System Modeling for Active Noise Control with Reservoir Computing

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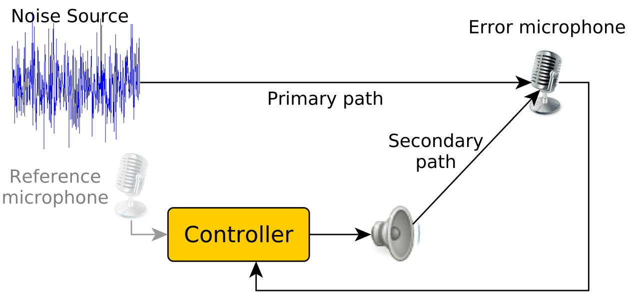

Figure 1. ANC setup with one and two microphones. The grey reference microphone is only present in the two microphone setup. In this setup, the controller is generally filtering the input from the reference microphone and is adapted by the error signal. In the one microphone setup, the controller generates a compensating signal from the error signal.

Active noise control (ANC) is a way of actively reducing the amplitude of disturbing noise in audio. ANC reproduces the incoming noise signal with opposite phase so the residual signal approaches zero. While the idea is simple, implementation faces some hard problems. Problems occurring in real setups range from speaker and microphone distortion to reflection and deformation of acoustic waves. Also, noise prediction is often needed as the compensator isn't infinitely fast. Typically, these problems are coped with by appropriate controllers. Many solutions have already been proposed. Recently, the use of genetic algorithms (GA) (Russo & Sicuranza, 2007) was considered, which we used as reference.

This work (Nyman et al., 2012) investigates the use of reservoir computing for the ANC problems of fig. 1. We showed that this problem can be solved by assessing the different subsystems (primary and secondary path in fig. 1), modelling them with reservoir computing and finally concatenating the right models to get a zero error signal. The reservoirs that model the subsystems are trained, using one shot learning. It should be noted that we did not consider predicting future samples which in fact is indispensable in the one-microphone setup. This task, however, highly depends on the signal type so we always assumed knowing the relevant part of the noise source beforehand.

The choice of the noise signal for training and evaluation was an important parameter because learning systems tend to overfit on strongly correlated inputs. Therefore, we trained our systems on uncorrelated white noise, which worked well[1], even on other types of test signals. This proved a first important advantage over GA, that only performs well with strong correlations on the input samples.

A second advantage over GA, is that our approach needs less data and this data can be gathered in one experiment only. Lastly, the reservoir approach allows for a lot of further improvement. It will be interesting to investigate adaptive re-weighting of the reservoir readout, or to check if noise prediction and system modelling can be combined into one reservoir.

References

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Russo, F., & Sicuranza, G. (2007). Accuracy and performance evaluation in the genetic optimization of nonlinear systems for active noise control. *Instrumentation and Measurement, IEEE Transactions on*, *56*, 1443–1450.

[1]With 2 microphones and white noise, GA attained 6.70 dB reduction while our approach could offer 13.64 dB reduction. Applying the same methodology on the one-microphone setup, we attained 12.62 dB reduction.