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Scenario for embedding AI in Acoustic Design.
Exploiting applications at several design stages.

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ABSTRACT

Holistic methods for acoustic design project are increasingly developed, combining the knowledge gained from physical acoustic researches, early stage noise mapping, architectural parameters and psychoacoustic. The aim of these methods is to combine subjective and objective parameters to achieve more performative outcomes to satisfy comfort needs. These methods require a methodological instrument to structure the design problem and to develop a heuristic mechanism acquiring broad rules to handle the specific solution.

Today, digital tools handle large complex problems evolving from generative into intuitive tools such as the Artificial Intelligence (AI). AI, through the deep learning, discovers intricate structure in large data sets, by using the backpropagation algorithm, to indicate machine's way to change its internal parameters thus helping to develop unpredictable innovative solutions. The paper intends to develop a theoretical background based on bibliographic survey of AI in architecture, with a focus on acoustics. The resultant reading grid will be implemented by a custom survey sent to main stakeholders of acoustic design aiming at understanding strength and weaknesses of its application.

Keywords: Acoustic design, Holistic methods, Artificial intelligence

1. INTRODUCTION

The objectivation of the sound perception has led to abstract subjective aspects through mathematical formulas and specific values. This process has led to have some legislation as reference to guide the designers in their choices.

A-weighted curve is the most commonly used of a family of curves defined in the International standard IEC 61672:2003 and various national standards relating to the measurement of sound pressure level. A-weighting is applied to instrument-measured sound levels to account for the relative loudness perceived by the human ear, as the ear is less sensitive to low audio frequencies.

In 1933 Fletcher and Munson began to work on A-weighting. Their work is mainly based on the response of people's listening to pure tones at various frequencies and over 10 dB increments in stimulus intensity. For each frequency and intensity, the listener also listened to a reference tone at 1000 Hz. Fletcher and Munson adjusted the reference tone until the listener perceived that it was the same loudness as the test tone. Loudness, being a psychological quantity, is difficult to measure, so Fletcher and Munson averaged their results over many test subjects to derive reasonable averages. The lowest equal-loudness contour represents the quietest audible tone—the absolute threshold of hearing.

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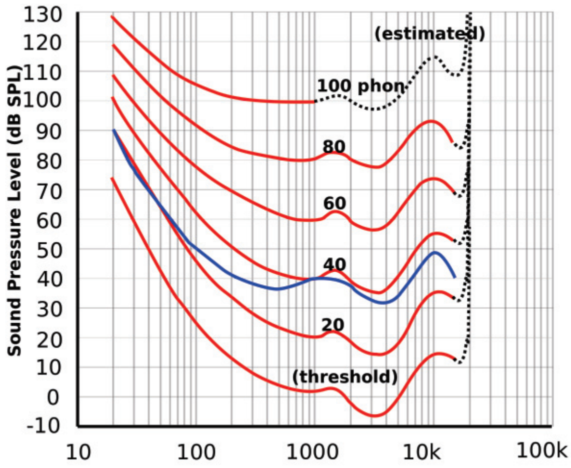

Figure 1. Equal-loudness contours (red). Source: ISO 226:2003 revision. Original ISO standard shown (blue) for 40-phons.

The highest contour is the threshold of pain. The A-weighting is based on the 40-phon Fletcher–Munson curves. Although the process has been revised by International Organization for Standardization (ISO) on the base of academic researchers, the 40-phon curve is particularly close to the modern ISO 226:2003 standard (Figure 1).

The specifications are based on the following conditions: the sound field in the absence of the listener consists of a free progressive plane wave; the source of sound is directly in front of the listener; the sound signals are pure tones; the sound pressure level is measured at the position where the centre of the listener's head would be, but in the absence of the listener; listening is binaural; the listeners are otologically normal persons in the age range from 18 years to 25 years inclusive.

The otologically normal person are “free from all signs or symptoms of ear disease and from obstructing wax in the ear canals, and who has no history of undue exposure to noise, exposure to potentially ototoxic drugs or familial hearing loss”.

But this way to collect data gave us a partial picture of the reality that is more complex than that.

In fact, according the World Health Organization, over 5% of the world’s population – about 466 million people – has disabling hearing loss (432 million adults and 34 million children). It is estimated that by 2050 over 900 million people – or one in every ten people – will have disabling hearing loss.

Disabling hearing loss refers to hearing loss greater than 40 decibels (dB) in the better hearing ear in adults and a hearing loss greater than 30 dB in the better hearing ear in children.

The causes of hearing loss and deafness can be congenital or acquired.

The acquired causes that may lead to hearing loss at any age, such as infectious diseases including meningitis, measles and mumps or chronic ear infections, injury to the head or ear, the excessive noise exposure, including occupational noise such as that from machinery and explosions can became an important factor. Among children, chronic otitis media is a common cause of hearing loss.

The loss of hearing and all the physical consequences can affect the assessment of sound conditions leading to endless way of sound perception. The choice to run an averaged discretized response in curves was based on the idea to use a mathematical method to handle a huge amount of data in order to use them in acoustic design. But today the innovations of computational tools in architecture have led to building information modelling and to data-driven design that have born with the aim to use data to design shapes and spaces. Moreover, these tools allow us to develop methodologies able to combine objective and subjective data achieving a holistic approach. The following paragraph will underline a state of art of case studies in which this method has been applied for acoustic projects in enclosed spaces.

2. HOLISTIC METHODS IN ACOUSTICS

2.1 Introduction

The subjective domain in room acoustic is the topic of several researches on intervention and design for speech and music. The two basic methodologies of field measures (questionnaire o interview) and laboratory experiments (presentation of recordings from spaces or audible simulations to the listeners) show certain limitations and the aim of this part of the paragraph is to show them.

However, in both cases, multidimensional statistical analysis is required since it corresponds to data which involves listening experiments with test subjects.

Numerous listening experiments in real rooms and simulated sound fields over past years have established a certain number of perception attributes of sound fields and as a result of consensus they have been described in objective measures included in standards.

The diversity of acoustic design of a room and the complexity of human perception and acoustic information relating to a room justify the effort put into the research that analyses correlations between objective measures (whether standardized or not) and the listening experiments of the acoustic comfort.

In the following paragraph we focus on three research studies that develop a holistic approach for three several programmatic spaces: churches, auditoria and classrooms.

2.2 Case studies

The following case studies represent paradigmatic examples of how develop a holistic approach for acoustic assessment of interiors.

The A.P.O. Carvalho's work focus on the relationships of the subjective parameters with the objective room acoustics measures and with the architectural features of the churches.

The study is part of research program initiated in 1991 and ended in 1998 and reports the measurements mad in a survey of 36 Catholic churches in Portugal (1).

The program has included two major components to date:

objective studies of existing churches such as reverberation time (RT), early decay time (EDT), clarity (C80), definition (D50), target strength (TS) and length (L) were taken at several source/receiver locations in each church evaluated live music performances at similar locations in each room;

subjective studies of existing churches such as loudness, reverberance, intimacy, envelopment, directionality, balance, clarity, echoes and background noise.

The measurements have been made in two moments, both involving analyses in (almost) empty churches. The first part was to gather objective results of the main room acoustics measures. The second part was to gather subjective evaluations from listeners, using live music performances, of the acoustical qualities of the churches using the same sample of churches.

For the assessment of mismatches between objective parameters and measured perception of concert halls the methodology was quite the same. First, the methodology requires as huge as possible numbers of case studies to consider. In this research 16 theatres and auditoriums were selected in Spain. Then a relatively unchanged group of experts were involved. In this case the group consisted of music lovers, final-year students from the music conservatory, and music teachers. They were placed in locations chosen in advance so that all parts of the seating would be covered: these seats coincided with the position of the microphones for the objective acoustic measurements. And the then the measurements of specific values (in this case the values given by ISO-3382-1 standard specific for performative space)(2).

Other researches demonstrate as other physical factors can be useful to find a relationship between acoustic conditions and perception.

The interdisciplinary research carried out from 2000 to 2006 at the Bremen University, Germany led by mixed team of acousticians, occupational health- and medical-scientists and pedagogues, investigated the work and communication behaviour in synchronization with classroom acoustic measurements in two elementary schools (3).

Based on observations of 175 lessons the effects of room characteristics (e. g. increased absorption, shortened reverberation time and improved speech intelligibility), basic data for all analyses made were more than the mean value of SPL. There are continuous and synchronous time series of basic and working SPL, each type of pedagogical work, detailed teaching phases, differentiated phases of speech by teacher or students and workload of the teacher by measuring the heart rate as very sensitive indicator for stress.

2.3 Comments

The researches demonstrate that methodologies of field measures and laboratory experiments lack flexibility and control of the independent variables and the latter lacks fidelity.

Moreover, there are certain limitations using this type of methodology for evaluation:

- The acoustical response depends on the presence of auditory and the extremized abstraction can lead to not consider all the variables;
- The characteristic of the sound sources heard during an event can affect the sound condition of the space;
- A huge amount of measurements must be considered to get the complexity of the event as much as possible;
- Most of the researches involved only music experts into collection of subjective parameters;

For all these reasons new approaches able to handle a huge amount of data in order to fix the previous limits need to be developed to be developed starting from the opportunities given by the evolution of 4th industrial revolution such as Artificial Intelligence.

3. ARTIFICIAL INTELLIGENCE IN ACOUSTIC DESIGN

3.1 Artificial intelligence

For many years' computers have been used to process experimental data in all scientific and engineering disciplines.

In the field of acoustics, the computer is now regularly used to generate a test signal, to control experiments, and to perform any necessary processing on the resultant acoustic signal, as well as processing and tabulating the results.

The advent of accessible powerful computing systems pushed to have enormous strides in both acoustical measurement techniques and in relating subjective response to sound fields to measurable, objective parameters. The stage is now set for computers to begin to play a larger role in the design process, and in this direction, AI seems to be a tool to take in account.

Artificial intelligence is the simulation of human intelligence processes by machines, especially computer systems. These processes include learning (the acquisition of information and rules for using the information such as Machine Learning), reasoning (using rules to reach approximate or definite conclusions) and self-correction. Applications of AI include expert systems, speech recognition and machine vision (4).

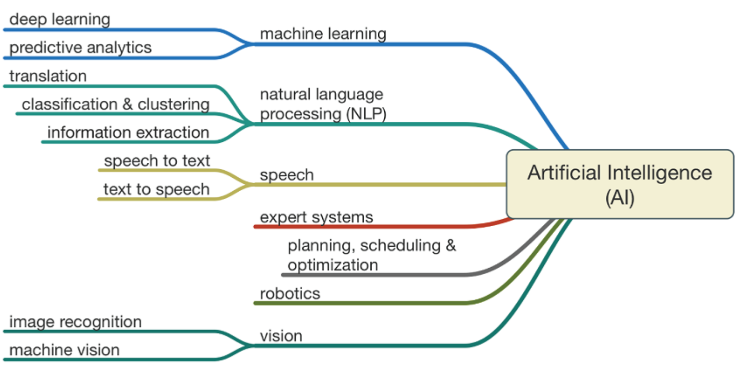

Figure 2. What's required for a machine to be intelligent.

source: http://futurearchitectureplatform.org/news/28/ai-architecture-intelligence/

The main idea behind machine learning is to let machines learn how to solve a task, without having to explicitly explain the method behind the solution. This concept is like how humans learn, where for example, infants develop language skills not by reading grammatical rules but by imitation and practice. Thus, instead of defining rules, data is fed into a computer, so that patterns can be extracted, and the rules that define task are learned implicitly.

More formally, machine learning are algorithms that utilize experience E, to improve performance measure P, for task T. The task should be clearly defined: translating a text between two languages, finding faces in a photograph, or transcribing audio into sheet music, are all examples of tasks. Furthermore, each task should include a performance measure, such as classification accuracy, prediction error, or distance to an objective. Lastly, the experience will be conformed of data, where multiple observations that are relevant to the tasks are collected to form a dataset (5).

This definition of machine learning is remarkably different from a general artificial intelligence, as the goal is not to create a sentient, autonomous program than can think and understand the world as a human being; rather, the goal is simply to maximize an objective parameter, for a particular application. Therefore, machine learning can be explained as applied statistics to approximate functions and solve optimization problems. This distinction becomes blurrier as tasks get more involved. The basic workflow of a machine learning solution is to first use raw data to extract meaningful features; relevant numerical or categorical values that describe the problem. Then process these features to extract patterns, finding relationships between inputs and outputs. Complex systems can build complex features from simple ones, and then find more intricate patterns.

Although there are many different types of tasks that can be solved with machine learning, most can be generally explained as either supervised learning, where each data sample has features (input variables) and labels (output variables), or unsupervised learning where there are only features, and no labels.

In these terms AI, and machine learning, can be considered as tool that can help into reducing the gap between objectivity and subjectivity of sound perception developing the holistic approach. In the next paragraph we discuss some researches that go in this direction.

3.2 Case studies of ML applications in acoustics

We analyse applications of ML theory to the following acoustics fields: speaker localization in reverberant environments, source localization in ocean acoustics, bioacoustics, seismic exploration, and reverberation and environmental sounds in everyday scene (6).

- Speech enhancement is a core problem in audio signal processing, with commercial applications in devices as diverse as mobile phones, hands-free systems, human car communication, smart homes or hearing aids. An essential component in the design of speech enhancement algorithms is acoustic source localization. This topic has attracted significant research attention, resulting a several amount of localization methods. The application of ML in this field was facilitated by establishing a database of acoustic recordings from real-life scenarios. This dataset is achievable by research teams that can use it to train the algorithms.
- The application of ML to underwater source localization (7) is a relatively new research area with the potential to leverage recent advancements in computing for accurate, real-time prediction. Underwater source localization methodologies in ocean acoustics have conventionally relied on physics-based propagation models of the known environment. Unlike conventional methods, ML methods may be considered "model-free" as they do not rely on physics-based forward-modelling to predict source location. ML instead infers patterns from acoustic data which allows for a purely data-driven approach to source localization. However, in lieu of enough data, model simulations can also be incorporated with experimental data for training, in which case ML may not be fully model-free.
- The researches of ML application in bioacoustics are increasing the last decades. Bioacoustics is the study of sound production and perception including, but not limited to, the role of sound in communication and the effects of natural and anthropogenic sounds on living organisms. ML has the potential to identify presence of animals and vocalizing, (8), to identify the type of animal (9) and to identify the call or song that was produced and understands how these sounds relate to one another (10). Among these issues, species detection and identification are a primary driver of many bioacoustics' studies due to the reasonably.
- ML and especially deep leaning (DL) methods, have recently seen significant increases in seismic exploration applications, including seismic data processing, imaging, interpretation and inversion. Seismic exploration for hydrocarbon discovery involves generating seismic waves from sources at or near the surface of the Earth or ocean water

column and recording the waves after they have propagated through the Earth using large sensor arrays. New results from these methods are frequently published in the society of exploration geophysicists (SEG) publications such as Geophysics, Interpretation and annual conferences and workshops.

- Humankind have to encounter complex acoustic scenes in daily life. These scenes are the consequences of the overlays of wide range of sources such as speech, music, animals etc, each with its own structure and each highly variable in its own right (11). The overlay is affected by the environmental and spatial condition creating reverberation phenomena that distorts the original source waveform. Thus, the signal that reaches a listener usually contains a mixture of highly variable unknown sources, each distorted by the environment in an unknown fashion. This variability of sounds in everyday scenes poses a great challenge for acoustic classification and inference. Classification algorithms must be sensitive to inter-class variation, robust to intra-class variation, and robust to reverberation—all of which are context dependent. The development of these classifications must deal with the complexities of natural acoustic scenes. Because environmental sounds are so variable and occur in so many different contexts—the very fact which makes them difficult to model and to parse—and ML system can overcome these challenges will likely yield a broad set of technological innovations.

The attempt of ML algorithms to replace the same biological systems can raises the possibility to use them to understand the mechanisms of auditory perception in both humans and animals. Basically, to develop processes able to assess objective and subjective responses to a sound scene.

4. SURVEY

The selection of the sample for the survey has been an important phase of the research. In fact, only experts in acoustic design field have been involved in the survey. The selection of the experts has been made looking at the most important studio firms that provide acoustic consultancy. Basically, the companies were selected from the top 500 design firms ranked by Engineering News-Record according to revenue for design services performed in 2018 in $ millions.

For each expert involved also other categories have been collected in order to obtain the table 1. The columns of the table are set according this information:

- The company, such as name and type of company (A (Architect), AE (Architect-Engineer), EA (Engineer-Architect), EC (Engineer-contractor), E (Engineer), L (Landscape architect);
- The experts' references, such as name, last name, role in the company, personal corporate-based email, general corporate-based email and the contact of LinkedIn;
- Data related to the survey, such as date of mailing, date of answering and if they completed questionnaire or not.

Table 1. Table to collect systematically the sample

Type of firm	Firm	Name, Last Name	Role	Personal firm-based email	General firm-based email	LinkedIn	Date of mailing	Date of answering	Completed questionnaire

The questions of the survey aim to collect useful information in order to define the scenario and point of view of experts.

First, it has been important fix the level of knowledge on Artificial Intelligence (Question number 1). The level has been assessed according three levels:

- Low knowledge: for those that have just heard about it
- Medium knowledge: for those that know it, but they have never applied it;
- High level: for those that have applied Artificial intelligence at least once

Then the survey splits in two directions: from one side there are questions to collect information by who have already experience in AI in acoustic design (question number 2,3,4). The question number 2 intends in which stage of the design process the AI has been applied.

From the other side the questions are designed to collect opinions by who have not experience in AI but, since its experience in acoustic design can give a contribution to the research anyway (question 5,6). The last question (number 7) intends to open a debate about possible time it will take to embed AI in acoustic design systematically. Basically, the last question aims to understand if this field is mature enough to embed a so advanced process.

Table 2. Questions survey

ID	Questions
1	AI Level of knowledge (Low= I've just heard about it; Medium= I know about it, but I've never applied it; High= I heard about it and I have applied it at least once).
2	If you have applied Artificial Intelligence in Acoustic design, in which stage of design process?
3	If you have applied Artificial Intelligence in Acoustic design, do you applied it to design which kind of programme activity?
4	If you have applied Artificial Intelligence in Acoustic design, what have been the advantages?
5	If you have never applied Artificial Intelligence in Acoustic design, in which phase do you think that AI can be embedded?
6	Please explain the reason briefly.
7	According to you how long does it take to embed AI in acoustic design process systematically?

Here we are going to present part of the results.

After two months these are the aggregate results:

- 60% of who received the survey has a medium knowledge on AI, 30% has a low knowledge on AI and the 10% has a high knowledge of it;
- The 10% with high knowledge affirms to have had opportunities to apply it in schematic design phase (60%), design development phase (30%) and conceptual design (10%).
- The 10% that admit having a high knowledge says that the most important advantages related the increment of degree of reliable of simulation phase in design process (40%);
- The 30% that have never used AI in acoustics says that the schematic design (50%) could be the main phase to apply AI, the 30% in design development and the 20% open to possibility to use it for assessment phase when the acoustic intervention is completed.
- About the timeline, it merges a quite negative view of the systematically embed of this process until now. In fact, more than 50% thinks that it will take between 1 and 5 years. (35% more than 5 years, 15% in 1 year)

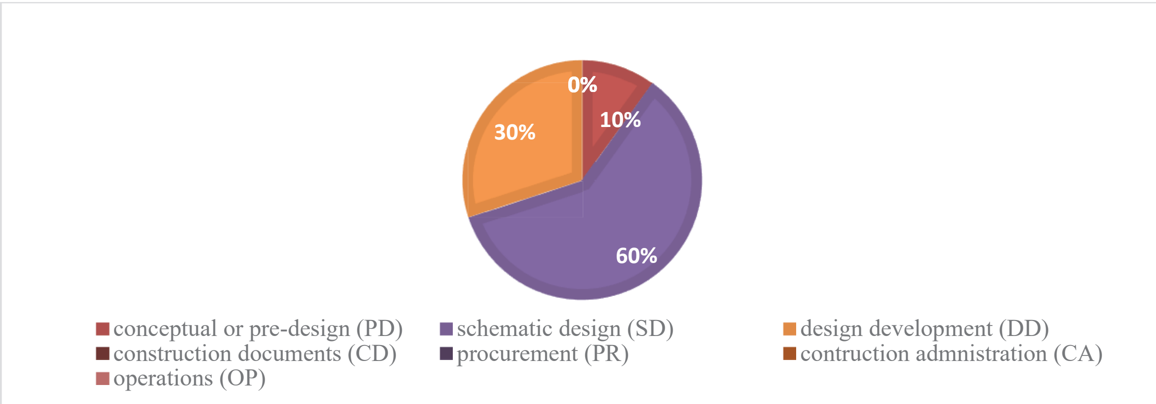

Figure 3. Percentage of AI use in design stages

This survey can be considered as starting base for a debate on this topic. For this reason, we decided to not stop collecting answers in order to get more opinions as possible.

5. SCENARIO AND FUTURE IMPLEMENTATIONS

In this review we have introduced the holistic methods and ML theory, including deep learning (DL), and discussed several case studies in acoustics research areas. The aim of this work is to describe future scenario in which apply ML theory to develop holistic approach. To do that we have focused on the weakness of modern holistic approaches underlining how ML theory can be an opportunity to solve them. The systematic introduction of AI in acoustic design process can facilitate the development of new approaches that can led to unpredictable and more performative outcomes. The understanding how to embed it can be a first step to define an approach that sees the acoustic in the centre of design process for interiors or exteriors combining subjective and objective parameters. We can define it sound-drive design.

Despite their limitations, these methods provide good performance relative to conventional processing in many scenarios.

- The first scenario sees the application of AI theory to assess the acoustic conditions of a space monitoring objective data (RT, clarity, definition etc) and human behaviour. This scenario sees the opportunity to collect data to embed in next similar jobs reducing mistakes and increasing the reliability of simulations models.
- The second scenario sees the application of ML in pre-design phase, based on training algorithm to acoustic conditions of existing spaces, to find optimized layouts spaces according changing external sound sources.
- The third scenario goes more in product design, developing a real time system able to fix acoustic condition of a space modifying the position of acoustic panels. The movement of these panels will affect the soundwave paths and the amount of absorptive material in the space.

In general, we can say that AI in acoustics has enormous transformative potential, and its benefits are increased with open data.

However, AI-based methods are data driven and require large amounts of representative training data to obtain reasonable performance. For this reason, we hope that the debate on this topic can increase also sharing the researches with others research fields.

REFERENCES

1. Carvalho APO, Morgado AEJ, Henrique L. Relationships between Subjective and Objective Acoustical Measures in Churches. Build Acoust. 1 marzo 1997;4(1):1–20.
2. Gimenez, Alicia, Rosa Maria Cibrian, Cerda S, Giron S, Zamarreno T. Mismatches between objective parameters and measured perception assessment in room acoustics: A holistic approach.
3. Kristiansen, Jesper L Sten Persson, Roger Shibuya Hitomi Nielsen, Per Mober Scholz, Matthias. A study of classroom acoustics and school teachers' noise exposure, voice load and speaking time during teaching, and the effects on vocal and mental fatigue development.
4. Jordan MI, Mitchell TM. Machine learning: Trends, perspectives, and prospects. Science. 17 luglio 2015;349(6245):255–60.
5. Bishop CM. Pattern recognition and machine learning. New York: Springer; 2006. 738 pag. (Information science and statistics).
6. Michael J. Bianco, Peter Gerstoft, James Traer, Emma Ozanich, Marie A. Roch, Sharon Gannot, Charles-Alban Deledalle, Weichang Li. Machine learning in acoustics: theory and applications
7. Niu, Haiqiang. Gong, Zaixiao. Ozanich, Emma Reeves. Li, Zhenglin. Gerstoft, Peter. Wang, Haibin. Deep learning for ocean acoustic source localization using one sensor. ResearchGate.
8. Mellinger DK, Clark CW. Methods for automatic detection of mysticete sounds. Mar Freshw Behav Physiol. 1 gennaio 1997;29(1–4):163–81.
9. Clemins PJ. Automatic classification and speaker identification of African elephant (Loxodonta africana) vocalizations. J Acoust Soc Am
10. Kershenbaum E, Blumstein DT, Roch MA, Akçay Ç, Backus G, Bee MA, et al. Acoustic sequences in non-human animals: a tutorial review and prospectus. 26 novembre 2014
11. Gaver W. What in the World Do We Hear?: An Ecological Approach to Auditory Event Perception. In 1993.