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Ensembles of evolutionary product unit or RBF neural networks for the identification of sound for pass-by noise test in vehicles

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ABSTRACT

In order to ensure the success of new product developments and to study different alternatives of designs before their manufacture, it is primordial to assess identification models. This practice is an extensive one in the automotive industry. Automotive manufacturers invest a lot of effort and money to improve the vibro-acoustics performance of their products because they have to comply with the noise emission standards. International standards, commonly known as pass-by and coast-by noise test, define a procedure for measuring vehicle noise at different receptor positions. The aim of this work is to develop a novel model which can be used in pass-by noise test in vehicles based on ensembles of hybrid evolutionary product unit or radial basis function neural networks (EPUNNs or ERBFNNs) at high frequencies. Statistical models and ensembles of hybrid EPUNN and ERBFNN approaches have been used to develop different noise identification models. The results obtained using different ensembles of hybrid EPUNNs and ERBFNNs show that the functional model and the hybrid algorithms proposed provide a very accurate identification compared to other statistical methodologies used to solve this regression problem.

1. Introduction

Despite the new noise regulations which limit the noise levels, it seems that the noise levels have increased in urban areas. According to the reports of the European Energy Agency published in the last years, the problem of traffic noise has become an important political issue in many communities. Moreover, the World Health Organisation (WHO) estimates that about 40% of the population in the European Union (EU) is exposed to road traffic. With this increase in exposure, people is more aware of noise due to media attention which make citizens criticize noise even in places where the levels measured were stable or in some cases even reduced. For this reason, environmental noise is making EU citizens more and more concerned and is now the focus of the EU and the national legislations. The EU Directive (2002/49/EC) related to the assessment and management of environmental noise was published in 2002 and it aims to create a quieter and more pleasant environment for European citizens within the framework of "Sustainable Development and Growth in Europe" [1]. It deals mainly with the definition of universal noise indicators, strategic noise mapping, noise management action plans and methodologies for identification. The European Commission states that the harmful effects of noise exposure from all sources should be avoided and that quiet areas need to be preserved.

Motivated by the appearance of new regularizations, automobile manufacturers are supervised to certify that their vehicles comply with noise emission standards by measuring noise levels according to procedures defined by international standards, commonly known as pass-by and coast-by noise tests [2–4]. Furthermore, in order to establish the quality of their products, more and more companies try to achieve certain sound quality targets [5]. In the automobile sector, exterior and interior sound quality in vehicles has become a marketing feature to attract new consumers. This important change in viewpoint results in a need for new identification models and noise abatement techniques [6,7]. In this context, auralization techniques will play an important role [2–4].

Auralization is the process of rendering audible the sound field of a physical sound source in a space, in such a way as to simulate the listening experience at a given position in the modelled space [8]. The process of auralization is achieved by modelling the physical source in a sound synthesis model. Although there are some synthesis procedures that work purely in the time

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domain, there are numerous advantages in working partially in the frequency domain [9]. By means of the resulting real listening experience, a reliable method is established for the evaluation of the sound quality. Sound synthesis models aim at auralizing the sound produced by a physical sound source at an arbitrary receiver location, and they are identification methods based on linear models [10]. Their main advantage is their robustness, while the drawback is their resolution limitations at high frequencies since the system shows a nonlinear behaviour.

On the other hand, various methods, such as artificial neural networks (ANNs) and wavelet networks have been developed in recent years for analysing and solving identification problems [11]. Depending on the basis function used in the hidden nodes the following ANNs [12], among others, can be distinguished: (1) ANNs based on projection basis functions, where the transfer functions are sigmoidal units (SUs) or the product units (PUs) [13], and (2) ANNs based on kernel basis functions, such as the radial basis functions (RBFs) [14–16].

Kernel functions are functions of the local environment and have a greater ability to fit outliers. However, kernel function performance decreases drastically in global and high dimensionality environments. On the other hand, projection functions are functions of the global environment, and, due to their global nature, they present some difficulties for fitting outliers but do tend to perform better in high dimensionality problems. This paper focuses on two types of ANNs: radial basis function neural networks (RBFNNs) and product unit neural networks (PUNN).

Although PUNNs and RBFNNs are very popular machine learning techniques, the search for the optimal ANN is still a challenging task: the ANN should learn input–output mapping without overfitting the data, and training algorithms may get trapped in local minima. Evolutionary algorithms (EAs) [17,18] are good candidates for PUNN and RBFNN design [19–21], since they perform a global multi-point search, quickly locating areas of high quality, even when the search space is very complex. The combination of EAs and ANNs, called evolutionary neural networks (ENNs), is a suitable candidate for topology design, due to the error surface features [17,18]: (1) the number of nodes/connections is unbounded and (2) the mapping from the structure to its performance is indirect (similar topologies may present different performances, while distinct topologies may result in similar behaviour). This paper analyses the good synergy between two types of ANNs (PUNNs and RBFNNs) and an EA: evolutionary product unit and radial basis function neural networks (EPUNNs and ERBFNNs).

Many researchers have shown that EAs perform well for global searching because they are capable of rapidly finding and exploring promising regions in the search space, although they take a relatively long time to converge to a local optimum [22]. Recently, new methods have been developed in order to improve the precision of EAs by adding local optimization algorithms. Within this context, the use of *Lamarckian evolution* [23,24] is a promising approach, where an EA is combined with a local search procedure (e.g. tabu search or gradient based algorithm), improving the fitness of the individuals during their lifetime. Martínez-Estudillo et al. [19] proposed the hybrid combination of three methods for the design of Evolutionary PUNNs (EPUNNs) for regression: an EA, a clustering process and a local search procedure. Clustering methods create groups (clusters) of mutually close points that could correspond to relevant regions of attraction. Then, local search procedures can be started once in every such region. In this work, this methodology has been extended to kernel-type models: specifically it has been adapted to RBFNN models.

Ensembles are another promising Machine Learning research field, where several models are combined to produce an answer [25,26]. Two factors must be considered to make an ANN ensemble generalize adequately. One is diversity and the other one is the performance of the ANNs that comprise the ensemble. There is a trade-off as to what the optimal measures of diversity and performance should be [26]. Generally speaking, the approaches to design the ANN ensemble can be classified into two groups. The first group of these approaches obtains diverse individuals by considering different architectures and settings of the parameters. The second one gets diverse individuals by training them on different training sets, such as bagging, boosting, cross-validation… [27–30]. Both of them directly generate a group of ANNs which are error uncorrelated. Partridge [31] experimentally compared the capabilities of the methods above and concluded that changing the ANN type and the training data are the two best ways to create ensembles of ANNs with the higher error diversity.

As previously stated, designing ANNs with EAs has emerged as a preferred alternative to the common practice of selecting the apparent best ANN [18]. Because EAs search from not only a single point but a large population of points, many researchers have actively exploited the combination of multiple ANNs from the last generation of the EA. However, these ANNs tend to be too similar between each other because the individual with the highest fitness frequently prevails after some generations. This phenomenon is known as premature convergence. Trying to avoid this problem, in this proposal, the ensemble is composed of the best individuals from different generations of the EA. Since the EA designs the structure of the ANNs, the models obtained at different generations are suitable to be combined, each of them having distinct topological characteristics (diversity and performance).

In summary, the main objective of this work is to assess the potential of ensembles of PUNNs and RBFNNs trained with different hybrid algorithms to reach the best approach in an industrial application, the identification of sound for the pass-by noise test for vehicles. Up to the authors' knowledge, artificial intelligence methods (and, specifically, nonlinear methods) have not been applied to solve this real problem. The transfer functions between the source and receiver are established by means of these models, but using only the data corresponding to the frequency range 2.5–10 kHz, because the system has a predictable quadratic behaviour at lower frequencies. Therefore, this novel strategy is proposed based on the auralization of sound to simulate the listening experience for high frequencies at a given position in the modelled space.

This paper is organized as follows: Section 2 describes the hybrid techniques proposed for the identification of noise regression problems. Section 3 explains the experiments that were carried out. Finally, Section 4 summarizes the conclusions of this work.

2. Description of the hybrid learning proposed

2.1. Product unit neural networks (PUNNs) and radial basis functions neural networks (RBFNNs)

PUNNs are an alternative to MLPs, and are based on multiplicative neurons instead of additive ones. Product-unit based neural networks have several advantages, including increased information capacity and the ability to express strong interactions between input variables. Despite these advantages, PUNNs have a major handicap: they have more local minima and more probability of finding themselves trapped in them [32]. The main reason for this difficulty is that small changes in the exponents can cause large changes in the total error surface.