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Application of time domain signal coding and artificial neural networks to passive acoustical identification of animals

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Abstract

The development of a computer-based system capable of identifying animals automatically from sounds they generate is described. The system uses time domain signal coding techniques and artificial neural networks for discriminating between the sounds of different animal species within a group. Results for British species of Orthoptera (bush crickets and crickets) show that it is capable of discriminating 13 species with 100% success and zero misidentification under low noise conditions. Results are also given for noise tests using 25 species of Orthoptera (including grasshoppers). The approach can be applied to other animal groups such as birds, mammals and amphibia; preliminary results are also presented for tests with 10 species of Japanese bird. The approach is generic and has application in many fields including non-destructive testing and physiological signal analysis. © 2001 Elsevier Science Ltd. All rights reserved.

1. Introduction

Many animals produce sound either deliberately for communications (non-incidental sounds) or as a by-product of their activity such as eating, moving or flying (incidental sounds). It is possible to make use of such bioacoustic sounds to detect and, in some cases, recognise species or even individuals within a species. Non-incidental sounds have been used for many years to provide information on species; this is particularly true for bird surveying and locating animals. The potential applications for detecting and identifying animal species, particularly automatically, are diverse but can be grouped into the following categories.

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1.1. Species identification

Applications of species identification range from pests (see below) to automated surveying, long term monitoring and rapid biodiversity assessment. A species inventory is often time consuming, very labour intensive and usually requires a degree of skill and knowledge of the groups under consideration. In many parts of the world it is difficult to provide accurate species counts because of the large number of species and the inaccessibility of the environment. It is unfortunate that the highest rates of species loss also occur in these areas and the ability to provide more rapid species counts is of paramount importance. Whilst bioacoustic methods will not give total species counts it has been suggested they have the potential to estimate biodiversity [1]. Also, Oba in Japan has used bird song as a measure of the "natural sound diversity" in rural, semi-urban and urban habitats [2,3]. The development of automated identification systems will speed up the process and are likely to lead to the development of continuous real-time monitoring of biodiversity in areas where many species use vocal communications.

Until recently, however, there have been very few attempts to develop automated identification tools and research in this area is still very much in its infancy [4–6]. Manual acoustic identification of species either takes place in the field or by listening to recordings, sometimes utilising spectrographs to separate sounds. This process is also very time consuming and it has been estimated that analysis time can be as much as 10 times longer than the recording (Oba, personal communication). Examples of current research include the identification of birds in general [7,8], nocturnal migrant birds [9], frogs and other amphibia [10], insects [11,12] and bats [22].

1.2. Identification of individuals within a species

The identification, subsequent monitoring and tracking of individuals within a population is an important ecological application. Examples of current research include distinguishing between individuals in a Fallow Deer (*Dama dama*) population using an artificial neural network [13] and classification of the repertoire of individual False Killer Whales (*Pseudorca crassidens*), again using neural networks [14]. It will not be possible to monitor individuals in populations of lower animals such as insects and amphibia because they do not exhibit sufficient intra-specific variation in sound production.

1.3. Detection of the presence of animals

In many applications, it is sufficient to be able to detect the presence of animals, with species identification either unnecessary or a bonus. One of the major application areas is in insect pest detection where the presence of pests is indicated by the generation of sound as a by-product of the animals' moving or eating. Insect pests are a major problem in many countries and it has been estimated that world-wide there are about 1000 species of major pests and 30,000 species of minor pests [15]. For example, the loss of sorghum crops because of infestation by the fall armyworm (*Spodoptera frugiperda*) in Georgia, USA in 1977 cost $137.5M alone [16]. The development of early warning and rapid detection systems would be of considerable commercial benefit. Acoustic detection of pests is possible and has been attempted for many years. For example, in the USA, it has been used for detecting beetle larvae in rice grains [17,18]. Other researchers have used similar techniques for monitoring *Rhizopertha dominica*, another beetle, in wheat kernels [19]. It is also possible to detect the presence of subterranean insect pests and stem borers [20,21].

2. Approaches to bioacoustic identification

Species identification by electronic means is an application of general pattern recognition in which an unknown (specimen) is placed into one of a number of possible classes depending on features extracted from measurements on the species. Pattern recognition has many applications ranging from handwriting recognition to speech analysis and identification of faults in machinery (condition monitoring). Automated species identification is very similar to many of these applications.

The majority of bioacoustic signal analysis and identification systems use frequency domain techniques, particularly FFT, wavelet transform and LPC to extract the relevant frequencies [7,10,13,22]. However, such techniques are computationally intensive and difficult to implement on low cost microcontroller-based systems. Indeed, in [10] the remotely-sited PC-based system could only record for 75% of the time, the rest devoted to signal processing even though the FFT size was limited to 32 points. The use of dedicated digital signal processors is also prohibitive in terms of cost and power consumption (important for remotely sited systems).

The remainder of this paper describes the development of a bioacoustic monitoring system utilising a purely time domain signal analysis technique known as time domain signal coding (TDSC) with an artificial neural network classifier for identification of insect sounds. TDSC is not only computationally less intensive than frequency domain methods but it has several other advantages including the generation of time invariant features (the A-matrix), frequency information can be extracted and does not suffer from the time-bandwidth product problems of spectral methods.

The current prototype system is based on a high speed PC using a standard 16-bit soundcard for signal digitisation with software written in Matlab^{TM} for rapid prototyping. Since TDSC is computationally much less complex than frequency domain the final system will be implemented on a custom designed low power microcontroller platform capable of battery power, possibly even hand-held. The paper describes the concept of TDSC and it's application to the recognition of 25 species of British Orthoptera (bushcrickets, crickets and grasshoppers). Preliminary results for 10 species of bird occurring in Japan are also presented.

3. Time domain signal coding

Time domain signal coding is based on a technique originally known as time encoded speech (TES) which was developed in the 1970s by King [23] as a purely time domain approach to the compression of speech for digital transmission. It has subsequently been used in a number of applications including acoustic condition monitoring of machinery [24] and heart sound analysis and defect identification [25]. The original TES encoding scheme made use of the fact that any bandlimited signal can be characterised by its real and complex zero locations. However, locating complex zeros is very difficult and it is sufficient to only consider real zeros. The author has extended the original concept of TES to include matrix normalisation, matrix scaling and automated codebook generation [4–6]. The term time domain signal processing (TDSC) is used to encompass these additions.

3.1. Segmentation of signals

TDSC characterises any bandlimited signal by its shape between successive real zeros (termed an epoch); generally this shape is taken between actual zero-crossings for practicality. Each epoch is described in terms of its duration in samples (D) and shape (S) usually taken as the number of minima as indicated in Fig. 1 which shows two epochs, the first with duration 20 samples and 1 minimum and the second with 2 minima and duration 30 samples. A zero crossing is detected when:

$$(x_{n-1} < 0) \bigcap (x_n \geqslant 0) \quad \text{positive transition} \tag{1}$$

or

$$(x_{n-1} > 0) \bigcap (x_n \leqslant 0) \quad \text{negative transition} \tag{2}$$

where x_n is the current sample and x_{n-1} is the previous sample.

Once a pair of zero-crossings have been detected, the number of positive minima or negative maxima can be determined. It is also possible to use signal energy and frequency-scaled signal energy as a measure of shape. TDSC provides information on the fundamental frequency (D^{-1}) and the number of harmonics but not their amplitude. The number of possible D–S combinations (symbols) is termed the natural alphabet which is unique to the overall structure of a given signal or signal

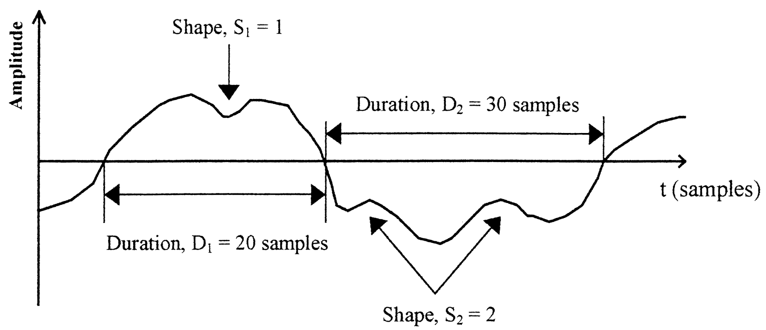

Fig. 1. Example of waveform epochs (D_1, S_1) and (D_2, S_2).

group. The number of different D–S pairs can be very large and it is useful to reduce the total by non-linearly mapping them onto a smaller symbol set (typically 30 symbols). This mapping is also dependent on sound structure and will not be the same for different sound groups. The codebook (mapping table) must therefore be generated for each sound group currently by manual examination of the distribution of D–S pairs. Currently, D–S distributions are generated by accumulating all D–S pairs from 2 s representative sounds from high quality recordings of each species. Table 1 gives the codebook derived for the 13 species of Orthoptera, showing that the majority of D–S pairs can be successfully mapped onto a much smaller number of codes (28 in this case). In the original speech application, the coded symbols were transmitted and used to regenerate the speech signal at the receiver thus providing digital speech transmission at substantially reduced data rates (–12 kbps) over basic encoding techniques [23].

3.2. Feature extraction: S-matrices and A-matrices

The sequential stream of symbols which may be further analysed by several methods, the simplest being the generation of a histogram of the frequency of occurrence of codes; this produces an S-matrix (1-dimensional). An alternative method is to examine the occurrence of pairs of symbols over time to give a histogram which describes the number or proportion of symbols i and j occurring in succession, i.e. the number of times i is followed by j by a lag L. A 2-dimensional histogram, the A-matrix, can be formed, expressed mathematically as:

$$a_{ij} = \frac{1}{(N-L)} \sum_{n=L+1}^{m=N} x_{ij}(n) \tag{3}$$

Table 1
TDSC codebook

	Shape					
Duration	0	1	2	3	4	5
1	1					
2	2					
3	3					
4	4					
5	5					
6–7	6					
8–10	7	8				
11–13	9	10				
14–18	11	12	13			
19–23	14	15	16	17		
24–30	18	19	20	21	22	
31–33	23	24	25	26	27	28

where

a_{ij} = element (i,j) of matrix **A**,
L = lag,
$x_{ij}(n) = 1$ if $t(n) = i$ and $t(n-L) = j$ (0 otherwise),
and $t(n)$ = nth symbol.

The entry at position (i,j) represents the frequency of occurrence of the TDSC symbol pair i and j where j is delayed relative to the first by the lag (in epochs). In this application, a lag $L = 1$ is used; multiple lags may also be employed giving rise to multi-dimensional matrices although this increases computational complexity considerably. The A-matrix is a fixed size histogram with time-invariant dimensions representing the conditional probability of finding pairs of symbols and is the feature set used here for subsequent classification purposes using an artificial neural network (ANN).

3.3. Classification

ANNs are now widely used in many classification and identification problems as they can be trained, are good at handling fuzzy and disparate data and are able to perform non-linear discrimination. There are many forms of ANN which can be divided into supervised (requires training) and unsupervised classification (no training). Much of the research carried out to date uses multilayer perceptrons (MLP) using back-propagation for training. More recently, self-organising features maps have been investigated with some success.

Fig. 2 shows the architecture of the ANN classifier used in this application. It is a 3 layer MLP with 784 neurons in the input layer, 20 in the hidden layer and the number of output neurons equal to the total species to be recognised (13 or 25 for Orthoptera and 10 for birds).

Representative samples of high quality sound 2 s in duration were used to obtain exemplar A-matrices for each species and the ANN trained using a backpropagation algorithm. Once trained, the network was tested with unseen inputs from different

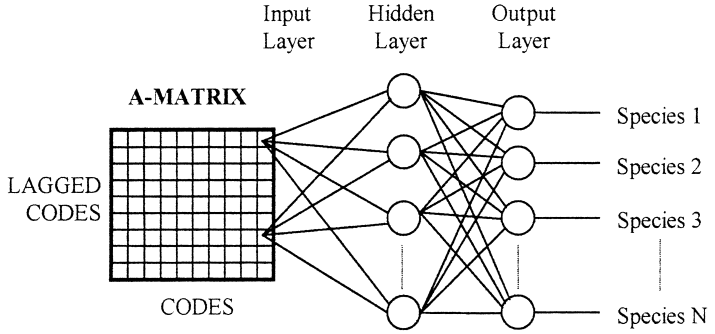

Fig. 2. Neural network architecture.

sections of the same songs of each species. Results for each test set are given in Section 4.1.

All software has been developed using Matlab™, a generic mathematical programming language optimised for matrix manipulation. Matlab™ has been chosen for two reasons — it is simple to use and a wide range of toolboxes are available, in this case the neural networks toolbox. Matlab will run on any 486 computer (or better) with at least 4 Mbytes of RAM and a hard disc, and is capable of running on portable PCs. The sounds are sampled at 44 kHz, 16-bits per sample using a shareware program called Goldwave V3.03 via the line input of a Soundblaster sound card and stored in .WAV format. No analogue or digital filtering is carried out and the only pre-processing required is to remove any DC offset that has been found to occur with some soundcards.

4. Test results

4.1. Results for 13 species of British Orthoptera

Exemplar sounds were derived from a widely available audio cassette [26] available as an accompaniment to "The Grasshoppers and Allied Insects of Great Britain and Ireland" [27] and digitised at 44 kHz. Figs. 3–6 give time domain waveforms, S-matrices and A-matrices for 4 of the species, showing that the A-matrix is a good feature for separation of species. Table 2 lists the species selected.

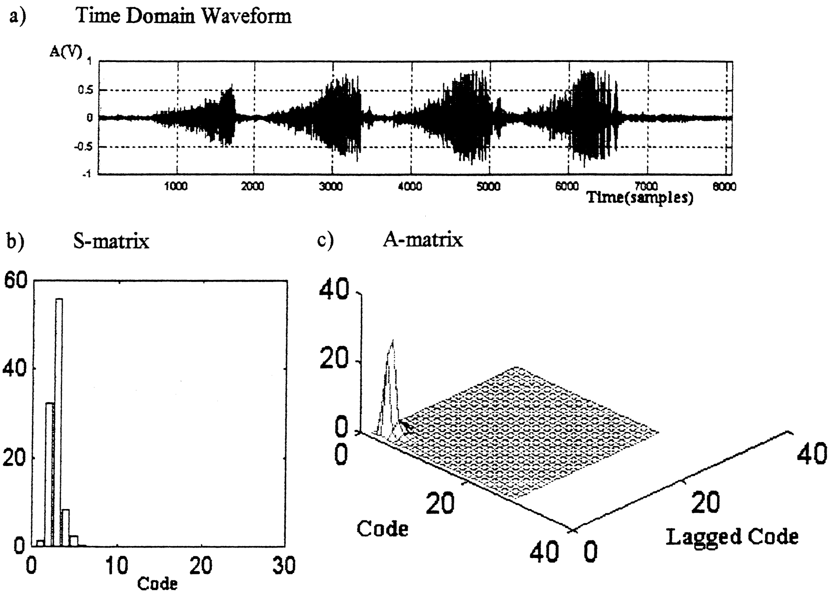

Fig. 3. Waveform, S-matrix and A-matrix for OR05 (*Platycleis albopunctata*).

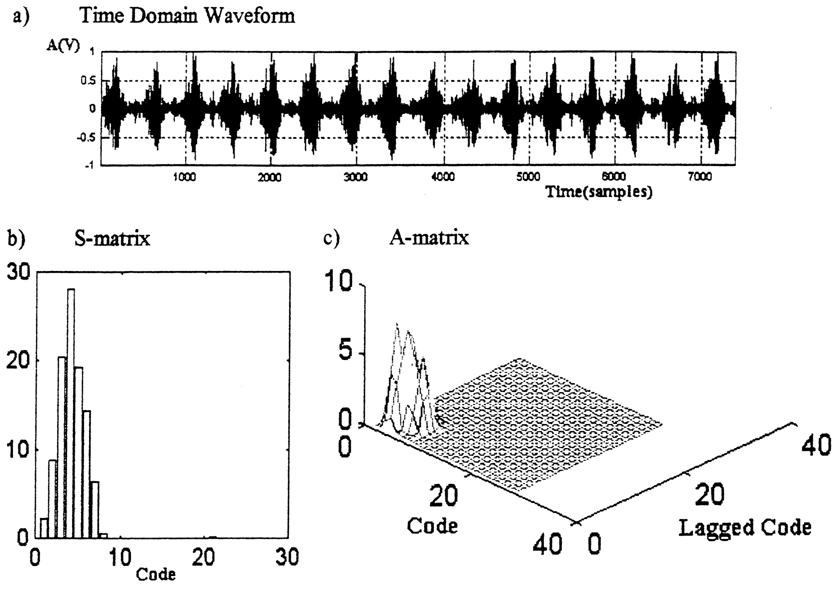

Fig. 4. Waveform, S-matrix and A-matrix for OR07 (*Metrioptera roeselii*).

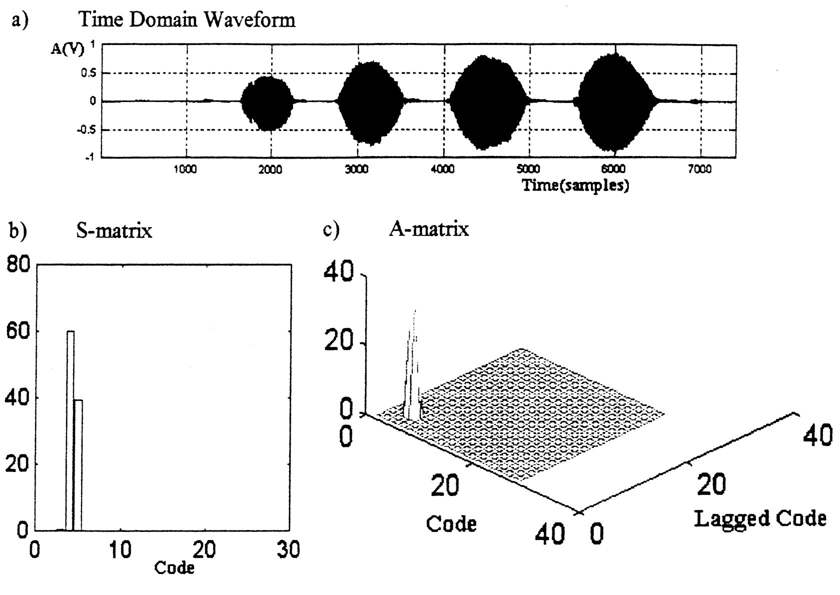

Fig. 5. Waveform, S-matrix and A-matrix for OR11 (*Gryllus campestris*).

Two tests were performed — a high signal level test involving 13 species (OR01 to OR13) and a test with varying noise levels involving all 25 species as described in Section 4.3. Table 3 gives the 13 species results in the form of a confusion matrix. It should be noted that the outputs do not represent probabilities of detection but the

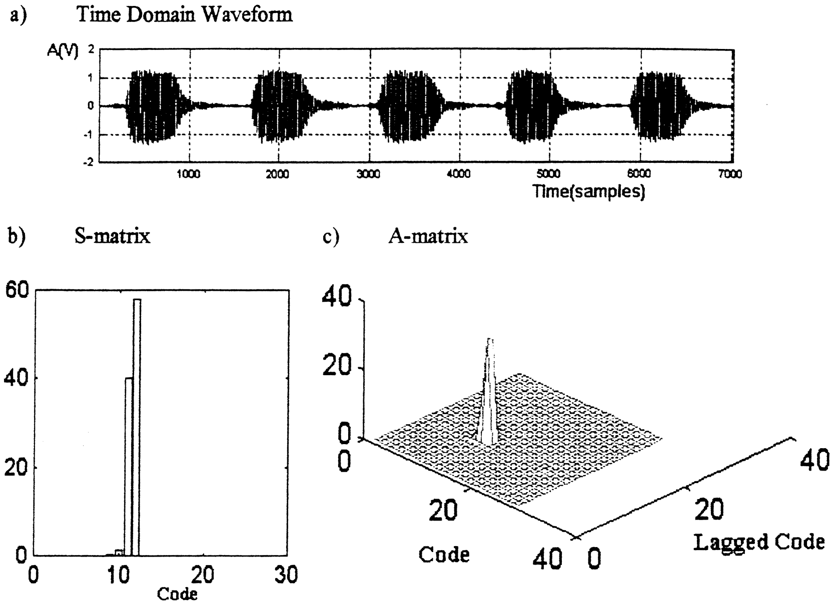

Fig. 6. S-matrix and A-matrix for OR13 (*Gryllotalpa gryllotalpa*).

relative confidence of recognition for each neuron. It is evident that the ANN recognises all species with very high confidence levels and, more importantly, gives no false identifications.

It should be noted that these results are for input signals with a high signal to noise ratio. Further tests using various levels of noise have been carried out and show that the system is robust as described in Section 4.3. Also, many species of bushcrickets (Tettigonidae) produce sound well above 40 kHz and recordings, even CD recordings, will only record signals below 20 kHz. Despite this problem, the system recognises these species well, showing that these species have sufficiently different low frequency signals. Crickets (Gryllidae) and grasshoppers (Acrididae) have lower carrier frequencies, generally several kHz and so do not pose a problem. It is beyond the scope of this paper to discuss sound production mechanisms in insects and Orthoptera; these can be found in references [27–32].

4.2. Results for Japanese woodland birds

The same basic system described above has also been trained to recognise 10 species of bird that occur in woodland in the environs of Tokyo. The tests were carried out during a visit to the Natural History Museum and Institute in the city of Chiba near Tokyo to investigate whether the system can speed up the analysis of bird song recordings. These recordings have been used to assess the "natural sound diversity" in rural, semi-urban and urban areas [2, 3]. Exemplar sounds for the training set were obtained from CDs [33] on sale in Japan. An identical neural network architecture

Table 2
Orthoptera species used in the tests

ID Code	Scientific name	English name
OR01	*Meconema thalassinum*	Oak Bushcricket
OR02	*Tettigonia viridissima*	Great Green Bushcricket
OR03	*Decticus verrucivorus*	Wartbiter
OR04	*Pholidoptera griseoaptera*	Dark Bushcricket
OR05	*Platycleis albopunctata*	Grey Bushcricket
OR06	*Metrioptera brachyptera*	Bog Bushcricket
OR07	*Metrioptera roeselii*	Roesel's Bushcricket
OR08	*Conocephalus discolor*	Long-winged Conehead
OR09	*Conocephalus dorsalis*	Short-winged Conehead
OR10	*Acheta domesticus*	Housecricket
OR11	*Gryllus campestris*	Fieldcricket
OR12	*Nemobius sylvestris*	Woodcricket
OR13	*Gryllotalpa gryllotalpa*	Molecricket
OR14	*Stethophyma grossum*	Large Marsh Grasshopper
OR15	*Stenobothrus lineatus*	Stripe-winged Grasshopper
OR16	*Stenobothrus stigmaticus*	Lesser Mottled Grasshopper
OR17	*Omocestus rufipes*	Woodland Grasshopper
OR18	*Omocestus viridulus*	Common Green Grasshopper
OR19	*Chorthippus brunneus*	Field Grasshopper
OR20	*Chorthippus vagans*	Heath Grasshopper
OR21	*Chorthippus parallelus*	Meadow Grasshopper
OR22	*Chorthippus albomarginatus*	Lesser Marsh Grasshopper
OR23	*Euchorthippus pulvinatus*	Jersey Grasshopper
OR24	*Gomophocerippus rufus*	Rufous Grasshopper
OR25	*Myrmeleotettix maculatus*	Mottled Grasshopper

to that in Fig. 2 was used, with the exception that only 10 outputs were required. Natural sounds from woodland were originally recorded on DAT by Dr. Oba at a sampling rate of 22 kHz, subsequently transferred to a high quality audio cassette tape and digitised using a soundcard as described in Section 3.3. Table 4 lists the species used; these were selected as they were present in one particular set of woodland recordings.

Classification results are shown in Table 5; these are preliminary and very encouraging but it should be noted that the unseen sounds were also obtained from the audio CDs and were therefore high quality. Success at classification using natural sounds was variable, however, some signals were classified to over 90%. Fig. 7 shows the A-matrix for the Little Cuckoo (*Cuculus poliocephalus*) under good conditions and Fig. 8 is for the same species under natural conditions. The additional peaks were caused by 2 factors — other species singing simultaneously and reverberation caused by long path lengths within the woodland. Despite this, the system recognised the species with 95% accuracy.

4.3. Noise test results for Orthoptera

In order to determine system response to varying noise levels, it was trained with all 25 species of Orthoptera and noise added to simulate more natural environments. Table 6 shows the results for noise levels of −40d B (1% of normalised signal level)

Table 3
Confusion matrix for Orthoptera tests under good conditions

	OR01	OR02	OR03	OR04	OR05	OR06	OR07	OR08	OR09	OR10	OR11	OR12	OR13
OR01	0.9999	0	0	0	0	0	0	0	0	0.0001	0.0001	0	0.0001
OR02	0	0.9995	0.0001	0.0003	0	0	0	0.0001	0	0	0	0	0.0001
OR03	0	0	0.9998	0.0002	0.0002	0.0001	0	0	0	0	0	0	0
OR04	0	0.0349	0	0.9693	0	0	0.0001	0	0	0	0	0	0
OR05	0	0	0.0002	0	0.9998	0	0.0001	0.0001	0	0	0	0	0
OR06	0	0	0.0001	0	0	0.9997	0	0.0001	0.0001	0	0.0001	0	0
OR07	0	0	0	0.0001	0	0.0001	0.9997	0	0	0.0002	0	0.0001	0
OR08	0.0001	0.0002	0.0001	0	0.0001	0.0002	0	0.9998	0	0	0	0	0
OR09	0	0	0	0	0.0001	0.0001	0.0001	0	0.9998	0.0001	0	0	0
OR10	0	0	0	0.0001	0	0	0.0001	0	0.0001	0.9999	0	0	0
OR11	0	0	0	0	0	0.0001	0	0	0	0	0.9999	0.0001	0
OR12	0	0	0	0.0001	0	0	0	0	0	0	0.0001	0.9999	0
OR13	0	0.0001	0	0	0	0	0.0002	0	0	0	0	0	0.9999

Table 4
Bird species used in the tests

ID code	Latin name	English name
JB01	*Acrocephalus arundinoceus*	Great Reed Warbler
JB02	*Cuculus canorus*	Common Cuckoo
JB03	*Cettia diphone*	Bush Warbler
JB04	*Cuculus poliocephalus*	Little Cuckoo
JB05	*Emberiza variabilis*	Gray Bunting
JB06	*Ficedula narcissina*	Narcissus Flycatcher
JB07	*Megalurus pryeri*	Japanese Marsh Warbler
JB08	*Parus major*	Great Tit
JB09	*Phylloscopus tenellipes*	Pale-legged Willow Warbler
JB10	*Turdus chrysolaus*	Brown Thrush

Table 5
Results for bird species

	JB01	JB02	JB03	JB04	JB05	JB06	JB07	JB08	JB09	JB10
JB01	1	0	0	0	0	0	0	0	0	0
JB02	0	1	0	0	0	0	0	0	0	0
JB03	0	0	1	0	0	0	0	0	0	0
JB04	0	0	0	1	0	0	0	0	0	0
JB05	0	0	0	0	1	0	0	0	0	0
JB06	0	0	0	0	0	1	0	0	0	0
JB07	0	0	0	0	0	0	1	0	0	0
JB08	0	0	0	0	0	0	0	1	0	0
JB09	0	0	0	0	0	0	0	0	1	0
JB10	0	0	0	0	0	0	0	0	0	1

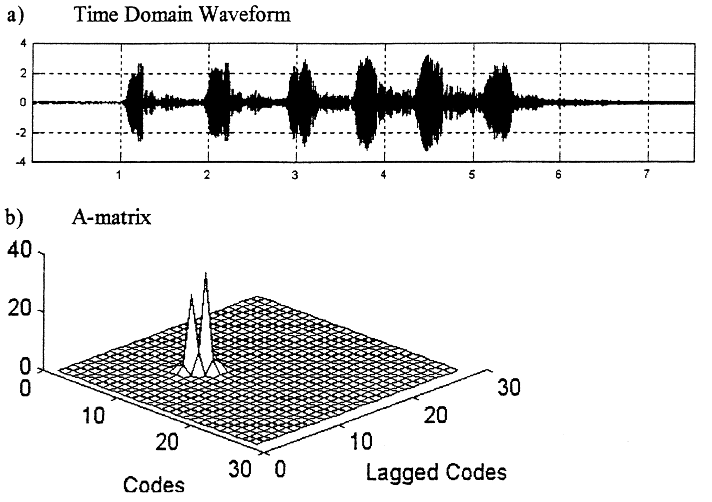

Fig. 7. Exemplar time domain waveform and A-matrix for *Cuculus poliocephalus*.

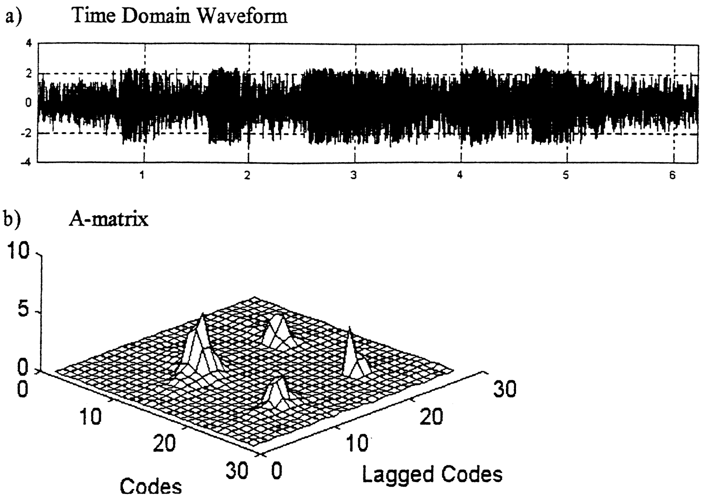

Fig. 8. Time domain waveform and A-matrix of *Cuculus poliocephalus* under natural conditions.

Table 6
Noise test results for 25 species of Orthoptera

	Noise level (dB)			
Species	−40	−30	−20	−10
OR01	99.9	83.5	24.3	5.3
OR02	100.0	100.0	100.0	89.3
OR03	100.0	99.6	76.8	60.6
OR04	100.0	100.0	99.9	86.8
OR05	100.0	100.0	90.1	66.9
OR06	85.6	65.5	54.3	52.0
OR07	100.0	100.0	94.2	45.1
OR08	100.0	100.0	100.0	95.1
OR09	100.0	100.0	100.0	99.7
OR10	100.0	100.0	100.0	94.8
OR11	100.0	100.0	100.0	100.0
OR12	100.0	100.0	100.0	93.8
OR13	100.0	84.9	34.2	9.3
OR14	100.0	100.0	100.0	85.7
OR15	100.0	100.0	89.3	61.5
OR16	100.0	99.9	84.9	63.8
OR17	100.0	86.4	63.4	52.8
OR18	100.0	98.1	59.7	38.1
OR19	100.0	100.0	95.6	71.5
OR20	100.0	100.0	91.3	67.7
OR21	100.0	100.0	100.0	97.5
OR22	99.8	86.1	62.3	56.4
OR23	100.0	100.0	99.7	84.6
OR24	100.0	99.6	65.8	39.6
OR25	100.0	100.0	100.0	99.8

to −10 dB (32%). Each entry is an average of 1000 normally distributed random A-matrices (zero mean, unity variance) added to the A-matrices which simulates Gaussian white noise over the whole frequency spectrum. It is evident from Table 6 that identification is very high (99–100%) under low noise conditions with the exception of OR06 (*Metrioptera brachyptera*). Two species, however, exhibit very poor recognition- OR01 (*Meconema thalassinum*) and OR13 (*Gryllotalpa gryllotalpa*). It is not yet known why this has occurred but it may be due to them both exhibiting characteristically low dominant frequencies. *Meconema thalassinum* would not be encountered acoustically in the field since it produces substrate-borne sounds and was included solely for testing purposes.

5. Discussion and conclusions

Whilst the bioacoustic signal identification system is still in prototype form, results for 2 different groups of animals indicate that the combination of TDSC feature extraction and ANN classification gives high recognition rates. The low computational complexity of TDSC has an added advantage of being implementable on low power microcontrollers leading to the possibility of hand-held recognisers and remotely sited long term bioacoustic monitoring. Such systems would be valuable in nearly all of the applications described in Section 1.

There are still many areas of investigation including:

- The current epoch description is very crude and contains no amplitude information. It is important to develop better waveform shape descriptors such as combining duration, shape and energy for each epoch.
- Extensive noise and interference tests. TDSC has good noise discrimination but interference from other sound sources must be considered. It is particularly important to examine methods of overcoming multiple simultaneous intra- and inter-specific calls.
- Investigation into signal-to-noise limitations of the system and the effects of attenuation of high frequencies due to sound transmission through vegetation. For low frequency signals, this will not be particularly significant but must be taken into account for bushcrickets.
- Development of real-time TDSC encoders. At present, the system is implemented on a portable PC which is not robust enough for practical field use. As noted above, TDSC can be implemented with ease on low power, low cost microcontroller systems and a real-time systems is currently under development. This system will be capable of sampling at over 500 kHz and will be able to directly record, analyse and recognise bushcrickets and bats.

In taxonomic (species identification) applications, it is vitally important not to misidentify species because this can produce incorrect species lists. Indeed, the general acceptance of automated identification systems by the taxonomic community is contingent on the development of systems that have zero misidentification. Nowhere is this more important than the recognition of pest species because the economic implications of misidentifying a quarantine species for a non-quarantine species can be disastrous for crop protection and may result in major crop losses. It is therefore important to create a "don't know" condition rather than misidentification. It is also important for the taxonomist to be able to retrain the system for new species.

The approach described here provides a sound basis for automated identification but it should be noted that the method is generic and can be applied to any bandlimited signal. There are therefore many suitable potential applications including non-destructive testing, analysis of seismic data, biophysiological data (e.g. EEG), sonar and radar.

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