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A study on optimal selection of reference accelerometers for active road noise control

노면소음 능동제어를 위한 최적 참조신호 가속도센서 선정에 관한 연구

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Abstract

Active noise control (ANC) is gradually expanding its application in the automotive industry. One of the reason is that passive noise control (PNC) methods are not advantageous for lightweighting as they increase the weight of the vehicle, and ANC is more effective to control low frequency range noise as compared to PNC methods. In terms of ANC application, the performance of ANC systems is directly affected by the selection of the reference signal. Currently, the issue of sensor placement leads to a compromise between time cost and performance of ANC systems. Trial and error methods that are commonly used consist of a brute-force approach simulating the result outcomes for all candidate sensor locations and present high computing costs. Consequently, a process that allows engineers to reduce the set of candidate sensor locations while obtaining target noise reduction results is needed to avoid the overwhelming time cost of the brute-force and trial-error approaches. This study suggests a method that determines candidates for the locations of the reference signal sensors by using the correlation between the input acceleration signal and output sound pressure level signal, which is a partial coherence function. This process evaluates the correlation of each acceleration signal with the interior noise and eliminates redundant sensor locations by maximizing the Fisher information matrix. This method enables the reduction of the total number of candidate locations, which in turn leads to a decrease in the total time cost while obtaining locally optimal results.

keywords: Active noise control, Fisher information matrix, Partial coherence function, Multiple coherence function

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CHAPTER 1

INTRODUCTION

The Automotive industry is at a turning point as the internal combustion engines are being replaced by electric motors. Therefore, automotive NVH issues such as road noise and wind noise that were masked by internal combustion engine noise highly affect the consumer's perception of the vehicle. Traditionally, road noise is reduced by modifying the vehicle's structure or adding sound absorbing materials. However, advancements in digital signal processor performance and the increased demand for lightweight solutions that effectively control road noise have increased the demand for improved active noise control systems. In addition, the effectiveness of ANC in controlling noise in the low frequency ranges allows it to compensate for weaknesses of conventional passive methods. To ensure effective noise reduction using ANC systems, the reference signals need to be highly correlated with the target signal and vehicle interior noise. This implies that it is crucial to determine the suitable locations of reference signal sensors. Ideally, attaching a large number of sensors on the structure of the vehicle would ensure a highly correlated reference signal. However, this method is unattractive to automotive original equipment manufacturers (OEM) due to cost inefficiency. Therefore, it is necessary to determine optimal reference sensor locations to ensure effective ANC performance. This study suggests a method to eliminate unnecessary sensor candidates to obtain the optimum reference signal. In general, to determine the optimal combination of reference sensors out of an initial candidate set, simulations are run to predict all system outputs based on different reference signal combinations. This process generates high computational loads and leads to inefficiencies in the vehicle development process. In order to avoid high computational costs, one of the ways to select reference signal sensors is to use the multiple coherence function (MCF). In the study of Duan [1], the optimal sensor locations and minimum number of accelerometers were determined using principal component analysis (PCA) and MCF. More recently, the location of the reference for automotive engine noise was suggested using a coherent power level (CPL), which is the time averaged power level of the coherent part of the reference signal [2]. However, in our paper, it was checked that high MCF does not always ensure high noise reduction in an ANC system. In addition, a robust method for the selection of the multiple channel reference sensor is necessary for coping with not only harmonic signals, but also random signals such as road noise. In this regard, we propose a method to reduce the number of initial reference sensor candidates without the loss of ANC system performance. In this study, partial coherence has been used to ensure that the influence of each accelerometer of the vehicle cabin noise is evaluated independently. In addition, analogous to the effective independence method (EFI) studied by Kammer, the Fisher information matrix allows us to compare the amount of information that each sensor contributes to the targeted system [3-5]. To eliminate the initial reference sensor candidates, the contribution of each sensor is determined by calculating the Fisher information matrix of the partial coherence functions between the vibration signals and interior noise signals. The contribution of each sensor is calculated by projecting their coherence data to the orthogonal eigenspace of the information matrix, and the sensors are ordered based on their contribution values. Afterwards, the initial reference sensor candidates are sorted from the obtained sensor index, which results in decreasing simulation time cost with the performance close to the global maximum noise reduction. Furthermore, in theory, the expected noise reduction is better for higher coherence. However, in the actual simulation, the combination of sensors with the highest MCF does not represent the highest noise reduction. Hence, instead of determining the optimal reference sensor combination using MCF, we suggest a partial coherence-based reference sensor selection method to reduce the computation burden and simultaneously ensure noise reduction similar to the global maximum value. In order to validate our results, the above procedure has been applied to three reference data sets.

CHAPTER 2

METHODOLOGY

2.1 Overview

The process for determining the optimal locations of the reference sensors consist of 3 steps. In the first step, all the initial sensor candidates are installed at the main force input points. Then, the initial set of sensors is reduced by selecting a subset of candidate locations that minimizes of the partial coherence function covariance matrix. In the final step, Wiener filter-based ANC simulations allow the determination of the final optimal sensor locations.

2.2 Wiener filter

In this study, the optimal noise reduction for ANC is simulated using a Wiener filter, also known as an optimal discrete time filter [7]. The input signal and desired signal are measured with sensors such as accelerometers and microphones. Then, measured signals are recorded by a signal acquisition device to simulate Wiener filter-based active noise control. The Wiener filter is designed to filter the input signal and generate the output signal such that the error between the desired signal and estimated signal is minimized (Figure 2.1). The error mean square value is described as follows equation

$$J = E[e^2(n)], \tag{2.1}$$

where $E[e^2(n)]$ is the expectation value of e . For optimal filter design, the mean square value of the error needs to be minimized by its derivative with respect to the filter coefficient w and by setting the resulting equation to 0. The equation for obtaining the Wiener filter coefficients is derived from the above minimization process and the Wiener-Hopf equation is derived as

$$\begin{gathered} E[d(n)x(n-k)] = \textstyle\sum_{i=1}^{\infty} w(i)x(i-k), \\ \rightarrow P[-k] = \textstyle\sum_{i=1}^{\infty} w(i)x(i-k), \end{gathered} \tag{2.2}$$

which consist of two correlation functions, the autocorrelation function of the input signals and the cross-correlation between the input signals and the desired signal [6]. Based on the Wiener filter, the optimal sensor combination is determined by comparing the noise reduction of each combination. The number of every sensor combinations to be examined is 3060 since 4 sensors are selected from initial 18 sensor candidates. Due to the large amount of time required to simulate 3060 combinations, the paper propose a sensor selection technique based on partial coherence function as a method to reduce the number of initially selected sensors.

2.3 Partial coherence

To reduce the initial candidate set of sensor locations, a comparison method is needed to allow the evaluation of the performance of each sensor. Therefore, the contribution of each sensor to the active road noise control (RANC) system is found based on the Fisher information matrix of the vibro-acoustic coherence data as shown in section 2.4. When the ordinary coherence function between the two variables x_1 and y is near unity, the linear relationship between x_1 and y cannot be verified. This is because there could be a third variable x_2 that is highly coherent to x_1 and is linearly related to the output y [8,9]. Therefore, the use of the partial coherence function, as defined in [8] is suggested because it allows the elimination of redundant input signals when evaluating the individual input-output coherence. The partial coherence function, $\gamma^2_{iy(i-1)!}$, is defined by the auto-spectral density function and cross-spectral density function

$$\gamma^2_{iy(i-1)!} = \frac{\left|L_{iy}\right|^2 G_{ii(i-1)!}}{G_{yy}}, \tag{2.3}$$

in which $G_{iy(i-1)!}$ is the conditioned cross-spectral density function, $G_{ii(i-1)!}$ is the conditioned auto-spectral density function of input and G_{yy} denotes the auto-spectral density function of output.

2.4 Partial coherence-based reference sensor selection method

The effective independence method (EFI) is a method to reduce the number of sensors needed for mode shape prediction of large dynamic structures. The Fisher information matrix (FIM), which is the inverse matrix of the mode shape covariance matrix, is used to select the final set of sensor candidates that would minimize the covariance matrix [3]. After calculating the eigenvalues and eigenvectors of the FIM, the contribution of each sensor is obtained by projecting the target mode onto the orthogonal eigenvector space. For the RANC project, the objective is to select the reference accelerometers for optimal RANC performance, and not mode shape prediction. Hence, the FIM is constructed using the partial coherence function that allows to quantify the relationship between the input vibration signal and vehicle interior noise. When the number of sensors is s and the frequency range is 1 to kHz, the covariance matrix of the partial coherence function can be calculated as follows

$$COV^{-1} = Q = [\gamma^2 - \mu]^T[\gamma^2 - \mu], \tag{2.4}$$

where γ^2 is the partial coherence function matrix and μ is the mean value of γ^2. In terms of the contribution of each degree of freedom, FIM is expressed as

$$Q = \sum_{i=1}^{s}[\gamma^2_{iy(i-1)!}{}^T - \mu_i][\gamma^2_{iy(i-1)!} - \mu_i], \tag{2.5}$$

where $\gamma^2_{iy(i-1)!}$ denotes the partial coherence function of i^{th} channel of a sensor and the subscript s represents the number of initial channel candidates.The first step to analyze contribution of each reference signal is solving the eigenvalue equation for FIM which is given by

$$[Q - \lambda I]\Psi = 0 \tag{2.6}$$

where λ is eigenvalues and Ψ eigenvectors. As the eigenvectors of the FIM are orthogonal, the eigen space is composed of s-orthogonal directions in s-dimensional space. When the partial coherence function is projected onto the eigen space, the contribution of each sensor can be compared, and the matrix G is constructed as

$$G = [\gamma^2\Psi] \otimes [\gamma^2\Psi] \tag{2.7}$$

in which $\otimes$ denotes the element-by-element product of the vector. Now each row of matrix G consists of the square of each row element of the partial coherence matrix as projected on the orthogonal direction defined by each eigenvector. Then the contribution of the i^{th} sensor to each respective eigenvalue is represented by each column of matrix G. The next step is multiplying the inverse of eigenvalue by G such that

$$G^{'} = G\lambda^{-1} \tag{2.8}$$

each projected component of G matrix represents equal weight. Finally, the total sensor contribution is obtained by summing j^{th} column in the i^{th} row of the matrix G'

$$P_c = [\sum_{j=1}^{k} G^{'}_{1j}, \sum_{j=1}^{k} G^{'}_{2j}, ... \sum_{j=1}^{k} G^{'}_{sj}] \tag{2.9}$$

where i denotes 1 to s and j denotes 1 to k. Each component in row vector P_c is sorted in descending order and designated upper sensors from the sorted vector are selected as the initial sensor candidates.

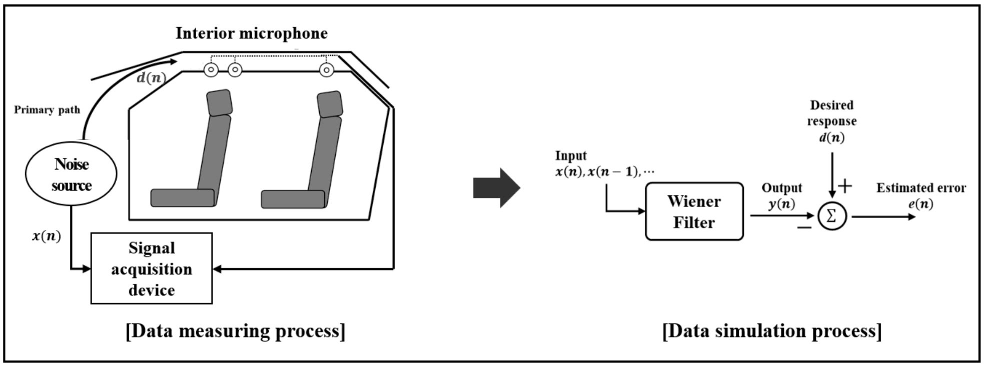

Figure 2.1: Overall process of active road noise control simulation

CHAPTER 3

Result

First, the data were collected that is used in the simulations. Operational cabin interior noise and vibration level time signals were recorded using 18 accelerometers placed on the chassis of the experimental vehicle and eight microphones measuring the car interior sound pressure level (see Figure 3.1). Eight and ten accelerometers were installed on the front and rear part of the vehicle chassis, respectively. For both front and rear suspension systems, the accelerometers were attached to the subframe mount, knuckles, and dampers, which were the main components of the structure-borne noise transfer paths. Additionally, as the rear suspension system of the experimental vehicle was of multi-link type, sensors were attached to the left and right trailing arms. A total of eight error microphones was used. Two microphones each were placed on the driver, front passenger, and rear window passenger seats. Next, the throughput time data were measured at three different driving speeds on the same road surface (50 km/h, 60 km/h, and 80 km/h) on the same road surface. The noise reduction of the RANC system was evaluated by two methods. First, the noise reduction was estimated using the Wiener filter for every sensor combination of all initial reference sensor candidates. For the next, the number of initially selected sensors was reduced using the partial coherence-based method suggested in this study and the optimal sensor combination was obtained using the Wiener filter. In order to evaluate the performance and results obtained by each of the above methods, the required simulation time as well as noise reduction levels was computed and are presented next.

3.1 Method 1 – ANC simulation with total sensor combination

For RANC, 4 triaxial accelerometers out of the initial 18 sensor candidates were used. The total number of combinations to be investigated was therefore 3060, and the noise reduction analysis was conducted using the Wiener filter ANC simulation. The simulation of all the combinations for each data set required 100–110 hours for completion. As 8 separate microphones were installed in the vehicle cabin, the sound pressure level reduction was obtained for 8 different positions in the vehicle cabin. The interior sound pressure level was evaluated for frequencies between 20 to 500 Hz. Among three frequency bands, the peaks generated in the cavity band (200 to 240 Hz) significantly decreased after application of ANC (see Figure 3.2). The same results were observed in all three driving conditions. The MCFs of the optimal sensor combination was also calculated to reflect the correlation between the input signal and output signal using the modified multiple coherence function [8]. In theory, the noise reduction is higher for a higher MCF value and the correlation between noise reduction and multiple coherence was identified using the calculated data [1]. From the result, although the MCF was not proportional to the noise reduction, an overall upward trend was observed (see Figure 3.3).

3.2 Method 2 – multiple coherence function-based reference sensor selection method

When selecting a combination using four out of 18 sensors, 3060 sensor combinations needed to be simulated. In the process of ANC simulation, the Wiener filter coefficients were calculated for the 3060 combinations, which required considerable time for solving the Wiener-Hopf equation (2). The combination having the maximum noise reduction was selected as the final reference signal position. Hence, if the number of combinations could be reduced, the time cost can also be significantly reduced. In section 3.1, an upward trend of mean noise reduction as a function of the mean MCFs was observed in Figure 3.2. In this regard, the method proposed that the total number of sensor combinations were reduced by selecting the sensor combinations that had high multiple coherence and by evaluating their respective performance. Accordingly, active road noise control simulation was conducted only for the 20 sensor combinations having the highest multiple coherence out of the total 3060 sensor combinations. First, as eight microphones were installed inside the vehicle, eight sets of MCFs, and hereby a total of 24480 MCFs were calculated. The required time to calculate the 24480 MCFs was 20 hours. Moreover, the ANC simulation required an additional 6 hours to compute the noise reduction for 160 sensor combinations. The overall procedure was applied to the throughput time data for each driving condition and the result showed only a 2 percent difference in performance compared to the result from section 3.1. Additionally, the required time was reduced from 100 hours to 26 hours (Table 3.1). However, other methods were sought because as observed in figure 3.2, low noise reduction could still be obtained from sensor combinations with high MCFs, and therefore the consistency of this method could not be validated.

3.3 Method 3 – partial coherence function-based reference sensor selection method

In this section the performance of the method using partial coherence function covariance optimization is presented. Based on the partial coherence functions between the reference signal and output signal, the contribution of the initial reference sensor candidates was analyzed to obtain an optimal subset of sensor locations. Additionally, a total of 8 partial coherence function matrices were obtained for each microphone installed in the vehicle. Partial coherence function data was applied to equation (10) to construct a sensor index vector, and ANC simulation was performed by selecting the top 10, 8, and 7 sensors of the index. For calculating the partial coherence of each mic in the vehicle cabin, a total of 1680, 560, and 280 sensor combinations were calculated, respectively, and each result is summarized in Table 3.2. In the table, the first column indicates the number of initial sensor selected by applying method 3, the second colunm means the number of sensor combinations which were used as input for Wiener filter ANC system, and the time cost of the third column is the total simualtion process time including coherence function calculation time and Wiener filter simulation. After selecting the top 10 sensors, a time reduction of 60% and noise reduction error of only 1% was obtained compared to the global maximum noise reduction. However, as the required time still exceeded that of the method 2 procedure, simulations were run for subsets of 8 and 7 sensors. Such a decrease in the number of sensors allowed for a time cost reduction by three and six times, respectively. As the performance difference between the above two cases did not exceed 0.07 dBA and the time cost of using one additional reference candidate doubled, it was inferred that reducing the 18 initial candidates to 7 using this method lead to satisfactory results. The simulation time of the 7 sensor subset was reduced to 10% compared to the time required for the brute force method and 38% compared to that of the method 2. Moreover, the performance error obtained by the 7 sensor subset was found to be 4.49% compared to the globally optimal result found in method 1 (see Figure 3.4). In addition, the results of selected sensor combinations were represented with respect to MCFs similar with Figure 3.2 (Figure 3.5-7). The complete simulation results are summarized in Table 3.3. Both the aforementioned ANC reference sensor selection procedures include the coherence functions between every microphone installed in the vehicle cabin, and therefore the simulation load is increased by 8 times compared to a single microphone simulation. As observed in Table 3.4, the results of the ANC system using different microphones do not vary considerably, and therefore it can be inferred that the use of one microphone can suffice for good ANC system performance. According to the results from method 3, the difference in noise reduction for each microphone is approximately 0.1 dBA. Thus, if a partial coherence functions are obtained at one microphone of a targeted vehicle interior seat, the required combinations decrease from 3060 to 35, which reduces the simulation time to 1.25% of the maximum time required and the ANC performance can be maintained with an error of 3.7% (Table 3.5).

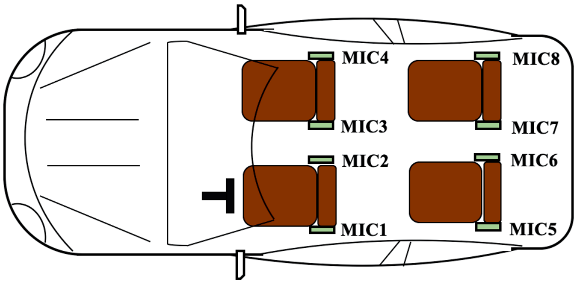

Figure 3.1: The upper view of vehicle interior error microphone location. The figure illustrates the position of error microphones inside of vehicle. 2 microphones are installed on each headrest.

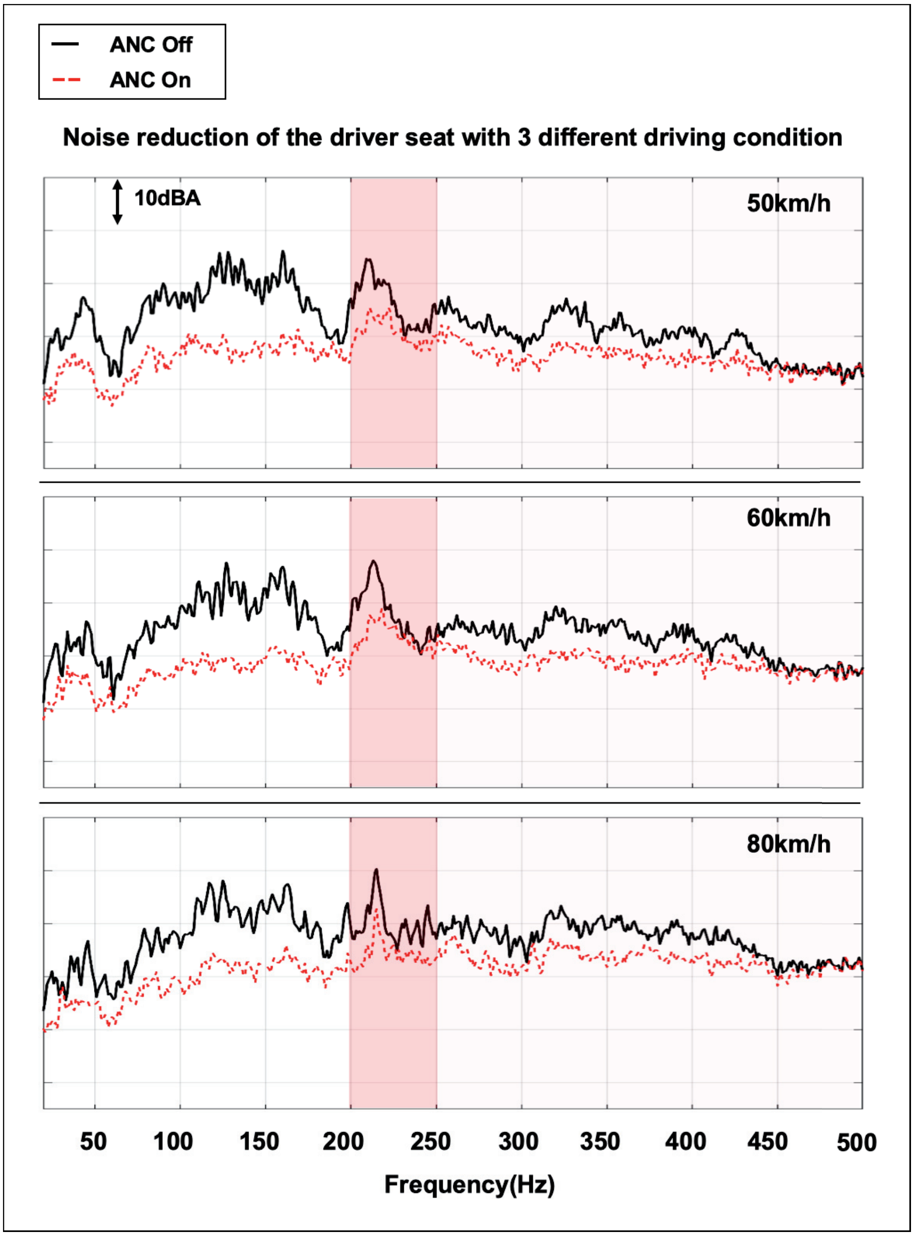

Figure 3.2: The noise reduction level of the left side of driver seat with 3 different driving conditions.

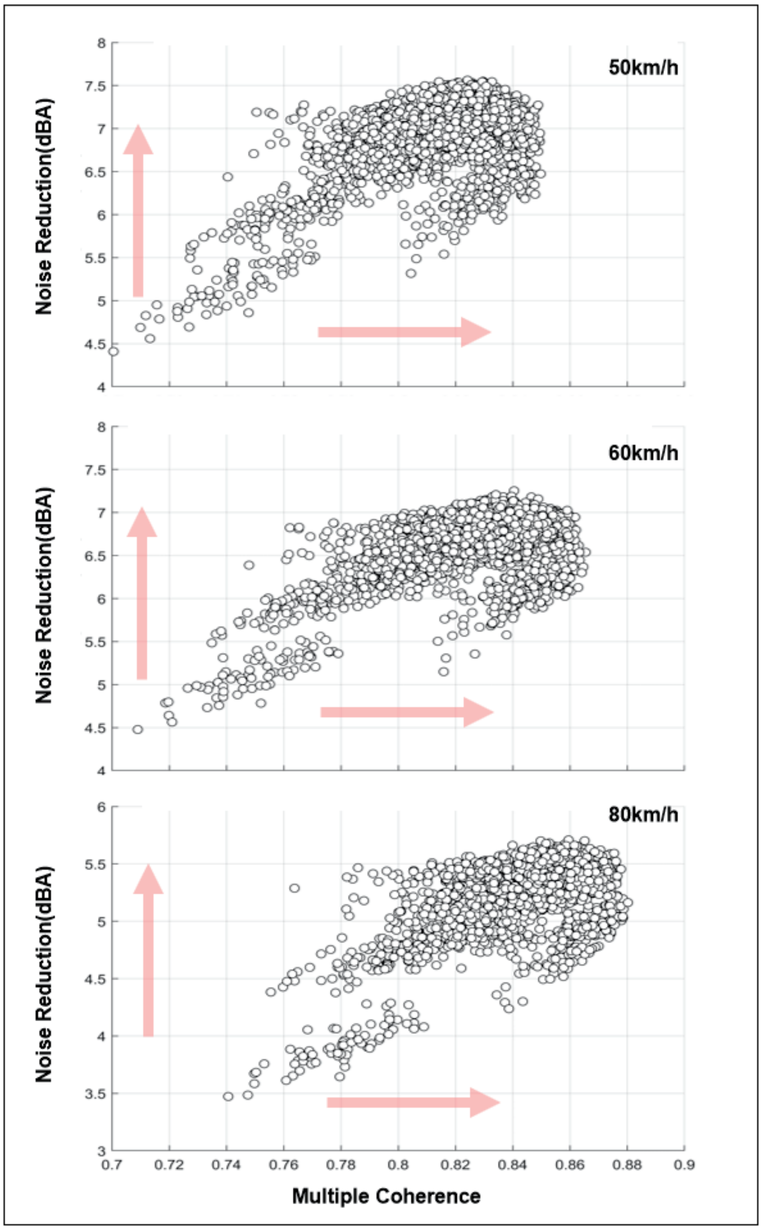

Figure 3.3: The figure presents the noise reduction distribution depending on multiple coherence functions. Each circle is a sensor combination out of 3060 combinations. Although the relation between noise reduction and multiple coherence function is not proportional, the figure shows that the distribution of high noise reduction is denser when multiple coherence functions are high.

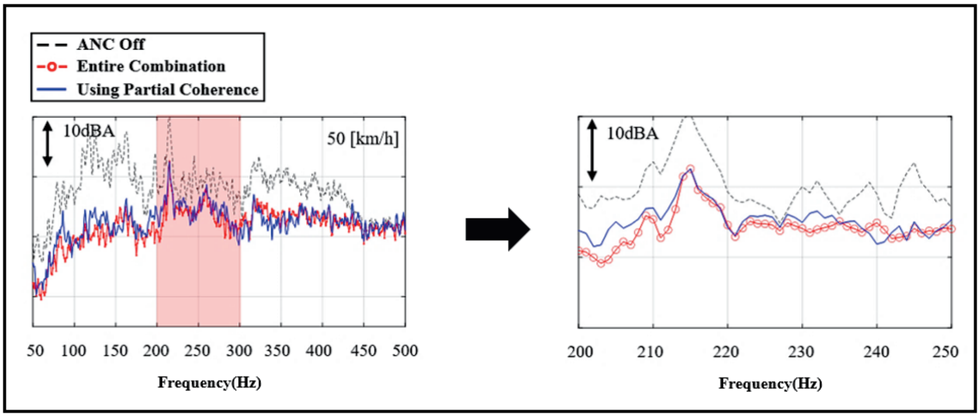

Figure 3.4: ANC simulation result at 50km/h driving condition. The red dot line indicates the result with optimal filter with entire sensor combinations and the blue line means the reuslts from partial coherence function-based reference sensor selection method.

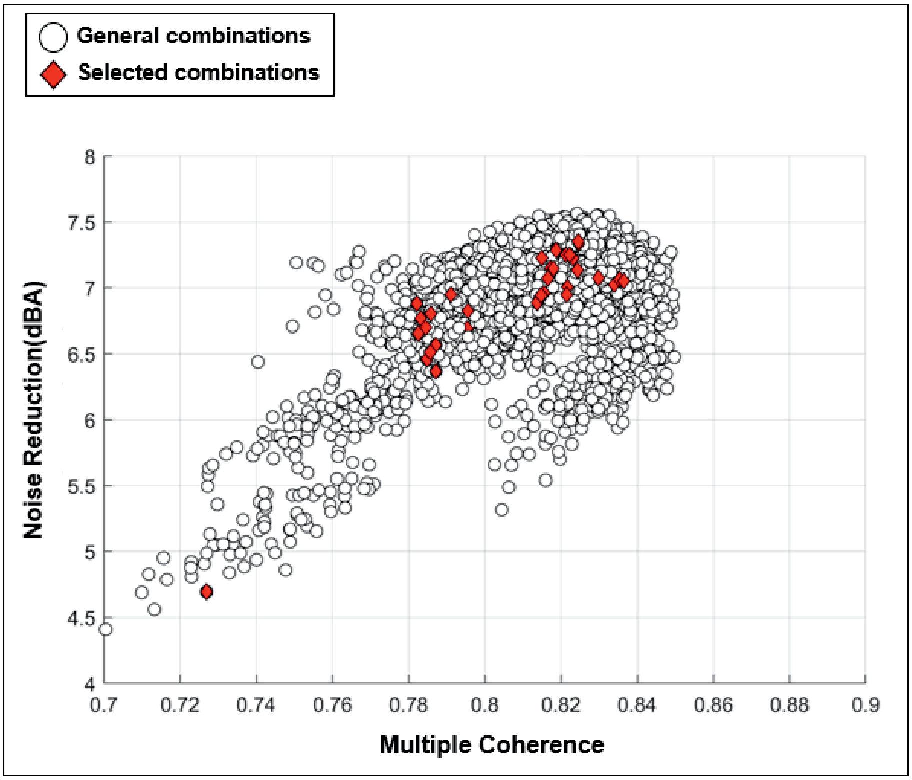

Figure 3.5: The figure represents the number of reduced sensor combinations after using partial coherence based refrerence selection method. The data is plotted in terms of multiple coherence function and noise reduction for 50km/h driving condition. As figure indicates, the local maximum is approximately close to the global maximum.

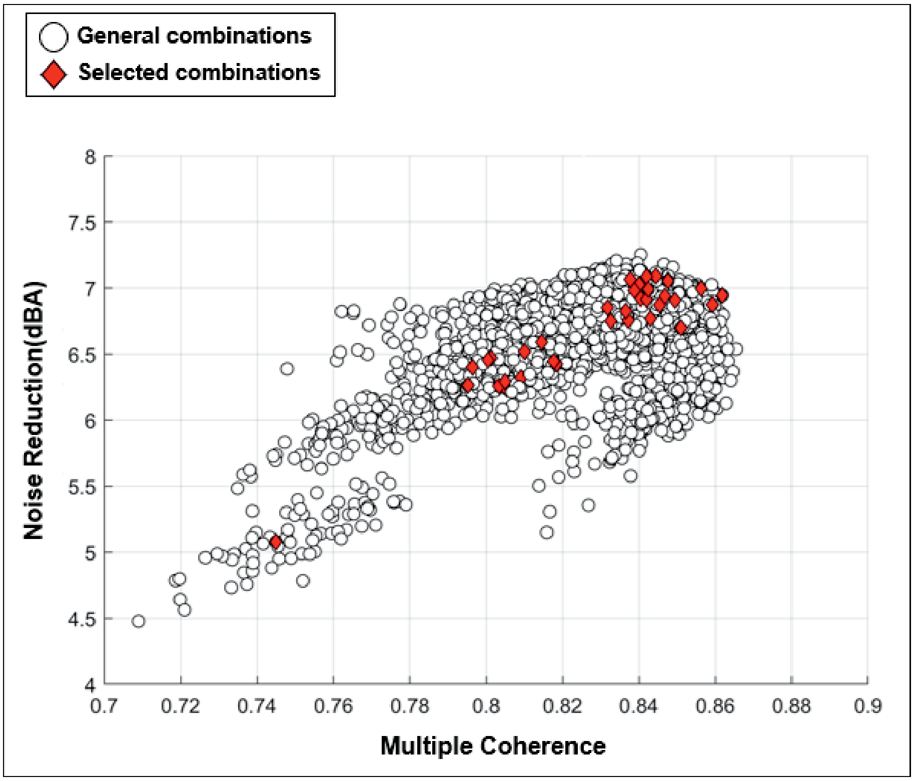

Figure 3.6: The figure represents the number of reduced sensor combinations after using partial coherence based refrerence selection method. The data is plotted in terms of multiple coherence function and noise reduction for 60km/h driving condition. As figure indicates, the local maximum is approximately close to the global maximum.

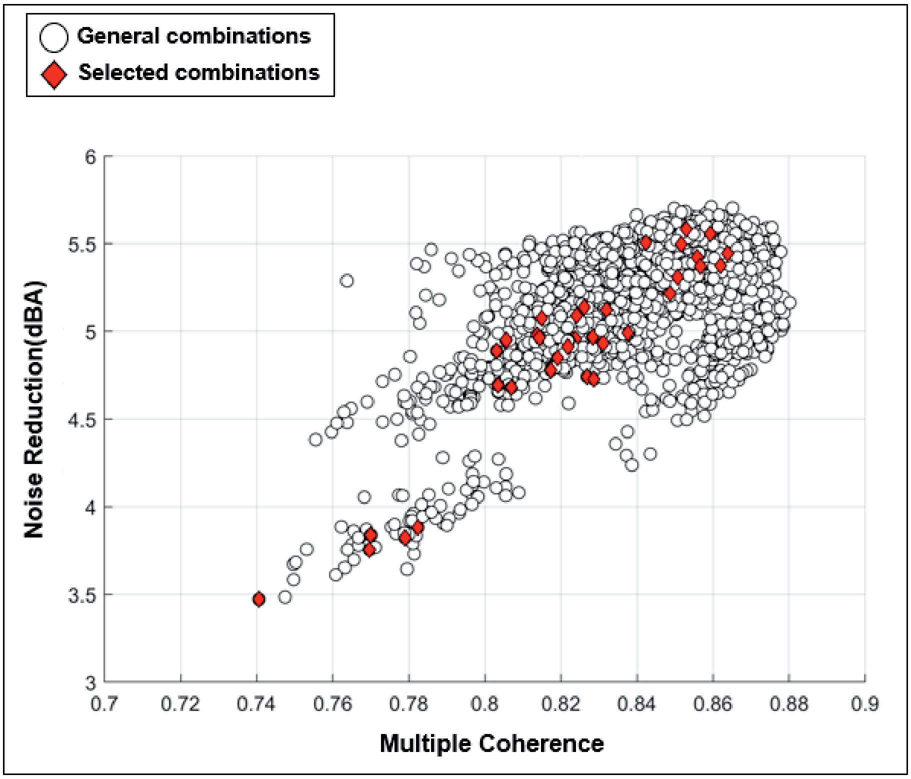

Figure 3.7: The figure represents the number of reduced sensor combinations after using partial coherence based refrerence selection method. The data is plotted in terms of multiple coherence function and noise reduction for 80km/h driving condition. As figure indicates, the local maximum is approximately close to the global maximum.

Method	Combination number	Time cost (hours)	Noise reduction($\triangle$dBA)		
			50km/h	60km/h	80km/h
OPT	3060	100	7.56	7.25	5.71
MCOH	160	26	7.40	7.08	5.61

Table 3.1: This table compares the ANC simulation results of OPT and MCOH. The number of combinations decreases from 3060 to 160. Since the time cost to obtaion multiple coherence function of every combination is over 22 hours, the total time cost to select reference sensor location with MCOH is exceed 20 hours. In case of noise reduction, the performance difference is less than 2.5%

Method	Combination number	Time cost (hours)	Noise reduction(ΔdBA)		
			50km/h	60km/h	80km/h
10 sensors	1680	60	7.48	7.11	5.63
8 sensors	560	20	7.28	6.96	5.61
7 sensors	280	10	7.22	6.95	5.57

Table 3.2: Noise reduction level depending on the selected number of sensors using the partial coherence-based reference sensor selection method. Although the results with 10 initial referenece sensors are the best, there is less than 0.3dBA difference with 7 initial referenece sensors. Furethermore, the time cost decreases 100 hours to 10 hours.

Method	Combination number	Time cost (hours)	Noise reduction(ΔdBA)		
			50km/h	60km/h	80km/h
OPT	3060	100	7.56	7.25	5.71
MCOH	160	26	7.40	7.08	5.61
PCOH	280	10	7.22	6.99	5.57

Table 3.3: Noise reduction level depending on applied simulation process. OPT is the procedure mention in the section 3.1, MCOH is the method mention in the section 3.1, and PCOH is partial coherence function-based reference sensor selection method. This table reflects the results with coherence functions between 8 microphones and reference sensors.

Noise reduction level [dBA]							
Mic1	Mic2	Mic3	Mic4	Mic5	Mic6	Mic7	Mic8
5.58	5.57	5.54	5.61	5.43	5.55	5.22	5.59

Table 3.4: Noise reduction level at each microphone location with 80 km/h driving condition.

Method	Combination number	Time cost (hours)	Noise reduction($\triangle$dBA)		
			50km/h	60km/h	80km/h
OPT	3060	100	7.56	7.25	5.71
MCOH	20	3	7.53	7.18	5.70
PCOH	35	1.25	7.28	7.00	5.61

Table 3.5: Noise reduction level depending on applied simulation process as mentioned on Table 3.3. This table reflects the results with coherence functions between a microphone and reference sensors.

CHAPTER 4

Conclusion

In an ANC system, the reference signal plays an important role in the overall performance of the system. In active road noise control systems, the reference acceleration signal performance is strongly determined by the positioning of the reference sensor. The selection of the locations of the reference signal sensor for complex structures is currently conducted based on trial and error methods and the intuition and experience of an NVH engineer. In the domain of NVH, the main noise transfer paths have been extensively studied and are well established. An initial candidate set of sensors is therefore attached to these points to determine the optimal reference signal sensor positions. The noise reduction level is obtained using the Wiener filter based RANC algorithm that calculates the filter coefficients for an input signal to minimize the difference between the predicted control signal and desired signal. However, calculating the filter coefficients for all sensor locations and sorting the optimal sensor location require heavy computations. Therefore, this study aims to decrease the time required to select the optimal reference sensor positions by reducing the number of sensors of the initial sensor set. In the method proposed in our study, we evaluate the contribution of each reference signal sensor by projecting the coherence of the input signal and desired signal using an input-output vibro-acoustic partial coherence function. The partial coherence function is a function that represents the coherence between an input signal and output signal while excluding the influence of other input signals. This allows the identification of the independent association of each input signal. Subsequently, the partial coherence function of each channel is projected on to the eigenvector space of the FIM obtained from the partial coherence function matrix. This allows the sorting of the sensors based on their contribution to the maximization of the FIM matrix through which the candidate sensor subset is selected. The ANC simulation of the initial set of sensor positions requires a total of 100 h of computation. However, the partial coherence-based reference sensor selection method reduces the initial selected sensors from 18 to seven and requires only 10% of the computation time, while maintaining an overall performance error of less than 4.5% with respect to the global maximum noise reduction. Moreover, the above results have been validated by observing the consistent performance of the three methods when applied to three different data sets corresponding to three different driving conditions respectively (50 km/h, 60 km/h, and 80 km/h). Furthermore, as eight microphones have been installed in the test vehicle, eight optimal sensor combinations are obtained based on the multiple coherence or partial coherence of each interior microphone. In addition, as the noise reduction level using different microphones does not vary substantially, the time cost reduces to 1.25% of 100 h while maintaining a performance error less than 3.7% through the use of one target reference microphone. However, the lack of clear criteria for the number of sensors to be used in the final system remains an issue that requires future research [10, 11]. In addition, the global maximum noise reduction level can be improved by not selecting the initial sensor candidates empirically.

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초 록

능동형 소음제어(ANC)가 자동차 산업에서 점차 적용 범위를 넓혀가고 있다. 그 이유 중 하나는 패시브 노이즈 컨트롤(PNC) 방식이 차량 중량을 늘려 경량화에 유리하지 않고, ANC 방식이 PNC 방식에 비해 저주파 범위의 소음을 더 효과적으로 제어할 수 있기 때문이다. ANC 적용 측면에서 ANC 시스템의 성능은 참조 신호의 선택에 직접적인 영향을 받는다. 현재 센서선정 문제는 소요시간과 성능 사이의 절충으로 이어진다. 일반적으로 사용되는 시행착오 방법은 모든 후보 센서 위치에 대한 소음저감량을 얻기 위해 시뮬레이션을 진행하고 이에 따라 많은 시간이 소요된다. 따라서 시행착오 방법을 통해 얻은 최적결과에 근접한 결과를 얻으면서 후보 센서 위치 개수를 감소 시킬 수 있도록 하는 프로세스가 필요하다. 본 연구에서는 입력 가속도 신호와 출력 음압 수준 신호의 상관관계를 이용하여 참조 신호 센서의 위치 후보를 결정하는 기법을 제안한다. 이 프로세스는 각 가속 신호와 내부 노이즈의 부분 기여도함수를 바탕으로 구성된 피셔 정보 매트릭스를 극대화하여 중복 센서 위치를 제거한다. 이 방법을 통해 초기 참조신호 후보군을 줄일 수 있으며, 이는 목표했던 결과를 얻으면서 총 시간비용의 감소로 이어진다.

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