



# INTER-NOISE 2007

28-31 AUGUST 2007

ISTANBUL, TURKEY

## Soundscape classifying ants

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### ABSTRACT

In this paper, the use of fuzzy ant clustering in classifying a large database of environmental soundscape recordings is outlined. Fuzzy ant clustering is a soft computing technique inspired by the clustering behaviour observed in colonies of several ant species. Virtual ants or “agents” move through the database, “pick up” soundscape recordings and drop them on places where similar recordings are present. Similarity of soundscape recordings is expressed by fuzzy resemblance of the shape of the SPL histogram, the frequency spectrum and the spectrum of temporal fluctuations, representing loudness, spectral and temporal content. The fuzzy IF-THEN rules, governing the behaviour of the virtual ants, are optimized using a specially adapted genetic algorithm, in order to achieve an optimal set of homogeneous clusters. Advantages of this approach, as compared to traditional clustering methods, are that no a priori information, such as the desired number of clusters, is needed, and that a more flexible set of indicators can be used. The clustering model is validated on a database of acoustic measurements of 1116 soundscapes, made in 16 urban parks in Stockholm, and results are compared with visitor survey data on soundscape quality.

## 1 INTRODUCTION

There is a growing awareness that outdoor areas with a high quality soundscape deserve special attention. For example, because rural and urban quiet areas have great potential for recreation and psychological restoration, their preservation and management has been subscribed in the EC environmental noise directive [1] and in policy intentions of many countries. Nevertheless, clear and objective environmental soundscape quality assessment procedures are still lacking, because of the multiple dimensions (loudness, spectrum, time, context, personal factors etc.) involved in soundscape perception. An active subfield of soundscape research is therefore directed towards finding suitable (sets of) quality indicators, well grounded in soundscape perception [2]. It is commonly acknowledged that physical, contextual and perception-based indicators will have to be combined.

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A number of methods have been applied to relate physical indicators (derived from acoustic measurements and recordings) to soundscape perception and evaluation (often derived from questionnaires), most of them involving PCA analysis, data clustering and regression. In this paper, an algorithm for automatic classification of soundscape recordings is presented, based on several techniques that mimic biological systems – often commonly referred to as *soft computing* techniques.

The similarity between two soundscapes is determined by the *fuzzy resemblance* of the shape of three statistical distributions derived from the spectrograms of both recordings, i.e. the SPL histogram, the frequency spectrum and the spectrum of temporal fluctuations [3]. The proposed distance measure (Section 2.1) is purely based on physical measures, but obviously goes beyond the use of single-valued indicators such as  $L_{Aeq}$  or  $L_{A95}$ . The clustering algorithm (Section 2.2) is inspired by the clustering behaviour observed in colonies of several ant species. Compared to well known hierarchical or partitional clustering algorithms, such as *k*-means or the more general fuzzy *c*-means algorithms, *ant clustering* has the advantage that an initial estimate of the number of clusters does not have to be provided. The behaviour of the ants, and as a consequence the number and composition of the resulting clusters, is governed by fuzzy IF-THEN rules, optimized using a specially adapted *genetic algorithm* (Section 2.3) in order to achieve an optimal set of homogeneous clusters.

In Section 3, a validation of the classification algorithm will be given. A large set of 10-minute soundscape recordings, made in several urban parks in Stockholm [4], will be used as a case study database. Finally, the results will be compared with visitor survey data.

## 2 METHODOLOGY

### 2.1 Soundscape similarity

A soundscape recording can be fully characterized by its spectrogram, in which the frequency spectrum is plotted against time. However, directly comparing two spectrograms is not very meaningful, due to the stochastic nature of soundscapes. Also, comparing spectrograms of different durations is not trivial. An analysis of several field studies in which soundscapes were assessed using semantic differentials [5], has shown that at least three principle components seem to arise in most cases: a factor related to the loudness of the soundscape, a factor related to the spectral content and a factor related to the temporal structure. Therefore, three statistical distributions derived from the spectrogram of the soundscape were selected, representing the above mentioned factors: the (A-weighted) SPL histogram, the (1/3-octave band) frequency spectrum and the spectrum of temporal fluctuations (for a definition, see [3]). Two soundscapes are defined to be similar when these distributions are similar.

To quantify the similarity measure (distance measure), we note that each statistical distribution may be interpreted as a *fuzzy membership function* [6]. More in particular, the SPL histogram of a soundscape may be seen as a fuzzy set on the loudness universe of discourse, the frequency spectrum as a fuzzy set on the frequency universe of discourse, and the spectrum of temporal fluctuations as a fuzzy set on the universe of discourse of temporal content. For the spectrum, this is illustrated with an example in Figure 1. The three distributions were “vertically” rescaled to the interval [0,1]. Additionally, the SPL histogram was shifted “horizontally” to a common centre of gravity. This excludes the influence of the average SPL in the clustering algorithm, since it is desired that soundscapes with a similar histogram shape end up in the same cluster, rather than soundscapes with the same  $L_{Aeq}$ .

The notion of similarity is well-known in fuzzy set theory, and a large number of methods exist to quantify the resemblance of two fuzzy sets. Generally, the similarity measure is a binary fuzzy relation on the class of fuzzy sets on the universe of discourse considered (loudness, frequency and temporal content), which yields a value in [0,1], and which yields

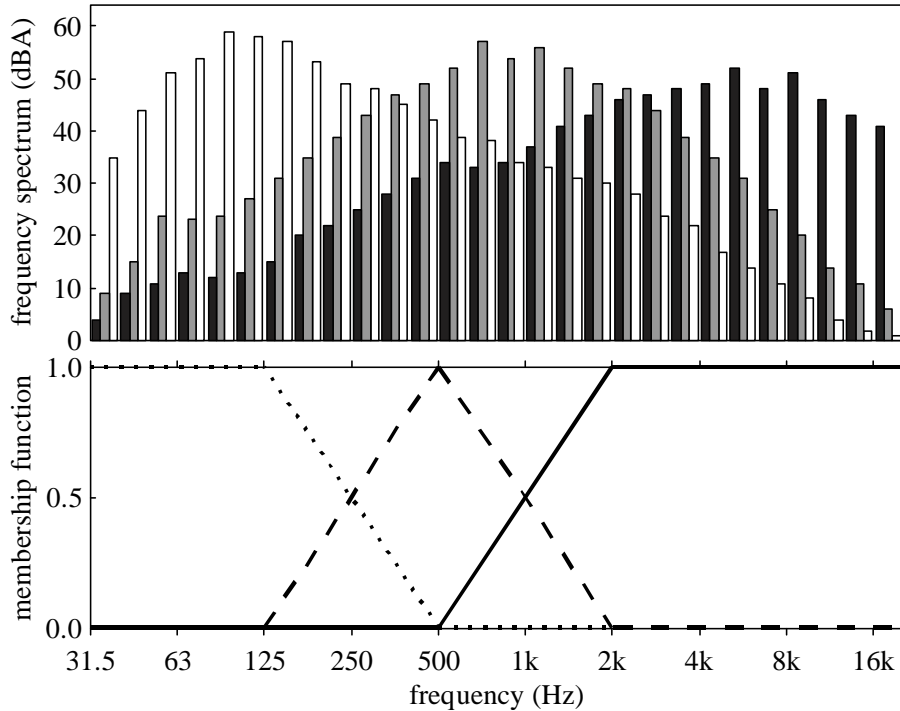


Figure 1: The upper panel shows the frequency spectra of three soundscape recordings. The lower panel shows an illustrative fuzzy partition of the frequency universe of discourse; the sets shown may be labeled with the linguistic values “low” (dotted), “medium” (dashed) and “high” (solid) frequency.

the value 1 if both sets are equal. In [7], a distinction is made between measures inspired by set equality and measures inspired by the degree of overlap. In [8], it is argued that it is often most worthwhile to use an aggregation of several similarity assessments, and a hybrid similarity measure is proposed, which takes into account shape similarity and similarity of peak regions. In this work, the similarity measure defined in [8] is considered for the three distributions separately, and the resulting values are combined using a fuzzy  $t$ -norm (see further for an example) to obtain the global similarity measure  $E(a,b)$ , with  $a$  and  $b$  two soundscapes.

## 2.2 Fuzzy ant clustering

Ants are, because of their limited brain capacity, often assumed to reason only by means of rules of thumb [9]. However, the resulting behaviour on the colony-level can be quite complex. A particular example is the clustering of the corpses of dead nestmates by taking only simple actions and without negotiating on where to gather the corpses. Because of the conceptual simplicity of this phenomenon, a computational clustering technique based on ant behaviour was introduced by Deneubourg *et al.* [10], which was later refined by Monmarché [11][12]. In this work, a slightly modified version of the algorithm by Schockaert *et al.* [13] is used, which is based on the work by Monmarché. The algorithm in [13] uses fuzzy rules to control the behaviour of the ants. Furthermore, no spatial relationship between clusters is considered (i.e. the clusters are kept in a list), so the algorithm is suited to cluster database records.

At the start of the algorithm, each soundscape is considered to form a cluster by itself (indicated by a cluster index added to the database of distributions associated to the soundscapes considered). At each timestep of the algorithm, an artificial ant selects a cluster (heap) at random, and undertakes one of the following actions. If it is carrying nothing, it can pick up a single item of the selected heap or it can pick up the entire heap. If it is carrying a load, it can drop the items it is carrying on the selected heap, thereby moving them to a different cluster, it can drop its load in an empty place, or it can decide to do nothing. The

decision process is governed by a model of division of labour. A certain stimulus value  $s$  and a response threshold value  $\mathcal{G}$  are associated with each task the ant may perform. The response threshold value is fixed, but the stimulus can change, and represents the need for someone to perform the task. The probability that the ant starts performing the task is given by

$$p_n(s, \mathcal{G}) = \frac{s^n}{s^n + \mathcal{G}^n} \quad (1)$$

where  $n$  is a positive integer [13]. For example, a loaded ant may drop its load, with a probability given by

$$P_{drop} = p_m(s_{drop}, \mathcal{G}_{drop}) \quad (2)$$

where  $m$  is a positive integer, which differs if the ant is carrying only a single item or several items.

For each cluster  $H$ , the center soundscape  $c_H$  is defined as the soundscape which has the highest average similarity  $E$  with all other soundscapes of the cluster. Note that this definition is independent of the problem at hand. The *average similarity*  $A_H$  and the *minimal similarity*  $M_H$  of a cluster  $H$  are defined as

$$A_H = \frac{1}{|H|} \sum_{v \in H} E(v, c_H) \quad M_H = \min_{v \in H} [E(v, c_H)] \quad (3)$$

with  $|H|$  the number of elements in  $H$ . When a load  $L$  is considered, the average similarity between the center of  $H$  and the items of  $L$  can be estimated by

$$B_{L,H} = T_w(E(c_L, c_H), A_L) \quad (4)$$

with  $T_w$  the Łucasiewicz  $t$ -norm given by

$$T_w(x, y) = \max(0, x + y - 1) \quad x, y \in [0, 1] \quad (5)$$

The values of the stimuli are calculated by evaluating a fuzzy rule base, of which the rules are constructed as follows (from [13]):

- **Dropping items.** The stimulus for a loaded ant to drop its load  $L$  on a heap  $H$  is based on the average similarity  $A_H$  and the estimation of the inter-cluster similarity  $B_{L,H}$ . If  $B_{L,H} < A_H$ , then the stimulus for dropping the load should be low; if  $B_{L,H} \geq A_H$ , then the stimulus should be high. The rules are summarized in Table 1.
- **Picking up items.** An unloaded ant should pick up the most dissimilar item from a heap  $H$ , if the similarity between this item and  $c_H$  is far less than the average similarity of the heap  $A_H$ . This means that by loading the item, the heap will become more homogeneous. An unloaded ant should only pick up an entire heap, if the heap is already homogeneous. Consequently,  $A_H$  and  $M_H$  are used to build a rule base similar to Table 1 for picking up items.

For evaluating the fuzzy rules, the Sugeno fuzzy inference system was used because of its calculation speed. The linguistic terms as shown in Table 1 are represented by triangular fuzzy sets.

The clustering algorithm only uses a single ant, since the use of multiple ants has no advantages in a non-parallel implementation. However, parts of the clustering can be performed by ants with different parameters. More specifically, when  $q$  different ants are used, each of them will cluster for  $N/q$  iterations, with  $N$  the total number of iterations.

Table 1: Stimulus for dropping the load. The linguistic terms are very very high (VVH), very high (VH), high (H), rather high (RH), medium (M), rather low (RL), low (L), very low (VL) and very very low (VVL).

$B_{L,H} \setminus A_H$	VH	H	M	L	VL
VH	RH	H	VH	VVH	VVH
H	L	RH	H	VH	VVH
M	VVL	L	RH	H	VH
L	VVL	VVL	L	RH	H
VL	VVL	VVL	VVL	L	RH

### 2.3 Post-clustering optimization

The algorithm contains no stop criterion, so a predefined number of time steps  $N$  are simulated, depending on the number of soundscapes in the database. Since the above sketched algorithm is probabilistic in nature, the clustering result will often contain “impurities”, such as singleton clusters or clusters that are non-homogeneous due to a single item. In a first post-clustering step, all clusters that contain less elements than a given threshold number are removed and their elements are relocated to the best suiting remaining cluster. In a second post-clustering step, the least fitting item in each cluster is relocated (if necessary) to the best fitting cluster.

To compensate for the stochastic nature of the algorithm, a third optimization step was implemented, which merges the clustering results obtained in different clustering runs (10 in this algorithm). The merged clusters contain items which were clustered together in more than half of the separate clustering runs. This optimization step was found to significantly enhance the results.

### 2.4 Ant behaviour optimization using a genetic algorithm

The ant clustering algorithm contains a number of parameters that influence the evaluation of the fuzzy rule bases and the behaviour of the ant(s), and as a consequence the number and composition of the resulting clusters. Examples are the parameter  $m$  in the evaluation of the chance for dropping the load, and the various threshold values associated with each action. The performance of the clustering algorithm will therefore depend on the particular parameter values (11 in total for each ant).

To find the ant parameters resulting in an optimal clustering, a genetic algorithm (GA) [14][15] – a global search heuristic which uses techniques inspired by evolutionary biology – was used. Each possible solution of the problem is represented by a *genome* (the set of ant parameters) and a corresponding *phenome* (the clustering result produced by the ant). Roughly, the algorithm works as follows. At the start, a generation of random solutions is created. At each iteration, a new generation of solutions is produced, which tries to combine the positive elements of the previous generation. Each solution of the new generation (the offspring) is generated by selecting at random one or two solutions of the previous generation (the parents) taking into account their quality or “fitness” (see further), and by applying the genetic operators of crossover and mutation on their genomes. Usually the algorithm is terminated when the variance of the fitness within the current generation has become small, indicating that the algorithm has converged, when the best solution’s fitness has reached a plateau such that successive iterations no longer produce better results, or when a maximum number of iterations is reached.

It has to be noted that a GA is a stochastic search algorithm, which implies that the optimal solution is not guaranteed to be found. However, GA’s are applicable to a broad range of problems, and usually reach a good solution relatively fast. Instead of giving a detailed specification of the algorithm implemented in this work, we highlight the most important aspects:

- **Coding of the genome.** The genome of a solution simply consists of the set of parameters of the clustering ant(s), coded as floating point numbers. Since a variable number of ants may be used, the genome has a variable length, and consists of separate segments, each corresponding to the parameters of a single ant<sup>f</sup>.
- **Fitness evaluation.** The quality of a solution corresponds to the quality of the clustering result, and is evaluated using a fuzzy rule base. An optimal clustering will have the following qualities: (i) the average similarity within clusters is high; (ii) the average similarity between clusters is low; (iii) the number and size of the clusters is within reasonable bounds, relative to the number of soundscapes in the database. Note that the fitness function is not deterministic – the same ant may produce clustering of different quality when used again – due to the stochastic nature of the ant clustering.
- **Selection.** Parents are selected for reproduction based on their fitness. A tournament selection procedure was used: a subgroup of  $k$  solutions is selected at random, and the best solution of this subgroup is elected to be a parent. The tournament size  $k$  determines the selection pressure; a value of 2 was used.
- **Reproduction.** Offspring is produced from parents by applying crossover (2 parents needed) or mutation (1 parent needed) operators. Each operator has the same probability to be used. Various crossover operations included exchanging single ant parameters or exchanging whole ants. Various mutation operations included randomly changing a single parameter, inserting a random ant or removing an ant, if the solution uses multiple ants.
- **Survival.** An elitism survival mechanism is used: the next generation consists for 2/3 of offspring, and for 1/3 of the best solutions of the previous generation (the elitists).

### 3 VALIDATION

#### 3.1 Data set

The classification algorithm was validated on a database of acoustic measurements, made in 16 urban parks in Stockholm [4]. The measurements were conducted in the framework of a questionnaire survey. In total 1116 respondents answered questions on perceived soundscape quality and road traffic annoyance. While the questionnaires were conducted, the 1/3-octave band spectrogram was recorded at about the same location, resulting in a database of 1116 sound spectrogram registrations with associated quality assessments. The SPL histogram, frequency spectrum and the spectrum of temporal fluctuations was calculated for each soundscape, based on the recorded spectrograms, and formed the input for our clustering algorithm.

#### 3.2 Convergence of the genetic algorithm

The ant parameters for clustering were optimized using the described genetic algorithm. A single generation consisted of 100 solutions, and the GA was run for 65 generations. Figure 2 shows the average and maximum clustering fitness within each generation. From the graph it could be concluded that the algorithm did not converge: generation 65 still consisted of a broad range of good and less good clustering results, reflected in the difference between maximum and average fitness. The maximum fitness reached a plateau at about the 40th generation. However, most solutions in the 65th generation had about the same genome; small variations resulted in a drop in fitness, explaining the lower average. The best solution encountered (in generation 56) made use of 3 ants, of which 2 were very similar (only 1 parameter differing slightly), and was used to produce the clustering results described in the next section. A total of 49 clusters were obtained, with an average of 23 soundscapes in each cluster.

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<sup>f</sup>The total number of clustering iterations  $N$  is kept constant, independent of the number of ants used, in order not to favor the use of a large number of different ants.

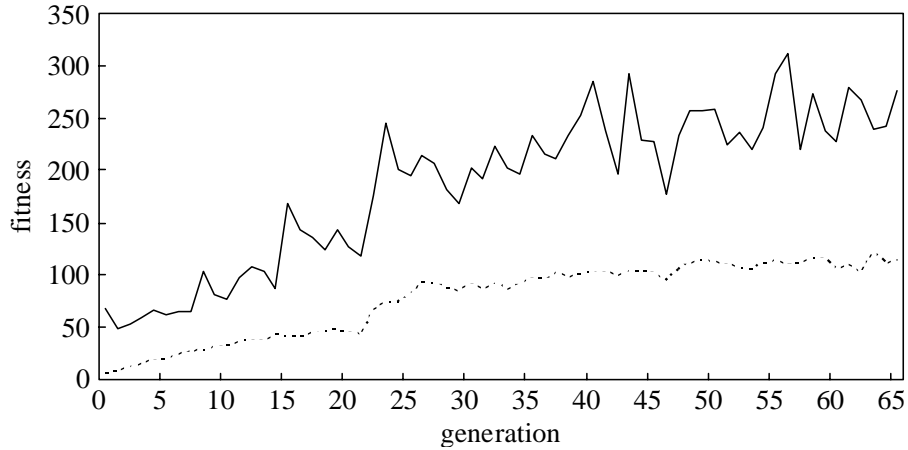


Figure 2: Maximum (solid line) and average (dashed line) fitness in the GA.

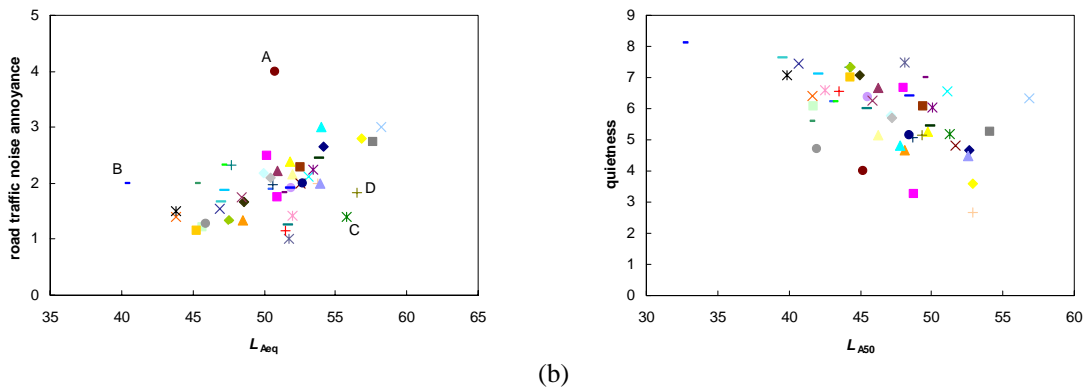


Figure 3: Scatter plots of road traffic noise annoyance (assessed on a 5-point scale) and perception of quietness (assessed on a 9-point scale) as a function of resp.  $L_{Aeq}$  and  $L_{A50}$ , averaged within clusters shown as dots.

### 3.3 Clustering results

Classical regression analysis results, relating physical indicators ( $L_{Aeq}$ ,  $L_{A50}$ ,  $L_{A95}$  etc.) to soundscape perception and evaluation for the same dataset, can be found in [4]. In this work, we will focus on results in light of the clustering algorithm introduced above. Figure 3 shows graphs relating  $L_{Aeq}$  and  $L_{A50}$  to road traffic noise annoyance and perception of quietness. The graphs show the expected trends in exposure and effect; however, there is a high spread.

Plotting results clustered with the above described algorithm has the main advantage that cluster dots aggregate soundscapes with similar statistical loudness, spectral and temporal features. Outlier clusters can be used to trace for specific physical features of the soundscape that may have modified perception. Figure 4 shows the fuzzy membership functions based on the A-weighted SPL histogram for several outlier clusters, marked A-D on panel (a) of Figure 3, together with the average histogram of the remaining clusters. Note that the SPL levels are relative, since the histograms were shifted horizontally to have a common centre of gravity. Clusters A and B aggregate soundscapes which were found to be more annoying due to road traffic noise than can be expected on the basis of the  $L_{Aeq}$ ; clusters C and D aggregate soundscapes which were found to be less annoying. Compared to the mean, the histogram of clusters A and B is narrower. This indicates a “grey” or low fidelity soundscape [16], with few dynamics, foreground and background. Compared to the mean, the histograms of clusters C and D are much wider, and show a peak at lower levels. This indicates a (relatively) low background noise level with noise events which can have a high level (high fidelity soundscape). If anything, this analysis shows that  $L_{Aeq}$  or  $L_{A50}$  on themselves are not sufficient to predict annoyance or perception of quietness.

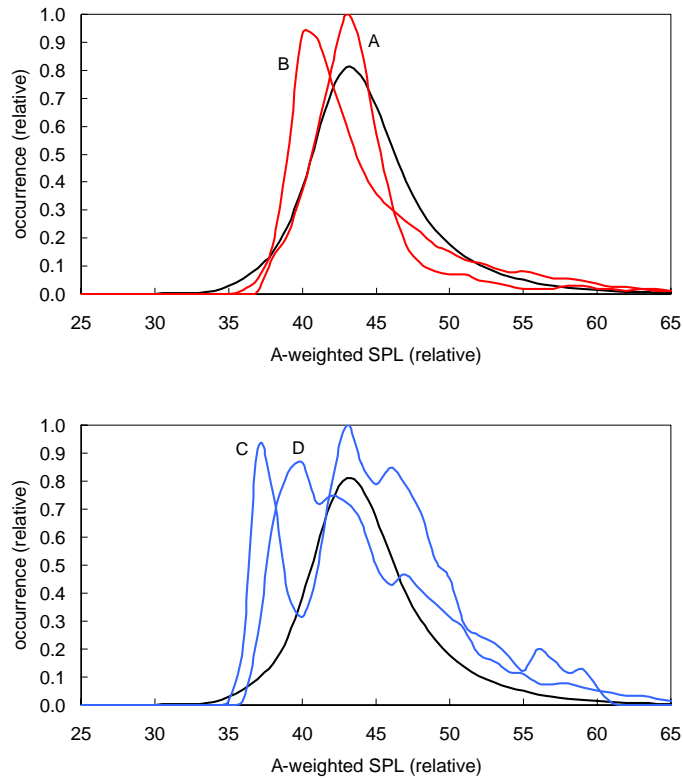


Figure 4: Fuzzy membership function based on the A-weighted SPL histogram of several outlier clusters (colored), compared to the mean histogram of the remaining clusters (black).

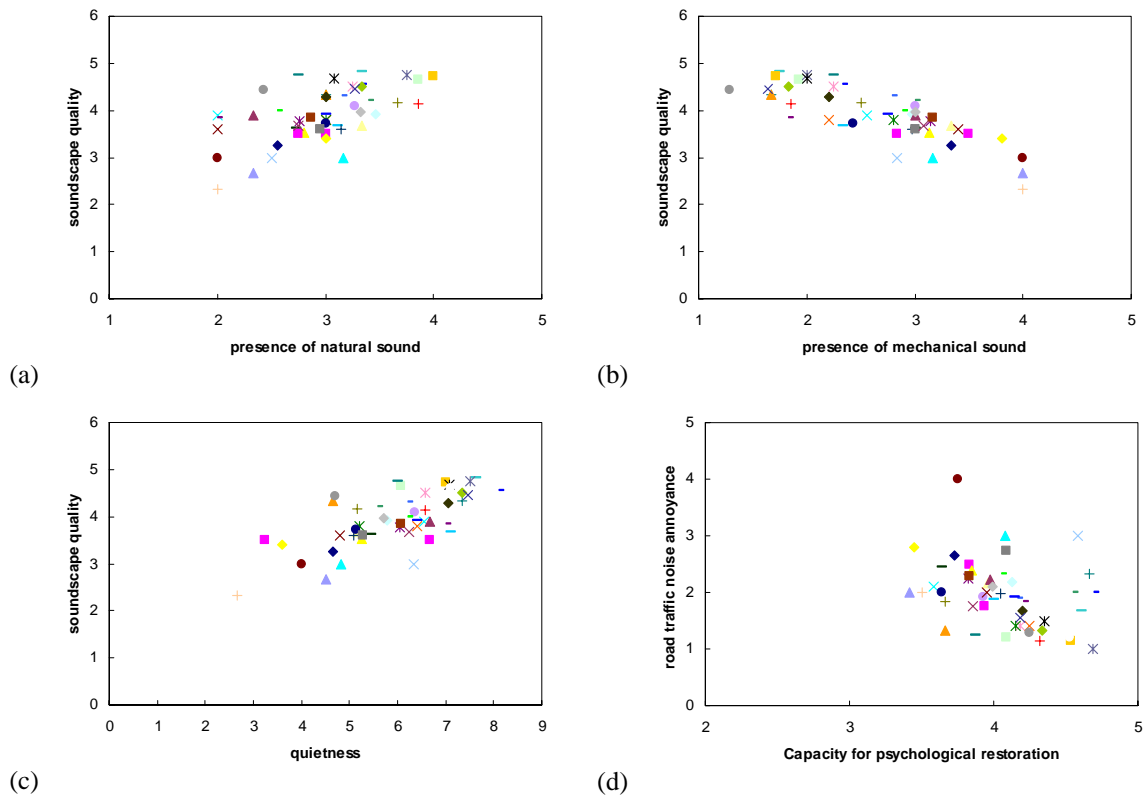


Figure 5: Scatter plots of various perceptual soundscape indicators, averaged within clusters shown as dots. Soundscape quality, capacity for psychological restoration, presence of natural sound and presence of mechanical sound were assessed on a 5-point scale, quietness on a 9-point scale.



Figure 5 shows graphs relating various perceptual soundscape indicators, averaged over all soundscapes within each cluster. From the trends, some expected conclusions can be drawn, e.g. soundscape quality in urban parks is strongly related to the presence of natural sound ( $r^2 = 0.36$ ) and the absence of mechanical sound ( $r^2 = 0.66$ ). The broad variance in the position of the dots corresponding to various clusters show that clustering based on physical parameters alone can reproduce (part of) the variation between soundscapes observed in survey results.

#### 4 CONCLUSIONS

In this paper a novel approach was outlined for clustering soundscapes. Virtual ants sort a soundscape database based on similarity of the A-weighted SPL histogram, the frequency spectrum and the spectrum of temporal fluctuations. Parameters of the ants are optimized using a genetic algorithm, in order to obtain ants that produce a well balanced clustering result. Compared to classical clustering algorithms, the ant clustering algorithm has the advantage that no a priori information is needed, such as the number of clusters, and that a flexible set of indicators can be used to assess soundscape similarity. The algorithm was validated on a database of 1116 soundscapes with associated quality assessments, which were recorded in 16 urban parks in Stockholm. Since clusters aggregate soundscapes with similar loudness, spectral and temporal features, outliers in graphs relating quality assessment indicators can be used to trace for specific features which may have caused the anomaly. This technique was used to show that  $L_{Aeq}$  or  $L_{A50}$  on themselves are not sufficient to predict annoyance or perception of quietness, and that clustering based on physical parameters alone can reproduce (part of) the variation between soundscapes observed in survey results.

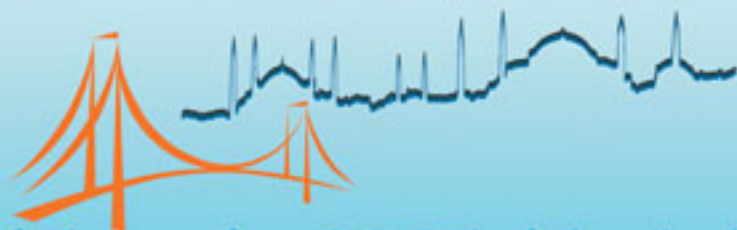
#### 5 ACKNOWLEDGEMENTS

This research was partly supported by grants to the research programme “Soundscape Support to Health” from the Swedish Foundation for Strategic Research (MISTRA), the Swedish National Road Administration (VV), and the Swedish Agency for Innovation Systems (Vinnova) as well as a supplementary grant from the City of Stockholm. We would like to thank Erika Gyllensvärd Wentzel, Owe Gustafsson and Nader Farahani for valuable assistance in collecting the data.

#### 6 REFERENCES

- [1] Directive 2002/49/EC of the European Parliament and of the Council of 25 June 2002 relating to the assessment and management of environmental noise, Official Journal of the European Communities L 189/12, 18.7.2002, Brussels (2002).
- [2] See for example the special issue on soundscapes, *Acta Acustica united with Acustica*, **92**(6) (2006).
- [3] D. Botteldooren, B. De Coensel and T. De Muer, “The temporal structure of urban soundscapes,” *Journal of Sound and Vibration*, **292**(1-2), 105-123 (2006).
- [4] M. E. Nilsson, D. Botteldooren and B. De Coensel, “Acoustic indicators of soundscape quality and noise annoyance in outdoor urban areas,” *Proceedings of the 19th International Congress on Acoustics*, Madrid, Spain (to appear) (2007).
- [5] B. De Coensel and D. Botteldooren, “The quiet rural soundscape and how to characterize it,” *Acta Acustica united with Acustica*, **92**(6), 887-897 (2006).
- [6] D. Dubois and H. Prade, *Fundamentals of Fuzzy Sets* (Kluwer Academic, Boston, Massachusetts, USA, 2000).
- [7] E. Tsiporkova and H.-J. Zimmermann, “Aggregation of compatibility and equality: a new class of similarity measures for fuzzy sets,” *Proceedings of the 7th International Conference on Information Processing and Management of Uncertainty in Knowledge-based Systems (IPMU)*, Paris, France (1998), pp. 1769-1776.

- [8] C. Cornelis, M. De Cock, D. Botteldooren and E. E. Kerre, "Fuzzy set theory: a useful interlingua?," *Proceedings of Knowledge-based intelligent information engineering systems and allied technologies (KES)*, Osaka, Japan (2001), pp. 1137-1141.
- [9] B. Hölldobler and E. O. Wilson, *The ants* (Springer-Verlag, Heidelberg, 1990).
- [10] J. L. Deneubourg, S. Goss, N. Franks, A. Sendova-Franks, C. Detrain and L. Chrétien, "The dynamics of collective sorting robot-like ants and ant-like robots," *From Animals to Animats: Proceedings of the 1st International Conference on Simulation of Adaptive Behaviour*, Paris, France (1990), pp. 356-363.
- [11] N. Monmarché, M. Slimane and G. Venturini, "On improving clustering in numerical databases with artificial ants," *Proceedings of the 5th European Conference on Artificial Life (ECAL'99)*, Swiss Federal Institute of Technology, Lausanne, Switzerland (1999), pp. 626-635.
- [12] N. Monmarché, *Artificial ant based algorithms applied to clustering and optimization problems (in French)*, Ph.D. dissertation, François Rabelais University, Tours, France (2000).
- [13] S. Schockaert, M. De Cock, C. Cornelis and E. E. Kerre, "Clustering web search results using fuzzy ants," *International Journal of Intelligent Systems*, **22**(5), 455-474 (2007).
- [14] J. H. Holland, *Adaptation in natural and artificial systems* (The University of Michigan Press, Ann Arbor, Michigan, USA, 1975).
- [15] M. Mitchell, *An Introduction to Genetic Algorithms* (The MIT Press, Cambridge, Massachusetts, USA, 1998).
- [16] R. M. Schafer, *The soundscape: our sonic environment and the tuning of the world* (Destiny Books, Rochester, Vermont, USA, 1994).



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