical composition elements may be highly personal (every person has their own preferred running playlist), we hypothesize that using deep learning, it becomes possible to steer individual running technique into a controlled direction by exposing the runner to music with the appropriate musical parameters. To test our hypothesis, we designed a versatile sensing and sonification platform described in Section 2. We describe our experimental approach in Section 3.

2 Real-time sensor, analysis, and sonification platform

We designed a platform that works both in a field and lab setting and is able to provide real-time audio feedback based on (machine learned) sensor data analysis. At the same time, the platform is designed as an experimentation sandbox and should be flexible in its use of sensors, feedback and analysis. Figure 1a depicts an overview of the platform.

2.1 Platform

At the core of the sonification platform are a smartphone (iPhone) and a web server. The mobile device runs a native app that acts as a hub for all sensor data and provides audio feedback through connected headphones. All supported external sensors use the BlueTooth Low Energy (BLE) protocol to connect directly to the iPhone that subsequently transfers the data over WebSockets to a server. To provide flexibility in experiments, the iPhone app contains a view that exposes web-based applications, allowing for rapid prototyping without rebuilding and deploying the main iPhone app. Due to the limited resources of smartphones, the server performs most sensor processing. It comprises of several independent modules in Docker containers with at its core the WebSockets server that handles all communications, making it easily extendable.

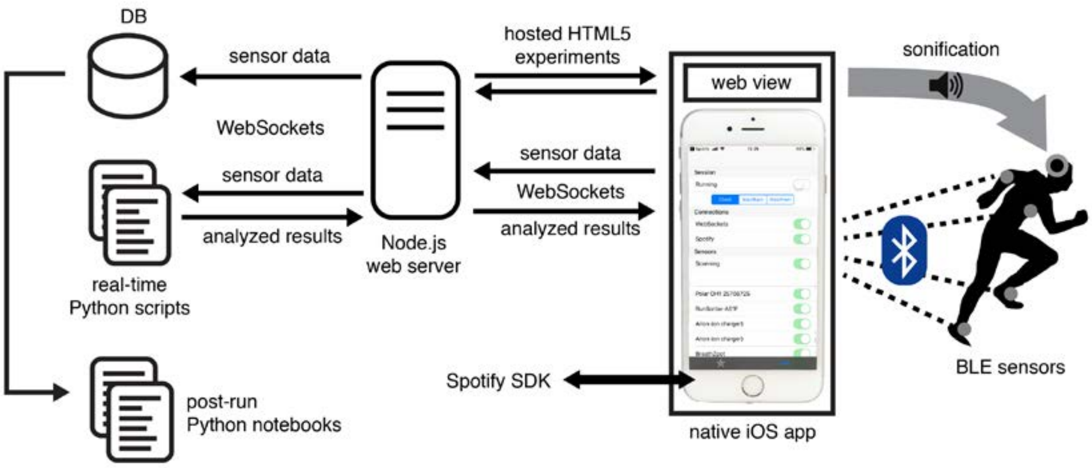

Figure 1. Diagram of the developed sensor, analysis, and sonification platform.

2.2 Sensors

The supported sensors are a combination of the IMU data of the iPhone with a sampling rate of 100Hz, and several smart sensors. These are: heart rate sensors (HR GATT protocol), speed and cadence (RSC GATT protocol), RunScribe Plus foot pods for per-stride impact, braking, contact time, and more, BreathZpot for ribcage volume, and Arion insoles. A proper 4G connection can transmit all sensor data effortlessly.

2.3 Analysis

On the server, Python scripts buffer and process the data in real time to compute for instance foot strike timings, cadence and the outcome of a Human Activity Recognition (HAR) model from accelerometer data. The analyzed results are sent back to the smartphone. All data is stored in MongoDB and as csv-files so that post-run data analysis is also possible.

2.4 Sonification

We distinguish two forms of personalized audio feedback. First, audio can follow the runner by direct sonification of the sensor data on the mobile device, e.g. engineered step sounds for every foot strike. Second, audio can lead the runner by playing (engineered) music based on server-side data analysis.

The iPhone app also connects to the Spotify music streaming app to store current song information and control programmatically the music being played. In addition, Spotify specifies a range of musical parameters (including valence and arousal) of the music it hosts, allowing analysis of a runner's response to music using their personal playlist.

3 Translating music to motor and running quality

We propose to treat the interaction between music and running technique as a translation problem, tackling it with (deep) machine learning. First, a gallery of gait patterns is extracted for each runner from either the accelerometer data as Angle Enhanced Gait Dynamic Images [9], or from the RunScribe Plus stride data. Second, a deep Convolutional Neural Network (CNN) is trained for feature extraction to detect the runner from the gallery, similar to [10]. When exited, the last hidden layer of the CNN now contains a vector representing the features of the input. Third, a Self-Organizing Map (SOM) can be created based on the feature space, as in [8]. Individual runs can be plotted on this map.

Changes in running technique during exposure to music shows up as shifts on the map. Consequently, a relation can be learned between an individual runner and certain musical parameters, and this relation can be exploited to steer the runner in (certain) controlled directions. In the future, experts can label proper running technique and relate this to the same abstract map. With this data-centric approach we develop a system that may steer recreational runners subconsciously towards better running technique with personalized musical feedback.

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