AudioSentibank: Large-scale Semantic Ontology of Acoustic Concepts for Audio Content Analysis

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Abstract—Audio carries substantial information about the content of our surroundings. The content has been explored at the semantic level using acoustic concepts, but rarely on concept pairs such as happy crowd and angry crowd. Concept pairs convey unique information and complement other audio and multimedia applications. Hence, in this work we explored for the first time the classification’s performance of acoustic concepts pairs. For this study, we introduce the AudioSentiBank corpus, which is a large-scale folksology containing over 1,123 adjective and verb noun pairs. Our contribution consists on providing the research corpus, the benchmark for classification of acoustic concept pairs, and an analysis on the pairs.

Index Terms—Audio databases, Machine Learning, Affective Computing, Multimedia Systems, Data collection.

I. INTRODUCTION AND RELATED WORK

MACHINE hearing, as described by R. Lyon in [1], aims to develop the AI capable of learning what is heard, name recognizable objects, actions, events and places as well as retrieving audio by reference to those names. The machines and systems with this AI should be able to listen and react in real time, to take appropriate actions and to naturally interact with humans.

Audio carries substantial information about the content of our surroundings. The content has been explored at the semantic level using acoustic concepts, also called in the literature sound events. Acoustic concepts convey unique information and complement other audio and multimedia applications. One example is the TRECVID Multimedia Event Detection [2] (2010-2015), consisting on the detection of categories such as Birthday Party on web-videos. The analysis was based on image and audio content, utilizing for audio mainly low-level features but also semantic concepts [3], [4], [5]. In a similar manner, for Multimedia Geo-tagging [6], audio and audio concepts, images and text, were employed. On the other hand, audio-only content analysis on soundscape was investigated in 2014 by Salomon et al [7] and on environmental sound in 2015 by Piczak et al [8] with two different corpora defined by a taxonomies of sound events. Moreover, sound events have been used in Human Robot Interaction (HRI) by recognizing everyday sound events in indoor environments with a consumer robot in [9]. Lastly, sound events and acoustic scenes from microphone recordings have also been investigated for safety, surveillance and environment characterization, supported by the two iterations of the DCASE challenge, 2013 [10] and 2016 [11]. Particularly, in the former iteration, there were two scenes which included an adjective–quite street and busy street. The results published by DCASE showed how although both scenes referred to a street, the adjective implied differences in the audio content and the semantics. Despite the different applications and data sets available for concepts or sound events, concept pairs have not been collected in a corpus and hence studied.

Contrary to the audio, concept pairs have been widely used by text and image processing and supported by communities such as the Workshop on Affect and Sentiment in Multimedia [12]. In the text domain, SentiWordnet 3.0, is a lexical resource explicitly devised for supporting sentiment classification and opinion mining applications based on synsets. In the computer vision domain, Borth et al in [14] introduced the VisualSentiBank to performed sentiment analysis using images. The SentiBank consisted on a Visual Sentiment Ontology (VSO) based on Adjective Noun Pairs (ANPs). Therefore, there is a need to collect a corpus of concept pairs for audio-only and multimedia content analysis to describe characteristics such as sentiment, emotions, affect, or lexical relation.

In this work we explored for the first time classification of acoustic concepts pairs. For this study, we introduce the AudioSentiBank corpus, which is a large-scale folksology containing over 1,123 adjective and verb noun pairs. Our contribution consists on providing the research corpus, the benchmark for classification of acoustic concept pairs, and an analysis on the classification of the pairs.

II. COLLECTION OF THE AUDIOSENTIBANK CORPUS

This section describes the process of constructing the semantic ontology by defining a seed vocabulary for initial retrieval of audio files tagged by the seed vocabulary and the analysis of this initial data corpus.

A. Overview of the Collection Pipeline

In order to have our final data set we have a pipeline with multiple steps that are visualized in Figure 1. First, in Section II-B we defined the type of concept pairs and an initial set of labels for the AudioSentiBank corpus. Then, in Section II-C we used these labels as queries to retrieve audio recordings and their tags from the web. Later, we computed statistics on the retrieved data and analyzed it in Section III. The analysis was used to refine the corpus as explained in Section IV. As a result, we refined the initial collection of the data and restructured it into the final set presented in Section IV.
B. Acoustic Concepts Seed

There are multiple types of concepts which can express or convey semantics such as sentiment, affects, or emotions. Our first selection of a seed-concepts was inspired by the Visual Sentiment Ontology (VSO) and SentiBank presented in [14], which represents a vocabulary of Adjective Noun Pairs (ANPs) to express sentiment. The use of adjectives can turn a neutral noun like cat into an ANP with an adjective like cute cat. Our second selection of seed-concepts are Verb Noun Pairs (VNPs). Sounds are actions, they move and change and hence can be represented with verbs. Our selection was inspired by Schafer in [15], who developed an ontology of audio where sounds were classified by their generating source, which implied a verb.

It is important to mention that the ANPs and VNPs, depend on the perception of the listener and thus, there is an implicit degree of subjectivity. The subjectivity, as discussed in [16], could be explained by an evolving theme in the user's head, because the definition depends on the experiencer (user) and the stimulus (sound). Verbs tend to be less subjective or more neutral than adjectives. For example, people might debate about what is the sound of a beautiful car, but it would be less debatable the sound of a car passing. The principle is supported in [17], where authors developed a lexicon of sentiment using SentiWordNet and applied sentiment [positivity and negativity] scores to affixes such as adjectives and verbs. They found that more accurate sentiment scores were obtained for adjectives in contrast to verbs. These aspects are relevant to build and evaluate statistical models and all in all, they suggest that VNPs could perform better than ANPs for a pure audio classification task.

C. Retrieval of Audio Files

For collecting and retrieving the audio for the SentiBank we decided to mine the web, rather than creating our own data annotations. Collecting our own annotations allows us to craft data to our needs and have consistency at the inter and intra class level, but it will be significantly costly to do it on the large-scale. On the other hand, mining data from the web tackles the scalability problem, however, the data represents the public opinion which might imply assumptions and errors in the tag-audio relationship.

For such purpose, we investigated multiple websites such as soundcloud.com, findsounds.com and freesound.org. Nevertheless, we faced issues with soundcloud.com because it contained mainly music. In the case of findsounds.com, the files did not contain multiple tags and a preliminary search for concept pairs did not fetch many samples. In contrast, freesound.org offered a large amount of files with a better tag availability. Moreover, datasets such as ESC-50 [8] and Urban Sounds [7] have mined audio retrieved from freesound.org. Another important point is that our goal was to create a corpus that can be used for scientific research and freesound.org offers a Creative-Commons license for the files. To collect the data from freesound.org we used our ANPs and VNPs labels as search queries to perform keyword matching. Each pair consisted of two words, so we retrieve all files with the corresponding two words in their tags. Moreover, we looked through the most frequent tags on freesound.org1 and extended our lists.

For the construction of the concept pairs, first, we collected lists of adjectives and nouns to generate all the possible ANPs introduced in the Visual SentiBank, which are mainly based on the 24 emotions defined in Plutchik's Wheel of Emotions as described in [14]. Nevertheless, those concept pairs were selected with the purpose of visual content analysis and not all of them apply to audio analysis such as fresh food or favorite book. Therefore, we also considered existing audio ontologies which have dealt with the description and perception of sounds in order to add more adjectives, nouns and also verbs. For example, Schafer defines an ontology of soundscapes and environments in [15]. Then, Axelsen in [18] acknowledged that physical characteristics of a sounds could be insufficient to explain the human perception and sentiment, thus he suggested adjectives to describe sounds with a semantic approach in order to describe the feeling that sounds produce to individuals. Additionally, Davies [19] focuses on three semantic levels which are sound sources, sound modifiers, and soundscape modifiers. Here the sound sources and sound modifiers levels are interesting since they provide nouns, verbs and adjectives that are based on a research experiment with participants that were asked to describe sounds.

After an inspection on the lists of concept pairs and preliminary searches, we noticed lexical variations, synonyms and

\[^{1}\text{http://freesound.org/browse/tags/}\]
singular-plural forms and thus, we grouped them together to increase pair variability. One example was fast, faster, and fastest, which were grouped together when referring to the same noun. Another example was car, cars, auto, automobile and vehicle are grouped together as the main noun car and hence, pairs such as fast car and fast automobile were grouped as samples representing the pair fast car. This process implied assumptions which might not always hold true for the audio content. For instance, the sound of one car is acoustically different depending on the car type and is also different from the sound of multiple cars. Nevertheless, this grouping approach helped to reduced the problem of having multiple similar pairs which could affect the overall goal of focusing on the diversity of pairs semantics. Moreover, it also helped to find more (similar) data for the pairs. We took these words together with their grouped words to generate 10,829 queries for ANPs and 9,996 queries for VNPs.

III. ANALYSIS OF THE CORPUS

The data mined and collected from the web could contain biases and assumptions and other errors inherent to public opinion and folksonomies. However, AudioSentiBank is the first data set of its kind and thus it’s uncertain what kind of quality flaws we could find. For this reason we performed an analysis on a subset of around 250 ANPs and 200 VNPs from the AudioSentiBank by computing statistics and performing manual inspections.

A. Tag co-occurrences

We analyzed the co-occurrences of the tags used for the retrieval. For example it has to be investigated if synonyms occur together or if there are patterns that are specific for the combinations of adjectives, verbs and nouns. Furthermore, co-occurrences can help to explain the context and a higher level meaning of a recording.

Verbs - Verbs One pattern observed for verbs, is that they can occur together where one verb is the descriptor of the sound and another verb is the sound source. For example, open and squeaking, close occurs with squeaking and with banging. Although these pairs have plausible sounds, it is ambiguous whether squeaking and banging are the verbs or the adjectives. Although the pairs might not describe the same sound, we kept them as VNPs since it was implausible to assure the right order. Additionally, a third pattern of co-occurrences happened when using sequences of actions describing a higher level meaning such as singing and clapping corresponding to an extract of a music concert. Finally, another pattern happened when verbs served to clarify other verbs. For instance, some inspected recordings containing the tags singing and tweeting, the meaning was birds singing as opposed to humans singing.

Nouns - Nouns Noise is a very frequent tag co-occurring often with other tags. This indeed indicate for some files a type of noise or an unintelligible sound. However, it was also employed by users to define sounds happening in the background which were unrelated to the targeted sound. Environmental sounds such as wind, water, and noise are frequent and occur in different pairs. Another co-occurrence of tags happened between the source of the sound and the object to which such source belongs to. For example, the tags engine and-- car, or train, or airplane or ship could happened together. However, the sound source corresponds to the engine rather than the whole combination of sounds that could come from the vehicle. In the same way as verbs-verbs, these combinations clarify the source type in case a distinction between engines is needed, nevertheless, our scope was to have diversity on the pairs’ semantics. Finally, co-occurrences of nouns could be used to describe a context based on multiple related sounds despite of them having different meanings and acoustic characteristics. For example thunder, rain and wind described the acoustics of a storm, also frogs and insects and water described the acoustics of a Savannah.

Adjectives - Adjectives When analyzing the co-occurrences, we found adjectives with opposite meaning such as slow and fast or peaceful and loud. After manual inspection
of some examples, the presence of opposite adjectives was an indicator of changes throughout the time within the audio, for example, a slow driving car accelerates to become a fast driving car.

**Verbs - Nouns** Verbs tend to occur mainly with certain subsets of nouns for instance, *flying* occurs mainly with *airplane, engine, bird, helicopter* and *noise*. There is no verb occurring with every noun and in general verbs occur with a frequency of one or two per noun. In a similar manner, human-related tags such as *baby, child, man* and *woman* occur with nearly the same verbs.

**Adjectives - Nouns** In contrast to verbs, there is a wide range of quantity and type of adjectives occurring with nearly all nouns such as *loud, heavy, scary or noisy* and only very few adjectives such as *exotic* occur with a smaller subset of nouns. Another interesting co-occurrence of adjectives is when they occur frequently with nouns describing objects which cannot perform actions like for example *landscape, coast or nature*. Moreover, among our pairs we found almost no tags containing colors, but colors were used by the user mainly on the descriptions.

**Adjectives - Verbs** In a similar manner to nouns, adjectives and verbs co-occurred with words expressing similar meanings. Examples are *cry and growl, or cry and scream* for verbs and *happy and funny or creepy and scary* for adjectives. A reason might be because users used multiple similar terms to attempt to have a broader description of their files and also to increase the keyword-matching hits. Moreover, nouns with synonyms and singular-plural forms were grouped together before to increase pairs variability. However, we found out that even if we would not have grouped these words together, the co-occurrences of tags would have resulted in retrieving nearly the same audio files.

**B. Audio file duration**

We analyzed the duration of the audio files to determine data availability for our classes, as well as to find patterns between the length and the descriptors.

Since verbs describe actions, we expected the duration of VNP audios to correspond to the approximate length of such actions. However, the analysis showed that even if most actions lasted between one and five seconds, the median duration was above 10 seconds. After listening to some examples, the reason was because most of the sound start-end time did not correspond to the start-end time of the file. In general, we expected this to happen in nearly all of the audio files but we did not know to what extent. On the other hand, audio with nouns corresponding to short events such as *fireworks or door* have shorter duration in comparison to audio from nouns corresponding to events with commonly longer duration such as *rain*.

Adjectives can hint the duration of a sound for example, *fast vs slow*. Therefore, we expected variable lengths depending on the adjectives. After further inspection of files, on average, audio containing *calm, rural, peaceful* and *quiet* have longer duration than *accelerating or rushing*.

With nouns we observed that the duration of files tagged with locations or environments such as *city, market, beach* or *school* are the longest. By listening to some of these files we confirmed that in most cases, the audio corresponded to field recordings tagged by people with keywords describing the elements such as *garden or street*, and objects that are present in the background such as *people or car*. Moreover, users sometimes included the name of the location or city such as *Florida*; or the time of the day such as *day or night*; or the season such as *spring*.

In general, for adjectives, verbs and nouns, we observed a large duration variance depending on the terms used. This is due to multiple reasons, for example, the inherent characteristics of the concept pairs’ combination. Also, because people recorded audio in different ways and with different purposes. Additionally, sometimes users also edited the files before uploading them. Nevertheless, a few concept pairs existed with a significantly small variance such as *fast water* and *strange woman*. A closer look into these files revealed a single user responsible of most of the samples.
C. Statistics of the AudioSentiBank

We show statistics about AudioSentiBank in Table I. The data set contains more ANPs (1,016) than VNPs (824) and in the same way there are more files for ANPs (81,771) than for VNPs (72,424). However, there are audio files corresponding to multiple concept pairs, because these files were tagged with multiple words. In column two, we can see the number of total and unique audio files. Note that VNPs have more unique files, in comparison to ANPs and relative to the total number of VNPs files. Moreover, VNPs were uploaded by a larger number of different users than ANPs. Additionally, it has to be noted that the last row showing the total number of unique files and users does not correspond to the sum of the previous rows. The reason is because there are files repeated in both categories, ANPs and VNPs, and thus we didn’t count them twice. Regarding the length, we can see how the ratio between total files and length suggests a larger file duration for ANPs than for VNPs, accounting to about twice the length. The last column shows the total disk space of the audio data.

| Pairs  | Total - Unique Files | Users | Length | Size   |
|--------|----------------------|-------|--------|--------|
| ANPs   | 1,016                | 81,771| 2,806  | 892 h  | 1.4 TB |
| VNPs   | 824                  | 72,424| 3,905  | 375 h  | 0.8 TB |
| Total  | 1,840                | 154,195| 5,080 | 1,267 h| 2.2 TB |

To understand better the distribution of number files per concept pair, we computed Figure 2, which is sorted in decreasing order by the number of sample files. Despite only including concept pairs with at least 400 files due to space limitations, both graphs have the expected trend of a near Zipfian distribution with a long tail. However, ANPs showed a smoother decrement, which translates to a more uniform number of samples per concept pair than VNPs. The average number of samples for ANPs are 80 samples and 90 samples for VNPs.
D. Number of tags per audio file

The number of tags for each file is an interesting characteristic we wanted to investigate further. Especially, we wanted to know if there was a correlation between the number of tags and the length of the file, because we expected the presence of multiple tags to define multiple sounds occurring within the file. Some general observations are that files tagged with verbs have less tags than files tagged with adjectives and no verbs. Also, ANPs have more tags on average than VNPs (see Table VI). Lastly, the majority of files have between 10 to 20 tags.

Our analysis of the relation between the audio file duration and the number of tags shows no correlation between them despite a few outliers. A plot showing this correlation can be seen in Figure 3. Additionally, we validated our observation by computing Spearman’s rank correlation coefficient (SRCC), which is a non-parametric measure of statistical dependence between two variables. A SRCC value close to zero in combination with a very small p-value indicates no correlation in the data. In our case, the SRCC values for ANPs are 0.073 with a p-value of 5.358e-97, and for VNPs 0.0149 with a p-value of 6.31e-05. In consequence, a different explanation could be that the number of tags depend on the user’s intention.

Another pattern happened for a few classes were all the files had exactly the same number of tags. A closer investigation revealed that these files were uploaded by a single user. We found this is a characteristic of freesound.org related to the creation of sound packs, which bundled similar sounds together on a certain topic. In consequence, there are files containing tags which are unrelated to the sound itself, but to the sound pack. For example, there was a sound pack containing sounds of objects falling on the floor, and all the files will have tags such as falling and the names of all objects. Since it is hard to track these bundles in a larger scale and due to the low number of cases, we kept them.

Finally, the quantity and the type of tags assigned by users as well as the duration of the recording, suggests a distinction between acoustic scenes and isolated sounds, but it will be further analyzed as future work.

E. Number of users

Our analysis on the number of users consisted of two parts, in the first part we investigated how users tagged their audio recordings by looking into the amount of tags per file given by the user. Furthermore, we looked at which tags are used and how diverse the set of used tags are. In the second part, we investigated the contribution of audio samples per user. The results are needed to determine the potential user bias caused by audio recorded on similar conditions. Therefore, this information is essential to reduce and eliminate the bias on the data partitions—training, cross validation and testing.

We observed that most users commonly employed a small set of tags with high frequency for both, ANPs and VNPs. On the other hand, few users have a larger set of tags where not all tags are used frequently. High-frequency tags common across nearly all users are shown in Table II. The most frequent tags are all distributed over most of the users. There is not a single user that dominates a frequently occurring tag, but for rarely occurring tags it is often the case that they are dominated by a single user. A special case of this is for example the tag piano, which is either used often or not used at all. In this case, the tag suggests users focusing on generating sound effects for music.

A closer look into the most frequent ANPs and VNPs and how many different users contributed to them is visualized in Figure 4. The figure gives a first intuition about the diversity of users per concept pairs, but it does not tell us if the data is equally distributed between the uploading users. For example it would be possible that a concept pair with 1,000 files is uploaded by 200 users, but 199 users only upload a single file and one user uploads all remaining files. Therefore, we also created Figure 5 which helps to visualize how the files are distributed among users. We can see how talking woman, talking english or whistling voice are dominated by a single user. Interestingly this problem is much stronger for VNPs than for the ANPs. In conclusion, most concept pairs are very diverse with respect to the uploading users, and only a few are dominated by single users.

IV. REFINEMENT OF THE CORPUS

The analysis on the collected data exposed multiple issues that could affect our results and conclusions. Therefore, we filtered our AudioSentiBank based on several constraints with the goal of increasing its quality and diversity of concept pairs. Our filtering process consisted of seven steps as shown in Figure 6.

A. Sampling rate below 16 kHz

The minimum sampling rate was set to 16 kHz and files with a lower value were discarded. We chose this value mainly because the datasets we described on our related work have a sampling rate value of 16kHz or 44.1kHz.

| Tags | Table II |
|------|----------|
| Adjectives | scary, creepy, industrial, funny |
| Verbs | talking, walking, laughing, singing |
| Nouns | atmosphere, horror, noise, voice |
B. Files with no available tags

For several audio files we were not able to retrieve their corresponding tags. The main reason was because in some cases we downloaded the files a few days before we downloaded the tags and in the meantime freesound.org removed some files together with their metadata.

C. Tagged with "loop"

We removed files tagged loop, loops or looping because after inspection of some files we found sounds repeating over and over again. The repetition of a sound is an artificial periodicity or cycle potentially affecting statistical models.

D. Duration outliers

There are recordings with much longer duration than the average of the recordings belonging to a given concept pair. The most common tendency for these files is to contain more than just the isolated event and thus, we removed them. For this purpose, we computed the distribution of the audio duration for each class pair and removed the outliers in the distribution based on Tukey’s range test. Therefore, we defined outliers as values bigger than the third quartile of the distribution plus 1.5 times the Interquartile range (IQR), formally: outlier > Q3 + 1.5 * IQR

E. Duration above 900 seconds

After the removal of the outliers per class, we looked into classes with significantly long recordings. Listening to some of these files revealed audio from field-recordings longer than 900 seconds (15 minutes). We then discarded files with equal to or longer than a duration of 900 seconds.

F. Concept pairs with less than 20 files

At this point we have already removed individual files from several concept pairs, hence we performed a sanity check for each class to review the number of audio samples remaining. If a concept pair had less than 20 recordings, we discarded the class completely because it is significantly small amount of data in comparison to the minimum of other available data sets mentioned in the related work.

G. Implausible concept pairs

In a first pass, we manually went through all the concept pairs and based on our judgment, we decided which of them seemed plausible to us and which did not, similarly to what was done in the VisualSentiBank [14]. In the second pass, we used a data-driven approach and defined a plausibility score to determine the degree of plausibility for a given pair. All implausible concept pairs were removed from the main data set. The total numbers of plausible and implausible concept pairs are shown in Table III.

\[ \text{TABLE III} \]

|       | Plausible | Implausible |
|-------|-----------|-------------|
| ANPs  | 852       | 122         |
| VNP   | 377       | 397         |

\[ \text{TABLE IV} \]

| Implausible | Plausible |
|-------------|-----------|
| ANPs        | VNP       |
| happy music | singing bird |
| slow car    | crying baby |
| industrial hands | falling autumn |
| echoing footsteps | flying bee |
| rattling machine | honking car |

\[ a) \text{Using manual inspection:} \] In the Visual SentiBank [14] tags such as image and photo were removed from the vocabulary since they did not add discriminative information to complement the pair. In the same manner, we discarded pairs with words such as sound, audio or effect. Moreover, we rejected the tag processed because these audio samples commonly contained music. We also removed pairs with redundancy of terms such as in noisy noise or natural nature. Another discarded pattern happened with terms related to music genre such as heavy metal and classic rap or types such as waving techno and ringing music. Nevertheless, we did not reject everything related to music, because there were classes such as happy music, sad music or dramatic guitar, which expressed a sentiment to the user.

Another observation is that adjectives often add scene context to a noun, e.g. recordings tagged with tropical water contain sounds of water with sounds of tropical animals in the background. Nouns on the other usually determine a time, a place or an object that does something. This results in VNPs like walking winter or walking park which are implausible. Moreover, some nouns like future or design are very abstract and are not connected to certain sound events, so we defined them as implausible too. A few examples of plausible and implausible concept pairs are shown in Table IV.

An interesting concept pair is talking bird. It appears to be semantically wrong, but possible. A closer look into the dataset revealed indeed recordings of a bird talking, but these recordings were rare and the majority of recordings contained talking people with bird sounds in the background. Due to the poor consistency of the concept pair in our dataset we removed it.

Additionally, we observed an overlap of concept pairs as for example we had talking man or talking child and on the other side there is talking english or talking spanish. Hence, the same recording could be tagged with multiple concept pairs and make the classification ambiguous. In this case we decided to keep them, because the acoustics of from children’s speech and man’s speech are sufficiently different, as well as the phonetics from languages.

\[ b) \text{Using the plausibility score:} \] A manual refinement could be reasonable for specific cases, but it does not scale to our needs and the future plans of adding data. Therefore, we complemented the first pass with a suggested data-driven...
metric to determine the degree of plausibility for a given concept pair. The objective of the score is to favor diversity of users, number of files and uniqueness of files among classes. For example, we have an implausible concept pair like `singing park` because a park cannot sing. This pair might have emerged because many files were tagged with combinations of the tags `singing`, `park`, `bird`, `people` and `crowd`. Although `singing park` has a large number of samples, it has no unique files, and the same sample files are also assigned to other classes. Hence, these kind of classes will yield a low plausibility score. More formally the score is defined as following:

\[
P S(cp) = \frac{u_{cp} + f_{cp}}{2cp} = \frac{u_{cp} + f_{cp}}{2n_{cp}} \quad (1)
\]

where \(n_{cp}\) is the total number of files belonging to concept pair \(cp\), then, \(u_{cp}\) is the number of unique users that uploaded files for concept pair \(cp\) and \(f_{cp}\) is the number of files that are unique to concept pair \(cp\). A file is unique to a concept pair if it is not tagged with any other concept pair in the existing set. The division by 2 is necessary because for a perfectly plausible concept pair the numerator becomes 1 + 1 and so the division by two will keep the metric in the range between 0 and 1 where one is the maximum score.

**H. Dominating Users**

Users contributing with multiple samples to a concept pair may use similar recording devices and have similar recording conditions. As a consequence, classification results can be biased because machine learning algorithms can focus on these properties instead of the audio content as demonstrated by [20]. Therefore, we wanted to reduce the influence of users responsible of uploading the majority of files corresponding to a given pair. One way to do it would be to set a limit to the maximum number of files a user is allowed to contribute to a single class. Following this approach and setting a maximum of 25% of files per user; around 6,000 files - 30 classes of VNP and 11,000 files - 60 classes of ANP would have to be removed. These values are a small part of our dataset, but we kept them because there were some interesting classes and we expected the influence of the over all classification results to be small.

**I. Construction of final Corpus and Ontology**

Finally, we obtained a refined dataset still significantly larger than most, if not all, of the available datasets for sound events also known as acoustic concepts. A few statistics of the filtered dataset are given in Table V, while the statistics of the complete pre-refined dataset are given in Table IV.

Since we filtered the data by several constraints, we compared the filtered data to the final data with respect to several metrics. Therefore, Table VI shows how the mean and median of the duration and tags per file changed. As expected, the duration decreased, but the effect is much stronger for the mean than for the median because we only removed extreme values and the median was robust. The number of tags per file decreased, but only slightly for mean and median.

Next step was to construct an ontology defining a taxonomy for the nouns and discovering relationships between adjective and verbs and their interplay with nouns. This ontological structure will be of great use to define scenarios using AudioSentiBank.

Finally, we converted all the audio the WAV format, because it is a lossless and standard format. Since most recordings in the data have a sampling rate of 44.1 kHz, we re-sampled all files to this sampling rate with 16 bits per sample. The number of channels was untouched because even though we only used one channel on our experiments, other tasks might benefit from multiple channels. The corpus was split in three partitions, Training, Cross Validation (CV) and Testings with a ratio of 40%-30%-30%.

**V. Experiments and Results for AudioSentiBank**

The two experiments, detection (or binary classification) and multi-class classification, were computed to define the benchmark for both types, ANPs and VNPs. For each type, our system’s pipeline operates on the audio files. However, audio files have variable length and thus we trimmed the recordings into four second segments, which was recommended in [21], with a 50% overlap. Then, the audio feature extraction consisted on conventional MFCCs features with 13, 20, and 30 coefficients and their first and second derivatives using the toolbox Yaafe [22]. The features from the training set were used to train a Random Forest for multi-class classification, in this case all VNP or ANP pairs were used together. In addition, we used the features to train one-vs-all-SVMs for binary classification, in this case we trained one SVM per concept pair. The CV set is used to tuned the classifiers and lastly, the testing set was used to evaluate performance. The classifier’s output were probability scores and class labels, which were used together with the ground truth to compute different performance metrics.

For detection, we used a linear kernel SVM [23] and tuned the soft margin parameter \(C\) with the following values: 5.0, 2.0, 1.0, 0.5 and 0.01. Each of the one-vs-all SVMs were trained with 100 samples for the positive class and 200 for the negative class. The 100 files segments were randomly selected from the pool of positive samples. The 200 files were randomly selected from the pool of other classes avoiding repeated files. To evaluate the detection performance we computed accuracy.
TABLE VII
Detection results with linear SVMs. More coefficients yielded better results.

| Features      | ANP: Accuracy | F-score  | AUC   |
|---------------|--------------|----------|-------|
| 13 MFCCs+∆+∆+∆ | 0.68         | 0.514    | 0.69  |
| 20 MFCCs+∆+∆+∆ | 0.69         | 0.506    | 0.697 |
| 30 MFCCs+∆+∆+∆ | 0.7          | 0.5      | 0.7   |
| VNP: Accuracy | 0.693        | 0.529    | 0.714 |
| 20 MFCCs+∆+∆+∆ | 0.705        | 0.532    | 0.72  |
| 30 MFCCs+∆+∆+∆ | 0.707        | 0.51     | 0.726 |

TABLE VIII
Multi-class classification results with Random Forests. Contrary to detection results, less coefficients yielded better results.

| Features      | ANP: Accuracy | VNP: Accuracy |
|---------------|--------------|--------------|
| 13 MFCCs+∆+∆+∆ | 0.016        | 0.045        |
| 20 MFCCs+∆+∆+∆ | 0.015        | 0.044        |

F-score with $\beta = 1$ and AUC for each class and then we computed the overall mean performance as can be seen in Table VII. The best overall accuracy for ANPs and VNPs was achieved by using 30 coefficients and was quite similar for both: accuracy of 70% and 70.7%, F-score of 50% and 51% and AUC of 70% and 72.6%. Although there are almost as twice ANPs as we there are VNPs, in general VNPs performed slightly better than ANPs.

For the multi-class classification we tuned a Random Forest [23] using 5, 10, 20, 50 and 100 trees and used MFCCs with 13 and 20 coefficients. Using more than 100 trees or 30 coefficients surpassed the capabilities of our computing resources. To evaluate performance, we computed accuracy results as shown in Table VIII. Contrary to the detection results, the best performance for ANPs and VNPs was achieved by the lowest dimension MFCCs. For ANPs the accuracy was 1.6% and the random guess was 0.13%, for VNPs the accuracy was 4.5% and the random guess was 0.28%. Similar to the detection results, we achieved better performance for VNPs than for ANPs. Nevertheless, having a higher number of classes in multi-class classification has a higher detrimental effect, because the classifier has to deal with ambiguities.

VI. Analysis and Discussion of the Results

A. Detection

In general the results showed that the detection becomes better using more coefficients. However, more coefficients increased training time and memory consumption, which is not feasible for large-scale computations. Therefore, we would recommend 13 coefficients for detection with linear SVMs since the results were close to the best results, but required less than half of the memory consumption and training time.

A more detailed look into the detection performance results of the individual concept pairs showed large variance between the concept pairs. Table IX shows the five ANPs and VNPs with the highest detection performance and the five with the lowest. At first glance, it stands out that ANPs containing words like weird, echoing, ring, phone or alert are well detected. On the contrary, for each adjective, verb and noun there are a few concept pairs with low detection scores close to 0. Another observation is that many of the low detected concept pairs are related to water such as splashing water, splashing bath or heavy rain.

If we consider only a single adjective or verb to see how the detection performance varies in combination with different nouns, we found for each adjective or verb a set of nouns yielding above average performance as well as low detection performance. As an example, the verb singing in combination with choir, mass, crowd, man, child or woman was well detected but singing voice was not. On the other side, if only single nouns are considered we observed nearly all nouns have some verbs and adjectives with good and low detection performance, but in this case there are a few outliers. For example power, glitch and action occurred only a few times and always performed badly. The reason could be because these words have an abstract meaning and the acoustic content is not consistent. In contrast, nouns such as alert, phone and guitar performed well for different adjectives and verbs, which could be suggested by more well defined audio content.

We also investigated the poor performance of background sounds such as rain, a river or just noise. We found that many recordings do not contain the background sounds as isolated events but they are commonly overlapping with other sound events. Often, field recordings of several minutes were tagged with almost every sound occurring in the recording, even if some of those tagged sounds only occurred for a few seconds. For foreground sounds this problem also exists, but it is significantly less frequent.

B. Multi-class classification

We computed confusion matrices to analyze the classification performance and discrimination among classes for ANPs and VNPs separately. At a semantic level, confusions seemed reasonable because the confused classes often described similar acoustics but with different words such as passing railway and passing train as well as closely related acoustics such as extreme rain and heavy thunder. Moreover, many confused pairs shared one of their elements as for example relaxing water and relaxing creek both contain the verb relaxing. More examples can be seen in Table X.

VII. Conclusions

In this work we have presented for the first time an investigation on acoustic concept pairs to describe audio content. For this purpose, we introduced a large-scale corpus,
AudioSentiBank, built up on web crawled folksonomies of adjective and verb noun concept pairs. Moreover, we provided a classification benchmark for detection and multi-class classification. Results showed and average detection accuracy for 761 ANPs and 362 VNP s of 71%, and an average multi-class classification accuracy of 4.5%. The scores describe performance on a large-scale for audio concepts, which was unreported in literature, being less than 100 classes the nearest number. In addition, we released the corpus for researchers to use it for audio and multimedia tasks.

**TABLE X**

| ANP       | VNP       |
|-----------|-----------|
| extreme rain | passing railway |
| heavy thunder | singing bird |
| heavy wind   | talking crowd  |
| distant rain | splashing lake |
| relaxing water | burning tire |
| echoing church bell | crackling fire |

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