FUZZY ACTIVE NOISE MODELING AND CONTROL OF ENCLOSURES


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Abstract: The design of active noise control has been developed in the last two decades based on linear identification and control tools. However, acoustic processes present nonlinearities coming both from the characteristics of the actuator and from the nature of the process. Recent research has emphasized the importance of nonlinear model-based controllers, which increase the performance of several types of systems. Direct and inverse multivariable fuzzy models can be identified directly from data using fuzzy clustering. Inverse models can then be applied directly as controllers, which can be included in an active noise control scheme. This paper proposes the use of fuzzy techniques in active noise control. The performance of the proposed control schemes is compared to classical FIR active noise control in an experimental setup. Model-based fuzzy controllers clearly outperform classical active noise controllers.

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Keywords: Active noise control, fuzzy modeling, fuzzy control, multivariable control, control algorithms.

1. INTRODUCTION

Technological and industrial development has resulted in an increase of noise level from machines, factories, traffic, etc. Many reasons have been taken into account to develop research in the sound attenuation field, as e.g. environmental and legal restrictions concerning people’s safety and health. Noise reduction can be achieved in two different ways. The first one consists of passive systems, which are based on the absorption and reflection properties of materials, and present excellent results for frequencies higher than 1 kHz (Bies and Hansen 1996). The other consists of active systems, which present good performance for frequencies below 1 kHz. Active systems are based on the principle of wave interference, where a sound is generated with the same amplitude as the noise source but with an adequate phase shift, in order to cancel the primary noise (Nelson and Elliott 1999). This is usually known as Active Noise Control (ANC).

Most of ANC applications use linear identification and control techniques, relying on the linear superposition of a primary field and a destructively interfering secondary field to achieve the desired noise cancellation. In practical terms, this means that one pressure fluctuation will not become distorted by the presence of another. However, in some situations it is not possible to neglect nonlinear terms. Examples of these situations are when the loudspeaker excites both the frequency of interest and its respective harmonics, or when it operates close to or lower than its minimum operating
frequency. The process by itself may be responsible for the appearance of nonlinearities, as distortion and reverberation.

This paper uses black-box models identified directly from data, and presents a new approach of fuzzy active noise control based on nonlinear models. An appropriate experimental setup, consisting of an enclosure, is developed to test the proposed control schemes. This type of system is known to have strong nonlinearities. Both direct and inverse black-box models are identified from real data, and are applied to active noise control of the enclosure.

The outline of this paper is as follows. Section 2 presents a brief overview of fuzzy modeling and identification. In Section 3, a short review of classical active noise control is presented. The motivation to apply fuzzy techniques in active noise control is discussed. The experimental setup is presented in Section 4. Section 5 shows the experimental results for both modeling and control, and a comparison between the proposed method and classical techniques is made. Finally, Section 6 concludes the paper.

2. FUZZY MODELING

Fuzzy models are flexible mathematical structures that, in analogy to neural networks and radial basis functions, have also been recognized as universal approximators (Zeng and Singh 1995). Takagi and Sugeno (1985) introduced a fuzzy rule based model that can approximate a large number of nonlinear systems. The Takagi-Sugeno (TS) fuzzy model consists of fuzzy rules, where each rule describes a local linear input-output relation:

\[ R_i : \text{If } x \text{ is } A_i \text{ then } y_i = a_i^T x + b_i, \]  

where \( i = 1, \ldots, K \), \( R_i \) denotes the \( i \)th rule, \( K \) is the number of rules, \( x = [x_1, \ldots, x_n] \) is the input (antecedent) variable, \( A_i \) is the antecedent fuzzy set, \( y_i \) is the consequent variable (rule output), \( a_i \) is a parameter vector and \( b_i \) is a scalar offset. The overall output of the model \( \hat{y} \) is calculated by taking the weighted average of the \( K \) rule consequents:

\[ \hat{y} = \frac{\sum_{i=1}^{K} \bar{\beta}_i y_i}{\sum_{i=1}^{K} \bar{\beta}_i}, \]  

where \( \bar{\beta}_i \) is the degree of activation of the \( i \)th rule:

\[ \bar{\beta}_i = \Pi_{j=1}^{n} \mu_{A_j}(x), \quad i = 1, \ldots, K, \]  

and \( \mu_{A_j}(x) \) is the membership function of the multidimensional fuzzy set \( A_j \). The structure presented here for multi-input single-output systems can be easily generalized to the multi-input multi-output (MIMO) case.

A fuzzy model can be constructed entirely on the basis of system’s measurements. Assuming that the input and the output variables are known, the nonlinear identification problem is solved in two steps:

1. Structure identification – consists of transforming the dynamic identification problem into a static nonlinear regression, by choosing the system’s structure: input delays, output delays and pure delays.

2. Parameter estimation – is done by fuzzy clustering, where data is divided in \( K \) clusters. The antecedent membership functions are extracted by projecting the clusters in the respective variables, and the consequent parameters in (1) are obtained by local or global mean-squares.

This paper considers data-driven modeling based on fuzzy clustering, as described in (Babuška 1998).

3. ACTIVE NOISE CONTROL

The earliest ideas for active noise control are outlined in the patent granted to Paul Lueg in 1936, see e.g. (Tokhi and Leitch 1992). But it was only in the 80’s, when the digital controllers became readily accessible, that active noise control became efficient.

ANC strategies can be divided into two groups: Feedback systems, where a reference signal is available from a detection sensor and the information of a monitoring sensor is used to adapt the controller; Feedback systems, where there is no detection of the noise source and the signals from the sensors are fed back to the actuator which produces an acoustic signal at the sensor to be added to the signal produced by the noise source.

ANC was already implemented successfully in several systems, such as air conditioning ducts or in transport systems, e.g., cars or planes. In many other applications sound attenuation would be desirable but the sound field is far more complex, as in enclosures or free field applications. Classical controllers have their bounds of application well defined and nonlinear modeling techniques bring a new insight and develop the possibilities of active noise control. This section describes the classical finite impulse response (FIR) feedforward control for multivariable systems. Then, fuzzy active noise control, as proposed in this paper, is presented.

3.1 FIR feedforward control

In the present-day ANC applications, the controllers are usually Finite Impulse Response (FIR) adaptive filters, which are implemented in a feedforward control loop.

The wave nature of sound leads naturally to a feedforward approach of control design. In this approach, it
is assumed that the signal used to drive the actuator is derived from a detection sensor \( x(k) \). This sensor captures an electric signal, which provides a prediction of the noise at the control point. Another microphone, called the error sensor, is introduced at the control point. This sensor provides the error signal \( e(k) \), which is normally used to monitor the performance of the active noise controller and adapt the controller parameters.

The idea behind this control strategy is quite simple. The controller is fed by the detection signal \( x(k) \) and generates a control action \( u(k) \) to the plant, in this case, the actuator. The output of the actuator \( y(k) \) will cancel the noise disturbance \( d(k) \) at the control point. The resulting error signal \( e(k) \) is then given by the pressure at the control point, which is the superposition of the primary noise pressure \( d(k) \) and the output pressure \( y(k) \):

\[
e(k) = d(k) + y(k)
\]

To control sound over large regions of space, multiple actuators and sensors are needed. Using a number \( L \) of loudspeakers and a number \( M \) of error microphones, each of the \( M \) error signals is the superposition of noise produced by the primary source and the contribution of the \( L \) secondary sources in each error sensor. It is also considered that there are \( N \) reference signals available. In this way, the number of models of the system is \( L \times M \), corresponding to the combinations of acoustic paths between the \( L \) actuators and \( M \) error sensors.

The \( N \times L \) FIR filters \( w_{ln}(k) \) coefficients are adapted based on the minimization of the error signal using the least mean squares (LMS) algorithm:

\[
w_{ln}(k+1) = w_{ln}(k) - \alpha R(k)^T e(k)
\]

where \( e(k) \) are the \( M \) error signals and \( R(k) \) is the matrix of the MLN filtered reference signals \( r_{ref} \). These reference signals are given by the \( N \) detection signals \( x(k) \) defined previously, filtered by the MLN FIR filter models of the actuators \( \hat{g}_j \):

\[
r_{m,n}(k) = \sum_{j=0}^{J-1} \hat{g}_{mj} x(k-j).
\]

Fig. 1 shows the described control loop. In fact, this type of controller acts like an inverse model controller (Nelson and Elliott 1999). Note that although this controller uses the error signal, the control loop is said to be feedforward, since the error is not directly used by the controller.

The ratio between the number \( L \) of loudspeakers and the number \( M \) of microphones limits the performance of the feedforward multi-channel control system. In general, it is advisable to have \( M \geq L \).

3.2 Fuzzy Active Noise Control

Most of ANC applications use linear identification and control techniques, relying on the linear superposition of a primary field and a destructively interfering secondary field to achieve the desired noise cancellation. In some situations however it is not possible to neglect nonlinear terms. Nonlinearities are important when the sound field is quite complex, as in enclosures or free field applications, where phenomena like distortion and reverberation must be considered. However, it is very difficult to obtain physical models of such systems. This paper proposes a fuzzy modeling technique in Section 2, that can be used in ANC.

Using an acoustic model, the controller may predict the noise at the control point, as proposed in several ANC schemes. Internal model control strategies using artificial neural networks, for instance, have been proposed recently (Elliott 2000, Bouchard and Dinh 1999, Conchinha et al. 2000). Also fuzzy models have already been used to obtain accurate models of acoustic actuators (Silva et al. 2000).

This paper proposes fuzzy ANC strategies, using the control loop shown in Fig. 2, where both the acoustic model \( A(k) \) of the acoustic path and the inverse model of the plant \( G^{-1}(k) \) are identified using fuzzy model techniques. The proposed control strategy is applied to a multi-input multi-output (MIMO) acoustic process presented in Section 4. The fuzzy identification techniques can achieve compact representations of the models, which is fundamental to apply ANC in real-time. Note that in classical ANC the number of operations required to obtain the reference signal and to update the classical FIR controller is very large for multivariable processes. By using the inverse control loop proposed in this paper, the complexity of the intelligent MIMO models do not increase as much as in the classical MIMO models, leading to simplified and more compacted models.
4. EXPERIMENTAL SETUP

The intelligent active noise control strategies proposed in this paper are tested in an experimental setup. This consists of a closed and isolated box with a rectangular shape with dimensions $90 \times 70 \times 40$ cm$^3$, which is convenient for both providing modal responses and search for the best location of sound absorbers for sound control. This box must receive the less possible sound from any other source but the loudspeakers. Its construction guarantees perfect isolation from the outside. Each side of the enclosure is composed by two wood partitions with thickness of 19 mm on the outer wall and 12 mm in the inner wall, and an air interface between them. To avoid undesirable reflections, the air interface was filled with glass wool. Figure 3 shows the inside of the enclosure and the configuration of the equipment. The primary noise source is placed at one corner of the enclosure, radiating in the direction of the actuators. The ElectroMechanical Films (EMF) actuators produce the control actions that will cancel the noise at two particular points inside the box, which are represented in Fig. 3 as Microphones. In order to apply the proposed control strategy, models of the loudspeakers are required. Each of these models represents the output of the loudspeaker at a microphone placed in a specified point inside the box, where it is desired to cancel the sound when an input is applied. This sensors/actuators disposition leads to the fully-determined optimization case, as described in Section 3.

Dynamic loudspeakers are a relatively old device. They are built from many different elements and their incapability and reproduction defects have to be corrected electronically. Their poor efficiency demands high powered amplifiers so that sufficient pressure can be achieved. Moreover, loudspeakers can be difficult to handle in some situations due to their weight. For these reasons, this paper uses as actuators ElectroMechanical Films (EMF) (Antila et al. 1999), which consist of a thin biaxial oriented plastic film coated with electrode layers. Models of these elements and control applications using these panels are presented in (Conchinha et al. 2000, Silva et al. 2000).

The control configuration used in this paper needs a disturbance signal, which is generated by a conventional sound board of a PC computer and added to a loudspeaker. The experimental setup contains also two error microphones.

The sensors and actuators described previously are connected to a PC Pentium III, using a National Instruments NI6024-E data acquisition board and the Matlab’s toolbox Data Acquisition. A Wavetek Rockland spectrum analyzer is used to generate white noise. The simulation and control programs were developed in Matlab. The nonlinear models were identified using the fuzzy modeling toolbox developed by (Babuška 1998). A sampling rate of 3 kHz is considered. An acoustic toolbox for Matlab was developed to provide a modeling and control acoustical environment for the experiments.

5. EXPERIMENTAL RESULTS

In order to apply the configuration shown in Fig. 2, three different models must be identified: the direct, the acoustic and the inverse model. White noise is used as the excitation signal to derive the three models. The accuracy of the models is measured using the root mean square (RMS) error, and the percentile variance accounted for (VAF). The VAF rates the variance $\sigma$ of the difference between two signals, the original signal $y$ and the modeled signal $y_{m}$, over the variance of the original signal $y$. Both measures were done using the power spectrum density of the signals $S_y$, as the analysis must be done in the frequency domain. Therefore, the VAF is defined as

$$VAF = \left(1 - \frac{\sigma(S_y - S_{ym})}{\sigma(S_y)} \right) \times 100\% .$$  \hspace{1cm} (7)

Note that when the real output power spectrum $S_y$ and the models output power spectrum $S_{ym}$ are equal, the VAF has the value of 100%. The experimental results are presented for the bandwidth [50,500] Hz, which is the bandwidth of interest for the proposed experimental setup. In order to obtain accurate models, 6000 sample points were considered, where 3000 are used for the training of the models, and the other 3000 to validate the results. Two methods are used to identify the models: FIR filters and fuzzy techniques.

5.1 FIR models

The FIR filter models are digital filters whose impulse response is zero after some finite number of samples. These filters are also called Moving Average (MA) filters and they are always stable, for bounded coefficients. They are called finite impulse response filters.
since its \( I \) coefficients represent the impulse response of the plant. An optimization method must be used to adapt the desired coefficients to the impulse response of the system. Usually, the LMS algorithm is used to achieve these coefficients. In this case, the number of actuators \( M \) is 2, the number of detection sensors \( N \) is 1, and the number of error sensors \( L \) is 2, see Section 3. Thus, four SISO models, one for every possible combination between the error sensors and the actuators are identified, see Fig. 1. The models identified are direct models, and four control configurations one for each possible combination between the number of reference signals and actuators (Elliott 2000), are necessary. The number of coefficients \( I \) for each model is 128. Table 5.1 presents the accuracy for each SISO model.

### Table 1. Measures of FIR models accuracy.

<table>
<thead>
<tr>
<th>SISO Model</th>
<th>( G_{11} )</th>
<th>( G_{12} )</th>
<th>( G_{21} )</th>
<th>( G_{22} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMS (dB)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Output1</td>
<td>0.03</td>
<td>0.02</td>
<td>0.07</td>
<td>0.03</td>
</tr>
<tr>
<td>Output2</td>
<td>0.05</td>
<td>0.03</td>
<td>0.04</td>
<td>0.02</td>
</tr>
<tr>
<td>VAF</td>
<td>97.64</td>
<td>96.89</td>
<td>97.23</td>
<td>98.93</td>
</tr>
<tr>
<td></td>
<td>98.34</td>
<td>98.25</td>
<td>97.91</td>
<td>98.01</td>
</tr>
</tbody>
</table>

5.2 Fuzzy models

The identified fuzzy models represent the measurements at both microphones based on the inputs of the loudspeakers, either acting as actuators (direct and inverse models) or acting as noise source (acoustical model), see Fig. 2. In this type of models it is necessary to define the model parameters, which are the pure delays \( d_i \), the input delays \( n_u \) and the output delays \( n_y \), as well as the number of clusters. The inputs are the signals that feed the loudspeakers, and the outputs are the pressures measured at the microphones in the control points. The pure delay \( n_y \) represent the time delay of the sound traveling from the loudspeaker to the microphone. The air sound speed is 331.5 ms\(^{-1}\) (Kinsler et al. 2000) and the distance between the loudspeaker and the microphone is 20 cm. The sound takes 0.6 ms to travel between the loudspeaker and the microphone, which is less than 1 sampling rate to travel this distance. Thus, the system has no pure delays. The lags in the input and in the output \( n_u \) and \( n_y \) are a mathematical representation of the output of the system based on the inputs and the outputs. These parameters were determined experimentally. All models have 2 clusters, i.e., 2 TS fuzzy rules. This low number of rules is important because it reduces the computational burden. The fuzzy models have the following parameters:

- Fuzzy direct model \(- n_{u1} = 20, n_{u2} = 25, n_{y1} = 10, n_{y2} = 10, n_{d1} = 1 \) and \( n_{d2} = 1 \).
- Fuzzy inverse model \(- n_{u1} = 40, n_{u2} = 50, n_{y1} = 20, n_{y2} = 20, n_{d1} = 0 \) and \( n_{d2} = 0 \).
- Fuzzy acoustic plant model \(- n_{u1} = 20, n_{u2} = 20, n_{y1} = 20, n_{y2} = 20, n_{d1} = 1 \) and \( n_{d2} = 1 \).

### Table 2. Accuracy of the fuzzy models.

<table>
<thead>
<tr>
<th>Models</th>
<th>Direct</th>
<th>Acoustic</th>
<th>Inverse</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMS (dB)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Output1</td>
<td>0.26</td>
<td>0.02</td>
<td>0.27</td>
</tr>
<tr>
<td>Output2</td>
<td>0.25</td>
<td>0.037</td>
<td>0.24</td>
</tr>
<tr>
<td>VAF</td>
<td>95.64</td>
<td>96.48</td>
<td>60.32</td>
</tr>
<tr>
<td></td>
<td>97.43</td>
<td>97.52</td>
<td>77.79</td>
</tr>
</tbody>
</table>

Fig. 4. Control results using FIR filters (noise — dashed, controlled signal — solid).

The accuracy of fuzzy models in the region of interest, i.e. in the [50,1000]Hz bandwidth, is presented in Table 5.2. The FIR direct models have similar accuracy to the direct and the acoustic fuzzy models. The inverse model is less accurate, but anyway it is still possible to apply it in control, as it will be shown in Section 5.3.

5.3 Control results

The FIR filters are applied using the control scheme presented in Fig. 1. and the fuzzy controller uses the scheme in Fig. 2. Note that the FIR filters can not be applied using this last control scheme (Elliott 2000). Several tests were made to analyze the repeatability of the results. The results obtained using the FIR filters are presented in Fig. 4. Fuzzy active noise control is presented in Fig. 5. The control performance in
Table 3. Attenuation achieved in dB by the proposed controllers.

<table>
<thead>
<tr>
<th>Microphone</th>
<th>FIR filters</th>
<th>Fuzzy control</th>
</tr>
</thead>
<tbody>
<tr>
<td>Microphone 1</td>
<td>0.9</td>
<td>5.5</td>
</tr>
<tr>
<td>Microphone 2</td>
<td>1.0</td>
<td>4.8</td>
</tr>
</tbody>
</table>

the range of interest is compared by measuring the attenuation achieved by each controller. The results for the range of frequencies of interest ([50,500] Hz) are presented in Table 5.3.

The fuzzy control techniques proposed in this paper clearly outperform classical FIR filters.

6. CONCLUSIONS

This paper proposed active noise controllers based on fuzzy modeling techniques for multivariable systems. Inverse control was developed based on direct and inverse models identified directly from data, using fuzzy approaches. The strategy was applied in an enclosure, which has a highly nonlinear behavior. Real time implementation of both classical FIR filters and fuzzy controllers were compared. Fuzzy control techniques clearly outperform the classical FIR filter. The attenuation of noise is in general 5 times superior using the proposed technique. In the future, the proposed open-loop strategy will be implemented in an internal model control scheme in order to cope better with disturbances and model-plant mismatches.

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7. REFERENCES


