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Research proposal: Psychoacoustic Modeling of Noise Annoyance in the Workplace - Application of Machine Learning

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ABSTRACT

In addition to noise detrimental to hearing, the non-auditory effects on cognitive performance and well-being are becoming more relevant in an increasingly digitized workflow. Not only the work type is currently changing, but also the work environment: Many jobs have been moved to the home or other places outside formal workspaces during the covid pandemic. The noise is changing dynamically at these new work locations and there is a need for a flexible form of risk assessment. This project is intended to develop the foundation for the assessment of noise regarding its effect on mental processes based on subjective judgments. The aim is to explore how machine learning (ML) techniques can support the assessment of noise exposure at low-intensity sound levels. The Technical Rules according to the German Workplace Ordinance have so far provided for a primarily sound pressure level-oriented evaluation. Such an assessment only partially considers the risks from information-containing noise environments, such as irrelevant speech. Noise exposure at low levels can trigger non-auditory noise effects and should be considered with psychoacoustic measures (e.g., noise annoyance). A more recent approach is the annoyance evaluation model (AEM), which introduces the methodology of artificial intelligence to noise assessments. Here, the perceived annoyance is mapped to the properties of the physical sound. This research project aims to compose realistic soundscapes that can be analyzed and modified for applications as experimental stimuli. The digital composition of soundscapes allows the variation of acoustic parameters. The annoyance of these scenarios should then be assessed in a hearing task with subjects. Using machine learning, a mathematical model is trained regarding the subjective annoyance in the hearing task. To improve assessments of the acoustic working environment it should be determined whether ML systems can provide additional assessment criteria for the implementation in future regulation.

Keywords: noise, non-auditory effects, machine learning, risk assessment, annoyance, psychoacoustics

INTRODUCTION

In this project, we want to use machine listening to predict the annoyance of occupational soundscapes [1, 2]. We propose to study soundscapes that are synthetically reproduced to have control over the psychoacoustic parameters in the laboratory. Finally, the produced soundscapes are rated regarding their continued, perceived annoyance by human study participants, noise raters in a new community-based approach [3]. The aim is to train a mathematical model with an appropriate algorithm that can predict the annoyance probability of realistic soundscapes in situ. In this way, occupational health and safety can benefit from similar investigations regarding disturbing soundscapes in environmental psychology and urban planning [see 4]. Thereby, the machine can learn what acoustic aspects of the auditory signal are disturbing to the listening employees [5]. This instrument allows the assessment of auditory scenes beyond the individual subjective impressions of a single rater or listener. Instead, the evaluation of workplace safety with artificial intelligence-based assistants can complement the existing objective measurements. Occupational soundscape assessment can benefit from the judgments of machine listening that can be integrated as predictions into the technical model and prevent distraction or annoyance at the workplace. Annoyance is one leading factor for descending well-being at work [6]. With the proposed assistive technology in this project, we want to support the well-being of the employees and improve health by application of recent developments in artificial intelligence.

Machine listening: artificial intelligence in sound perception and sound source understanding

The detection capabilities of machines for realistic auditory scenes have improved rapidly during the last few years [7]. The field is sometimes referred to as “machine listening” and has the target, e.g., to train mathematical models with the capability that can be found in humans during everyday hearing tasks [8]. The auditory system in humans had an extensive training time and is also shaped by the primary targets of the organism (e.g., coordination, survival, etc.). The system however still exhibits considerable flexibility for the variety in the soundscape of the world. The capability of the hearing system to process completely unknown stimuli and adapt to the information contained is an integral part of the auditory system and its underlying architecture. The sensitivity of humans to certain sounds describes, among others, how a change in sound enters the consciousness. This decision-making process is dynamic and relies on different factors (i.e., internal, and external). The crossing of the threshold from subconsciousness to consciousness has not only to do with the intensity of sounds but their semantics, the pattern of appearance, and the momentary mental state [9].

These advances in the human auditory system are now replicated by computational power, technological evolution in microphone technology, and software developments in artificial neuronal networks that can represent the human auditory system. The computational auditory scene analysis has faced technical and conceptual challenges successfully and can now autonomously interpret some sound events in complex auditory situations without the continuous monitoring of humans [10-12]. A useful field with numerous applications can be referred to as algorithms and systems of speech recognition, i.e., natural language processing [13] or large language models. How can this advance in model-based annoyance prediction be transferred to annoyance measures in a soundscape of the workplace? We propose a new approach during this project. Fundamentally, salient stimuli can distract auditory attention and bind cognitive resources, such as attention [14].

The aim of “understanding” an auditory scene is depending also on the capability of the auditory system to bind all auditory streams together into coherent auditory objects and, eventually, into one plausible auditory scene [8]. This process is called grouping of sounds or sound source separation. An auditory object can often be associated with a single sound source, for example, a physical object like a saw, that is close to the listener and can be harmful. The resulting awareness of what sound sources are in the direct environment supplies the listener with valuable information, even if the sound source is (visually) occluded [15]. Many sound sources can signal risks and therefore prevent the employee from danger. The cognitive categorization of auditory objects that are dangerous, irrelevant, or task-relevant is primarily depending on the physical auditory scene and its controllability, the current task, and, often, individual preferences.

Occupational environments are plastered with sound sources that might be detrimental to work performance, well-being and in the end harmful to the listeners' hearing. On the other hand, many sound sources are just irrelevant to the current task [16]. The irrelevant and unwanted proportion of the sound is labeled as noise. The relevant part of the soundscape is called the signal. The changing classification of a sound as relevant or irrelevant is a dynamic process. The signal-to-noise ratio in an occupational setting has therefore to do with the momentary and general goal that the listener has [17]. The attentional capacity to make this decision is limited. The continuous mental workload with noise-related cognitive tasks can lead to exhaustion and stress. The cumulative effect of noise-related stress by filtering should be considered here.

The attentional resources of machine listening are not as limited, as they are in humans. Machine listening can theoretically process several sound sources simultaneously. The attention pool can be scaled according to the sound sources perceived. Instead, humans continuously make decisions about which sound source needs to be attended to further. Due to the limitations of the attentional resources and situational demands of humans, e.g., task-related workload or motivation, the decision can require additional mental resources. Thus, coping with distraction reserves concentration and lowers work performance in the short term in soundscapes. However, the coping process can be stressful in the long run. In contrast, the processing depth of a stimulus is theoretically equal for all sound sources in machine listening. The available cognitive resources are not equally distributed among the sound sources in humans. The AEM can be taught the general annoyance that the soundscape has for the distractibility and annoyance of the listener.

In this way, the machine listening technology can support the risk assessment with the annoyance perception that humans have by an occupational soundscape [18].

Assistance in risk assessment by automation procedures

The noise-related risk assessment of the workplace investigates the physical properties of the soundscape itself, the employee, and the job characteristics [19-22]. The assessment is driven by the question of what sounds can be harmful or annoying (for the employee) when executing the job task (i.e., see ASR 3.7 or VDI 2058-3). During the risk assessment at the workplace, the average sound pressure level is a basic value that is considered to detect potentially harmful or detrimental sound pressure levels. Noise reduction is a general obligation for the employer. Either the sound pressure levels need to be reduced at the emission source, on its transmission path, or by the application of personal protective equipment. Besides the sound pressure level, numerous other factors should be regarded in the assessment process: the perceived annoyance, the preventability of a specific sound, its informational content, tonality, and impulsiveness, among others. Common questions are: Is a certain sound connected to the work activity itself? Can the sound be prevented? Is it perceived as annoying by the employee, at all?

The considerations in the German Technical Rules and Regulations, such as ordinances on workplaces (see ASR A3.7) are designed to be practical, and effective and help to prevent many work-related non-auditory effects of noise [23, 24]. However, in the future, the risk assessment of workplaces regarding the annoyance of noise can be supported by machine listening (below critical action level). The objective description of workplace safety can be complemented with the artificial intelligence tool that is researched in this project. The subjective judgments of noise annoyance can be integrated by the AEM into the workflow of the risk assessment. [25]. In addition to considering the demands of the working task the proposed AEM could also integrate individual sensitivities or preferences, of employees working in the soundscape.

The flexibility of the proposed AEM regarding the sensitivity to noise only reflects one aspect of the usefulness of the risk assessment system proposed. Another aspect is the flexibility of the model and the derived predictions regarding the (expected) work task. Depending on the type of work task (i.e., mental, communication, monitoring), the AEM can be charged with different ratings to cater to the appropriate cognitive resources that are drained by the characteristics of the specific work task.

By the means of subjective ratings structured in the AEM the risk assessment can benefit from another important aspect when evaluating a sound scenario: the shared perception of many raters that report on their personal experience when being exposed to noise. We want to investigate the usability of the technique for occupational health experts. Can the noise specialist be supported by information that numerous acoustic raters gave for the perception of a soundscape?

Psychoacoustic modeling

Psychoacoustics bridges the gap between the physical stimuli, the wave propagation in sounds, and the psychological impression, the perceived sound in the listener. The AEM builds upon the insight of Zwicker's model of psychoacoustic noise annoyance (PA) and recent developments in the modeling field [26]. The Zwicker model considers the four acoustical parameters loudness, sharpness, fluctuation strength, and roughness. The PA tries to map acoustics parameters on the subjectively perceived annoyance for the individual. Here, we sharpen this approach by extracting the acoustic features that are proposed in the PA model and combining those with the subjective rating from a questionnaire by human listeners. The annoyance evaluation model has proposed a similar approach [28]. In the AEM, we want to link acoustic properties (e.g., loudness, sharpness, and roughness) to subjective ratings on the acoustic annoyance of soundscapes employing machine learning.

The assumption of the psychoacoustic approach is, that proportions of the distracting soundscape, such as the change in pitch, and the frequency modulations do have a specific effect on the cognitive system. That insight is partially independent of the semantics of a signal behind the sound's source (e.g., meaning, emotions, reference). Instead, the origin of annoyance is identified in the acoustic signal itself. The influence of irrelevant speech and sound (sound quality) on the cognitive process, like memory, could be substantiated in earlier empirical experiments [see 29].

For the appropriate ML algorithm, we want to compare different candidates from supervised learning: artificial neural networks (ANN), K-nearest neighbors (KNN), and long-short-term memory (LSTM). These techniques have been successfully used in the past to predict noise annoyance [25]. As a competing classifier, we test the support vector machine (SVM) on the features that are extracted from the soundscape. The models will be evaluated regarding their accuracy of the predicted noise annoyance in the synthetically produced soundscapes. The ground truth is defined by the self-reported noise annoyance level in the survey. For the rating scale of noise annoyance, we use the established approach proposed by [9]. The evaluation of neural network techniques allows us to compare which model is effective in the differentiation of the extracted features, that can be found in the noisy soundscape.

Synthetic soundscape design

In assessing the acoustic ergonomics of the workplace, it is necessary to understand the characteristics of the physical factors that can be a danger to the employee [30-32]. At the same time, it is crucial to understand how the physical factor evokes a certain effect that can lead to annoyance. However, the soundscape is a sensitive part for experimentalists because the recording and reproduction of specific sound field characteristics are challenging when a realistic immersion level should be perceived by the listener [33, 34]. Limiting factors can be the microphone, the compression level, the reproduction system, and so on. Besides these technical limitations, which require experience and knowledge to overcome, legal problems are equally involved. The recording of machines at the workplace to present a soundscape in a laboratory might be straightforward to implement. However, the situation is different, if the work environment is a social place with speech information being involved in the auditory scene in the form of, e.g., conversations between two talkers. The recording of such an authentic workplace soundscape is for many scenarios a combination of different sound sources, such as social noise (e.g., irrelevant speech), machine noise, and warning sounds. The recording of the individual voice is considered part of the personal identity and therefore heavily protected by law. The unique recognizability of voices makes the recording of all sounds in the work environment a problem of data personal protection and privacy laws [35, 36]. Therefore, the so collected data becomes subject to the German and European General Data Protection Regulation (GDPR).

In practice, the speaker needs to be informed before being recorded and declare consent to be recorded. Consequently, the quality of a realistic soundscape will partially lose its ecological validity and will fall back to staged stimuli such as audiobooks or fabricated conversational fragments. The occupational researchers who want to study social workplaces have therefore to produce auditory stimuli that satisfy data protection laws and ecological validity at the same time [37]. We propose for that reason a new approach that has only been tested in a minority of cases: The digital composition of sounds into one coherent soundscape. The speech stimuli can be produced by text-to-speech algorithms that are capable of mimicking natural voices. The content of the speech in this setting is adopted from real-world examples that can be stripped by information that relates to personal information or identity. In any case, the voice is a synthetic product that has no relation to a real person. The recording of professional speakers is expensive and slow. Synthetic voices are sufficient for this purpose.

Combining speech sounds and environmental sounds in a soundscape that was observed in situ, allows us to parameterize the acoustic feature space in specific limits that are considered in the resulting models. It would be one aim to vary the synthetical soundscapes in such a fashion that the extracted feature space represents a spectrum of parameters that can be found in many workplaces.

Mission statement

1. Relevant soundscapes are identified based on the literature review and described by the listener/employee.
2. The soundscape is synthetically reproduced based on the diary of the listener. The acoustic features PA are extracted.
3. The synthetically reproduced soundscapes are rated regarding their annoyance by raters.
4. Different types of ML models (AEM) are trained with subjective ratings and acoustic features.
5. The accuracy of the models is compared.

The acoustic feature space is explored for different annoyance ratings.

REQUIRED MATERIALS AND PLANNED WORKING PACKAGES

The required materials include software for synthetic sound production, ML platform (python), statistical analysis (R), and acoustic settings to administer experiments (control of disturbance and loudspeaker). The cooperation of subjects will be necessary at two stages of the project: (1) Employees that are working in vulnerable jobs will be asked to gather information by digital protocol (mobile phone app) and summarize the components of the soundscapes in a survey (a). The study participant will rate the annoyance of the observed real soundscapes (b). No recording of the soundscape is necessary.

Finally, when the synthetic soundscapes have been designed and the models trained, (2) the same employees need to rate the annoyance of the synthetical soundscapes to train the models with judgments. Eventually, the model is validated with real soundscapes. The project is split into four distinct working packages that are being processed in a sequential order to reach the project goal. The main aims are the (1) composition of the soundscapes and (2) the annoyance ratings by raters and (3) the training and validation of competing supervised learning techniques.

Work package 1: Identification and description of relevant soundscapes

In the first step, the relevant soundscapes must be identified. For that purpose, a new approach is chosen. Employees in vulnerable noise situations are identified, based on the survey of EU OSHA and BIBB/BAuA Employment Survey, and contacted. Then, they should describe how their surrounding soundscape is designed in detail.

For this survey, different anchor questions are requested in a diary: What sound sources are existing, at what loudness, and for which duration? The work types are considered in the model as well. This sample of individuals is later requested to participate in the subjective rating of the synthetical soundscape in working package 4.

Work package 2: Digital composition of realistic soundscape

In the second step, the originally described soundscapes from the real world are digitally and synthetically reproduced with a digital audio workstation (DAW), e.g., Ardour, Apple Logic, or similar. At this stage, it is necessary to evaluate the authenticity. For that purpose, a validation study will be designed that measures the subjective, self-reported ratings about originality (1) and the annoyance (2) of the soundscape. For the authentic proportion of the soundscape, the annoyance ratings can be considered in the next step. This work package aims to validate the procedure of designing soundscape synthetically.

Work package 3: Training and validation of ML models

We choose a research design to compare different ML models to each other to eventually choose the one that is the most accurate in predicting noise annoyance. For such kinds of comparisons, the Kappa coefficient has been applied successfully, since this score reacts more robustly to imbalances in the data compared to a classic accuracy estimation. Commonly, the Kappa (or Cohen's Kappa) is used to measure inter-rater reliability [38]. Here, the Kappa score is used to measure the performance of a classification concerning competing models considering the rater judgment as ground truth.

The best-performing model is then chosen to predict the noise annoyance in the synthetic soundscape.

Work package 4: Modulations of acoustic features and effect on annoyance prediction

The acoustic features allow the parametric approach in the soundscape design. Once the general workflow is established variation of the soundscape design should cover different parameter spaces of acoustic features. We let those soundscapes be rated by the subjects to determine the annoyance level. To add to the understanding of noise annoyance models we add those stimuli to explain the prediction power of the models.

EXPECTED RESULTS AND CONCLUSION

We plan to investigate the potential of equipping occupational health and safety specialists with a tool that can predict noise annoyance with simple, fast, and easy-to-use risk assessment technology. The rapid assessment of a soundscape at the workplace through modeled annoyance ratings allows for a safer and ergonomic soundscape at work. It is the prerequisite for this risk assessment technology to understand whether mathematical models can indeed be charged with the information necessary to allow conclusive judgments upon the general safety of the workplace soundscape.

The application of ML models in risk assessment might have the potential to complement the objectively measured threshold values in the rules and regulations, in the long term. Thus, objective noise intensity-related measures can be expanded by information on the maximum annoyance level for a certain task by the AEM. The usefulness of the models is not exhausted by predicting the annoyance for a general population but can make predictions based on the task type.

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