



---

# Audio Engineering Society Convention Paper

Presented at the 133rd Convention  
2012 October 26–29 San Francisco, USA

*This Convention paper was selected based on a submitted abstract and 750-word precis that have been peer reviewed by at least two qualified anonymous reviewers. The complete manuscript was not peer reviewed. This convention paper has been reproduced from the author's advance manuscript without editing, corrections, or consideration by the Review Board. The AES takes no responsibility for the contents. Additional papers may be obtained by sending request and remittance to Audio Engineering Society, 60 East 42<sup>nd</sup> Street, New York, New York 10165-2520, USA; also see [www.aes.org](http://www.aes.org). All rights reserved. Reproduction of this paper, or any portion thereof, is not permitted without direct permission from the Journal of the Audio Engineering Society.*

---

## Matching Artificial Reverb Settings to Unknown Room Recordings: a Recommendation System for Reverb Plugins

Nils Peters<sup>1 2</sup>, Jaeyoung Choi<sup>1</sup>, Howard Lei<sup>1</sup>

<sup>1</sup>International Computer Science Institute, Berkeley, CA, 94704, USA

<sup>2</sup>Center for New Music and Audio Technologies, UC Berkeley, CA, 94720, USA

Correspondence should be addressed to Nils Peters ([nils@icsi.berkeley.edu](mailto:nils@icsi.berkeley.edu))

### ABSTRACT

For creating artificial room impressions, numerous reverb plugins exist, and are often controllable by many parameters. To efficiently create a desired room impression, the sound engineer must be familiar with all the available reverb setting possibilities. Although plugins are usually equipped with many factory presets for exploring available reverb options, it is a time-consuming learning process to find the ideal reverb settings to create the desired room impression, especially if various reverberation plugins are available. For creating a desired room impression based on a reference audio sample, we present a method to automatically determine the best matching reverb preset across different reverb plugins. Our method uses a supervised machine-learning approach and can dramatically reduce the time spent on the reverb selection process.

### 1. INTRODUCTION

Artificial reverberation is one of the most common audio effects in music or movie production. Sound samples can be enhanced with reverb so that the sample's sound matches the room impression of a given recording, e.g., adding dry sound effects from a database into an existing movie scene. The patent

[5] proposes a suggestion method for selecting dry sound effects from a database based on the image within a movie, to ease the content creation process. To the author's knowledge, there is no recommendation system that helps the user in selecting the ideal reverb preset.

## 2. IMPROVING THE WORKFLOW WITH ARTIFICIAL REVERBS

Beginning with [20] artificial reverbs have been under development for over 50 years. A recent review of this development process with an exhaustive reference section can be found in [22]. There are three technical concepts of artificial digital reverbs: delay-networks, convolution based, and physical room models. While the latter concept is currently primarily used for architectural acoustics modeling (due to its high computational demand), delay-networks and convolution-based concepts are popular in content creation of music, games, and motion pictures because of their control features and real-time capabilities.

During these fifty years of development, uncountable artificial reverbs have been implemented and many of them have complex, unique controls. Consequently, those reverbs are hard to use, especially for non-trained or non-professional users.

To simplify the workflow with artificial reverbs, a few control strategies have been proposed in the past. One strategy focuses on providing a layer of subjective control parameters rather than technical parameters. The reverb unit of Ircam's Spatialisateur [11] is an example of such a control approach. Here, the mapping of the perceptual user controls to the underlying technical reverb parameters is based on a series of listening tests conducted by the author of [14] and colleagues.

On an individual level, in [18] a method is described to train a personal interface on top of a given artificial reverb for an individual users. A linear regression model is used to map the parameters of the underlying reverb to the personal interface. This mapping can be learned by rating 35 reverberated audio samples in less than 3 minutes.

In a third simplification, the authors of [25] propose a unified API based on Open Sound Control (OSC) to control different artificial reverbs from one single user interface.

The approach in this paper is different, yet complementary. Rather than improving the user interface, the system suggests reverb settings that match the room impression of a given reference recording.

Based on this recommendation, the user can then fine tune the individual parameters to fully create

the desired acoustic impression. Therefore, time spent listening to numerous reverb presets can be avoided.

## 3. BLIND ESTIMATION ROOM ACOUSTIC FEATURES

Based on identifying room acoustic properties from reverberant audio signals, this paper explores the potential of machine-learning techniques to support the audio engineer in finding the ideal artificial reverb available at a given DAW. To the author's knowledge, there is little prior work on this topic. In [21] a Gaussian Mixture Model (GMM) approach was used to estimate and categorize the room volume in reverberant speech recordings into six room classes, ranging from  $40\text{ m}^3$  to  $18000\text{ m}^3$ . From the four tested feature extraction approaches, the best results were achieved by computing RIR features from an estimated RIR derived from abrupt stops in speech signals with an equal error rate (EER) of 22%. The authors of [6] trained a Support-Vector Machine (SVM) with features from a binaural model to classify four different rooms from binaurally captured environmental sounds. Because binaural features rely on a two-channel binaural recording, their approach cannot be used for one-channel or conventional two-channel stereo recordings, e.g., those with a boom microphone at a film set. In [9] three different methods to estimate the reverberation time  $T_{60}$  from reverberated speech were compared. These methods are based on the Modulation Energy Ratio, Spectral Decay Distribution, and on a maximum likelihood of a statistical model of the sound decay. In low noise conditions the latter two methods were found to provide accurate estimation to within  $\pm 0.2$  sec for  $T_{60} \leq 0.8$  sec.

## 4. METHODOLOGY

Our recommendation system is derived from a GMM-based system historically used in speaker recognition [19] and more recently in other acoustic-related tasks such as room identification [17], event detection [16], and geo-location estimation [15]. These systems employ Mel-Frequency Cepstral Coefficient (MFCC) audio features, a short-term power spectrum representation based on the discrete cosine transform of a log power spectrum on the nonlinear mel frequency scale [8].

From each audio file, MFCC C0-C19 along with deltas and double-deltas are extracted, 60 dimensions in total. The window lengths is 25 ms and frame intervals are 10 ms. One Gaussian Mixture Model (GMM) is trained for each reverb preset, using a bag of randomly selected MFCC vectors from all the audio files processed with that reverb preset. The GMM training is done via MAP adaptation [19] from a reverb-independent GMM, which is trained using MFCC features from all audio tracks of all reverb-presets in the development set. A total of 128 mixtures are used for each GMM. Figure 1 depicts the process. The 60-dimensional MFCC features are extracted using HTK [24], and the open-source ALIZE toolkit [4] is used for GMM training, factor analysis implementation, and likelihood ratio computation for the reference audio. Factor analysis seeks to obtain a low-dimensional subspace representing the undesired variations of RIR-processed audio [12], with the RIRs coming from the same reverb preset. The undesired variations would be subsequently removed from each preset-related GMM and reference audio. Factor analysis is computationally intensive and can be done offline. The resulting model is stored and will be recalled when a reverb recommendation is requested.

For a reverb recommendation, the same MFCC features (MFCC with deltas and double-deltas) are extracted from the provided reference audio file. Using these MFCC features, their likelihood ratio between each of the preset-related GMMs and the preset-independent GMM is computed. The reverb preset with the largest likelihood ratio is the recommended reverb. To provide the user instantaneously with a reverb recommendation, this computation needs to be carried out in real-time.

Many delay-based reverbs feature a low-frequency modulation of the delay time of individual delay lines to avoid undesired coloration in the reverb tail as suggested in [7]. Due to this time-variant behavior, it is not possible to extract one static impulse response that would characterize the system. To have a unified approach that works with convolution, as well as delay-network based reverbs, we decided to train our model with audio files processed with each reverb preset rather than to train on sampled impulse responses.

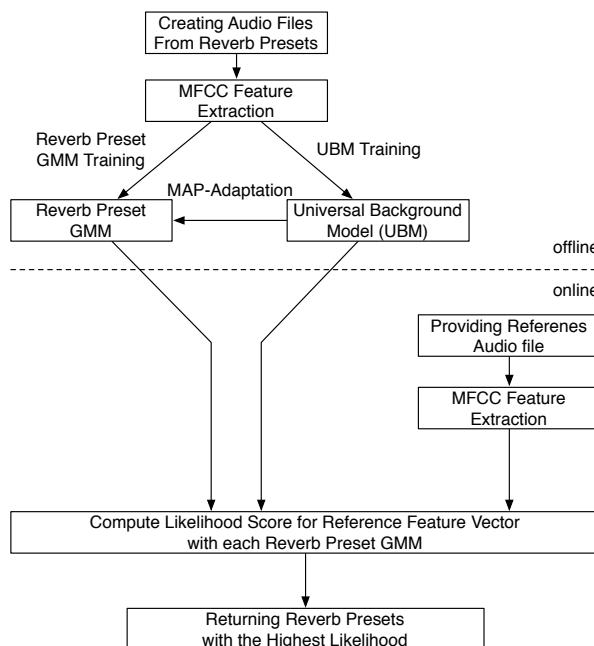


Fig. 1: Flow chart of the recommendation system

## 5. A PROTOTYPE

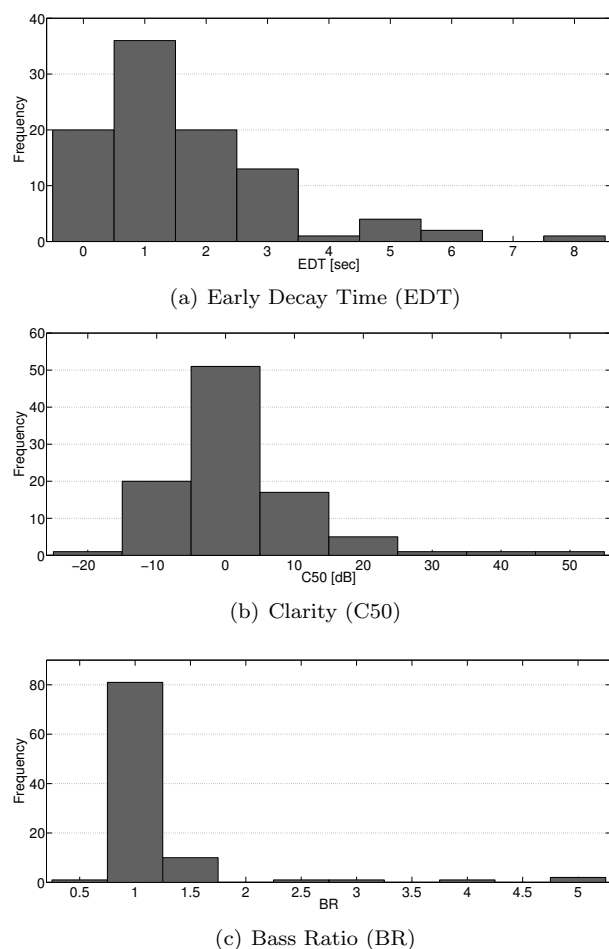
As a proof-of-concept we created a prototype of the recommendation system for 97 monaural reverb presets. As depicted in Figure 1 the system was trained with reverberant audio files created with those reverb units and tested with real room recordings found on the internet.

### 5.1. The reverb presets

Three reverb units are Lexicon MPX1 (31 factory presets), TC Electronics M3000 (53 factory presets), and Apple’s AU-Matrix Reverb (13 factory presets), captured as impulse responses in 16 bit/44.1 kHz. Because all those impulse responses are publicly available [1], it is possible to reproduce our results.

The only indicator a novice user has to envision the reverberant quality of a reverb preset is the preset name. For instance “Large Hall” suggests a bright concert hall reverb whereas “Dialog Booth” probably creates a rather unreverberant, damped impression one would find in a dialog booth. Many factory preset names are less descriptive and their qualities are therefore harder to anticipate. For example, factory presets such as “In the room” or “Room with a view” are ambiguous and a user needs to try them

out to clarify their reverberant qualities. As a reference, the names of all the 97 factory presets used for this prototype are listed in Table 3.



**Fig. 2:** Histogram for EDT, Clarity, and Bass Ratio across all 97 reverb presets.

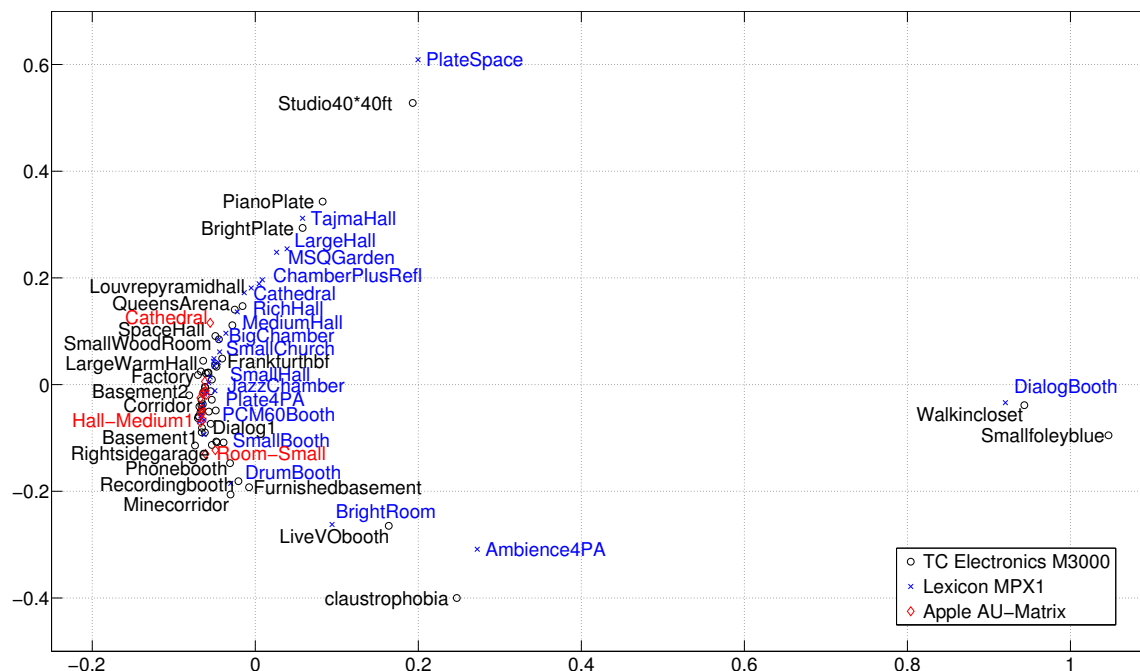
To grasp the range of acoustical characteristics that can be covered by the 97 factory presets, we extracted and analyzed 44 common monophonic features (see e.g., [3, 10]) from these impulse response. For instance, the early decay time (EDT), a measure that was found to be related to perceived reverberation time, varies between 48 msec (preset “Small foley blue”) and 7.75 sec (preset “Subway tunnel”) across these reverb presets. As shown in the histogram of Figure 2(a), more than a third of all reverb presets (37%) have an EDT between 0.5 and

1.5 sec. In terms of Clarity, a ratio of the early to late arriving sound energy ratio, more than 50% of all presets have a Clarity value between  $-5$  and  $5$  dB (see Figure 2(b)). The Clarity value ranges between  $-15$  dB (preset “Bright Plate”) and  $44$  dB (preset “Small foley blue”). As a third objective measure, Figure 2(c) depicts the Bass Ratio (BR), the ratio of the low-frequency reverb time compared to the mid-frequency reverb time. More than 80% of the presets have a BR between 0.75 and 1.25. The AU-Matrix Reverb preset “Hall-Medium1” has the lowest BR (0.67) and the M3000 “Walk in Closet” has the highest BR (4.8).

The histograms of the objective parameters suggest that many reverb presets have similar objective parameters. To put all 97 reverb presets in context to each other, we computed the correlation coefficient across all reverb presets based on these 44 objective reverb parameters. A classic multidimensional scaling procedure (MDS) was performed on these correlation matrix and the first two dimensions are displayed in Figure 3. This Figure shows that the majority of presets are grouped in one cluster and suggests that (based on the extracted objective features) most of the reverbs are somehow similar. The vertical dimension seems to be related to the reverberation time with “Tajma Hall” and “Cathedral” on one end and “Phone booth” and “Furnished basement” in the other. Several other reverb presets are spread across the space and form smaller clusters. For instance the “Dialog booth”, “Walk in closet”, and “Small foley blue” on the right side. Also visible in Figure 3, compared to the other reverb units, the factory presets of Apple’s AU-Matrix are very close together, suggesting that these 13 presets are similar.

## 5.2. Training

To train the GMM model, 40 anechoic speech recordings were taken from [23] and [2]. This data set comprises 20 different male and 20 female speaker samples each 20-seconds long. All anechoic samples are lexically unique within the dataset. In total 3880 one-channel reverberant audio files were created in 16 bit and 44.1 kHz. Half of these reverberant audio files were used for the reverb preset GMM training (see Figure 1) and the entire dataset was used for training the UBM as described in Section 4.



**Fig. 3:** Similarity of the reverb presets displayed after Multidimensional Scaling. Some presets are unnamed.

### 5.3. Testing

As an initial test, anechoic musical recordings were filtered with all 97 reverb presets and fed as reference audio files to the recommendation system. The resulted equal error rate (EER) of the system was about 3%, which is very low. This low EER is possibly due to the fact that the identical impulse responses were used for creating the training and testing data. In a real-world use case, this scenario is unlikely. Therefore we created a more realistic scenario.

To test the recommendation system, audio tracks of 18 videos from the Flickr video database<sup>1</sup> were extracted. Half of these videos were tagged with “Living room” and were captured in a living room environment, whereas the other half were tagged with “Church acoustics”, suggesting that these videos were recorded in churches or equivalent buildings. The videos have a maximum length of 30 seconds and all were captured with consumer video cameras or mobile phones. In some of the footage, either the audio is clipping or an active gain compression notably affects the dynamic.

<sup>1</sup><http://www.flickr.com/explore/video>

### 5.4. Results

Based on the video tags, we would expect that the “Living room” videos will be matches with relatively warm and short reverbs due to the high amount of (high-frequency) absorption in living rooms. Contrarily, for the “Church acoustics” videos, one could expect reverb presets that generate bright reverbs with large  $T_{60}$  reverb times because of larger room sizes and less high frequency damping due to plaster and hard walls. A few factory reverb presets have church-related name, such as “Cathedral”, “Small Church”, or “Singing In The Abbey”. We would expect these presets to match. Table 1 and Table 2 shows the most recommended (Top 5) and least recommended (Bottom 5) reverb presets for both testing sets.

	Screenshot	Top 5	Bottom 5	Screenshot	Top 5	Bottom 5
1		Watchtower inside Subway platform 2 Room with a view Mine corridor Walk in closet	Hall-Large2 Dialog Booth LongSwimmingPool Drum Booth Subway tunnel	1		Overhead Mics Plate Space Stage and Hall Studio 40*40 ft Large Hall Phonebooth Ambience 4 PA Drum Booth Dialog Booth Subway tunnel
2		Overhead Mics Stage and Hall Plate Space Snare Plate Bright Plate	Ambience 4 PA Dialog Booth Drum Booth LongSwimmingPool Subway tunnel	2		Rich Hall The Mens Room Small Hall Large Hall Mine corridor Dialog Booth LongSwimmingPool Hall-Large2 Drum Booth Subway tunnel
3		Subway platform 2 Mine corridor Swim distant Warehouse VocalBright	Basement 1 Short NonLin Plate Drum Booth Subway tunnel	3		Vocal Plate Hall 4 PA Rich Hall Snare Plate Chamber 4 PA Room-Large1 BudapestWestRlwayst Warm Cathedral LongSwimmingPool Subway tunnel
4		Bright Room Small foley blue Live VO booth Right side garage Claustrophobia	Frankfurt hbf Empty indoor pool Plate Space Warm Cathedral Subway tunnel	4		Mine corridor Subway platform 2 Empty niteclub BudapestWestRlwayst Warehouse Short NonLin Bright Plate Space Hall Drum Booth Cathedral
5		Live VO booth Small foley blue Bright Room Walk in closet Wide garage	Hall-Large2 Warm Cathedral Space Hall Plate Space Subway tunnel	5		Plate Space M SQ Garden Large Hall Vocal Plate Tajma Hall LongSwimmingPool Recording booth Room-Large1 Subway tunnel Drum Booth
6		Mine corridor Subway platform 2 Watchtower inside Wide garage Right side garage	Room-Large1 Drum Booth Space Hall Hall-Large2 Subway tunnel	6		Plate Space Hall 4 PA Large Hall Vocal Plate M SQ Garden Phonebooth Claustrophobia Drum Booth Dialog Booth Subway tunnel
7		Mine corridor Subway platform 2 Wide garage Watchtower inside Live VO booth	Plate Space Hall-Large1 Hall-Medium3 Chamber-Large Subway tunnel	7		Big Chamber M SQ Garden Tajma Hall Rich Hall Large Hall Walk in closet Ambience 4 PA Dialog Booth Drum Booth Subway tunnel
8		Bright Plate The Mens Room Rich Hall Vocal Plate Big Chamber	Frankfurt hbf Warm Cathedral Dialog Booth LongSwimmingPool Subway tunnel	8		Tajma Hall LouvrePyramidHall Studio 40*40 ft Plate Space Piano Plate Plate Ambience 4 PA Drum Booth Room-Large1 Subway tunnel
9		Small Hall Subway platform 2 SmallChurch Wide garage BandRehearsalRoom	Hall-Large2 Dialog Booth LongSwimmingPool Drum Booth Subway tunnel	9		Mine corridor Vocal Bright Studio 40*40 ft Room with a view Large Hall Dialog Booth Phonebooth Warm Cathedral Drum Booth Subway tunnel

**Table 1:** Resulting reverb recommendations based on the “Living room” testing files

**Table 2:** Resulting reverb recommendations based on the “Church acoustics” testing files

#### 5.4.1. The “Living room” set

In the “living room” set, the most recommended reverb presets for video 4 are “Bright Room”, “Small foley blue”, and “Live VO booth”. Similarly plausible, for video 5, the best matching reverbs are “Live VO booth”, “Small foley blue” and “Bright Room”. Remarkably, the preset “Subway Platform 2” appears with an unexpectedly high frequency in the recommendations. Although the reverberation time of “Subway platform 2” is higher than other matched reverbs (EDT is 2.14 sec), other parameters are similar, e.g., the Bass Ratio, Center Time, or the Initial Time Delay Gap (ITDG, see e.g., [13]). Also, initially, the recommendations for video 9 seem to be wrong: “Small Hall”, “Subway platform 2”, or “Small Church” do not sound like a reasonable match for a living room scenario. When inspecting the original video, it turned out that the video shows construction workers in an unfinished apartment. This has naturally a larger reverb compared to a furnished living room. Therefore, these system recommendations somehow fit. Table 1 also lists the least likely reverb preset to match the living room recordings. Candidates such as “Long swimming pool”, “Subway tunnel”, “Warm Cathedral”, or “Empty indoor pool” suggest that the recommendation system correctly identifies negatives (inversely affirming positive matches by identifying the least likely candidates).

#### 5.4.2. The “Church acoustics” set

For the videos apparently captured in churches, the least recommended reverb presets are either related to small spaces (“Phonebooth”, “Dialog Booth”, “Drum Booth”) or to one of the more exotic presets (“Long swimming pool”, “Subway tunnel”). Notably, instead of the church-related factory presets, other presets (“Rich Hall”, “Big Chamber”, “Tajma Hall”) which have a somehow comparable reverb characteristic were recommended. Similar to video 9 the “Living room” set, we also found an acoustic outlier: the Video 4 was matched with a small-space reverb (“Mine corridor”, see also Figure 3). When reading the description of the video, we found that the recording of a female singing group was not recorded inside a typical church, but rather in a church alcove with fast and strong early reflections. Therefore the suggestion of the “Mine corridor” reverb might be reasonable.

## 6. DISCUSSION AND CONCLUSION

To simplify the workflow with artificial reverbs, we presented a method to automatically determine the best matching reverb preset based on a reference recording. This method is based on a supervised machine learning approach derived from a speaker recognition system.

The goal of this system is to circumvent the time-consuming task of listening to numerous reverb settings in order to find a preset that best matches a desired room impression. This system could support the workflow in movie postproduction studios, where sound effects, foley, or voiceovers need be produced in a short amount of time. It could also be integrated in consumer DAW software to help novice users navigate through the overwhelming reverb settings. We showed a prototype implementation based on 97 reverb presets from 3 popular reverb units and tested the system with consumer videos captured in living rooms and churches. The resulting reverb recommendations show that the system is often able to suggest plausible reverb presets. This plausibility clearly depends on the quality and diversity of the available reverb presets. Therefore the system’s goal is not to reproduce the room impression of the reference recording but to provide the closest possible match. Subsequently, the user can then fine tune the recommended reverb as desired.

To potentially improve the accuracy of the recommendation, we want to explore additional features such as those based on the modulation spectrogram. We also plan to extend the system to work with stereo and multichannel reverbs.

## 7. ACKNOWLEDGMENTS

Nils Peters is supported by the German Academic Exchange Service (DAAD). Support comes also from Microsoft (Award #024263), Intel (Award #024894), matching U.C. Discovery funding (Award #DIG07-10227).

## 8. REFERENCES

- [1] <http://www.1-1-1-1.net>.
- [2] Bang & Olufsen. Music for Archimedes. Audio CD.

- 
- [3] J. Bitzer, D. Extra, S. Fischer, and U. Simmer. Artificial reverberation: Comparing algorithms by using monaural analysis tools. In *Audio Engineering Society Convention 121*, 10 2006.
  - [4] J. Bonastre, F. Wils, and S. Meignier. ALIZE, a free toolkit for speaker recognition. In *Proc. of ICASSP*, volume 1, pages 737–740. IEEE, 2005.
  - [5] S. Choi and Y. Jin. Apparatus for providing sound effects according to an image and method thereof, Mar. 9 2005. US Patent App. 11/074,798.
  - [6] S. Ciba, K. Helwani, H. Wierstorf, K. Obermayer, A. Raake, and S. Spors. Employing a binaural auditory model to classify everyday sound events. In *Deutsche Jahrestagung für Akustik*, Darmstadt, Germany, 2012.
  - [7] J. Dattorro. Effect design. *J. Audio Eng. Soc.*, 45:660–684, 1997.
  - [8] S. Davis and P. Mermelstein. Comparison of parametric representations for monosyllabic word recognition in continuously spoken sentences. *Acoustics, Speech and Signal Processing, IEEE Transactions on*, 28(4):357–366, 1980.
  - [9] N. D. Gaubitch, H. W. Löllmann, M. Jeub, T. H. Falk, P. A. Naylor, P. Vary, and M. Brookes. Performance comparison of algorithms for blind reverberation time estimation for speech. In *Proc. of int'l Workshop on Acoustics Signal Enhancement*, Aachen, Germany, 2012.
  - [10] ISO 3382-1. *Acoustics – Measurement of room acoustic parameters – Part 1: Performance spaces*. International Organization for Standardization (ISO), Geneva, Switzerland, 2009.
  - [11] J. Jullien, E. Kahle, M. Marin, and O. Warusfel. Spatializer: a perceptual approach. *94th Convention of the Audio Engineering Society, Preprint 3465*, 1993.
  - [12] P. Kenny and P. Dumouchel. Experiments in speaker verification using factor analysis likelihood ratios. In *Proc. of Odyssey*, 2004.
  - [13] H. Kuttruff. *Room Acoustics*. Spon Press, London, UK, 2009.
  - [14] C. Lavandier. *Validation perceptive d'un modèle objectif de caractérisation de la qualité acoustique des salles*. PhD thesis, Université du Maine, Le Mans, 1989.
  - [15] H. Lei, J. Choi, and G. Friedland. Multimodal city-verification on flickr videos using acoustic and textual features. In *Proc. of ICASSP*, Kyoto, Japan, 2012.
  - [16] R. Mertens, H. Lei, L. Gottlieb, and G. Friedland. Acoustic super models for large scale video event detection. In *Proc. of ACM Multimedia Workshop on Social Media*, Arizona, USA, 2011.
  - [17] N. Peters, H. Lei, and G. Friedland. Name That Room: Room Identification Using Acoustic Features in a Recording. In *Proc. of ACM Multimedia*, Nara, Japan, 2012.
  - [18] Z. Rafii and B. Pardo. Learning to control a reverberator using subjective perceptual descriptors. *10th International Society for Music Information Retrieval (ISMIR 2009)*, 2009.
  - [19] D. Reynolds, T. Quatieri, and R. Dunn. Speaker verification using adapted gaussian mixture models. *Digital signal processing*, 10(1-3):19–41, 2000.
  - [20] M. R. Schroeder and B. F. Logan. Colorless artificial reverberation. *J. Audio Eng. Soc.*, 9(3):192–197, July 1961.
  - [21] N. Shabtai, B. Rafaely, and Y. Zigel. Room volume classification from reverberant speech. In *Proc. of int'l Workshop on Acoustics Signal Enhancement*, Tel Aviv, Israel, 2010.
  - [22] V. Valimaki, J. Parker, L. Savioja, J. Smith, and J. Abel. Fifty years of artificial reverberation. *Audio, Speech, and Language Processing, IEEE Transactions on*, 20(5):1421–1448, 2012.
  - [23] M. Wester. The EMIME bilingual database. Technical Report EDI-INF-RR-1388, University of Edinburgh, September 2010.
  - [24] S. Young et al. The HMM toolkit (HTK), 1995.
  - [25] M. F. Zbyszynski and A. Freed. Control of VST plug-ins using OSC. In *Proc. of the International Computer Music Conference*, pages 263–266, Barcelona, Spain, 2005.
-



## APPENDIX - FACTORY PRESETS

Reverb Unit	Factory Preset Names
TC-Electronics M3000	Small foley blue, Live VO booth, Walk in closet, Claustrophobia, Furnished basement, basement1, Recording booth, Plasterwalls, Wide garage, Furnished room, Semifurnished Qntec, Corridor, Phonebooth, Dialog5, Bright Space, Small Wood Room, Watchtower inside, Dialog1, Room with a view, Band Rehearsal Room, Right side garage, Gated Reverb, Basement2, In the room, RMX Snare Room, Factory, Tijuana cantina, The Mens Room, Overhead Mics, Stage and Hall, Piano Plate, Mine corridor, Studio 40*40 ft, Empty niteclub, Subway platform 2, Vocal Bright, Warehouse, Louvre pyramid hall, All Up, Empty Arena, Bright Plate, Empty indoor pool, Subway platform 1, LargeWarmHall, Queens Arena, Space Hall, Singing In The Abbey, Swim distant, Frankfurt hbf, Warm Cathedral, Long swimming pool, Budapest west rlwayst, subway tunnel
Lexicon MPX1	Dialog Booth, Ambience 4 PA, Bright Room, Drum Booth, Small Booth, Short NonLin, Gate 4 PA, Percus Place, Live Room, PCM60 Booth, Plate 4 PA, Jazz Chamber, Empty Club, Big Studio, Chamber 4 PA, Bright Plate, Chamber&Refl, Snare Plate, Small Hall, Big Drum Plate, Hall 4 PA, Small Church, Vocal Plate, Rich Hall, Medium Hall, Large Hall, Big Chamber, Cathedral, M SQ Garden, Tajma Hall, Plate Space
Apple AU-Matrix Reverb	Plate, Room-Small, Room-Medium, Room-Large2, Hall-Medium3, Hall-Medium2, Chamber-Medium, Chamber-Large, Hall-Medium1, Room-Large1, Hall-Large1, Hall-Large2, Cathedral

**Table 3:** Names of all factory presets sorted from lowest to highest Early Decay Time (EDT)