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Annotating Soundscapes

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ABSTRACT

We describe a soundscape annotation tool for unconstrained environmental sounds. The tool segments the time-frequency-plane into regions that are likely to stem from a single source. A human annotator can classify these regions. The system learns to suggest possible annotations and presents these for acceptance. Accepted or corrected annotations will be used to improve the classification further. Automatic annotations with a very high probability of being correct might be accepted by default. This speeds up the annotation process and makes it possible to annotate complex soundscapes both quickly and in considerable detail. We performed a pilot on recordings of uncontrolled soundscapes at locations in Assen (NL) made in the early spring of 2009. Initial results show that the system is able to propose the correct class in 75% of the cases.

1. INTRODUCTION

Humans can recognize events in the sonic environment (soundscape) seemingly effortlessly. However, this ability thus far eludes our technical abilities¹. Automatic sound recognition has important applications in fields as diverse as environmental noise monitoring, robotics, security systems, content-based indexing of multi-media files, and even modern human-system interfaces. Most sound recognition research is aimed at improving one aspect of these application domains, such as speech recognition or music genre detection. These limited domain solutions can rely on domain dependent assumptions that simplify the problem considerably. For example, within music classification² or speech recognition³ it is typically assumed that the input does not

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contain multiple uncorrelated streams of sonic evidence. As a consequence, stream segregation and other problems are defined out of the problem-space and are not addressed scientifically.

In contrast to domain specific solutions, a general sound recognition system should be robust to the complexities of unconstrained soundscapes, such as strong and varying transmission effects and concurrent sources. To handle real-world complexities, human perception relies on signal-driven processing, but also on contextual knowledge and reasoning⁴. Therefore, a general sound recognition system should comprise an interaction of signal-driven techniques and interpretation of the context.

This paper focuses on the development of a tool to facilitate real-world sound annotation for training and benchmark purposes. It uses a set of simple algorithms to detect sonic events and to classify these events. The interaction between semantic content, in the form of annotations, and signal-based evidence forms the basis of future, more general, sound recognition systems.

The annotation of everyday sounds must lead to an adequate description of the content of a sound-file in terms of the interval in which an event occurred. Annotation is a time-consuming, and knowledge intensive task, which is usually quite boring as well. This is probably the reason why there is currently only a single annotated database of sounds in realistic everyday conditions⁵. Carefully selected everyday sounds in benign conditions have been used in other studies^{6,7}. However for these sounds the annotation problem is trivialized, because the data sets contain single sound events in a single file.

There are many difficulties associated with real-world sound annotation:

- The great within class diversity of sounds (e.g. cars at different distances and speeds) in combination with the co-occurrence of other classes makes it difficult to interpret a visual rendering of the signal as spectrogram and to annotate the visual representation without listening to the sounds in context. Visual inspection of spectro-temporal representations is an important aid for annotation, but attentive listening to the sound is essential.
- Sonic events are often difficult to recognize using sound as the only modality. It is important to annotate the sound during, or soon after, recording. The use of video information can be very helpful whenever the sound sources are clearly visible and easily attributable (which is often not the case).
- Anecdotic evidence suggests that annotation by someone who was not present when the sound was recorded is much more error-prone and often many sounds cannot be annotated in detail. For example, the difference between cars, truck, busses, and even motorcycles is usually not at all obvious.
- The co-occurrence of multiple qualitatively different sonic events and sound producing processes can lead to very complex signals, e.g. coffee-making in a lively kitchen. In these cases it is difficult to track multiple uncorrelated processes and describe each in detail. One might aim to annotate the so-called foreground or, alternatively, the events that attract attention. However, this creates the new problem of determining what attracts attention or what to assign to the foreground.
- The large number of individually distinguishable events of a similar kind, such as singing birds in a forest, entails a lot of repetitive work.

- Realistic environments contain many barely audible events, e.g. distant speakers, which might or might not be included in the annotation. Not including these might unjustly punish a detection system that detects the valid, but unannotated, events. Conversely, including even the faintest events is both time-consuming and prone to classification errors.
- Finally, the determination of the precise moment of the start and end of audible events is subject to similar difficulties as those in the previous point. Especially the detection of the on- or offset of a gradually developing event, like a passing car in a complex environment, is often quite arbitrary. If the measure of success of a recognition system is based on determining the intervals in which events occur, the system is punished for any deviation of this arbitrary choice.

The difference between annotators who were present and who were not, suggests that the sonic evidence may often be insufficient (for the human listener). This poses a fundamental problem for each sound-only annotation or recognition system, whether human or machine; a correct recognition result may simply be impossible. Hence, a perfect ground-truth is not a realistic goal for a real-world sound recognition system. Instead, a performance equivalent to human performance when not present during recording is more appropriate.

The current paper focuses on an annotation tool that helps to provide more insight in these problems and helps to alleviate a number of them. It assists a human annotator by reducing the number of repetitive actions by automatically suggesting annotations based on previous annotations. This allows for the human annotator to accept the suggested annotation simply as an instance of the proposed class, instead of having to select it from a (long) list of possible classes. Within the annotation system we try to maximize the probability that the true event class is on top of the list. Initially this list is simply alphabetic. During manual annotation the class list is reordered according to the estimated probability that a certain event is an instance of the most likely classes.

In the next section, we will give an overview of the annotation system. Furthermore, we present the data on which it is tested. In the third section we will give the results of a pilot-experiment on a set of real-world recordings. The paper ends with a short discussion of the annotation process.

2. METHODS

In this section we first describe the data set that is used to test the annotation system. This system is based on processing sound in the spectro-temporal domain. Therefore, the sound signal is first pre-processed, which will be explained in part B. Subsequently, we describe how the sound is segmented into regions that are likely to include the most energetic spectro-temporal evidence of the main sources. In part D we show how these regions are described in terms of a feature vector, and how this feature vector is used to classify the regions. The section is concluded with a system overview, which is shown in Figure 1.

A. Dataset

The dataset was collected under different weather conditions on a number of days in March 2009 in the town of Assen (65,000 inhabitants, in the north of the Netherlands). The recordings were made by six groups of three students as part of a master course on sound recognition. Each group made recordings of three minutes at six different locations: a railway station platform, a pedestrian crossing with traffic lights, a small park-like square, a pedestrian shopping area, the

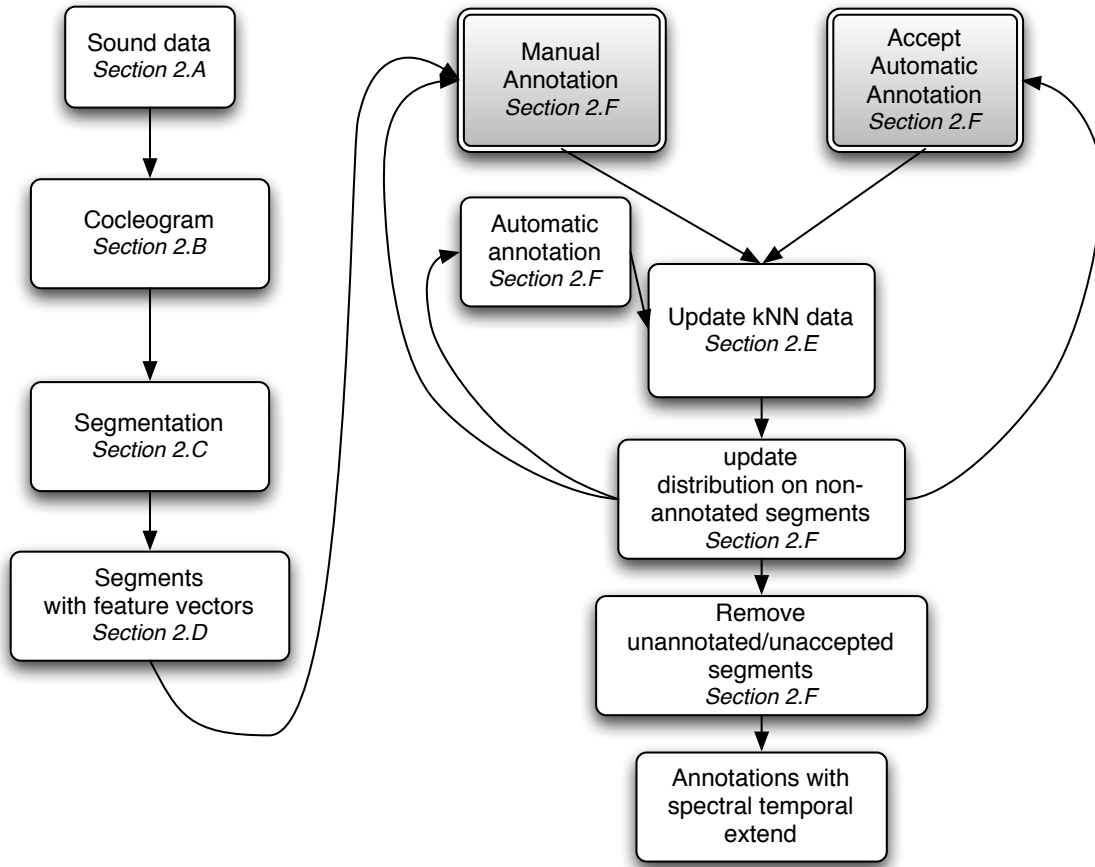


Figure 1. Overview of the assisted annotation system. The two gray blocks are the only places of human intervention.

edge of a forest near a cemetery, and a walk between two of the positions. Recordings were made using M-Audio Microtrack-II recorders with the supplied stereo microphone at 48 kHz and 24 bits stereo. This data, with annotations by the students, will be made available on <http://daresounds.org>.

B. Preprocessing

Conversion to the time-frequency domain is performed by a gamma-chirp filter-bank⁸ with 100 channels. The filters are given by:

$$h_{gc} = a t^{N-1} e^{-2 \pi b B(f_c)t} e^{j(2\pi f_c t + c \log(t))}$$

with $N = 4$, $a = 1$, $b = 0.71$ and $c = -3.7$. f_c is the channel center frequency. The center frequencies are equidistant on a logarithmic axis between 67 Hz and 4000 Hz. The channel bandwidth $B(f_c)$ is given by:

$$B(f_c) = 24.7 + 0.108 f_c$$

The output of the filter is squared and leaky-integrated with a channel-dependent time-constant: $\tau_c = \max(5, 2/f_c)$ ms. The resulting time-energy representation is down-sampled to 200 Hz and converted to the decibel domain. The resulting matrix of 100 channels with time-energy values is termed ‘cochleogram’.

This cochleogram representation shows minimal biases towards certain frequencies or points in time. For example, unlike an FFT-based representation a cochleogram does not show frequency dependent spectral leakage, which occur due to windowing effects when excited by a sine-sweep. This entails that visible details reflect signal properties and not processing artifacts. A cochleogram shows a combination of sinusoidal/tonal (horizontal), pulse-like (vertical), and noisy components, depending on the sound signal. While channel-dependent shapes characterize pulses and tones, noise is characterized by channel-dependent energy fluctuations that are normally distributed.

Many sources produce predominantly sinusoidal (harmonic) or pulse-like sounds (impact sounds)⁷. Thus measuring the local strength of tonal and pulse-like cochleogram contributions is informative of source identity and may be used in a feature vector. The local tonal and pulse-like contributions correlate to the height of the local energy value compared to neighboring values. These are called the peaks-above-surrounding (PAS) values^{9,10} and can be computed for both sinusoidal (PAS_S) and pulse-like (PAS_P) contributions. Both measures are expressed in terms of the standard deviation of noise. Strongly positive or negative values (e.g. more than three standard deviations from the mean of the noise) indicate values that are unlikely to originate from noisy (broadband) components.

Local PAS values are calculated through channel dependent filtering of the cochleogram (see figure 2). The filter for tones is designed by measuring the width of the energy-peak of a pure tone (in the frequency direction). This width is asymmetric, which is taken into account. The width is measured at an energy value corresponding to two standard deviations of white noise

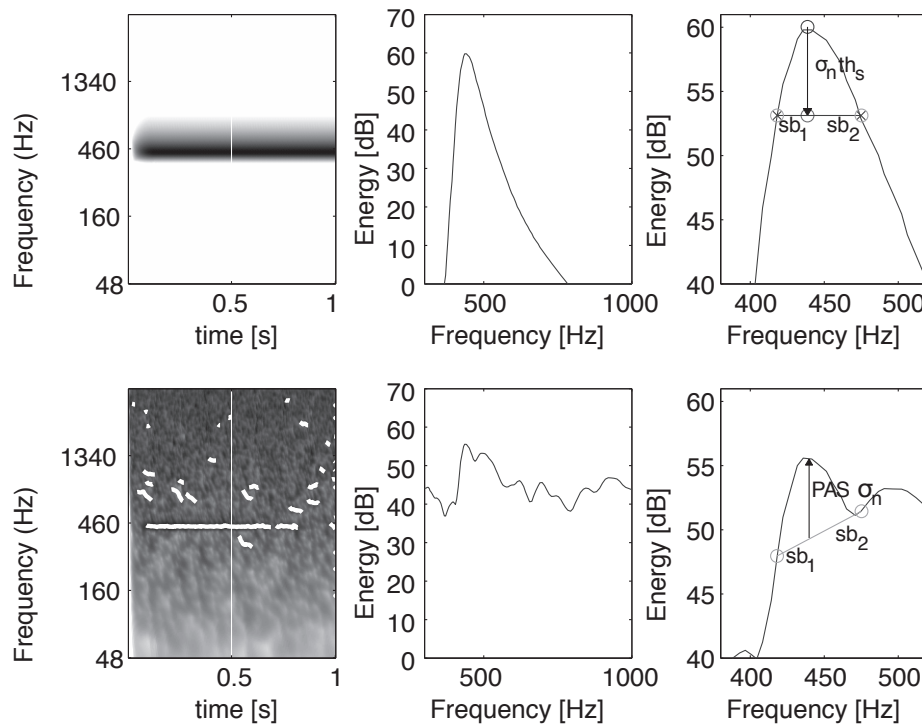


Figure 2. The left panels show two cochleograms of pure tones, in clean situations (upper) and in 0 dB white noise (lower). The middle and right panels show the energy profile at $t=0.5$ s. The upper panel show the derivation of the filter width (sb_1 and sb_2) at th_s times the standard deviation σ_n of white noise below the energy maximum. The lower panel shows the application of the filter in noisy conditions. The difference between the mean energy at sb_1 and sb_2 , and the energy at the TF point is the PAS_S.

under the energy maximum. Filtering corresponds to averaging the energy at the filter-width on both sides of the time-frequency point and subtracting the average from the energy value at the center. This value is normalized with the local standard deviation of white noise to yield the local PAS_S value. The computation of the pulse-like local contribution, PAS_P, is identical, except that the local width of a perfect pulse (in the temporal domain) is used.

C. Segmentation

The segmentation strategy is fairly basic. It is aimed at the inclusion of spectro-temporal maxima in the form of blobs in the spectral and/or temporal direction. These blobs become prominent by subtracting a strongly smoothed cochleogram from the original. The cochleogram is smoothed in the temporal direction through leaky integration with a time-constant $\tau = 5$ s. The time constant τ determines the separation between fast, typically foreground, sonic events and slow, typically background, events. The leaky integration operation corresponds to a delay in the expression of mean energy values that is corrected by time-shifting the resulting values backwards with the time-constant. This time-shift leads to a delay equal to the time-constant, which is not problematic for off-line processing, but that is not desirable for online and real-time processing. The temporal smoothing of time-series $x(t)$ to yield $x_s(t)$ is defined by:

$$x_s(t) = x(t-\Delta t) e^{(-\Delta t/\tau)} + x(t) (1-e^{(-t/\tau)})$$

Δ denotes the frame step of 5 ms. In addition to temporal smoothing, the cochleogram is also smoothed in the frequency direction by taking a moving average over 7 channels. The difference between the original cochleogram and the smoothed cochleogram can be termed a fast-to-slow-ratio and is expressed in dB.

The regions with a fast-to-slow-ratio of more than 2 dB are assigned a unit value in a binary mask. This mask is smoothed with a moving average in both the temporal direction (25 ms) and the spectral direction (5 channels). The final mask is obtained by selecting average mask values greater than 0.5, which smoothens region perimeters and reduces the number of supra-threshold time-frequency points in the inner-regions of the mask that lead to small holes in the mask. The final segmentation step is the estimation of individual coherent regions in the mask and to assign a unique number to each region. The smallest bounding box that contains the whole region is used to represent the region graphically (see figure 3). There are no special safeguards to ensure either that each region represents information of a single source, or that all information of the source is included in the regions. For example, when two cars pass at approximately the same time, a single region will represent both. Alternatively, sounds that are partially masked by (slowly developing) background sounds tend to break up into a number of smaller regions, that are each less characteristic of the source. Nevertheless, the current settings seem able to include important source information of a wide range of sources.

D. Feature vectors

The feature vectors must describe the source information represented by the regions. The 37-dimensional feature vector represents properties related to the physics of the source. Note that normal approaches to environmental sound feature estimation¹¹ make no effort to include source physics other than representing frequency content. The use of the PAS-values allows us to

attribute signal energy to tonal, pulse-like, or noisy contributions, which result from either source limitations or transmission effects. Table 1 describes the feature vector.

The feature vector reflects the channel contributions per region, the fast-to-slow ratio, and the distribution of tonal (PAS_S) and pulse-like (PAS_P) contributions. These signal descriptors are represented by 7 different percentile values from the histogram of the local indicators. Different percentile values might be indicative for different classes. For example, the 90 and 95 percentile values might be highly indicative for footsteps in noise, while the other percentiles might not discriminate from a the noisy contribution in a car passage.

Table 1: Region feature vector description

Feature	Dim	Percentile or range	Description
Size	1	> 0.02	Fraction of spectro-temporal area equivalent to 1 s
Channel mean	1	1 - 100	Average channel number (1 is highest, 100 is lowest). This corresponds to average log-frequency contribution.
Channel std	1	< 50	Provides a single number indication of the channel spread.
Fast-to-Slow-Ratio	7	[5 10 25 50 75 90 95]	The distribution of Fast-to-Slow-percentiles provides information about the distribution of strong foreground values
PAS_S	7	[5 10 25 50 75 90 95]	The distribution of PAS_S values provides information about the distribution of strong sinusoidal contributions.
PAS_P	7	[5 10 25 50 75 90 95]	The distribution of PAS_P values provides information about the distribution of strong pulse-like contributions.
Channel distribution	7	[5 10 25 50 75 90 95]	The channel distribution provides more detailed information about the pattern of contributing channels.
Channel spread	3	5-95, 10-90, 25-75	Provides more detailed information about the channel spread as the difference in channel numbers between three percentile pairs of the channel distribution
Frame spread	3	5-95, 10-90, 25-75	Provides more detailed information about the temporal spread as the difference in frame numbers between three percentile pairs of the frame distribution

E. Classification

Classification of regions based on the feature vector must lead to proposed classes for regions similar to annotated regions. The classifier should function in an on-line fashion and must not require long re-training phases. Additionally, the classifier should be able to function with minimal training data. This combination of demands suggests a simple k-nearest-neighbor (kNN) classifier¹². Such a classifier stores all training feature vectors in a matrix. It classifies each region by calculating the Euclidian distance d to all vectors in the training matrix and selecting the k closest training examples which each represent an example of a single class. A simple majority voting system is used to determine the best class for the region. To create a distribution over multiple classes we count the number of occurrences a class in the top $k = 5$ and divide this by $(k * d / \sum d)$ to get a number indicating the match.

F. System overview

An overview of the annotation system is given in Figure 1. The system loads, pre-processes, and segments the data of a single file and presents the result to the user. First, the user selects a region. The selected region can be played as sound and a matching class can either be selected from a class-list or added to the class-list. Initially the list is ordered alphabetically, but when sufficiently matching examples of the class have been encountered, the top-positions on the list will be ordered according to class-likelihood. After class assignment, the kNN training matrix is

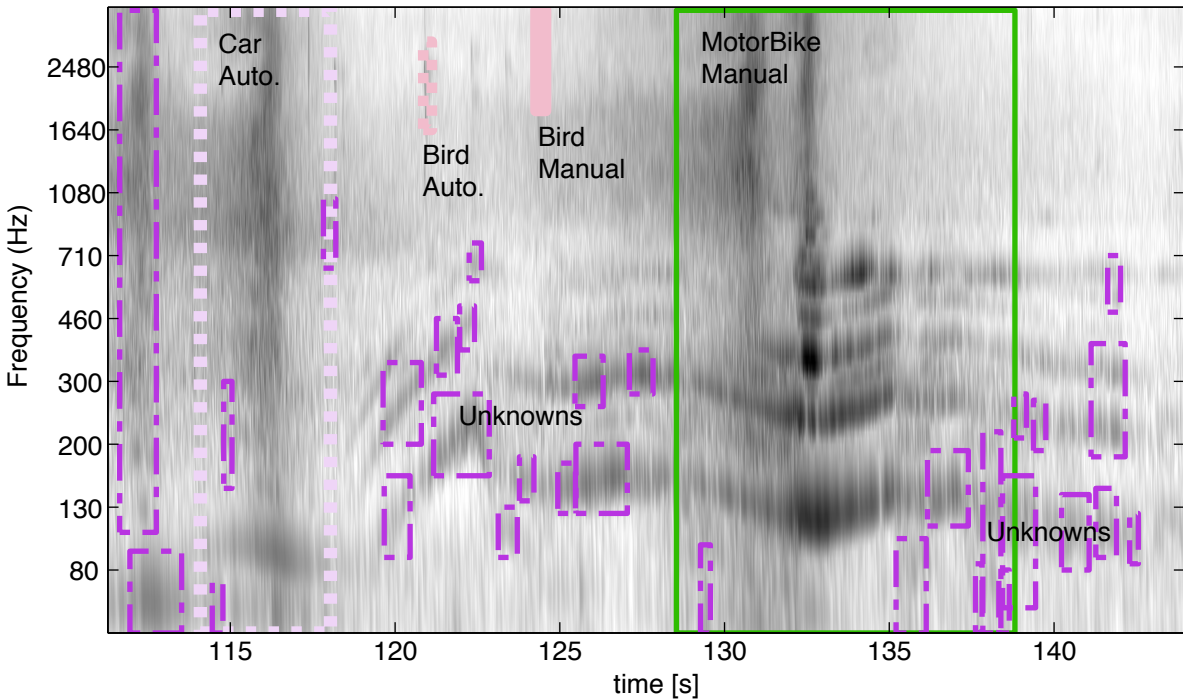


Figure 3. The cochleogram of several passing cars. Darker means more energy. Solid lines denote manual annotation. Dashed lines denote automatic classification, the dash-dotted lines denote still unclassified regions. The cars are segmented in the pink boxes. A bird is segmented in the green box. The purple boxes are not (yet) annotated.

extended with the feature vector of the region. If the match of a class exceeds a threshold (here set to $p > 0.04$), it is automatically classified as that class. If the match exceeds 0.01, the region will be conditionally classified, which entails that the user has to accept the classification before it is included in the kNN training matrix. Regions that end up without annotation are discarded after the user decides that the file is annotated in sufficient detail.

To measure the performance of the system we track the class-rank of manually annotated regions, the number of automatically annotated regions, and the number of accepted regions. The number of discarded regions is a measure for the performance of the segmentation. The final output of the system is a list of classes assigned to regions.

3. RESULTS AND DISCUSSION

Measuring the performance of the system in meaningful numbers is difficult. A sensible measure is the time saved by this system compared to full manual annotation of start and stop times of the sound events. However each annotation session will result in different annotations due to the reasons formulated in the introduction. This makes a fair comparison difficult. Furthermore the current system is not yet sufficiently user-friendly to allow a good comparison. Alternatively we measured how often the correct class was suggested by the kNN classifier. The results are shown in table 2. When a class is either not annotated yet or misclassified, it is marked as “alphabetical”, otherwise it is ranked as first or second. Without automated annotations one expects an average rank equal to half the number of classes. Note that with $k = 5$ it is possible to have 5 different classes in the list, but third, fourth or fifth ranked classes did not occur in the test.

The current system is a first installment of the annotation tool. Its initial performance is encouraging, but each aspect can and must be improved before it is truly useful. The further

Table 2: Results of an annotation session on the Assen dataset ($N = 101$)

alphabetical	first	second	total
15%	74%	13%	100%

improvement of the tool will depend strongly on an improved understanding of the annotation process, which in turn is a special form of listening. Initial experience with assisted annotation indicates that the annotator does not analyze the file from start to end, but instead prefers to focus either on individual environmental processes or on individual auditory streams. This allows maximal benefit from process/stream dependent knowledge. It is possible that everyday listening¹³ reflects this so that at most one stream is analyzed with all available knowledge: the focus of auditory attention. All other streams are analyzed in less detail. This observation in combination with the annotation problems formulated in this paper suggest that the question “What do we do when we listen” should become a focus of active research.

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