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SOUND EVENT DETECTION FROM PARTIALLY ANNOTATED DATA: TRENDS AND CHALLENGES

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ABSTRACT

This paper proposes an overview of the latest advances and challenges in sound event detection and classification with systems trained on partially annotated data. The paper focuses on the scientific aspects highlighted by the task 4 of DCASE 2018 challenge: large-scale weakly labeled semi-supervised sound event detection in domestic environments. Given a small training set composed of weakly labeled audio clips (without timestamps) and a larger training set composed of unlabeled audio clips, the target of the task is to provide not only the event class but also the event time boundaries given that multiple events can be present in an audio clip. This paper proposes a detailed analysis of the impact of the time segmentation, the event classification and the methods used to exploit unlabeled data on the final performance of sound event detection systems.

Index Terms— Sound event detection, Weakly labeled data, Semi-supervised learning, Audio segmentation, DCASE 2018

1. INTRODUCTION

We are constantly surrounded by sounds and we rely heavily on these sounds to obtain important information about what is happening around us. Ambient sound analysis aims at automatically extracting information from these sounds. It encompasses disciplines such as sound scene classification (in which context does this happen?) or sound event detection and classification (SED) (what happens during this recording?) [1]. This area of research has been attracting a continuously growing attention during the past years as it can have a great impact in many applications including smart cities, autonomous cars or ambient assisted living.

DCASE 2018 task 4 (large-scale weakly labeled semi-supervised sound event detection in domestic environments)

This work was made with the support of the French National Research Agency, in the framework of the project LEAUDS Learning to understand audio scenes (ANR-18-CE23-0020) and the French region Grand-Est. Experiments presented in this paper were carried out using the Grid5000 testbed, supported by a scientific interest group hosted by Inria and including CNRS, RENATER and several Universities as well as other organizations (see <https://www.grid5000>)

focused on SED with time boundaries in domestic applications [2]. The systems submitted had to detect when an sound event occurred in an audio clip and what was the class of the event (as opposed to audio tagging where only the presence of a sound event is important regardless of when it happened). We proposed to investigate the scenario where a large scale corpus is available but only a small amount of the data is labeled. Task 4 corpus was derived from the Audioset corpus [3] targeting classes of sound events related to domestic applications. The labels are provided at clip level (an event is present or not within a sound clip) but without the time boundaries (weak labels, that can also be referred to as tags) in order to decrease the annotation time. These constraints indeed correspond to constraints faced in many real applications where the budget allocated to annotating is limited.

In order to fully exploit this dataset, the submitted systems had to tackle two different problems. The first problem is related to the exploitation of the unlabeled part of the dataset either in unsupervised approaches [4, 5] or together with the labeled subset in semi-supervised approaches [6, 7, 8]. The second problem was related to the detection of the time boundaries and how to train a system that can detect these boundaries from weakly labeled data [9, 10]. The evaluation metric chosen was selected because it was penalizing these boundary estimation errors heavily. The goal was to encourage participants to focus on the time localization aspect.

Through a detailed overview of the systems submitted to DCASE 2018 task 4 we propose an overview of some recent advances in SED with partially annotated data¹. We will first briefly describe task 4 and the related audio corpus in Section 2. Systems performance over all classes will be presented and analyzed in Section 3. We will present a class-wise analyze in Section 4 and discuss the impact of the metric chosen in Section 5. Section 6 will draw the conclusions of the paper and present some perspectives for SED.

¹Additional result plots and analysis can be found at <https://turpaultn.github.io/dcase2018-results/>

2. DCASE 2018 TASK 4

2.1. Audio dataset

The task focuses on a subset of Audioset that focuses on 10 classes of sound events [2]. Audioset consists in 10-second audio clips extracted from youtube videos[3]. The development set provided for task 4 is split into a training set and a test set.

2.1.1. Training set

In order to reflect what could possibly happen in a real-world scenario, we provide three different splits of training data in task 4 training set: a labeled training set, an unlabeled in domain training set and an unlabeled out of domain training set (clips that do not contain any of the target classes):

Labeled training set: contains 1,578 audio clips (2,244 class occurrences) for which weak labels provided in Audioset have been verified and corrected by human annotators. One-third of the audio clips in this set contain at least two different classes of sound events.

Unlabeled in domain training set: contains 14,412 audio clips. The audio clips are selected such that the distribution per class of sound event (based on Audioset labels) is close to the distribution in the labeled set.

Unlabeled out of domain training set: is composed of 39,999 audio clips extracted from classes of sound events that are not considered in the task (according to unverified Audioset labels).

2.2. Test set

The test set is designed such that the distribution in term of clips per class of sound event is similar to that of the weakly labeled training set. The test set contains 288 audio clips (906 events). The test set is annotated with strong labels, with time boundaries (obtained by human annotators).

2.3. Evaluation set

The evaluation set contains 880 audio clips (3,187 events). The process to select the audio clips was similar to the process applied to select audio clips in the training set and the test set, in order to obtain a set with comparable classes distribution (See also Table 1). Labels with time boundaries are obtained by human annotators.

The duration distribution for each sound event class is presented on Figure 1. One of the focus of this task is the development of approaches that can provide fine time-level segmentation while learning on weakly labeled data. The observation of the event duration distribution confirms that in order to perform well it is essential to design approaches that are efficient at detecting both short events and events that have a longer duration.

Class	Test	Eval
Alarm/bell/ringing	112	306
Blender	40	56
Cat	97	243
Dishes	122	370
Dog	127	450
Electric shaver/toothbrush	28	37
Frying	24	67
Running water	76	154
Speech	261	1401
Vacuum cleaner	36	56
Total	906	3187

Table 1: Number of sound events per class in the test set and the evaluation set.

2.4. Task description

The task consists of detecting sound events within web videos using weakly labeled training data. The detection within a 10-seconds clip should be performed with start and end timestamps.

2.4.1. Task evaluation

Submissions were evaluated with event-based measures for which the system output is compared to the reference labels event by event [11] (see also Figure 2). The correspondence between sound event boundaries are estimated with a 200 ms tolerance collar on onsets and a tolerance collar on offsets that is the maximum of 200 ms and 20 % of the duration of the sound event.

- True positives are the occurrences when a sound event present in the system output corresponds to a sound event in the reference annotations.
- False positives are obtained when a sound event is present in the system output but not in the reference annotations (or not within the tolerance collars on the onset or the offset).
- False negatives are obtained when a sound event is present in the reference annotations but not in the system output (or not within the tolerance collars).

Submissions were ranked according to the event-based F1-score. The F1-score was first computed class-wise over the whole evaluation set:

$$F1_c = \frac{2TP_c}{2TP_c + FP_c + FN_c}, \quad (1)$$

where TP_c , FP_c and FN_c are the number of true positives, false positives and false negative for sound event class c over the whole evaluation set, respectively.

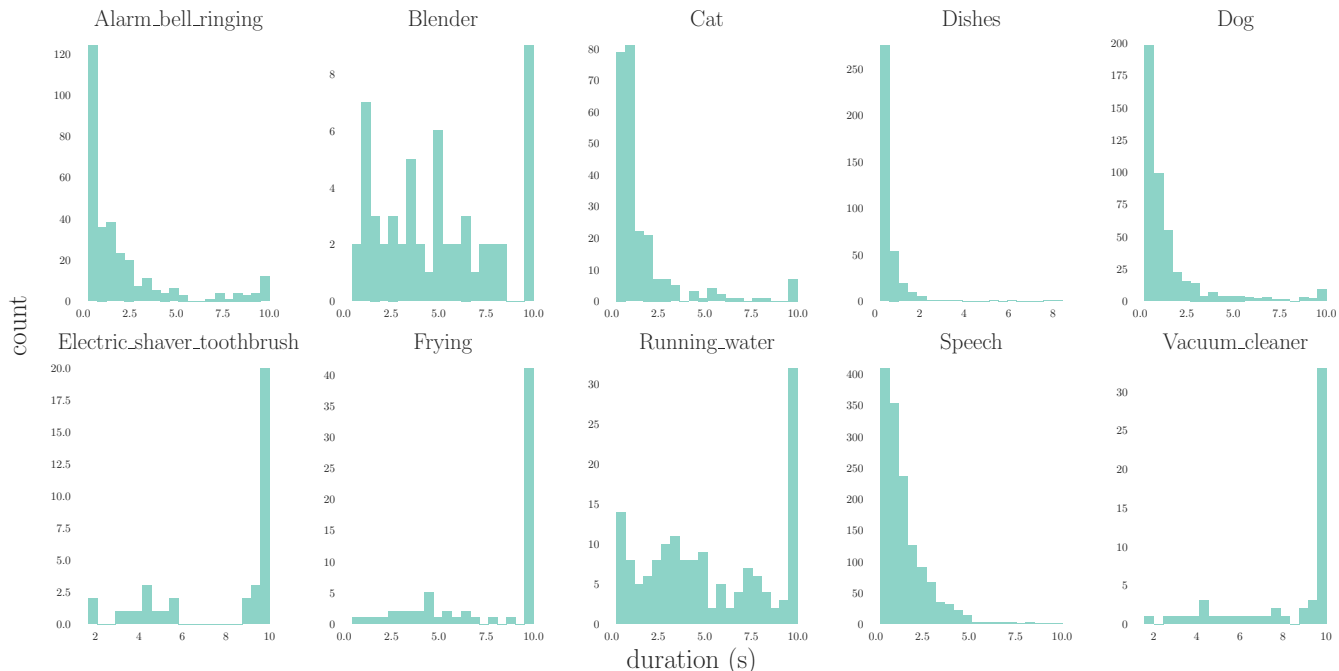


Fig. 1: Duration distribution by class of sound events on the evaluation set.

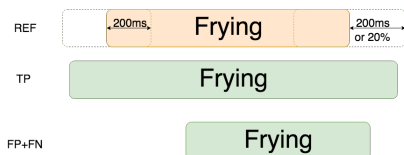


Fig. 2: Event-based F1-score.

The final score is the F1-score average over sound event classes regardless of the number of sound events per class (macro-average):

$$F1_{\text{macro}} = \frac{\sum_{c \in \mathcal{C}} F1_c}{n_{\mathcal{C}}}, \quad (2)$$

where \mathcal{C} is the sound event classes ensemble and $n_{\mathcal{C}}$ the number of sound event classes.

3. ANALYSIS OF THE PERFORMANCE OVER ALL SOUND EVENT CLASSES

In this section we present and analyze submissions performance regardless of the sound event classes.

3.1. Task submissions and results overview

DCASE 2018 task 4 gathered 50 submissions from 16 different research teams involving 57 researchers overall. The official team ranking and some characteristics of the submitted systems are presented in Table 2. The best two submis-

sions quite clearly stand out from other submissions. They also go beyond the rather standard approaches based convolutional neural networks (CNN) or stacked CNN and recurrent neural networks (RNN) also denoted as CRNN. The best system, submitted by JiaKai (**jiakai_psh**) [12], relies on a mean-teacher model that exploits unlabeled data to regularize the classifier learned on the weakly labeled data [28]. The system submitted by Liu et al. (**liu_ustc**) [13] that ranked second relies on an energy based sound event detection as a pre-processing to a capsule network [29]. The output of the network is then post processed to ensure that silence between events and events themselves are longer than a minimum duration.

Other notable submissions include the system from Kothinti et al. (**kothinti_jhu**) [15] that relies on a sound event detection based on restricted Boltzmann machines (RBM) as a pre-processing. This solution performs well at detecting onsets but not so much for offset detection (see also Section 4.1). Dinkel et al. proposed a system (**dinkel_sjtu**) that uses Gaussian mixture models (GMM) and hidden Markov models (HMM) to perform sound event alignment [25]. Gaussian filtering is then used as post-processing. Pellegrini et al. proposed a system (**pellegrini_irit**) that relies on multiple instance learning (MIL) to exploit weakly labeled data [23]. Both these systems perform pretty decently on segmentation (see also Section 3.2) but they suffer from pretty poor sound event classification performance (see also Figure 8).

Rank	System	Features	Classifier	Parameters	F1 (%)
1	jiakai_psh [12]	log-mel energies	CRNN	1M	32.4
2	liu_ustc [13]	log-mel energies	CRNN, Capsule-RNN	4M	29.9
3	kong_surrey [14]	log-mel energies	VGGish 8 layer CNN	4M	24.0
4	kothinti_jhu [15]	log-mel energies, auditory spectrogram	CRNN, RBM, cRBM, PCA	1M	22.4
5	harb_tug [16]	log-mel energies	CRNN, VAT	497k	21.6
6	koutini_jku [17]	log-mel energies	CRNN	126k	21.5
7	guo_thu [18]	log-mel energies	multi-scale CRNN	970k	21.3
8	hou_bupt [19]	log-mel energies & MFCC	CRNN	1M	21.1
9	lim_etri [20]	log-mel energies	CRNN	239k	20.4
10	avdeeva_itmo [21]	log-mel energies & MFCC	CRNN, CNN	200k	20.1
11	wangjun_bupt [22]	log-mel energies	RNN	1M	17.9
12	pellegrini_irit [23]	log-mel energies	CNN, CRNN with MIL	200k	16.6
13	moon_yonsei [24]	Raw wavforms	RseNet, SENet	10M	15.9
14	dinkel_sjtu [25]	log-mel energies & MFCC	CRNN, HMM-GMM	126k	13.4
15	wang_nudt [26]	log-mel energies & Δ features	CRNN	24M	12.6
	baseline [2]	log-mel energies	CRNN	126k	10.8
16	raj_iit [27]	CQT	CRNN	215k	9.4

Table 2: Team ranking and submitted systems characteristics.

3.2. Segmentation

In this section, we focus on the segmentation performance. That is, the ability of the submitted systems to localize sound events in time without having to predict the class. Figures 3, 4 and 5 present the event-based F1-score computed without taking the sound event class labels into account and for a tolerance collar of 200 ms, 1 s and 5 s, respectively. The fact that there is only little performance difference between the sound event detection performance (Table 2) and the segmentation performance tends to indicate that segmentation is possibly the main limiting factor in overall performance. This is actually confirmed by the rather high tagging performance of most systems presented on Figure 8.

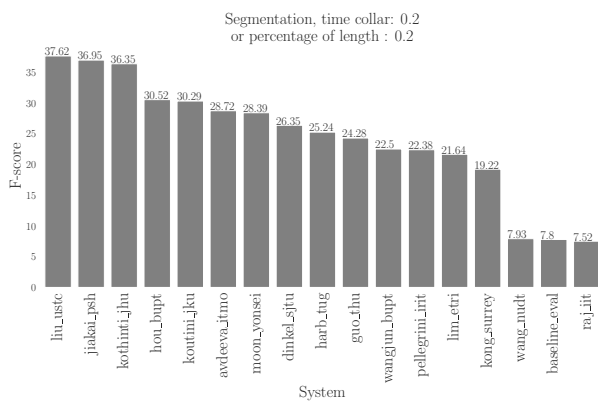


Fig. 3: Segmentation performance (tolerance collar on onsets is 200 ms and tolerance collar on offsets is the maximum of 200 ms and 20 % of the event length).

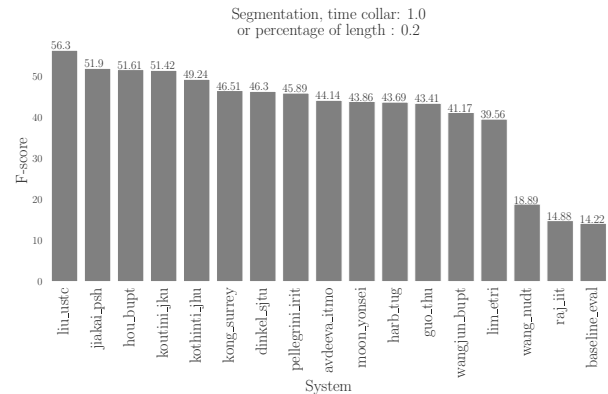


Fig. 4: Segmentation performance (tolerance collar on onsets is 1 s and tolerance collar on offsets is the maximum of 1 s and 20 % of the event length).

Currently, most of the systems are able to detect if an event occurred within a rather crude time area (see also Figure 5) but are not able to properly segment the audio clips in terms of sound events (see also Figure 3). The systems that performed best in terms of segmentation are the systems that actually implemented some sort of segmentation among which **liu_ustc** [13] and **kothinti_jhu** [15]. The winning system is ranked second in term of segmentation and owe its first overall rank to a much better classification than competing systems (see also Figure 8).

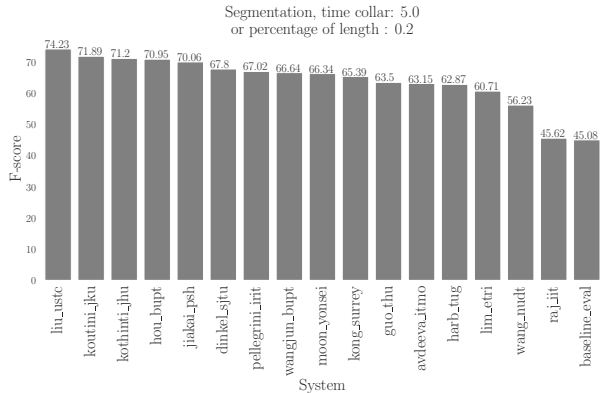


Fig. 5: Segmentation performance (tolerance collar on onsets is 5 s and tolerance collar on offsets is the maximum of 5 s and 20 % of the event length).

3.3. Use of unlabeled data

One of the challenges proposed by DCASE 2018 task 4 was to exploit a large amount of unlabeled data. In the section we analyze the approaches proposed by participants. Most of the systems submitted used a pseudo-labeling approach where a first system trained on the labeled data is used to obtain labels for the unlabeled set (**liu_ustc** [13], **hou_bupt** [19]). Variations on this included setting a confidence threshold to decide to keep the label or not (**koutini_jku** [17], **wang_nudt** [26], **pellegrini_irit** [23], **harb_tug** [16], **moon_yonse** [24]) and gradually introducing new audio clips with these pseudo labels (**wangjun_bupt** [22]).

The winning system (**jiakai_psh** [12]) used the unlabeled data within a mean-teacher scheme [28]. It is composed of two models: a student model and a mean-teacher model whose weights are the exponential average of the student’s weights. On labeled data, the student model weights are updated to optimize a classification cost on the sound event classes. Additionally, consistency costs are computed to compare the output of the student model and the mean-teacher model on both the labeled and the unlabeled data. Kothinti et al. (**kothinti_jhu** [15]) proposed to use both the weakly labeled and unlabeled in-domain data to train several RBM that are used to detect sound event boundaries.

3.4. Complexity

The complexity of the submitted systems (in terms of number of parameters) is presented in Table 2. The only system that used raw waveforms as input (**moon_yonse** [24]) is among the most complex systems yet it is not even among the top 10 systems. This tends to indicate that the dataset proposed for task 4 is too small to train SED systems using raw waveforms that are usually known to require a lot of training data. The most complex system (**wang_nudt** [26]) is about 200 times more complex than the baseline in particular because

it combines several complex models. However it performs only slightly better than the baseline. The winning system (**jiakai_psh** [12]) is about 10 times more complex than the baseline and the best performing system that has a number of parameters similar to that of the baseline (**koutini_jku** [17]) improves the baseline F1-score performance by more than 10 % absolute.

3.5. Duration of events

It has been shown above that the systems performance largely depends on the systems ability to properly segment the audio clips in terms of sound events. Figure 1 presents the duration distribution for each class of sound events on the evaluation set. From this distribution we can separate the sound events into two categories of events: short sound events (‘Alarm/bell/ringing’, ‘Cat’, ‘Dishes’, ‘Dog’ and ‘Speech’) and long sound events (‘Blender’, ‘Electric shaver/toothbrush’, ‘Frying’, ‘Running water’ and ‘Vacuum cleaner’).

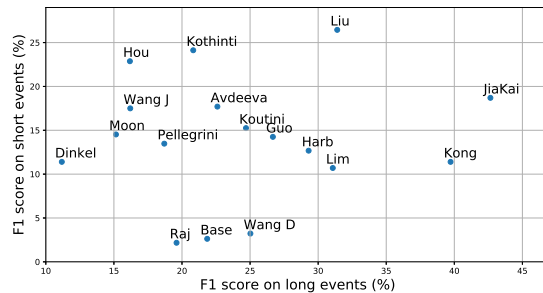


Fig. 6: Systems performance on short sound events depending on their performance on long sound events.

System	Short	Long	All	Rank
liu_ustc [13]	26.4	31.4	29.9	2
kothinti_jhu [15]	24.1	20.8	22.4	4
hou_bupt [19]	22.9	16.2	21.1	8
jiakai_psh [12]	18.7	42.6	32.4	1
avdeeva_itmo [21]	17.7	22.6	20.1	10
baseline [2]	2.6	21.8	10.8	16

Table 3: Top 5 systems on short events (‘Alarm/bell/ringing’, ‘Cat’, ‘Dishes’, ‘Dog’ and ‘Speech’).

Figure 6 presents the performance of the submitted systems on short sound events depending on their performance on long sound events. No system is clearly outperforming the others on both short and long sound events. This is confirmed when looking at the top performing systems on short sound events (Table 3) and on long sound events (Table 4). These rankings tend to show that the approaches proposed

System	Long	Short	All	Rank
jiakai_psh [12]	42.6	18.7	32.4	1
kong_surrey [14]	39.7	11.4	24	3
liu_ustc [13]	31.4	26.4	29.9	2
lim_etri [20]	31.1	10.7	20.4	9
harb_tug [16]	29.3	12.7	21.6	5
baseline [2]	21.8	2.6	10.8	16

Table 4: Top 5 systems on long events (‘Blender’, ‘Electric shaver/toothbrush’, ‘Frying’, ‘Running water’ and ‘Vacuum cleaner’).

were either tailored to perform well on short sound events (top systems are also the systems that performed best in terms of segmentation, see also Figure 3) or on long sound events (top systems are also among the best systems in terms of tagging, see also Figure 8). However, in order to perform well on the SED task systems had to perform reasonably well on both short and long sound events. This is the case for the top two systems (**jiakai_psh** [12] and **liu_ustc**) [13]) that are in the top five both short and long sound events.

4. ANALYSIS OF THE CLASS-WISE PERFORMANCE

It have been shown above that systems performance can vary to a great extent depending on the sound events duration that is tightly related to the sound event class itself. Therefore, in this section we focus on the performance of the submitted systems depending on the sound event classes. Table 5 presents the class-wise event-based F1-score for the 10 best performing submitted systems. The best system (**jiakai_psh** [12]) outperforms other systems on five sound event classes upon ten (mainly long sound events). However, it performs rather poorly on some of the remaining sound event classes (mainly short sound events). On the other hand, the second best system (**liu_ustc** [13]) outperforms other systems on a single sound event class (‘Dog’) but is generally not too far from the best performance on several other sound event class. This explains why it can still compare with the winning system in terms of overall performance.

In general ‘Speech’ and ‘Alarm bell ringing’ seem to be the easiest sound event classes to detect and classify. This could be explained by the fact that sound events from these classes are not too short (with a median duration of 1.17 s and 0.57 s, respectively), occurs many times in the training set (in 550 clips and 205 clips, respectively) and generally have rather clear onsets and offsets (see also Section 4.1). There is a clear separation between ‘Cat’, ‘Dishes’ and ‘Dog’ and other sound event classes. The former seems more difficult to detect and classify than the latter. This can be due to the fact that sound events in these classes are short and present a large acoustic variability. Interestingly, the submitted systems that

perform best on these sound event classes are not necessarily among the top three systems. For example **hou_bupt** [19] obtains the best performance on ‘Dishes’ and clearly outperforms other submissions with 23.5 % F1-score. However, it ranked eighth overall (but was among the top five systems on short sound events, see also Table 3). The best system on ‘Cat’ (by a rather large margin) with 25.3 % F1-score is **pellegriani_irit** [23] that relies on MIL and that is not even in the top 10 in terms of overall performance.

4.1. Performance on onset and offset detection

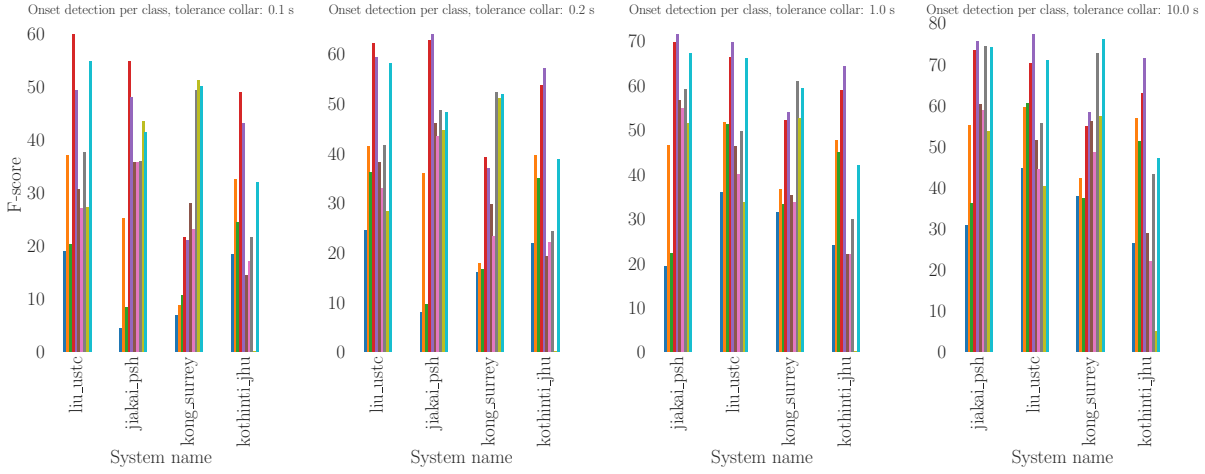
For some sound event classes that slowly decay the time location of offsets can be difficult to locate (and the concept of offset itself can even become ambiguous in reverberant scenarios). Therefore, we now focus on the detection of onsets and offsets separately. In the plots presented in this section (see also Figure 7), sound events are classified from the shortest (on the left) to the longest (on the right) according to their median duration. Additionally, for the sake of clarity, only the systems among the top four in overall performance are presented here. Systems are presented in decaying overall onset or offset detection performance (the best system is on the left side).

4.1.1. Onset

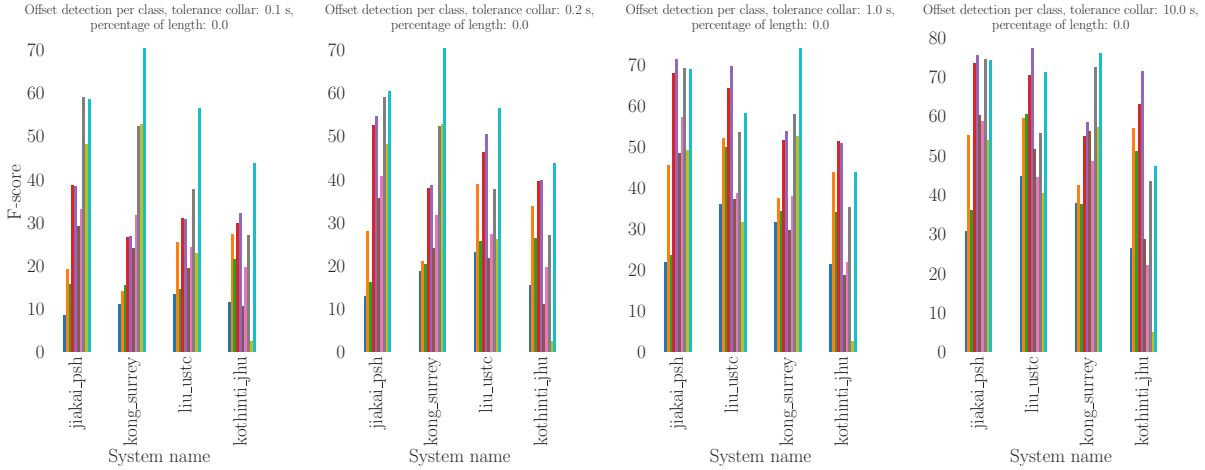
Figure 7a presents F1-score for onset detection for varying tolerance collars (in seconds). Performance generally increases when the tolerance collar is increased. For small tolerance collars, **liu_ustc** [13] performs best which confirms previous analysis about the relatively good segmentation of their system. When the tolerance collar is larger than 0.5 s **jiakai_psh** [12] outperforms other system which also confirm that the proposed segmentation is a bit too coarse.

The remaining errors for a 10 sec tolerance collar indicate that the systems were not able to predict how many onsets for the specific sound event class occurred within the audio clip. In most cases this could also corresponds to the case where the sound event was not detected at all (see also Figure 7b).

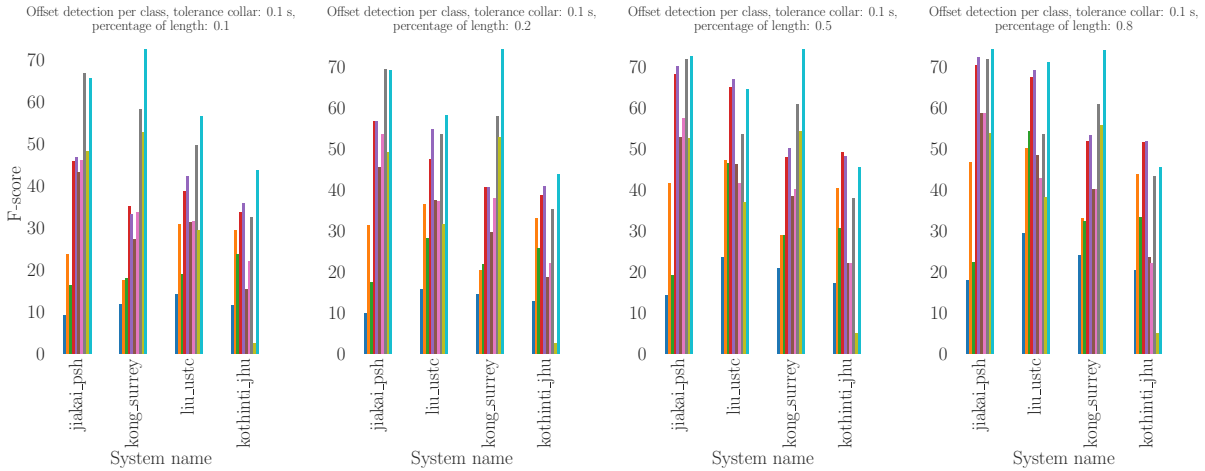
When looking at particular sound event classes, in general systems exhibit good onset detection performance for ‘Speech’ and ‘Alarm bell ringing’. As mentioned above, this can be due to the fact that these sound events occur frequently in the training set but it can also be related to the fact that the sound events from these classes indeed have rather clear onsets that appear to be easier to detect. On the other hand, sound event classes as ‘Cat’ and ‘Dishes’ seem to be difficult to detect. For the former it is probably due to the fact that the onsets are not always clear as for the latter it is most generally related to sound events that are simply missed by the systems because they are too short. For the remaining sound event classes, the performance varies a lot from one system to another and seems to be affected by the segmentation strategy implemented.



(a) F1-score for onset detection with absolute tolerance collars.



(b) F1-score for offset detection with absolute tolerance collars.



(c) F1-score for offset detection with tolerance collars relative to event duration.

Fig. 7: Event-based F1-score for onset and offset detection with varying tolerance.

System	Alarm	Blender	Cat	Dishes	Dog	Electric	Frying	Water	Speech	Vacuum
jiakai_psh [12]	49.9	38.2	3.6	3.2	18.1	48.7	35.4	31.2	46.8	48.3
liu_ustc [13]	46.0	27.1	20.3	13.0	26.5	37.6	10.9	23.9	43.1	50.0
kong_surrey [14]	24.5	18.9	7.8	7.7	5.6	46.4	43.6	15.2	19.9	50.0
kothinti_jhu [15]	36.7	22.0	20.5	12.8	26.5	24.3	0.0	9.6	34.3	37.0
harb_tug [16]	15.4	30.0	8.1	17.5	9.7	21.0	34.7	17.3	31.1	31.5
koutini_jku [17]	30.0	16.4	13.1	9.5	8.4	23.5	18.1	12.6	42.9	40.8
guo_thu [18]	35.3	31.8	7.8	4.0	9.9	17.4	32.7	18.3	31.0	24.8
hou_bupt [19]	41.4	16.4	6.4	23.5	20.2	9.8	6.2	14.0	40.6	32.3
lim_etri [20]	11.6	21.6	7.9	5.9	17.4	27.8	14.9	15.5	21.0	60.0
avdeeva_itmo [21]	33.3	15.2	14.9	6.3	16.3	15.8	24.6	13.3	27.2	34.8
baseline [2]	4.8	12.7	2.9	0.4	2.4	20.0	24.5	10.1	0.1	30.2

Table 5: Class-wise event-based F1-score for the top 10 submitted systems.

4.1.2. Offset

Figure 7b presents F1-score for offset detection for varying tolerance collars (in seconds). When comparing with Figure 7a it appears that offsets are indeed more difficult to detect. The high F1-score for some sound event classes such as (‘Electric shaver toothbrush’, ‘Frying’ or ‘Vacuum cleaner’) is mainly due to the fact that many of the sound events in these classes do not have an offset within the audio clips and therefore the offset to be detected is simply the final boundary of the audio clip.

It is generally admitted that penalizing offset detection based on an absolute time tolerance collar is not a reasonable choice specially for long sound events. In particular because this type of tolerance collar might be affecting long sound events (with longer decay) much more than short (possibly percussive) sound events. Therefore, the metric retained for DCASE 2018 task 4 include both an absolute time tolerance collar and a tolerance collar that was computed as a percentage of the sound event duration (the maximum of these two values was retained). With this approach, the absolute time tolerance collar usually applies to short sound events while the tolerance collar relative to event length applies to longer sound events.

Figure 7c presents F1-score for offset detection for varying tolerance collars (in percent of the sound event duration). Note that the absolute time tolerance collar is kept to 0.1 s here in order to avoid unreasonably small tolerance collars for short sound events. As expected, this kind of tolerance collar has less effect than absolute time tolerance collar on offset detection of short sound events such as ‘Cat’, ‘Dishes’ or ‘Dog’ but can affect greatly the offset detection performance on long sound events such as ‘Running water’ or ‘Blender’.

Quite surprisingly, **jiakai_psh** [12] outperforms the other submitted systems (even those which had demonstrated a better segmentation performance until now) including with low tolerance collars. When looking at particular sound event classes, in general the submitted systems exhibit good offset

detection performance for ‘Speech’ and ‘Alarm bell ringing’ even if in this case offsets are usually not as well defined as onsets were.

5. IMPACT OF THE METRIC

For DCASE 2018, the F1-score was computed in an event-based fashion in order to put on strong focus on the sound event segmentation. Class-wise performance was averaged in order to discard the effects of the sound event classes imbalance (2). In this section, we study the impact of these choices on the performance evaluation of the submitted systems.

5.1. F1-score computation relatively to events or segments

As opposed to event-based metrics, segmented-based metrics are computed by comparing the system outputs and the reference on short segments. The sound event classes are then considered to be active or not on the full segment. The final metric is computed on all the segments [11]. This approach reports if a system is able to detect if a sound event class is active with a specific time resolution (the segment length) and can prove more robust than event-based metrics to phenomena such as short pauses between consecutive sound events. Figure 8 presents a comparison between the event-based F1-scores (on the left) and the segment-based F1-scores (on the right) for varying tolerance collars and time resolutions, respectively.

As expected, segmented-based metrics are more permissive to errors in the detection of the sound event boundaries. Indeed the reported segment-based F1-scores (from 40 % to 70 % depending on the time resolution) are much higher than their event-based counterpart (from 5 % to 60 % depending on the tolerance collar). Additionally, the segment-based F1-score seems to be favoring systems that are good at tagging while event-based F1-score favors systems that have good segmentation performance. This is particularly clear for sys-

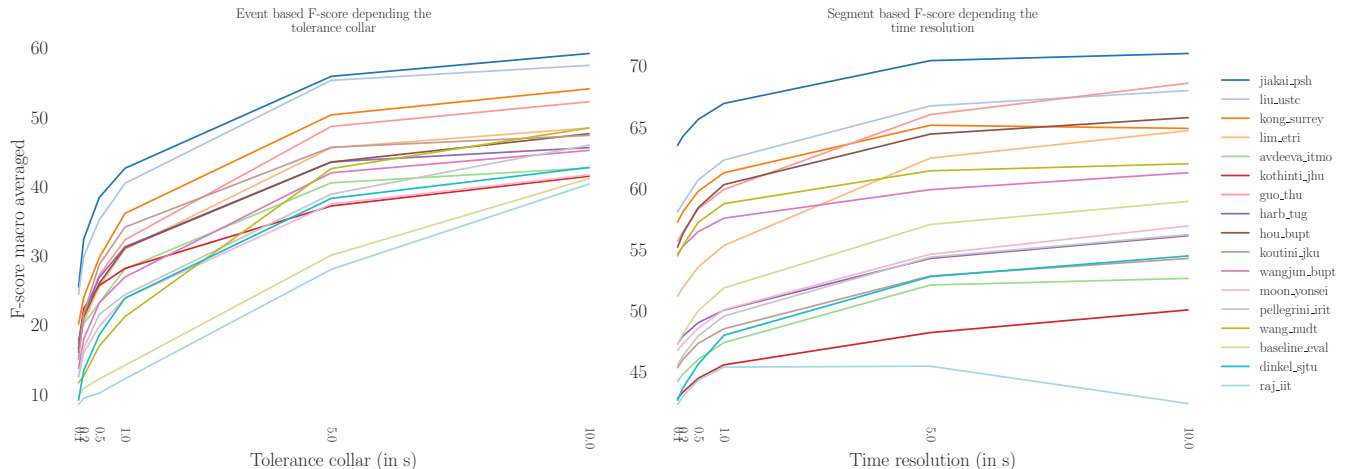


Fig. 8: Comparison between event-based and segmented-based F1-scores depending on the tolerance collar and time resolution, respectively.

tems like **hou.bupt** [19], **guo.thu** [18] and the task baseline [2] which perform much better in terms of segment-based F1-score and for **kothinti.jhu** [15] that performs much better in terms of event-based F1-score.

When the time resolution for the segment-based F1-scores is 10 s the reported performance is actually that of a tagging task. The tagging ranking is then rather different than the general ranking (see also Table 2) and the ranking for segmentation (see also Figure 3). This emphasizes once again that none of the submitted systems is actually outperforming others in both segmentation and tagging but that in order to perform well on the task, systems had to perform at least decently on both. This is the case for **jiakai.psh** [12] and **liu.ustc** [13] that clearly stand out in the final ranking.

As the choice of the metric is tightly related to the targeted application, some approaches can be better suited when you need to know exactly when a sound event from a specific class did occur (in which case you might select a system that performs well in terms event-based F1-score) some other approaches can be suited to monitor the activity within a time period (approximately when was each sound event class active, depending on the time resolution, in which case we might select systems that perform well in terms segment-based F1-score)

5.2. Micro average

While macro-averaging (used in task 4) computes the final F1-score as the average across sound event classes (regardless of the number of events for each class), micro-averaging computes the final F1-score as the average of each single decision. It therefore gives more importance to sound event classes that occur more frequently (see also Table 1 for the distribution). For example, ‘Speech’ events will account for almost half of the performance when using micro-averaged F1-score.

Figure 9 presents event-based F1-score depending on the averaging method. We can observe a clear performance improvement between macro-averaged and micro-averaged F1-score for the systems that performed well the most frequent sound event classes (‘Alarm bell ringing’, ‘Dishes’, ‘Dog’ or ‘Speech’) such as **lim.etri** [20]. On the other hand the systems that were able to perform well on less frequent sound event classes (‘Electric shaver/toothbrush’, ‘Frying’...) but not on frequent sound event classes can see their performance decreased between macro-averaged and micro-averaged F1-score as this is the case for **kong.surrey** [14]. The top two systems (**jiakai.psh** [12] and **liu.ustc** [13]) were performing reasonably well on the most frequent sound event classes and therefore still outperform other systems in terms of micro-averaged F1-score.

Once again, the choice of the metric is related to the targeted application. If you want to detect mainly the sound event classes that occur the most frequently and that missing rare sound event classes is not really a problem then you should select approaches that perform well in terms of micro-averaged F1-score. On the contrary if detecting rare sound event classes is important then approaches that perform well in terms of macro-averaged F1-score seem better suited.

6. CONCLUSION

In this paper we proposed an overview of some of the latest advances and challenges in sound event detection with systems trained on partially annotated data through the analysis of the results of DCASE 2018 challenge task 4. The paper focused on the scientific aspects highlighted by the task: exploiting both unlabeled and weakly labeled data to train a system that provides not only the event class but also the event time boundaries. It has been shown that both the segmen-

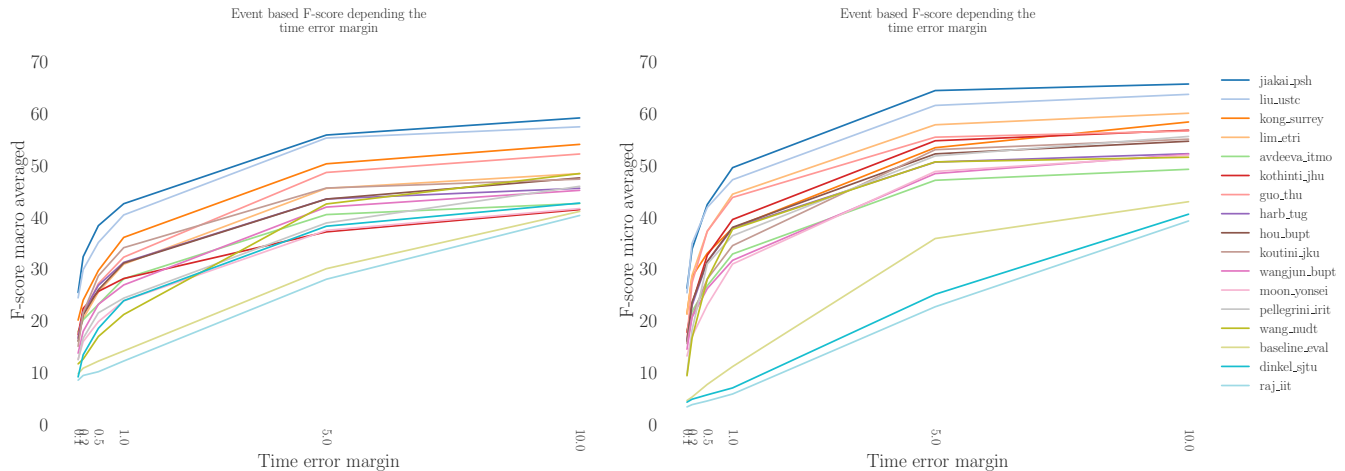


Fig. 9: Event-based F1-score depending on the class averaging method.

tation and the classification ability play an important role in the final performance. However whereas the tagging performance (related to the classification ability) is generally rather good for many systems, only few systems did implement an explicit segmentation strategy. This aspect actually remains quite challenging as training a system to detect sound events and predict their time localization from weakly labeled data is far from trivial. Therefore, one question for future works is to investigate if strongly labeled data that is generated synthetically can help solving this issue. This is one of the challenges investigated in the task 4 of DCASE 2019 challenge.

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