Science of the Total Environment 482-483 (2014) 440–451

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

A tool for urban soundscape evaluation applying Support Vector Machines for developing a soundscape classification model

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HIGHLIGHTS

- Support Vector Machine algorithms are used to develop an urban soundscape classification model.
- SVM and SMO-based algorithms are implemented as a part of a comprehensive soundscape evaluation tool.
- These models allow the acoustical and (indirect) perceptual assessments of soundscapes with high classification performance.
- A new methodology for soundscape evaluation is proposed, using SVM algorithms implemented within this framework.
- Experimental data show that the SMO model outperforms the SVM model in classifying the urban soundscapes considered.

ARTICLE INFO

Article history:
Received 26 March 2013
Received in revised form 26 July 2013
Accepted 27 July 2013
Available online 2 September 2013

Editor: Pavlos Kassomenos

Keywords:
Soundscape classifier
Classification model
Acoustical assessment
Soundscape evaluation
Support Vector Machines
Sequential Minimal Optimization

ABSTRACT

To ensure appropriate soundscape management in urban environments, the urban-planning authorities need a range of tools that enable such a task to be performed. An essential step during the management of urban areas from a sound standpoint should be the evaluation of the soundscape in such an area. In this sense, it has been widely acknowledged that a subjective and acoustical categorization of a soundscape is the first step to evaluate it, providing a basis for designing or adapting it to match people's expectations as well. In this sense, this work proposes a model for automatic classification of urban soundscapes. This model is intended for the automatic classification of urban soundscapes based on underlying acoustical and perceptual criteria. Thus, this classification model is proposed to be used as a tool for a comprehensive urban soundscape evaluation. Because of the great complexity associated with the problem, two machine learning techniques, Support Vector Machines (SVM) and Support Vector Machines trained with Sequential Minimal Optimization (SMO), are implemented in developing model classification. The results indicate that the SMO model outperforms the SVM model in the specific task of soundscape classification. With the implementation of the SMO algorithm, the classification model achieves an outstanding performance (91.3% of instances correctly classified).

1. Introduction

It is widely acknowledged that noise has a major negative impact on the quality of life in cities (Montalvao Guedes et al., 2011; Kim et al., 2012). In fact, there is increasing evidence that, under steady-state conditions, environmental-noise exposure is associated with serious psychological, physiological, and social effects (Paunovic et al., 2009; Laszlo et al., 2012). Despite this, urban areas are still characterized by a serious sound degradation (Torija et al., 2012).

An urban area has a variety of different sound environments, which are dominated by sounds related not only to traffic, leisure, or industry, but also to human or natural sounds (e.g. water and birds). However, today, urban environments are highly impacted by road traffic, which masks and degrades different soundscapes (Montalvao Guedes et al., 2011; Torija and Ruiz, 2012). Moreover, impact of road traffic on soundscapes in urban environments can reach different values depending on its intensity and composition. Thus, for instance, Powered Two Wheelers (PTW) have been found as one of the most annoying environmental noise sources, so an increase in the number of these vehicles in traffic can lead to higher degradation of the sound environment (Paviotti and Vogiatzis, 2012).

Sound in outdoor environments has traditionally been considered in negative terms as both intrusive and undesirable (Jennings and Cain, 2013). However, sound may provide positive effects, such as enhancing a person's mood, triggering a pleasant memory of a prior experience, or encouraging a person to relax and recover (Payne, 2013). Thus, soundscape framework proposes a positive approach, which claims not only to reduce sound exposure but also to preserve, conserve, or even encourage certain sounds that may be of great interest to the population.

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http://dx.doi.org/10.1016/j.scitotenv.2013.07.108

To improve urban soundscapes, sound criteria should be incorporated in effective urban planning (Torija et al., 2012). In this sense, planners, architects, or engineers need tools that enable them to make decisions in line with the design and management of sound spaces (Jennings and Cain, 2013). In managing urban sound environments, an evaluation phase should be the first step. This evaluation would focus on the main acoustical characteristics of the soundscape, ascertaining how the soundscape is perceived by the population exposed to it as well (Torija et al., 2013).

A method for evaluating soundscapes should consider an acoustical categorization (Rychtáriková and Vermeir, 2013). However, as they involve human perception, soundscape evaluation should not be restricted to acoustical determinations (Zannin et al., 2003), as the human element needs to be included (Dubois et al., 2006; Maris et al., 2007a,b).

For all the foregoing, this study develops and tests an automatic tool to classify urban soundscapes. The development of this tool is based on the previous results reported by Torija et al. (2013) which are briefly also outlined in this paper for completeness, who proposed a methodology for categorizing and differentiating urban soundscapes using acoustical descriptors and semantic-differential (SD) attributes. In the present study, a classification model is proposed to be constructed using: (i) Support Vector Machines (SVM) and (ii) Support Vector Machines trained with Sequential Minimal Optimization algorithm (SMO). This model seeks to allow an automatic classification of urban soundscapes on the basis of acoustical as well as perceptual criteria. The underlying hypothesis is that using the developed classification model an acoustical and (indirect) perceptual assessments of soundscapes can be approached, which will enable a proper evaluation of a given urban soundscape. It should be noted that this research is aimed at developing a statistical model for classifying urban sound environments into one of the categories of soundscapes previously identified by Torija et al. (2013).

Thus, Section 2 presents a brief introduction to SVM and SMO algorithms. In Section 3, the methodology is described for the collection of the acoustical data, the establishment of input variables used for model implementation, and the evaluation of model performance. Finally, in Section 4, the experimental results are presented and discussed.

2. Support Vector Machines for developing classification models

The development of models for environmental problems is becoming more relevant for environmental engineers and scientists. The application of machine learning methods for environmental modeling is extensive (Li et al., 2011), due to their robustness and ability to solve complex non-linear problems.

One the most widely used machine learning methods to approach environmental non-linear problems is SVM. This method has been successfully applied to a wide range of real problems, including document classification (Fu and Lee, 2012), bioinformatics (Noble, 2004), financial applications (Ince and Trafalis, 2002), and environmental modeling (Lu and Wang, 2005; Solomatine and Ostfeld, 2008; Yang et al., 2012).

The SVM method is a popular and promising tool for data classification (Chen and Lin, 2006), which provides several advantages: (i) better generalization performance compared with many other machine learning methods (Shao et al., 2012). This is due to the adoption of the Structure Risk Minimization Principle (SRM), which minimizes the upper bound of the generalization error (Vapnik, 1998; Cristianini and Shawe-Taylor, 2000; Deng et al., 2012). With the implementation of SRM, SVM models can avoid problems such as over-fitting training and local minima (typical drawback of conventional neural network models) (Lu and Wang, 2005); (ii) SVM models contain few free parameters to be estimated (Lu and Wang, 2005); and (iii) SVM models have proved highly expandable and robust (Lu and Wang, 2005).

2.1. Brief introduction to SVM techniques

A SVM is a machine learning technique able to approach a non-probabilistic non-linear classification by using kernel functions. Its basic idea is to construct a hyper-plane or a set of hyper-planes in a high- or infinite-dimensional space to achieve the largest separation between different classes (Steinwart and Christmann, 2008). Among all possible hyper-planes, the one with the maximum margin between classes (optimal hyper-plane) is selected (Chen and Lin, 2006).

SVM method maps original data x into a feature space F with higher dimensionality via a non-linear mapping function ϕ (Vapnik, 1995). With SVM used as the classifier, the different classes of data are separated by hyper-planes contained by the decision function in Eq. (1).

$$\mathrm{f}(x) = \mathrm{sgn}\left(\omega^T \phi(x_i) + \mathrm{b}\right) \tag{1}$$

where $\mathrm{f}(x_i)$ is the prediction function, $\mathrm{sgn}(\cdot)$ is a symbol function, ω^T is the permutation of normal vector ω, $\phi(\cdot)$ is a map function, and b is a scalar.

During the training stage of SVM the optimal hyper-planes are sought. This training phase involves the solution of a quadratic programming problem (QPP). However, because the original SVM (Vapnik, 1995, 1998) was developed for binary classification, various reformulations of SVM algorithm have been proposed to deal with more than two classes (Bolbol et al., 2012). Thus, Crammer and Singer (2000) introduced a reformulation of the support vector quadratic problem in order to extend binary SVM into a multi-class SVM. The proposed algorithm is presented in Eqs. (2), (3) and (4).

$$\text{Minimise} \quad t(\{\omega_n\}, \varepsilon) = \frac{1}{2}\sum\nolimits_{n=1}^{k} \|\omega_n\|^2 + \frac{C}{m}\sum\nolimits_{i=1}^{m} \varepsilon_i \tag{2}$$

$$\text{Subject to}: \quad \left\langle \phi(x_i), \omega_{yi} \right\rangle - \langle \phi(x_i), \omega_n \rangle \geq \mathrm{b}_i^n - \varepsilon_i \; (i = 1, \ldots, m) \tag{3}$$

for which the decision function is:

$$argmax_{n=1,\ldots,K} \langle \phi(x_i), \omega_n \rangle \tag{4}$$

where ε is the tolerance of the termination criterion, m is the number of training patterns (called support vectors) and C is the cost parameter. The cost parameter C controls how significant misclassifications should be treated —that is, high C values force the SVM to create a prediction function complex enough to misclassify as few training points as possible, while a lower C parameter will lead to a simpler prediction function (Bolbol et al., 2012). For the application of this method, the optimal value of C parameter, as well as the tolerance parameter used for checking the stop criterion have been sought and chosen.

2.2. Brief introduction to SMO

As stated above, the training of SVM requires the solution of a QPP. Because of this, SVM is characterized by high computational complexity, which restricts their applicability. Therefore, several improved algorithms have been proposed (Shao et al., 2012). One of these improved algorithms is SMO (Platt, 1999).

By training SVM with the SMO algorithm, a quick solution can be found, without using any extra matrix storage and without implementing numerical QPP optimization processes (Platt, 1999). The SMO algorithm breaks the classification problem into a series of possible sub-problems, which are then solved analytically using Osuna's theorem to ensure convergence. The SMO algorithm approaches the classification problem by finding two Lagrange multipliers, which are optimized with respect to each other, and by analytically computing the optimal step for the two Lagrange multipliers (Flake and Lawrence, 2001). The SMO algorithm actually has two components: an analytic method for solving