Acoustic clustering for vehicle based sounds

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I. Introduction & Motivation

Quality assurance of Volkswagen AG defined a wide range of noise types. Expertise on noise types can significantly simplify the search of noise emitting locations and cause of noticeable noises (e.g. emitted by worn-out parts).

So far no common objective procedure exists to get an automatic noise type declaration for unknown noise. Purpose of this investigation is to use clustering-algorithms for reproducible objective noise grouping. For this reason we are modeling a simplified automatic noise type clustering model for objective noise type recognition.

Many noise types occur only under certain driving conditions (e.g. acceleration). However, in all conditions additional driving noise is emitted. To deal with these car noises, we need to have reliable features, to guarantee stable clustering results for a defined noise type with varying car noise.

One of the major challenges is to get an objective decision with a small amount of examples per noise type.

II. Fundamentals

Clustering

Clustering [3] is a method to separate a set of objects into subsets by means of their category, called clusters. The goal is, having the elements in a subset (cluster) to be more similar to each other than to the elements assigned to the other clusters. There exist many possibilities to define similarities between objects, one of the most common is the Euclidean distance. Furthermore, there are many different clustering algorithms, from which we chose k-means and spectral clustering [1] for further evaluation. Both algorithms have in common, that the number of resulting clusters has to be known beforehand. The k-means algorithm was used in 2 variants: variant 1 is from [6] and variant 2 is from the Matlab® statistics toolbox. The spectral clustering algorithm is from [2] and the nearest neighbor algorithm is used to obtain the distance matrix, the number in parenthesis indicates the number of nearest neighbors to be used.

<u>k-means algorithm [3] in short:</u>

(1) Randomly distribute k centroids in the data, representing k clusters

(2) Assign each data object to the closest centroid (cluster)

(3) Calculate new centroid of each cluster

(4) If centroids have not changed **or** a predefined maximum number of cycles is reached → stop

(5) Otherwise continue with (2) until (4) is fulfilled

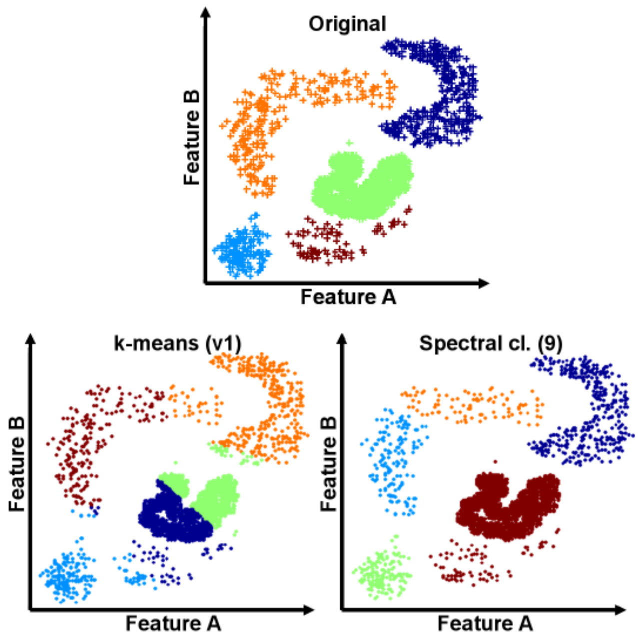

Figure 1: Comparison of k-means algorithm with the spectral clustering algorithm. Spectral clustering was used on data of the left side and k-means on the right.

<u>spectral clustering algorithm [2]:</u>

(1) Build a distance matrix on graph built with nearest neighbor algorithm

(2) Use spectrum of the adjacency matrix for dimensionality reduction

(3) Cluster resulting points with k-means

Figure 1 shows a comparison for different test datasets between clustering results of these two algorithms. Each color represents a class. Spectral clustering (left side) reaches better performance than k-means (right side).

Noise types database and feature calculation

The database consists of several hundred entries which were recorded and categorized. All records include significant noise types.

III. Model description

Preprocessing was done by listening to all the noise type examples and defining small intervals where each one isolates the specific noticeable noise. In several hearing experiments it was investigated that some noise types seem to be equal in their audible characteristic although they are declared as different ones. However, to reach better clustering results this variance shall be reduced. Therefore the amount of noise types is decreased. This was done by grouping certain noise types together. In a first database, one group held up to 8 different noise types, in a second database the amount was further reduced to contain no more than 2 different noise types per group; in both cases 5 groups were built.

Now certain features were calculated for all defined record-intervals in these two databases. Then statistical measures were used to select relevant and objective features. One measure we used, to rank the calculated features in their ability to separate the different groups, is the Fisher Linear Discriminant [3] (FLD). The FLD is a rating for the separability of two samples. FLD rating will be high, when the samples can be separated by the analyzed feature $m_{1.}$ In FLD calculation is defined in eq. 1; where μ_1, μ_2 are the means of groups 1, 2 and σ_1,σ_2 are the variance for groups 1, 2.

$$f = \frac{(\mu_1 - \mu_2)^2}{(\sigma_1^2 + \sigma_2^2)} \tag{1}$$

Another possibility for feature rating is for example the mutual information [5].

Finally, two datasets with relevant features (acoustic fingerprints, AFP's) were generated.

Table 1: dataset #1

	k-means (variant 1)					k-means (variant 2)				
	cl1	cl2	cl3	cl4	cl5	cl1	cl2	cl3	cl4	cl5
g1	0	21	6	**56**	17	**57**	14	15	0	14
g2	0	2	**58**	25	16	**38**	23	2	2	36
g3	**33**	2	21	16	29	17	2	2	38	**41**
g4	5	20	**64**	1	9	1	**41**	18	26	15
g5	3	**61**	14	20	2	20	12	**63**	3	2

	spectral clustering (09)					spectral clustering (69)				
	cl1	cl2	cl3	cl4	cl5	cl1	cl2	cl3	cl4	cl5
g1	**56**	13	0	18	13	17	13	0	13	**57**
g2	**41**	31	0	0	28	2	**59**	2	13	25
g3	17	**41**	33	3	6	3	11	34	**36**	16
g4	8	14	3	22	**54**	22	**58**	8	9	3
g5	24	2	2	**61**	12	**61**	14	2	2	22

IV. Results

Evaluation of approach "each group shall be defined by specific clusters in feature space" was done by means of different types of clustering algorithms for the defined fingerprints. The defined groups of noise types (for each of the two datasets) were compared to the resulting clusters. Further measures for cluster evaluation are mentioned in [4].

In table 1 we can see the results of dataset #1:

None of the four different clustering-algorithms assigned more than 64% of AFP's in one group to a cluster. In some cases one cluster holds up to 2 groups.

In table 2 we can see the results of dataset #2:

In all cases at least one group is fully covered by a cluster, but on the other hand the AFP's of up to 3 groups is covered by 1 cluster (except "k-means variant 1").

The multiple assignments of groups to 1 cluster are a drawback which we try to investigate with different variants of e.g. spectral clustering algorithm ([1]) and further pattern recognition methods.

Table 2: dataset #2

	k-means (variant 1)					k-means (variant 2)				
	cl1	cl2	cl3	cl4	cl5	cl1	cl2	cl3	cl4	cl5
g1	**100**	0	0	0	0	0	31	0	**69**	0
g2	17	31	**53**	0	0	**44**	39	17	1	0
g3	0	1	13	**86**	0	0	7	**93**	0	0
g4	0	0	0	0	**100**	0	0	0	0	**100**
g5	2	**68**	30	0	0	**58**	40	0	2	0

	spectral clustering (09)					spectral clustering (69)				
	cl1	cl2	cl3	cl4	cl5	cl1	cl2	cl3	cl4	cl5
g1	**100**	0	0	0	0	31	0	0	0	**69**
g2	**83**	17	0	0	0	**41**	17	31	0	12
g3	5	0	1	0	**94**	8	44	1	**47**	0
g4	0	0	0	**100**	0	0	0	0	0	**100**
g5	**76**	0	24	0	0	32	0	**58**	0	10

V. References

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