SIGNAL PROCESSING AND STORING OF HIGH DYNAMIC RANGE ACOUSTIC DATA FOR KNOWLEDGE DISCOVERY

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Abstract

The purpose of this paper is to present some difficulties when signal processing and storing of high dynamic range acoustic data is performed for knowledge discovery.

Typical examples from musical acoustics, archaeoacoustics and battlefield acoustics are considered. The characteristic acoustic environment signature in the audio capture recording depending from background noise, reverberations and from concrete setup is discussed.

Some datasets consisting of the raw data and extracted metadata from bell ringing and gunfire, noise and voice recordings are built and shared in a data repository. Guidelines are outlined for using these data to apply data mining methods for discovery useful information. Possible directions for using these data to apply data mining methods for retrieving useful information are outlined.

The results can be used in various areas of acoustics, electrodynamics, image processing in medical diagnostics, systems of detection and localization of tactical firing systems on the battlefield, etc.

1. INTRODUCTION

In the recent years, our team has worked on several important projects [1, 2, 3] related to the application of modern acoustic methods in interdisciplinary fields. Studies aimed at the acoustics of the battlefield were also conducted. A large amount of experimental data has been accumulated. Acoustic signal processing has made it possible to draw interesting conclusions. However, it is laborious work and it is made by highly qualified experts.

In order to facilitate the users of this information, who are usually specialists in other fields (archeology, music, military, etc.), we decided to use the methods for knowledge discovery.

2. SOME PROBLEMS IN ACOUSTIC DATA RETRIEVING AND DATA PROCESSING

Various factors could affect how a sound wave attenuates with distance in outdoor and indoor environments.

For example, the interaction of the wave with objects, such as the ground, obstacles, effects of reverberations, first reflections, interference and diffraction, absorption and many others. On the other hand some factors as variations in temperature, wind speed and direction, air pressure and humidity could affect. The sound picture is varying in accordance of type of concrete space: close, semi close or free space, in dependence of source and receiver points placement.

Some of effects were very difficult for formal analysis par example interactions within turbulence.

An understanding of how these factors change the sound pictures that are registered is important for the analysis of accumulated sounds.

The difficulty in computing these effects analytically for real-world situations, particularly the case in outdoor environments, means that experiments are important decision.

3. EXAMPLES OF EXPERIMENT DATA SETS FOR ANALISYS

It will regarded acoustic data set, one not big collection of signals, registered as a part of many experimental works, that was produced in the project “Thracians - genesis and development of ethnicity, cultural identities, interactions and civilizational heritage of antiquity”, [2] Analogical sound phenomena observations was produced for bell sound in project “BELL – Research and Identification of Valuable

Bells of the Historic and Culture Heritage of Bulgaria and…", [1,4], and for pulse noise from the training ranges of National military university, collected during the tactical exercises [5].

In closed spaces it can observed two types of reverberation with different characteristics: early reverberation and late reverberation. Here is represented the experimental setup within close space inside the "Thracian tomb Griffins. The scheme of the tomb is shown on figure 1, where it can be seen the position of measuring microphone 4193 Brüel&Kjær and the source. Reverberation time RT60 was estimated by impulse measurement techniques. The pistol shot and balloon boom were made for obtaining the impulse responses of a camera.

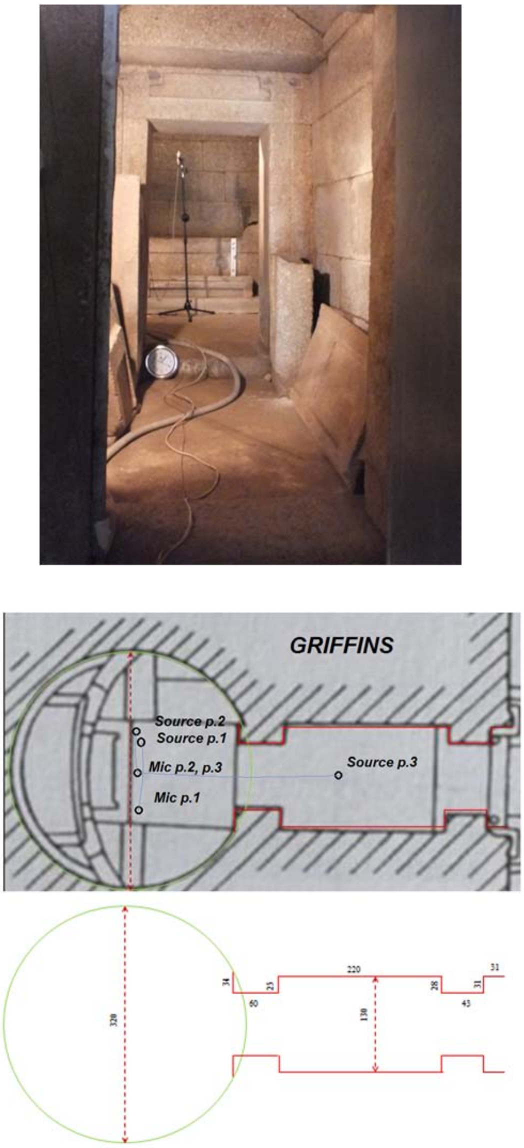


Figure 1. Measuring microphone disposition in "Thracian tomb Griffins" 42°42'19.8714"N 25°20'40.9554"E, 30 March 2016

The approximation of reverberation time RT60 was found in MatLab with the software - Signal Processing Utility Package V2 from Institute of Communication Systems RWTH Aachen University [6], see figure 2.

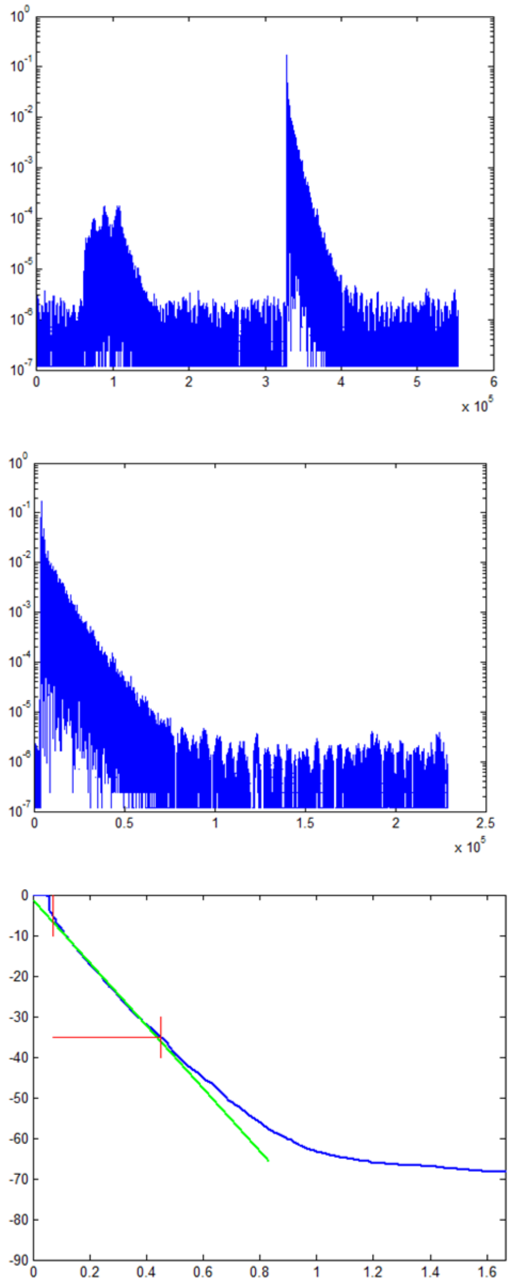


Figure 2. Signal waveforms from "tomb Griffins" (source p2 mic p2) and estimation of reverberation time RT60, 0.77s, Ts=1/65536 s

It was made experiments in larger close spaces – lecture hall 1121 (signal s3) and biggest theatre hall (signal s4) in National military university in V. Tarnovo and one free space musical improvisation in lawn near to Sveshari tomb (signal s5).

The results for RT60 approximation are seen in Table 1.

Table 1. The reverberation time RT60 estimation

name	RT60, s	Place
s1	0.774	Inside mound Thracian Tomb Griffins (before socialization), town Shipka, Province of Stara Zagora, Bulgaria, 2016
s2	no	Inside mound Thracian Tomb Griffins (after socialization), 2017
s3	0.802	Hall 1121 in Vasil Levski National Military University, Veliko Tarnovo, Bulgaria, 2018
s4	1.388	Inside biggest hall in National Military University, Veliko Tarnovo, 2018
s5	no	lawn near to Sveshari tomb no 13, Bulgaria, 2017

In the next it was made the analysis of a set of experiments where was investigated the energy characteristics of the different sound waves.

Wavelet Entropy is one known entropy measurement method by means of the discrete wavelet transform subband, [7]. The idea is that the accuracy of the selected wavelet basis is higher when the entropy is small.

Wavelet packet decomposition on one signal was defined as

$$\mathrm{d}_{\mathrm{j,n}}(k) = 2^{\frac{\mathrm{j}}{2}} \int_{-\infty}^{\infty} \mathrm{s(t)}\,\psi_{\mathrm{n}}\left(2^{-\mathrm{j}}\mathrm{t}-\mathrm{k}\right)\mathrm{dt},$$

$$0 \leq \mathrm{n} \leq 2^{\mathrm{N}}-1$$

where j denotes the scale, n the band and k the surge parameter

Wavelet packet entropy, [7,8] is expressed as:

$$\mathrm{WPE_N} = -\sum p_{j,n} log\, p_{j,n}$$

where $\mathrm{p_{j,n}}$ is relative energy

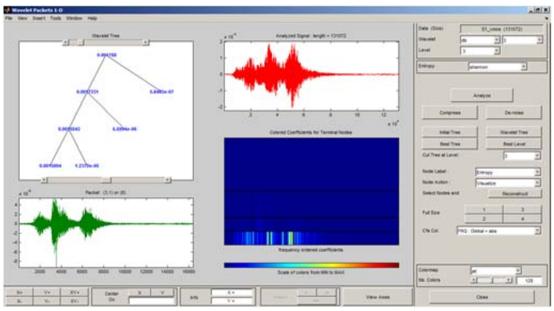
$$\mathrm{p_{j,n}}(k) = \frac{\mathrm{E_{j,n}}}{\mathrm{E_{tot}}} = \frac{\sum_{\mathrm{k}} \left|\mathrm{d_{j,n}}(k)\right|^2}{\sum_{\mathrm{n}} \mathrm{E_{j,n}}}$$

Figure 3 shows wavelet packets for two parts of acoustic signal waveform see fig. 2 voice, noise and shot from small pistol, recorded inside the Thracian tomb Griffins. This raw data was exported in MatLab and here were determined Shannon entropy coefficients for the wavelet tree for Daubechies3 wavelet level 3.

Table 2. Description of the signals

Name	time, sec	contains	category	c_name
S1_all	8	Male voice and pistol shot	small	S1_1
S1_pulse	2	shot by small start pistol	small	S1_2
S1_noise	2	noise	small	S1_3
S1_voice	2	Male voice	small	S1_4
S2_pulse2	2	hand claps	small	S2_1
S2_pulse	2.076	hand clap	small	S2_2
S2_noise	2	noise	small	S2_3
S2_voice	2	Male voice	small	S2_4
S3_all	11	balloon boom	hall	S3_1
S3_pulse	2	balloon boom	hall	S3_2
S3_noise	2	noise	hall	S3_3
S4_pulse	2	balloon boom	hall	S4_1
S4_noise	2	noise	hall	S4_2
S5_pulse	2	hand claps	free space	S5_1
S5_noise	2	noise	free space	S5_2
S5_nois	1	noise	free space	S5_3
S5_noise _pause	0.563	noise	free space	S5_4
S5_music	2	kaval music	free space	S5_5
S5_music 2	2	kaval music	free space	S5_6

Analogically wavelet packet entropies for the five categories (totally 19 examples from S1_1 to S5_6) were calculated. Part of results is shown in table 3.



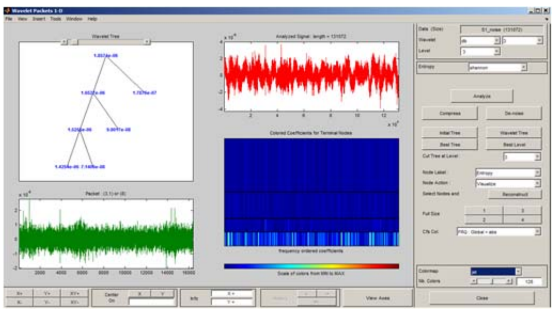


Figure 3. Calculated wavelet packets and Shannon entropies for waveforms correspondingly to fig. 2., Daubechies db3, level 3.

Table 3. The wavelet packets, Shannon entropies - db3,3.

c name	ShE(0,0)	ShE(1,0)	…	ShE(3,1)
S1_1	4.3306	3.7863		0.63957
S1_2	4.3288	3.7846		0.63956
S1_3	1.86E-06	6.53E-06		7.14E-08
S1_4	1.79E-03	1.72E-03		1.24E-05
S2_1	423.25	359.97		26.422
S2_2	223.14	189.37		13.105
S2_3	3.2667	3.0095		0.03363
S2_4	143.64	130.68		0.39973
S3_1	299.88	246.48		18.711
S3_2	299.73	246.66		18.51
S3_3	0.0326	0.02236		0.0031
S4_1	1220.2	910.8		91.656
S4_2	5.5622	4.5434		0.20388
S5_1	46.776	42.981		0.42473
S5_2	32.111	30.056		0.10593
S5_3	13.69	12.718		0.026823
S5_4	1.3329	1.2455		0.016731
S5_5	53.779	49.629		1.3118
S5_6	885.65	780.12		10.174

This wavelet packet entropies was regarded as attributes in data mining algorithm.

4. DATA MINING FOR ADDITIONAL ANALYSIS

The dataset, which consists of the signal characteristics (Table 2,3) extracted as described above, are further analysed by applying data mining algorithms. This dataset is used to build a data classification model for the purpose of automatically recognizing the type of location from which the signal is received. The previously defined categories are *small*, *hall*, *free space*; the first eight examples of the dataset, shown in Table 3 (s1_1, … s2_4) are associated with the category *small*; s3_1, …, s4_2 – *hall*; s5_1, …, s5_6 – *free space*. The data classification is performed by creating a process by using RapidMiner [9] (http://rapidminer.com). The k-NN (*k*-Nearest Neighbours) algorithm is applied, which is based on comparing a given test example with training examples that are similar to it. The cosine similarity is used to measure the similarity. If x (x_1, x_2, …, x_n) is a test example, t (t_1, t_2, …, t_n) is an example from the training dataset, then the cosine similarity between them is computed by the following way:

$$CosineSimilarity(x, t) = \frac{\sum_{i=1}^{n} x_i t_i}{\sqrt{\sum_{i=1}^{n} x_i^2}\sqrt{\sum_{i=1}^{n} t_i^2}}$$

The validation of the trained model is done by the so-called cross validation, i.e. dividing the dataset into m subsets of equal sizes. One of these m subsets is kept as a test dataset. The remaining m – 1 subsets are used as training dataset. Then the cross validation process is repeated m times, using each of these m subsets exactly once as test data. The obtained m result from the executed m iterations is averaged to obtain a single estimate.

The following measures are computed to evaluate the validity of the classification model:

– *Accuracy* is defined by the ratio of the number of correctly classified examples (TP) to the total number of examples (N);

Micro-average of accuracy = $(TP_1 + TP_2 + … + TP_m)/(N_1 + N_2 + … + N_m)$,

Macro-average of accuracy = $(TP_1/N_1 + TP_2/N_2 + … + TP_m/N_m)/m$,

where:

- TP_i is the number of correctly classified examples of the i-th iteration for i = 1, …, m;
- N_i is the number of the examples of the i-th dataset.

– *F-measure* is defined as the harmonic mean of the *precision P* and the *recall R*:

$$F = \frac{2.P.R}{P + R},$$

where:

– The precision P is calculated as the ratio of the number of correctly classified examples of a given category to the number of all examples classified in that category;

– The recall R is calculated as the ratio of the number of correctly classified examples of a given category to the number of all examples that are actually in that category.

Usually, the *F*-measure is useful for uneven distribution of categories in the dataset.

The calculated results obtained for m=5, k=1, are shown in Table 4.

Table 4

	small	hall	free space
Precision	71.43%	100%	62.50%
Recall	62.50%	80.00%	83.33%
F-measure	66.67%	88.89%	71.43%

The computed values of the accuracy are:

Micro-average of accuracy: 73.68%;

Macro-average of accuracy: 75.00%.

5. CONCLUSION AND FUTURE RESEARCH

Table 4 shows that the Precision parameter is in the range of 62-100%, the Recall varies from 62 to 83% and the F-measure is between 67 and 89%. The obtained results show acceptable accuracy and warrant experimentation with more data and different classifiers. Other data mining methods may also be tried in the future.

In addition, there are many other important acoustic parameters, that can be investigated by appling the data mining methods.

Our future work will be related to their application in aerial and underwater acoustics, in interdisciplinary fields such as music, archeoacoustics, noise study of significant natural phenomena, ecology and others. Particular attention will be paid to the study of the acoustics of the battlefield, and in particular the detection, localization and classification of weapons systems.

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