Applying bioacoustic monitoring to the detection of bird in a complicated environment

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A B S T R A C T :

Trends in bird population sizes are an important indicator in nature conservation but measuring such sizes is a very difficult, labour intensive process. Enormous progress in audio signal processing and pat- tern recognition in recent years makes it possible to incorporate automated methods into the detection of bird vocalisations. These methods can be employed to support the census of population sizes. We report about a study testing the feasibility of bird monitoring supported by automatic bird song detection. In particular, we describe novel algorithms for the detection of the vocalisations of two endangered bird species and show how these can be used in automatic habitat mapping. These methods are based on detecting temporal patterns in a given frequency band typical for the species. Special effort is put into the suppression of the noise present in real-world audio scenes. Our results show that even in real-world recording conditions high .

Keywords: birdwatchers, migrations of birds, complex acoustic environments.

Introduction:

In order to evaluate the impact of human activities on popula- tions of wild animals and to decide on the most effective actions for nature conservation, we need fundamental information on the extent of changes in the living environment. Birds are a good indicator for changes in biodiversity because they are distributed over a wide range of landscapes, are easy to detect in comparison to other animal groups and we have a good knowledge on the biol-ogy of most of the species. It is a fortunate fact that, at least in most European countries, we have huge associations of skilled and expe- rienced birdwatchers, who willingly give their knowledge to non-profit service and support monitoring programs. Due to the activity of birdwatchers, data regarding trends in population sizes for cer-tain European bird species has been recorded and made available since 1980 (Gregory et al., 2005). Different standardised methods for bird census have been developed (Bibby et al., 1992). Most of them are based on the mapping of singing males, assuming that the number of territorial males is equal to the number of breeding pairs. The most widely used method for estimating the number of breeding birds is based on point counts where all individuals heard and seen from stationary places are estimated (Klvaňová and Vorˇíšek, 2007).

Complementing traditional approaches, vocalisations of birds serving for territory maintenance and mate attraction can be used for an automated acoustic monitoring of bird populations (Bran- des, 2008; Frommolt et al., 2008). The main advantage of such an automated bioacoustic approach, as compared to previous meth- ods, lies in the long-term recording in the absence of an observer. It allows to estimate bird numbers in ecologically sensitive areas (like nature reserves) or in areas that are difficult to access (for example large reed habitats). Even nocturnal birds and birds with low vocal activity could thus be effectively counted. In addition to the need of an applicable autonomous recording device, the greatest challenge is the development of appropriate pattern recognition algorithms giving reliable results even in complex acoustic environments. In order to apply acoustic methods for the monitoring of bird species, we have to solve two problems. We need pattern recognition algorithms for the automatic detec- tion and identification of bird species and we need appropriate techniques for the estimation of the number of individuals.

However, these works mostly deal with relatively simple signals without back- ground noise. The number of detected calls was used as a criterion to assess the occurrence of migrating birds. For noisy environments, hidden Markov models were successfully applied to frequency modulated sounds (Brandes, 2008; Trifa et al., 2008).

In this work we report about an approach using pattern recog- nition techniques for continuous bird monitoring. Our techniques are based on event detection and repetition rate estimation of bird song elements. Additionally, the algorithms use noise estimation from frequency bands known not to contain the bird's vocalisa- tions and apply them to an effective noise reduction. They can be used in parallel with traditional monitoring methodology to yield methods with improved speed and reproducibility in those cases where reliable detectors for bird vocalisations are available. In con- trast to other applications our algorithms have been designed spe- cifically for certain endangered target species. This approach was chosen in order to improve recognition rates even under poor acoustic conditions and it leads to a larger range covered by a sin- gle sensor unit in comparison to human observers and algorithms requiring high signal-to-noise ratios. Moreover, we apply this methodology to a quantitative survey of a real bird population yielding automatic map generation of breeding territories for one of the considered bird species.

1. Pattern recognition for animal sounds

In comparison to other fields in pattern recognition, little work has been carried out regarding animal sound recognition. Never- theless, a wide variety of methods and animal species have been examined. In previous studies, bird song recognition with hidden Markov models has been proven to be a useful tool in the recogni- tion of bird song elements (Kogan et al., 1998). In this case, record-ings were made under laboratory conditions with captive birds and microphones close to the cages.

The most obvious candidates for species recognition by sound are birds. But a lot of other species have also been subject to efforts in automated recognition, for example, crickets and grasshoppers (Schwenker et al., 2003; Farr and Chesmore, 2007), marine mam- mals like whales and dolphins (Deecke et al., 1999; Brown and Miller, 2007; Mellinger et al., 2007), frogs and bats ([Obrist et al., 2004). Methods like these are of interest in applications such as monitoring for the presence of certain species in an area, behav- ioural studies, assessing the impact of anthropogenic noise on ani- mal vocalisations and many others.

Currently, there are no guidelines for the direct application of standard methods from machine learning to pattern recognition problems in time dependent data. The main problem here is how to decide which parts of a signal are to be used as input for such methods. Often, this problem is dealt with by applying segmentation algorithms. Unfortunately, this is equivalent to finding the starting and ending positions of animal vocalisations or their segments which is extremely difficult. This is particularly true for natural audio scenes where current solutions tend to be unreliable because of low signal-to-noise ratios. If, however, this gap is bridged in some

way or the other, numerous classification algorithms are available for application. The classical dynamic time warping algorithm Deller et al., 1993 has found application in cases where animal vocalisa- tions are not too variable and can thus be recognised by template matching (Brown and Miller, 2007). Neural networks present an obvious candidate for pattern classification. In addition to bird calls (Mills, 2000) and bird song elements (Nickerson et al., 2006), such networks have been applied to the recognition of animal species like marine mammals (Deecke et al., 1999) and crickets (Schwenker et al., 2003). Self-organising maps have also been used for various classification tasks concerning animal sounds (Mitsakakis et al., 1996; Somervuo and Härmä, 2003; Placer et al., 2006). Also, decision tree classifiers like C4.5 (Quinlan, 1993) have been used for bird song recognition (Taylor, 1995). When regarding spectrograms of animal vocalisations, the idea of applying image analysis methods springs to the mind, and several such approaches have been reported (Obrist et al., 2004; Brandes et al., 2006).

Several feature representations for animal sounds have been pro-posed. Because of the tonal quality of many bird songs, sinusoidal modelling is a promising feature extraction step for bird song recog-nition and has been studied extensively in this context (Härmä et al., 2003). Often, however, animal vocalisations are not very well repre- sented using the Fourier transform. This is the case when vocalisa- tions are noise-like in the sense that their energy spreads over a broad frequency range. Wavelets have been proposed as an alterna- tive for analysing such sounds. They have been shown to concentrate energy in comparatively few wavelet coefficients for sounds which otherwise need many Fourier coefficients for their representation (Selin et al., 2007). In (Possart, 2002; Seekings and Potter, 2003), wavelets have been applied as feature extractors for the classifica-tion of bird and whale songs. In the latter case improvements over spectrogram matching techniques have been achieved. Here, wave- lets were also introduced as a means to tackle the segmentation problem described above. In (Fagerlund and Härmä, 2005), other representations than wavelets have been proposed. For example, MFCCs have been found to give good representations in such cases. Moreover, some bird songs are rich in harmonic structure, a fact that can be used for their recognition (Härmä and Somervuo, 2004). More generally, several sets of features for the representation of bird songs have been compared in (Somervuo et al., 2006). Still, the recognition of bird calls in natural environments remains a great challenge (Tanttu et al., 2006). This is caused by the main source of complexity in natural audio scenes: the presence of multiple sound sources overlapping in time and frequency.

2. Bird song detectors

In this section, we describe algorithms designed for the purpose of detecting the presence of species specific vocalisations. The two target species, the Eurasian bittern (*Botaurus stellaris*) and the Sa-vi's warbler (*Locustella luscinioides*), were chosen for their value for nature conservation. They are indicator species for extended reed beds. The two types of special purpose algorithms described in this section are tailored for different types of signals. The first algorithm to be described will be useful for detecting very simple spectral events in the presence of broadband noise. The second algorithm deals with signals characterised by the periodic repeti- tion of simple elements which is often encountered in animal vocalisations.

2.1. Simple events: the Eurasian bittern

The most obvious indication of the presence of the Eurasian bit- tern is the booming vocalisation of the male. Acoustical monitoring allows for passive investigation of bittern activity.

The call of the Eurasian bittern is very simple. It is almost com-pletely characterised by its centre frequency of about 150 Hz. Calls typically occur in call sequences with a characteristic repetition frequency. In low noise conditions, this call can be detected by finding energy peaks in a suitable frequency band. Fig. 1 shows a spectrogram of the bittern call. Each call begins with a short seg-ment at a slightly higher frequency. This part, however, cannot be used for pattern recognition because it can no longer be de- tected reliably in the presence of noise or at larger distances from the animal.

In order to achieve sufficient frequency resolution in low fre- quency bands, input signals are downsampled to 6 kHz prior to further analysis. The signal is analysed with a sliding window of 21 ms length. Downsampling increases the effective window length to 170 ms.

Let $S(x; t)$ be the windowed power spectrum of a downsampled input signal s. The energy weighted novelty $N_{\ell;h}$ for a frequency range from ℓ to h at time t is defined by fixed factor a controls how much influence the noise measure has in the combined criterion. Values for a; ℓ_b; h_b; ℓ_n, and h_n are found experimentally. In particular, the values for ℓ_b and h_b are de-rived from a training set by spectrogram inspection. Suitable val-ues for a are in a range from 5 to 10.

Using the feature $B[S]$ directly for finding bittern calls still leads to a high number of false positive detections due to noise. We can, however, use the fact that the bittern usually calls in sequences with almost constant length pauses between calls. Fig. 3a shows the features $B[S]$ for a 97-min recording from our study site (see Section 4.1). The recording is characterised by a high amount of noise caused by trains, wind, and water. Direct interpretation of the features would lead to a large number of false positive detec- tions of the bittern call.

This feature sequence measures the strength of the autocorrela- tion at lags $a \ldots a + h - 1$ representing typical call repetition rates. We subtract the same measure for lags $b \ldots b + k - 1$ indicating shorter repetition rates in order to remove the impact of noise events showing short repetition rates. Finally, candidate positions for the bittern call can be found from R by peak picking combined with thresholding.

2.2. Element repetition: Savi's warbler

The Savi's warbler has a very characteristic song formed by the continuous repetition of simple song elements at an almost con- stant rate of roughly 50 repetitions per second. Most of the war- bler's song's energy is found in the frequency band between 3.8 and 8 kHz. When recording this song from a great distance, the lowest frequency .
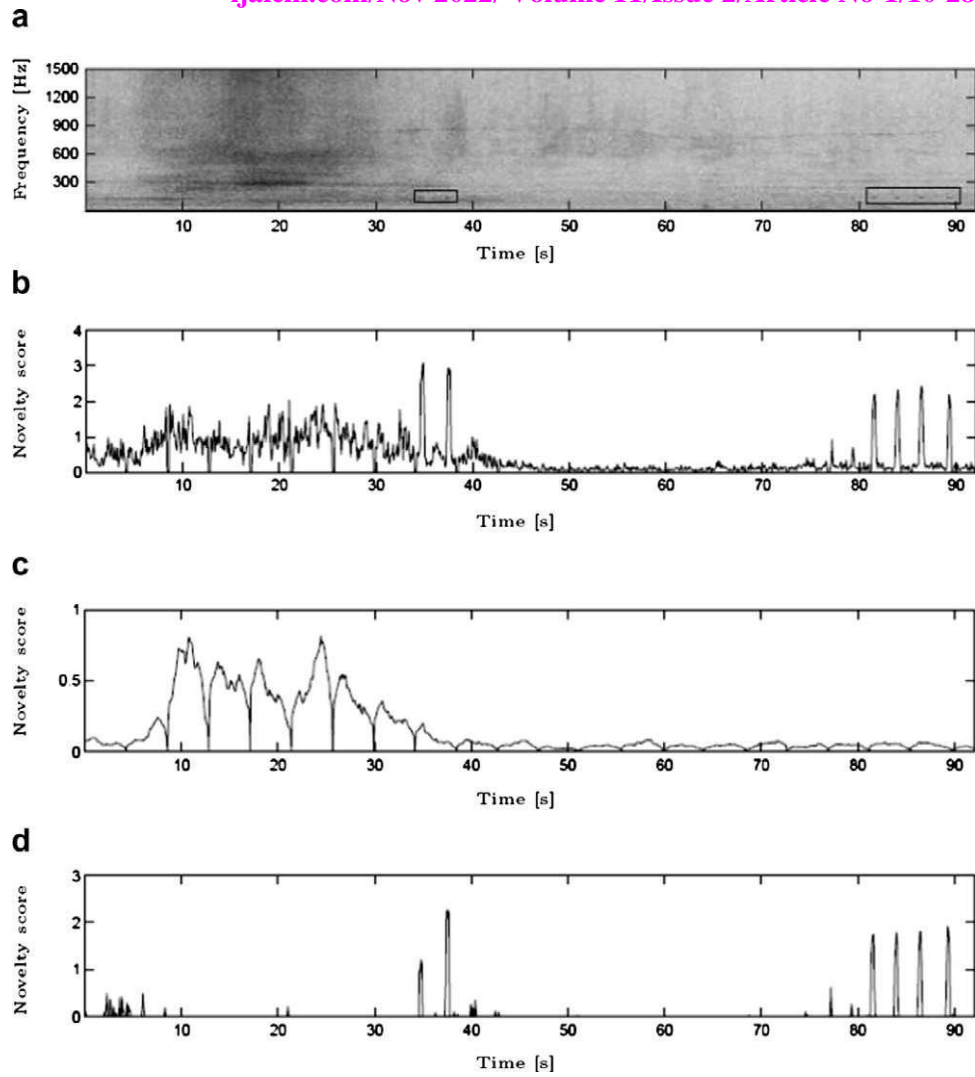
Fig. 2. Spectrogram S of a recording containing the call of the Eurasian bittern (marked by boxes) as well as broadband noise (a). The impact of this noise on the novelty score $N^{\cdot}_{b;h_b}[S]$ (b) is removed by subtracting the weighted low-pass filtered novelty $N^{\cdot}_{n;h_n}[S]$ (c) estimated from a neighbouring frequency band, resulting in a combined feature $B[S]$ (d).

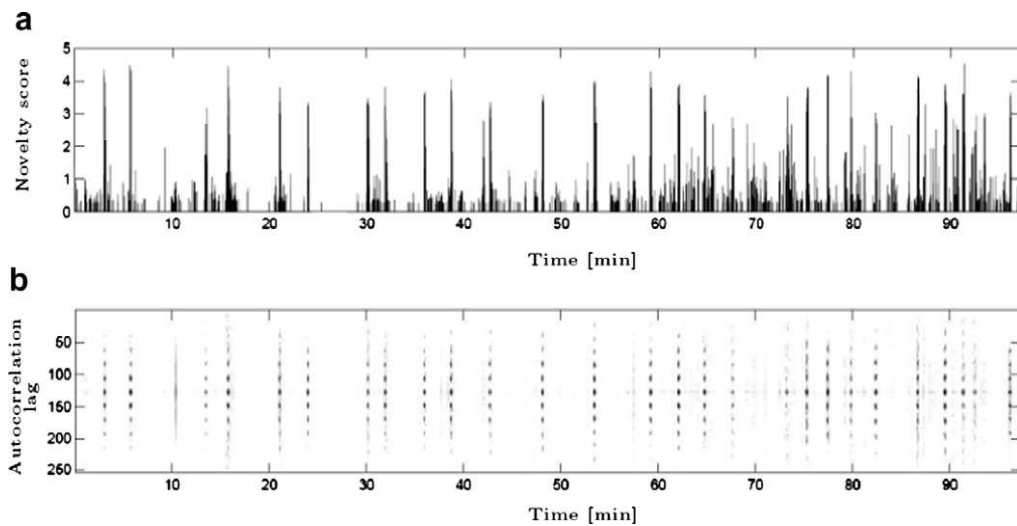Fig. 3. Features $B\natural S$] indicating activity in the frequency band characteristic for the Eurasian bittern after noise removal (a) and their windowed autocorrelation $A\eth s$; $t\text{\thorn}$ (b) indicating call repetitions.

3. Results for a real-world monitoring scenario

In order to evaluate our pattern recognition algorithms, we ap- plied it to recordings attained at Lake Parstein in the north-east of Germany (federal state Brandenburg) in 2006 and 2007. The north- ern part of the lake is surrounded by extended reed belts providing breeding habitats for the two target species. Recording was con- ducted in a project with the aim to examine the applicability of pattern recognition methods as a tool for monitoring bird vocalisa- tions. A four-channel stationary microphone array of cardioid microphones (Beyerdynamic MC 930, Sennheiser ME 64) was usedon several positions at the lake shore, from a lookout, and from a boat. The best recordings of vocalisations from the reed zone were achieved when the microphones were placed on a boat on the lake. In the best case, calls of the bittern could be recorded over dis- tances of about 1 km. Acoustic data were acquired by an EdirolR4 field recorder at a sampling rate of 48 kHz and 16 bit accuracy. Recordings were performed at dusk and during night in order to cover audio scenes with a complexity level somewhere between the simple situation of a laboratory recording and the extremely complex situation of bird choirs at daytime.

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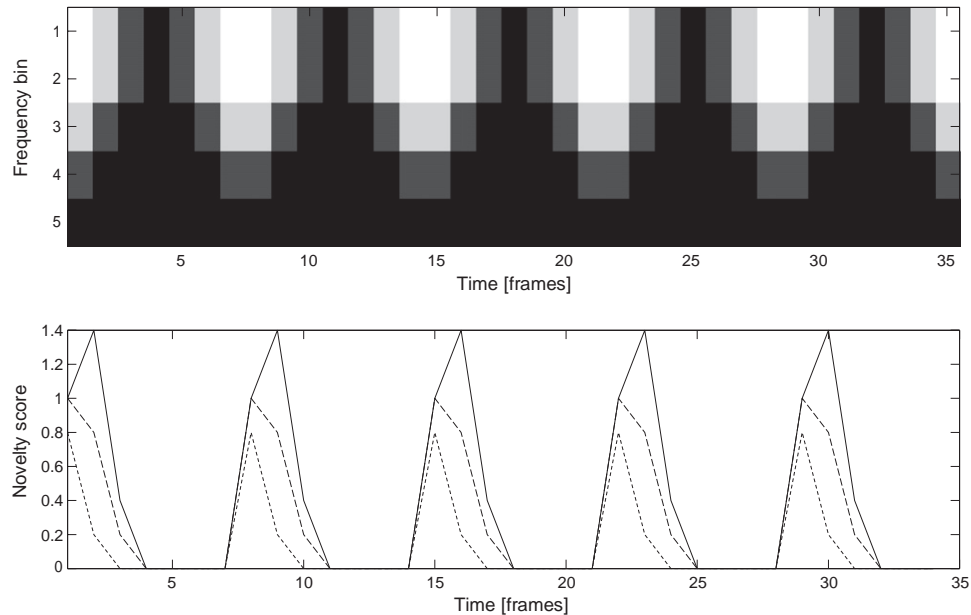

Fig. 5. The ability of the novelty features to reflect song element onsets depends on the subband. This is illustrated by an artificial example of a spectrogram (a). The sharpness of the novelty curves (b) depends on the frequency band from which they are extracted. The solid novelty curve is extracted from frequency bins 1–3, the dashed curve from bins 2–4, and the dot-dashed curve from bins 3–5.
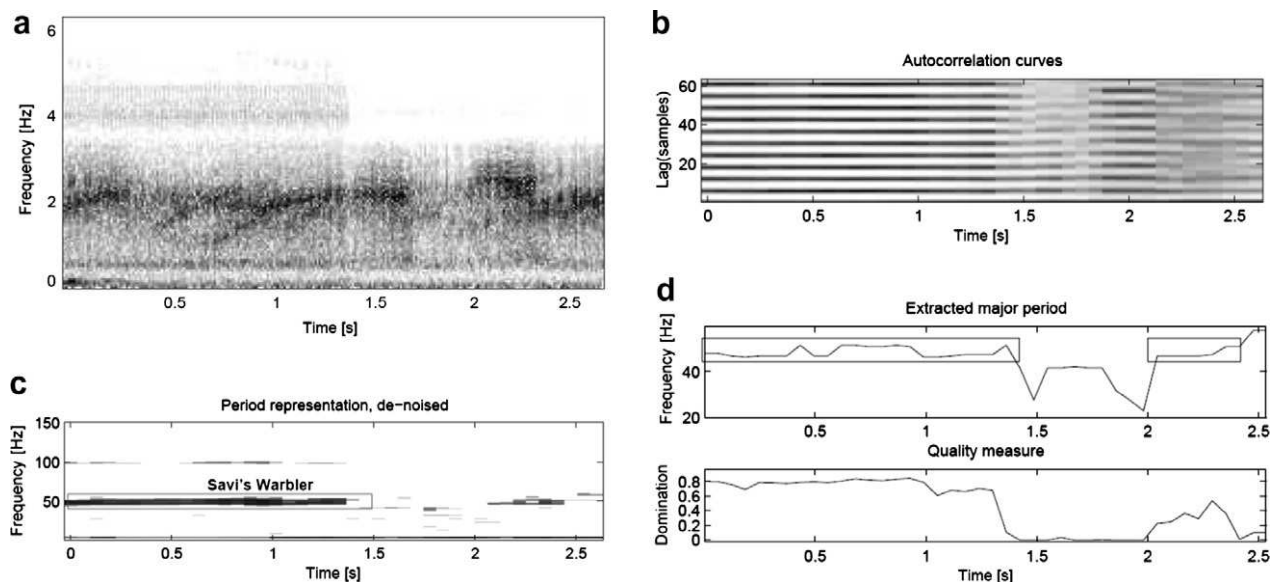
Fig. 6. The presence of elements repeated with a given repetition rate is estimated using autocorrelation-based features. (a) Spectrogram of the analysed signal. In the first half of the signal, a Savi's warbler's song is clearly visible. (b) Corresponding autocorrelation curves A_R for successive frames. (c) Fourier transformed autocorrelation curves after subtraction of the flanking band's features and (d) Extracted element repetition periods and corresponding domination values. Frames indicate detected warbler songs.

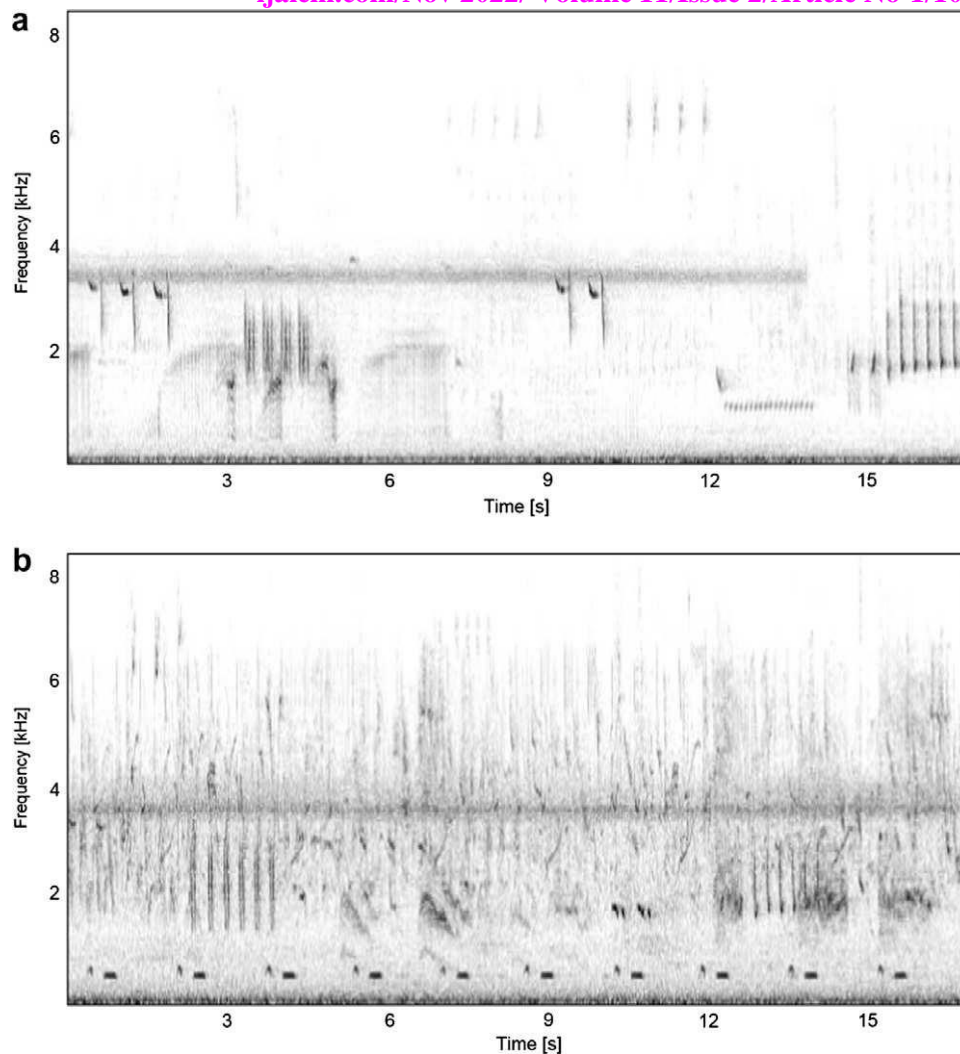*3.1. Acoustic environment at the study site*

Fig. 7. Spectrograms visualising biogenic noise at the study site during the night (a) and in the morning (b). Both spectrograms show the song of Savi's warbler at just below 4 kHz.

stein. The recordings are from five different days, some of them were taken from a boat, others from the lakeshore. In Table 1, we give the number of time positions reported by the algorithm, the number of false positive detections (reported positions where no bittern activity is audible) and the number of false negative detec-tions (positions, where bittern activity is audible, which were not reported by the algorithm).

The number of false positive detections is very much dependent on the acoustical situation. False positive rates were especially high on Day 3 and Day 5 for different reasons. On Day 3, a lot of speech is present in the recording. Especially in the beginning of the recording, a lengthy description of the recording equipment is spoken directly into the microphones and leads to a high number of false positives. While this kind of problem can often be elimi- nated before starting the analysis process, it still shows a typical problem met in long-term monitoring situations. When a lot of recording material from a field experiment is to be analysed, it is not always feasible to manually remove spoken annotations of the recording sessions. In that case it is a desirable property for detection algorithms to cope with this type of data.

On Day 5, the role of speech is replaced by wind rhythmically impacting on the microphone. Most of the false positives can be explained by these two effects. Some of the false positives may also be due to the fact that the autocorrelation feature $\hat{a}$ is computed from overlapping windows. This might result in finding one call se-quence twice at different time positions.

False negatives are seldom found with our algorithm, which is a satisfying result. They only occur in two situations: first, extremely silent calls are sometimes dismissed, especially when there are few consecutive calls. Second, our method for noise reduction in the features sometimes leads to a masking effect. When the energy in the band used for estimating noise levels is significantly higher than the energy in the band used for detecting the bittern call, the bittern call can be removed from the features although the call is clearly visible in the spectrogram. Such masking effects also occur in human hearing (Zwicker and Fastl, 1999) and can be the cause for calls which are undetectable by human listeners.

Altogether, our algorithm is a very helpful tool in analysing the presence of the Eurasian bittern. Currently, the main problem is the

high number of false positives from wind. How seriously this affects the utility of the algorithm depends on the task to be solved. For example, if the algorithm is used to demonstrate the presence of the Eurasian bittern in an area, most of the false positives can be disposed of by removing all reported positions with low values of

A. This would result in dropping detections of short sequences of

low calls of the bittern which is bearable as long as some longer or louder calls are present. If detecting very low calls is crucial then an additional feature discriminating wind from bittern calls .
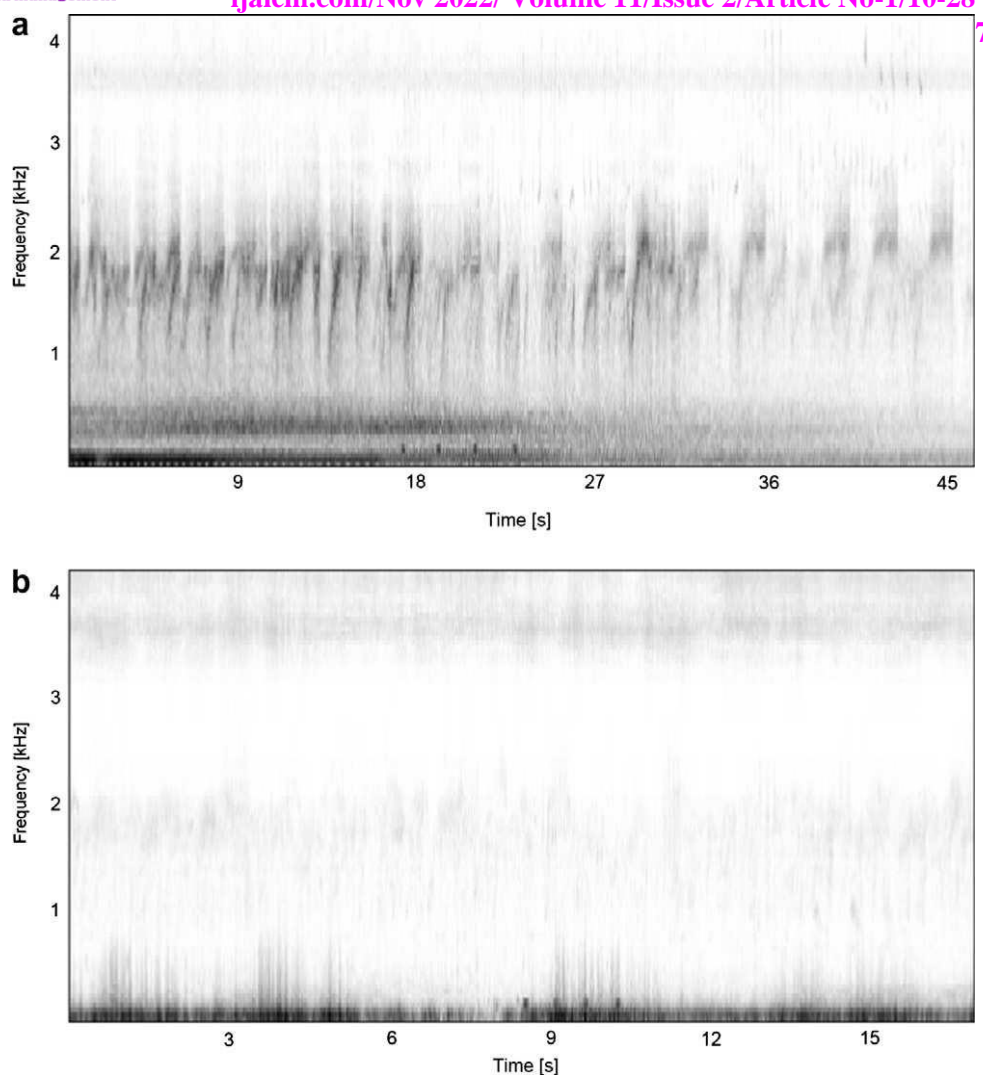
Fig. 8. Spectrograms visualising anthropogenic noise (a) and wind noise (b) at the study site. In this case noise is caused by a train passing by in the distance. Both spectrograms show calls of the Eurasian bittern in a noisy context ((a) from second 18 and (b) from second 9).

Table 1
Recognition results for the Eurasian bitter on five observation days.

Recording	Duration (min:s)	Detections	False positives	False negatives
Day 1	15:21	3	0	0
Day 2	15:41	9	0	0
Day 3	116:51	74	20	7
Day 4	174:30	77	12	2
Day 5	97:15	83	52	1
Sum	419:38	246	84	10

needed. In this context, it is possible to detect calls that are all butinaudible to the human ear.

3.2. Results for Savi's warbler

The recordings used for evaluating the detector for Savi's war-bler, have been attained during the sunrise and sunset periods. They contain a wide range of different birdsongs as well as a mul-titude of background noises. From a database containing several hundred hours of such recordings, an evaluation excerpt of 19 h has been composed to representatively cover the whole range of

Table 3
Number of breeding Savi's warblers in two different areas at the Lake Parstein estimated by two different methods.

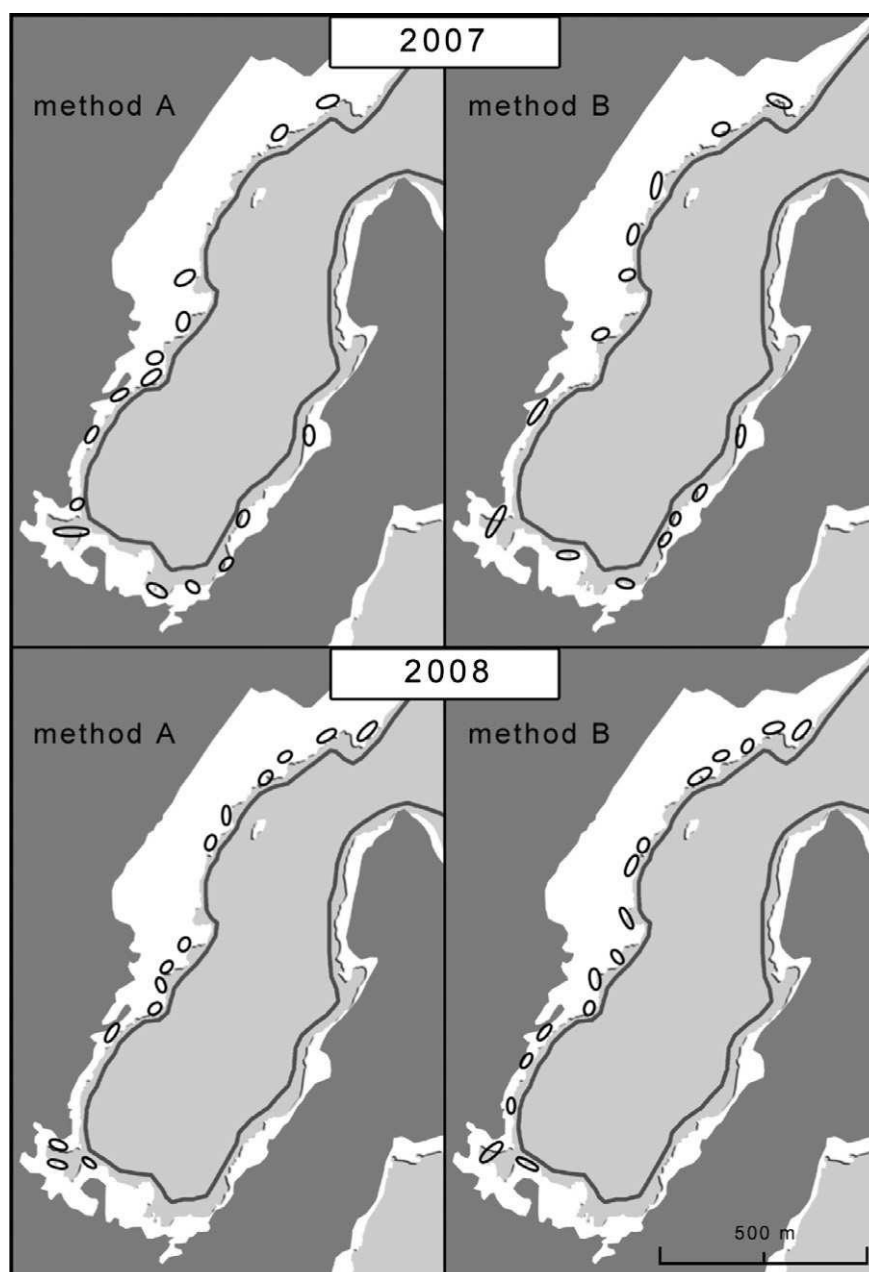| Method	Westernreed bed		Easternbed	reed	Total	
	2007	2008	2007	2008	2007	2008
(A) Mapping by experiencedobserver	15	14	9	15	24	29
(B) Application of pattern recognition algorithm andGPS data	14	16	10	15	24	31

Fig. 9. Estimation of breeding territories of Savi's warblers along the Western reed beds at Lake Parstein in the years 2007 and 2008. A – results from mapping by an experienced observer; B – results from the analysis of sound recordings by pattern recognition algorithm and estimating the position by GPS data. The estimated breeding territories are indicated by black circles. Reed beds are displayed as white areas. The solid grey line shows the GPS track of the boat tours.

becomes much simpler if a separation of the songs is possible. Though not reflected in the above evaluation, individual localisa-tion of multiple contributing warblers is also facilitated by the cur-rent recording setup.

4. Application of bird song detectors to the monitoring of Savi'swarblers

In our work, we could already successfully apply the pattern recognition algorithm for the Savi's warbler described above to the monitoring of the population of this species at our study site at Lake Parstein. For this purpose, we examined songposts of thewarblers at two different reed areas three times each year during the breeding seasons in the period from April to June in 2007 and 2008. In order to cover a more extended area, we decided to use a slow-moving small boat equipped with an electric motor. Itwas driven at constant speed (approximately 30 m/min) alongthe reed beds, keeping a distance of about 20 m from the vegeta- tion. During the boat trip, continuous sound recordings were takenusing two directional microphones (Sennheiser MKH 70) arranged at a 90 degree angle and facing towards the reeds. The position ofthe boat was continuously acquired by a GPS device (Garmin Geko).

On the sound recordings, songs of Savi's warbler were detected by the pattern recognition algorithm described in Section 2.2. De- tected songs with a domination value exceeding a fixed threshold were considered for mapping. The location of song posts was determined concerning the following criteria. If the domination va- lue was higher for the track recorded by the rear-facing micro- phone, a time mark was set to the beginning of the detected song because in this case the boat is moving away from the song- post and closest to it at the beginning of the song. If it was higher for the track recorded by the forward-facing microphone, the endof the detected song was marked respectively. If the total durationof a detected song sequence was longer than 160 s such long se- quences could only be explained as overlapping songs from neigh-bouring birds (for 332 songs uttered during morning hours, 95% areshorter than 161 s in duration, most of them considerably). There- fore, additional time marks were added at a distance of 160 s inthis sequence. Finally, the location of the birds was assessed onthe basis of the synchronised GPS data. The expected song post positions were estimated by first finding the boat position fromthe GPS track using the time markers. This position was then pro- jected into the reed bed.

In addition to the automated observations, an experienced sup-plementary observer on the boat marked every encountered ani- mal in a map as a control test. According to the criteria established for the monitoring program for common breeding birds, we counted a warbler as territorial for both the automated and direct observation when it was observed at least two times a year at the same or nearly the same place.

Applying the two different approaches to two different reed areas in two subsequent years, we found a high consistency inthe number of breeding pairs (Table 3). The maps of the spatial dis-tribution of the territories estimated by the different methods re- veal large similarities as well (Fig. 9). Even though the positions of song posts estimated by different ways did not match com- pletely, the accuracy of the results is sufficient for purposes of long-term monitoring.

5. Conclusion

The computational evaluation of monitoring recordings intro- duces potent technology complementary to the existing meansfor assessing animal populations. Using robust feature extraction
methods, the detectors introduced in the preceding sections fea- ture a high detection precision even when used with badly condi-tioned recordings.

For less specific animal population surveys, the introduced fea-tures may be combined and used for the detection of a wider rangeof animal species. Several approaches to detecting multiple species using a general feature set have been published (Farnsworth, 2005; Brandes, 2008; Selin et al., 2007; Fagerlund, 2007). However, when working with unsupervised recordings performed in an acousti- cally unpredictable area, a great amount of overlap between differ-ent bird vocalisations and other noise sources may occur. In this case, the use of general feature sets may be problematic, particu- larly because the mix of different vocalisations is likely to be re- flected in a complex mix in the feature space. As there is a high degree of variability of such mixtures when considering real sce- narios, the proper training of corresponding classifiers may be a difficult task and can result in considerably less reliable detectionoutputs. In such cases, we therefore recommend the use of highlycustomised detectors which are tailored to the recognition of a small set of species only. An elaborate acoustic scene analysis, also detecting various noise sources, should be considered for further research on large-scale species recognition. In particular, the im- pact of wind on microphones could be detected by using band- width and entropy estimates for strong signal components. In the proposed detectors, the acoustic background is accounted for by using features from an individually shaped flanking band, used for filtering ambiguous events. This flanking band strategy is suit-able for a wide range of animal sounds. Moreover, the feature extraction and classification methods developed in this project show further potential for successful application in the detection of a variety of other species. For example, the periodicity featuresused in the Savi's warbler detector also reflect elementary param-eters of calls from frogs or crickets.

In combination with recorded GPS data tracks, as described in
Section 5, robust localisation and mapping of Savi's warbler territo-ries has been achieved. The synchronised audio and GPS tracks alsoenable the application of detectors for other species.

Consequently, acoustic mapping could be successfully appliedto the survey of the selected species. Since the combination of sound recordings and GPS tracks allows highly standardised dataacquisition, this methodology is appropriate for future use even by observers with limited knowledge of bird songs. Moreover, weare currently improving the present pattern recognition algorithmin order to allow discrimination of neighbouring and simulta- neously singing individuals to guarantee a more autonomous andautomated analysis of the sound recordings. Thus, the populationof the species discussed above could be assessed in a precise man-ner. In contrast to the monitoring of nocturnal migrating birds by flight calls where the number of calls was a rough measure for assessing the intensity of migration (Hill and Hüppop, 2008; Schra- ma et al., 2008), the actual number of territorial males and there- fore the number of breeding pairs was

estimated in our study. In general, this promising approach could also be used for other birdspecies living in reed beds.

For the monitoring of population sizes using stationary recording devices, the proposed algorithms could be combined with existing source separation techniques. This is planned for future research. In particular, the four-channel microphone setup was chosen for applying an acoustic beamforming routine previous to the detection step. Thereby, multiple signal sources should first be separated and then analysed separately. In addi- tion to a simplified estimation of the number of individuals pres- ent, the signal-to-noise ratio will also be improved for each separated signal part. This should result in more precise detec- tions and thus improve the accuracy of the derived population estimations.

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