Feedforward Active Noise Control System with FxLMS

Qin Yi, Cui Jiadi, Li Dinghong, Zeng Xiangchen
SIST, Shanghaitech University

Abstract—*In this project, we define an ideal noise canceller as a system with three properties: persistence, stability and convergence almost everywhere. We use these three properties as a gauge to evaluate performance of noise cancellers generally, and digital active noise canceller (ANC) systems with the filtered-x-least-mean-square (FxLMS) algorithm specifically. Implementing FxLMS algorithm using MATLAB enables us to conduct experiments on FxLMS algorithm and evaluate its performance. This study also tests performance of noise cancellers in multilingual context to test its speech intelligibility. By making sensitivity analysis of time and frequency, we find that adaptive noise cancellers perform best in low frequency situations, but in high frequency situations, passive noise cancellers are better.*

I. Properties of an ideal noise canceller

Generally, a noise canceller, whether it is active or passive, is intended to filter noise from desired signals. An ideal noise canceller, or a good noise canceller, should eliminate noise as completely as possible, but it should not change desired signals. Thus, we can define the following three properties an ideal noise canceller is supposed to have.

A. Persistence

If a noise canceller performs well, it is undesirable that the same input leads to different output. Thus, we can define it more formally that:

If two signals $s_1 = s_2$, then the output of s_1 through the noise canceller system is the same as the output of s_2 through the noise canceller system.

B. Stability

An important purpose of noise cancelling is to protect human ears. If a system is unstable, which means undesirably or unboundedly high signal may exist. This will harm human ears. Thus, it seems reasonable to require a good noise canceller to be stable, i.e., bounded in, bounded out (BIBO).

As we have learned in this course, for a linear time-invariant system, the necessary and sufficient condition for BIBO stability is that L1-norm of its impulse response exists, i.e., its impulse response is absolutely integrable for continuous time linear time-invariant systems, and absolutely summable for discrete time linear time-invariant systems.

$$\int_{-\infty}^{+\infty} |h(t)|\, dt = ||h||_1 < \infty$$

$$\sum_{n=-\infty}^{+\infty} |h(n)| = ||h||_1 < \infty$$

C. Convergence almost everywhere

Considering noise cancelling is to eliminate noise, we expect noise in output signals to be low. We can define it formally by introducing the notation of convergence almost everywhere in real analysis. In an ideal noise canceller, we expect that:

$$noise(t) \to 0 \ almost\ everywhere$$

It is acceptable that the noise weight is high in some time intervals, but the measure of these intervals should be as little as possible, most ideally, zero.

II. Implementations

A. Filtered-x-least-mean-square (FXLMS) algorithm

In this project, we choose the filtered-x-least-mean-square (FXLMS) algorithm as the adaptive algorithm of our active noise canceller.

$$\hat{d}(n) = e(n) + \sum_{m=0}^{M-1} \hat{s}_m y(n-m)$$

Where $\hat{d}(n)$ denotes an estimate of the noise d(n), and $\hat{s}_m$ denotes the estimated coefficients of equivalent filter $\hat{s}(z)$.

$$y(n) = \sum_{i=0}^{L-1} w_l(n)\hat{d}(n-l)$$

Where $w_l(n)$ denotes the coefficients of the active-noise-cancellation filter $W(z)$ at time n.

$$w_l(n+l) = w_l(n) + \mu \hat{d}'(n-l)e(n), \ l = 0, 1, ..., L-1$$

Where μ denotes the step size and $\hat{d}'(n) = \sum_{m=0}^{M-1} \hat{s}_m d(n-m)$[1]

The LMS algorithm executes quickly but converges slowly. The complexity of LMS algorithm is O(n), where n denotes number of weights. It is faster compared with the RLS algorithm, whose complexity is O(n^2). However, it does not perform well when considering the property of convergence almost everywhere, especially when the noise is changing quickly.

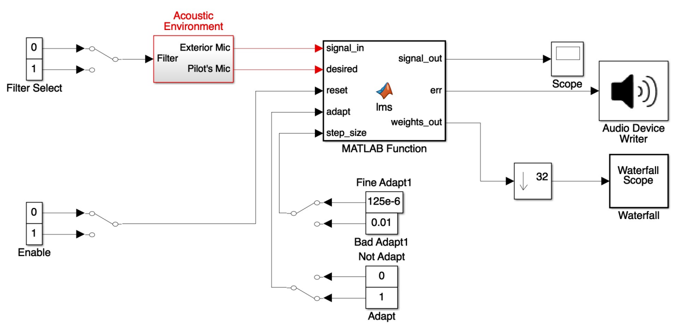

Fig.1. Block diagram of ANC system with the FXLMS algorithm in MATLAB

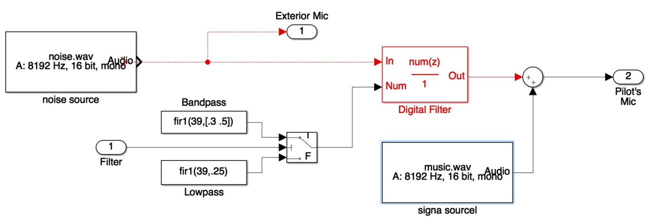

Fig.2. Block diagram of the acoustic environment in MATLAB

Because LMS algorithm is a deterministic algorithm rather than a stochastic algorithm, it is very unlikely to violate the property of persistence.

B. Parameters

The Input port accepts a column vector input signal. The Desired port receives a training sequence with a length that is less than or equal to the number of symbols in the Input signal. Valid training symbols are those symbols listed in the Signal constellation vector.

Define w as the vector of all weights w_i and define μ as the vector of all inputs μ_i. Based on the current set of weights, w, this adaptive algorithm creates the new set of weights given by

$$w + \mu^H e$$

Where ^{H} operator denotes the transpose conjugate, w denotes the leakage factor, and μ denotes the step size.[2] And the weight will be steady after training.

C. Predicted noise

According to previous noise signal, we can predict the estimated noise signal with a series of weights. Even the noise is irregular, the approximate frequency and amplitude are determined. Our canceller is adapted according to 32 samples before, which means we set step size to be 32. Since the number of datas we considerate about at a time is 32, the estimated noise signal has 32 versions, and it is updated every new sample in, which mean every signal out is the newest version. Since the sampling frequency is 8192Hz, the delay is approximately $\frac{32}{8192} = 3.90625 \times 10^{-3}$ seconds. It is a appropriate rate, because if it's small, it can't handle the signal immediately, which will cause bad performance; while if it's large, the computer wouldn't be able to compute the datas in time.

III. Sensitivity analysis

We test some factors that may affect the performance of our noise canceller. One is the total length of input signals. The other factor is the noise frequency.

A. Impact of time length

When the time length of input signal increases, LMS algorithms generally perform better. It is because our system is expected to have enough time to adapt to noise when time is long. In contrast, when time length is short, delay of LMS algorithms will be significant.

The result of our experiment is suited well to it. When we change the time length of input signal from 10 seconds to 60 seconds, the noise cancelling performance is considerably improved.

B. Impact of frequencies

When we increase frequency of input noise, the performance of our system goes worse. When noise frequency goes extremely high, our noise canceller even starts to violate property of stability.

By consulting some materials[3], we learn that ANC is best suited for low frequencies. For higher frequencies, the spacing requirements for free space and zone of silence techniques become difficult. In acoustic cavity and duct based systems, the number of nodes grows rapidly with increasing frequency, which quickly makes active noise control techniques unmanageable. Therefore, for noise in high frequency, passive noise canceller using noise-isolating materials such as insulation, sound-absorbing tiles, or a muffler rather than a power source is a better choice.

IV. Applications and possible optimizations

A. Impact of language

When we input signals in which the desired signals are speech in different languages, we find that the performance of our system is unaffected by kinds of language.

We choose three kinds of language as desired signals: Mandarin, English and Spanish. These three languages are among the top three languages spoken by the largest number of people in the contemporary world, and they differ greatly in grammar, lexical structure, phonetics and phonology. This enables us to test impact of these linguistic characteristics on noise cancelling. The desired signals we choose are daily dialogue.

The results of our experiment reveal that these factors have negligible effect on performance of our noise canceller with LMS algorithm. Thus, we can conclude that LMS algorithm is language-independent and have enough speech intelligibility.

B. Limitations and Imperfections

Because of our limited time and limited knowledge, we mainly make qualitative analysis rather than quantitative analysis in this project. This is also because the performance and all three properties of a noise canceller are difficult to measure and quantized. What's more, it is difficult to tell noise and desired signal in practice and it depends on subjective or psychological senses in many situations, which is difficult to implement.

Besides, we implement LMS algorithm on software level, but we fail to connect micro-phone as its input to implement it on hardware level. This is caused by our failure to implement hardware-software interface.

C. Improvements and optimizations

1) Optimization using genetic algorithm: The genetic algorithm is a well-known method with the search property of effectiveness, robustness and low complexity. Therefore, it seems tempting to introduce genetic algorithm into noise canceling to distinguish noise and desired signals. For instance, Chiang has proposed the genetic algorithm to search Mandarin disyllabic words that accord with the phonemic balance of a lexical corpus in 2005. [4]

2) Optimization using neural network: Our noise canceling system may fail in practice because what is noise may depend on psychological factors, so it seems natural to introduce philosophy of cognitive robotics and neural network into noise canceling.

When the desired signals are speech, it may be difficult for computers to extract speech from noise, but this task is easy for human brain. According to some psycholinguistic studies, infants have ability to tell the difference between sounds of natural language and noise before they have learned how to speak [5]. Besides, natural language processors and machine translators based on neural network generally perform better than those based on statistics [6]. Since LMS algorithm is a statistical method, it seems reasonable to expect that introducing neural network will give our noise canceller a better performance.

References

[1] S. M. Kuo, D. R. Morgan, Active noise control systems: algorithms and DSP implementation, New York: J. Wiley & Sons, 1996.

[2] MATLAB official document

[3] Aleksandar Milosevic and Urs Schaufelberger, Active Noise Control, Diploma Thesis, Rapperswil, December 14, 2005

[4] Jiun-Hung Lin, Shih-Tsang Tang1, Wei-Ru Han, Chih-Yuan Chuang, Ping-Ting Liu and Shuenn-Tsong Young, Evaluation of Speech Intelligibility for Feedback Adaptive Active Noise Cancellation Headset, 2006

[5] Seidner, Stanley S., Ethnicity, Language, and Power from a Psycholinguistic Perspective, 1982

[6] OpenNMT - Open-Source Neural Machine Translation, opennmt.net, 2017

V. Appendix: MATLAB codes

(We have attached the file.)