ELSEVIER

Behavioural Processes 52 (2000) 1–9

BEHAVIOURAL PROCESSES

www.elsevier.com/locate/behavproc

A fuzzy-neural system for identification of species-specific alarm calls of Gunnison's prairie dogs

J. Placer, C.N. Slobodchikoff *

Department of Biological Sciences, Northern Arizona University, Flagstaff, AZ 86011 5640, USA

Received 10 November 1999; received in revised form 1 May 2000; accepted 2 May 2000

Abstract

In this study we describe the design and application of an automated classification system that utilizes artificial intelligence to corroborate the finding that Gunnison's prairie dogs have different alarm calls for different species of predators. This corroboration is strong because it utilizes an entirely different analysis technique than that used in the original research by Slobodchikoff et al. [Slobodchikoff, C.N., Fischer, C., Shapiro, J., 1986. Predator-specific alarm calls of prairie dogs. Am. Zool. 26, 557] or in subsequent study done by Slobodchikoff et al. [Slobodchikoff, C.N., Kiriazis, J., Fischer, C., Creef, E., 1991. Semantic information distinguishing individual predators in the alarm calls of Gunnison's prairie dogs. Anim. Behav. 42, 713–719]. The study described here also is more completely automated than earlier study in this area. This automation allowed a large volume of field data to be processed where all measurements of relevant parameters were performed through software control. Previous study processed a smaller data set and utilized manual measurement techniques. The new classification system, which combines fuzzy logic and an artificial neural network, classified alarm calls correctly according to the eliciting predator species, achieving accuracy levels ranging from 78.6 to 96.3% on raw field data digitized with low quality audio equipment.

Keywords: Acoustic; Alarm calls; Fuzzy logic; Neural nets; Prairie dogs

1. Introduction

An increasing body of evidence shows that the alarm calls of some animals contain meaningful information of a semantic nature. Semantic content in predator-specific alarm calls has been found in the vocalizations of some ground squirrels (Owings and Virginia, 1978) and in vervet monkeys (Seyfarth et al., 1980). The California ground squirrel has a different call for aerial predators than it does for terrestrial predators. Vervet monkeys have different alarm calls for several species of predators, such as the leopard, martial eagle, and python. Semantic information has also been found in the alarm vocalizations of dwarf mongooses (Beynon and Rasa, 1989), and in the alarm calls of chickens (Gyger et al., 1987), lemurs (Pereira and Macedonia, 1991), and red squirrels (Greene and Meagher, 1998).

* Corresponding author.

0376-6357/00/$ - see front matter
PII: S0376-6357(00)00105-4

A diversity of information of a semantic nature has been associated with Gunnison's prairie dog alarm calls. This includes, (1) different alarm calls for different species of predators (Slobodchikoff et al., 1986; Kiriazis, 1991); (2) information about the size, shape, and color of different individuals within a predator species (Slobodchikoff et al., 1991); (3) information related to the direction and speed of approach of a predator (Kiriazis, 1991); (4) and dialects in alarm calls between colonies (Slobodchikoff and Coast, 1980; Slobodchikoff et al., 1998).

In this study we describe the design and application of an automated system of analysis that is used to corroborate the finding that Gunnison's prairie dogs have different alarm calls for different species of predators. Earlier techniques that demonstrated the existence of these predator-specific alarm calls were subject to various limitations. For example, using observational techniques, Kiriazis (1991) demonstrated that alarm calls, recorded in the presence of predators of various types, elicit predator-specific behaviors in prairie dogs that hear the recordings played back in the absence of any predators. Such observational techniques strongly suggest that there exist different alarm calls for different species of predators. However, these techniques do not provide quantitative or structural insights into the nature of the alarm calls under investigation.

Evidence for predator-specific alarm calls was also demonstrated by Slobodchikoff using a technique that relies on the analysis of audio waveforms (sonograms) generated by sophisticated signal processing programs (Slobodchikoff et al., 1991). In this methodology, a number of attributes of sonograms made from the prairie dog alarm calls were measured manually. These hand measurements were analyzed using multivariate statistics in order to demonstrate the existence of predator-specific alarm calls. Manual measurement techniques are time consuming and they tend to make the analysis of large numbers of alarm calls impractical. This limitation invites criticisms related to any statistical analysis that is tied to the measurements. Manual measurements are also imprecise and open the possibility that human bias is introduced into the measurements. Both of these weaknesses of manual measurement techniques can be overcome by enhanced automation of the experimental procedure. However, even if the methodology used by Slobodchikoff was more completely automated, the analysis technique of multivariate statistics itself presents some limitations that must be addressed. Although capable of identifying important alarm call parameters and, to some degree, their relative importance, multivariate statistics cannot easily be used to ascertain the manner in which these factors encode information in animal vocalizations. Since ultimate proof of the actual level of complexity of animal communications must rely on some exposition of the manner in which these communications encode information, this is a serious limitation that must be overcome.

The automated classification system described in this study addresses all of the limitations just discussed. Using a sophisticated numeric-processing environment, the new system of analysis is implemented as a fully automated software package where all measurements are made under software control. In addition to this, the power of fuzzy logic and artificial neural networks is used to analyze and classify the prairie dog alarm calls with high accuracy into predator-specific classes. Furthermore, the new system promises to support more sophisticated future research into the manner in which information is encoded in alarm calls. Fuzzy logic is a system of mathematics that allows the vagueness of linguistic concepts to be represented by sets with imprecise boundaries (Zadeh, 1965; Ross, 1995). In fuzzy logic, the membership of an element in a set does not always signify complete inclusion or complete exclusion but can assume values between these two extremes. Working with the degrees of membership allows the imprecision inherent in natural language to be represented and it supports a form of approximate reasoning that attempts to model the way human beings reason. Artificial neural networks refer to computer programs and also to actual hardware devices that have been designed to emulate some of the functionality and attributes of human neural networks (McCulloch and Pitts, 1943; Rumelhart et al., 1986). In artificial neural networks the information is distributed among the many links that connect the simple processing units contained in the network. A network gains information (i.e. trained) by example as data sets are repeatedly presented to it. During this training period the network itself adjusts the network's links in order to retain information gained from the inputs. A network continues to be trained in this manner until it is able to function at an acceptable level of performance.

2. Materials and methods

The research described in this study used tape recordings of Gunnison's prairie dog alarm calls obtained over a period of 10 years (1988–1997) at two separate prairie dog colonies, both described in Slobodchikoff et al. (1991). Recordings were made using a Sennheiser ME-88 directional microphone and two different models of cassette tape recorders, an Uher model 160 recorder and a Sony TC-D5PRO II recorder. For the purposes of this analysis, we used calls from 25 individual prairie dogs for each of the following predators: humans, represented by seven different individuals; red-tailed hawks, represented by 16 different individuals; domestic dogs, represented by eight different individuals; and coyotes, represented by five different individuals. Because the alarm call data were obtained over a 10-year period, we sampled calls from multiple generations of prairie dogs.

Copies of these data recordings were digitized using a generic sound card and software package in an IBM compatible PC with an Intel 486 processor. The sound card had 16-bit resolution and sampled data at 44 100 Hz. Following the digitization process a standard 'cut and paste' sound editor that was part of the package was used to manually extract the individual prairie dog 'barks' and save them in separate files. These files of single alarm call barks formed the library of files that was used for all of the classification tests described in this study. The files associated with a given recording session and species of predator were all given the same root name; each individual file with the same root name was given a unique index value. For example, one series of files that contain alarm call barks issued in the presence of a dog named Moby are named moby1, moby2, moby3, etc. while another series of calls recorded in the presence of a hawk are named aerial1, aerial2, aerial3, and so on. After completing this manual process of creating separate files, with each file containing an individual alarm call bark, all subsequent data manipulation was performed using a system of computer programs created by one of the authors. These programs were implemented using the high-performance numeric computation software called MATLAB and the neural network toolbox associated with MATLAB. Classification tests were run on all combinations of the different predator species associated with the alarm calls. In other words, all six combinations of two different species were tested, all four combinations of three different predator species were tested, and data associated with all four species was tested.

The automated classification system first preprocesses each of the prairie dog alarm calls and then trains and tests a neural network. In the preprocessing stage, the frequency ratios contained in each alarm call bark are determined and then vectors of fuzzy values are created that characterize each alarm call bark. These vectors are used as input for the training and testing of the neural network. A block diagram of the automated classification system is given in Fig. 1. The main functional units of the automated classification system are described in detail below.

2.1. Determination of the frequency ratios contained in each alarm call bark

When an experiment was to be run that attempted to classify a targeted combination of predator-specific alarm calls, each file used in that experiment was converted from a simple time domain recording of an alarm call bark into a matrix of sound frequencies contained within that bark. This conversion process was implemented in the following way. Each digitized data file representing an alarm call bark was divided into partitions of 256 data points each. Since alarm calls were recorded at a rate of 44 100 samples per s, each bark was effectively divided into a number of time periods of 0.0058 s each. The fast fourier transform algorithm was then used to transform each partition of data points (i.e. each time period) into a normalized power spectrum of the sound frequencies that were expressed during that time period. Thus, each alarm call bark was transformed into a matrix of values representing sound frequencies where each column in the matrix represented a different time period in the bark and recorded all of the frequencies that were expressed within that time period.

Once the matrix of frequencies was obtained, a complete collection of frequency ratios was computed in the following way. For each time period (matrix column) the set of frequency ratios was computed by dividing each frequency expressed in

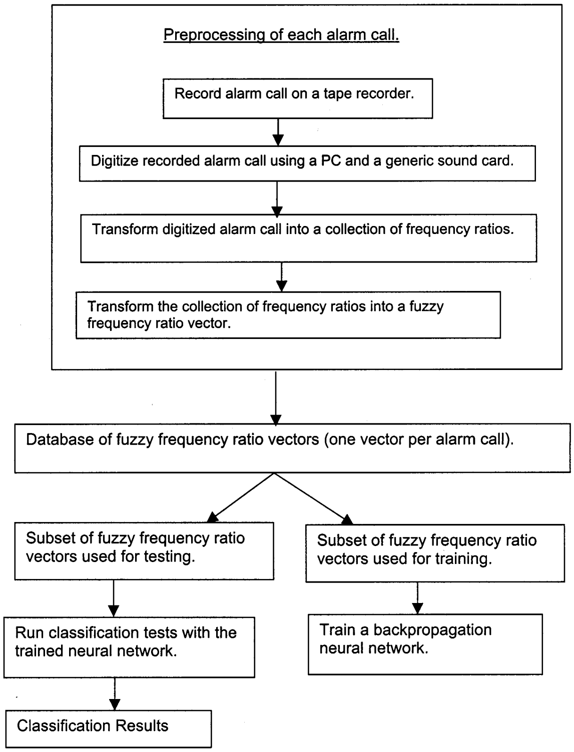

Fig. 1. Diagram of the automated classification system, showing the steps involved in processing and classifying alarm calls. Each alarm call becomes a component or vector of the database of fuzzy frequency ratio vectors. A part of this database is used for training a backpropagation neural network, and another part of the database is used for the classification tests with the trained neural network.

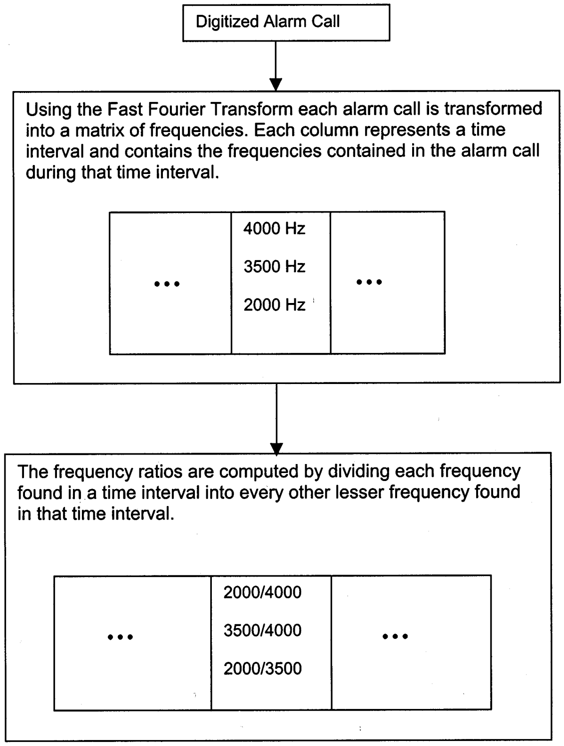

Fig. 2. Steps involved in transforming an alarm call into a collection of frequency ratios. In the time interval shown in the figure, there are three frequencies contained within the interval. To obtain the frequency ratios, each frequency within that time interval is divided into every other lesser frequency.

that time period into all other smaller frequencies expressed within that period. Thus, every time period was represented by a set of frequency ratios, all of which lay within the range of values 0–1. The frequency ratios computed in this manner for each time period were then combined into one total set of values that represented the entire alarm call bark that was being analyzed. Fig. 2 gives a simplified illustration of this process.

2.2. Creation of vectors of fuzzy values that characterize alarm call barks

Traditional or 'crisp' logic only allows for the elements of a given universe to belong to sets within that universe completely or not at all. An element x either belongs to set S completely and is said to have membership value 1 in that set, or it does not belong to set S at all and is said to have membership value 0 in that set. Unlike crisp logic, fuzzy logic allows for elements to possess partial membership in sets. One could think of such membership as being represented by a number in the range of values 0–1. At first this might seem strange, but in fact everyday logic is often more fuzzy than crisp. For example, a person that is 6 ft tall might be considered to have complete membership (i.e. have membership value 1) in the set of tall persons. Another person that is 5 ft 11 in. tall is smaller but still possesses the attribute of tallness and might be given a membership value of 0.95 in the set of tall persons. In other words, the second person has the attribute of tallness to degree 0.95. This example helps one to see that fuzzy sets are useful for characterizing the degree to which something possesses an attribute of interest. In the classification system being described in this study, fuzzy logic was used to characterize the degree to which different ranges of frequency ratios existed in each alarm call bark.

In order to characterize the collection of frequency ratios computed for each alarm call in a meaningful way, each collection was divided into 21 sub-ranges of ratios. Once this division was made, a vector of 21 fuzzy membership values was computed. Each membership value in the vector represented the degree to which a corresponding sub-range of frequency ratios approximated a particular fuzzy frequency ratio.

To make this more explicit, consider that the frequency ratios computed for a given bark lie in the range of values 0–1. These ratios were divided into 21 sub-ranges as indicated in Fig. 3. If the

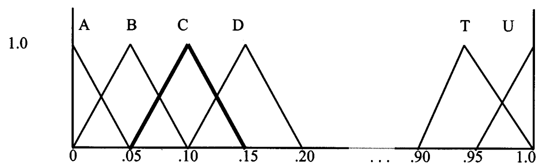

Fig. 3. Graph of fuzzy sets (triangles shown on graph) that partition the range of frequency ratios (given on the x-axis) into subsets. A line extended vertically from a particular frequency ratio found along the x-axis intersects a fuzzy set. The corresponding value of this point of intersection on the y-axis represents the membership value (μ) of that frequency ratio in that fuzzy set.

entire spectrum of sub-ranges was shown in Fig. 3, there would be 19 of the larger overlapping triangles (B–T) and two of the smaller right triangles, one on each end of the diagram (A and U). Each of these triangles encompasses a particular sub-range of frequency ratios and represents a membership function for a fuzzy set. For example, triangle C in Fig. 3 represents the fuzzy membership function 'approximately 0.10'. Similarly, each of the other membership functions represents a fuzzy frequency ratio. The fuzzy value corresponding to frequency ratio interval i was computed using the following formula:

$$\mu_i = g_i^* \vee (\mu_{1i}, \mu_{2i}, \mu_{Ni})$$

where, μ_i, the fuzzy membership value for fuzzy frequency ratio interval i; μ_{1i}, the fuzzy membership value for the first frequency ratio in interval i; μ_{Ni}, the fuzzy membership value for the last frequency ratio in interval i; $\vee$, the maximum function (the standard fuzzy union operator) g_i, (number of frequency ratios in interval i)/10.

A number of different formulations of the equation given above were investigated. The equation given produced the best results.

Each vector of fuzzy membership values computed represented a distribution of fuzzy frequency ratios that was used to represent an individual bark in a prairie dog alarm call; these were the values that were provided as input to the neural network. Each fuzzy frequency ratio distribution formed a particular signature that represented the presence of a specific combination of fuzzy frequency ratios. Therefore, the overall classification system created is a fuzzy-neural classifier because the input to the neural network was a vector of fuzzy values.

2.3. Training and testing of a neural network using the computed vectors of fuzzy values

After the set of alarm call barks selected for a given classification test were transformed into vectors of membership values for fuzzy frequency ratios as described earlier, the barks were divided into two roughly equal-sized sets of vectors. One set was used to train a neural network how to identify which predator was associated with each

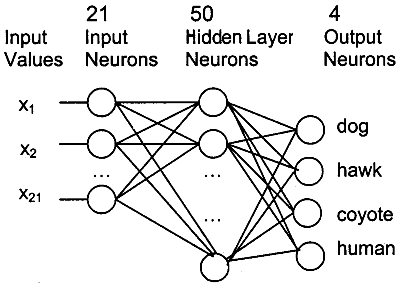

Fig. 4. A simplified diagram of the neural network used to classify alarm calls associated with all four species of predators.

alarm call bark. This data set was called the training set. The other data set was used to test the trained network for its ability to correctly guess which predator was associated with each alarm call bark. This second set was called the testing set. The two sets were disjoint which means that none of the vectors used to test the accuracy of the neural network were used to train the network. The complete data set consisted of a total of 359 alarm calls associated with humans, 171 associated with dogs, 275 associated with coyotes, and 213 associated with hawks. Recall that every alarm call bark was saved in a file whose name had a unique index that was appended to a common prefix used to represent each specific predator. The training set was composed of alarm call barks in files with odd numbered indices. The testing set came from files with even numbered indices.

The neural networks used to classify alarm call barks were feedforward networks. A feedforward network allows signals (values) to travel only in one direction in the network from the input layer to the output layer, no feedback is allowed. All of the tests described in this study were executed with neural networks that used 21 neurons in the input layer and 50 neurons in the hidden layer. The hidden layer size of 50 neurons gave the optimum combination of shortest training time and best accuracy. The number of different species-specific classes being investigated in a given test determined the number of neurons in the output layer of the network used in that test. For example, three neurons were used in the output layer of networks that classified alarm call barks vocalized in the presence of three different species of predators.

The input layer received the 21 fuzzy values that represented the ranges of frequency ratios as explained earlier. The values placed on the input nodes were passed on weighted connections to the neurons in the hidden layer. Each of the input nodes was connected to each node in the hidden layer and each hidden layer node was connected to each node in the output layer. Each hidden layer node applied its sigmoid transfer function to the weighted sum of the values sent to it by the input nodes. This resulted in the generation of new values at the output connection of the hidden layer nodes. The values generated by the hidden layer nodes were sent directly to the output nodes. Similarly, each output node applied its linear transfer function to the weighted sum of the input values it received from the hidden layer neurons. This generated a new set of values at the outputs of the output layer neurons. The output layer nodes were used to classify alarm call barks into different predator species. Each output node represented a particular species; the output node with the largest value for a given input vector named the species associated with that input. A simplified diagram of the neural network used to classify alarm calls associated with all four species of predators is given in Fig. 4.

In the neural networks, the information that linked input alarm calls to predator species was maintained in a distributed fashion in the weights that were associated with the connections in the network. A training algorithm was used to adjust the weights associated with each of the connections in the network. Each training cycle of the network caused the connection weights to be altered in such a way that the sum of squared errors of the network neurons were minimized. The changes in the weights were computed using the derivative of the square of the error at each neuron where the error was the difference between the expected output of the neuron and the actual output. This training algorithm is called the backpropagation gradient descent technique (Rumelhart et al., 1986) An adjustment of the connection weights represents a modification of the informa-

Table 1
Summary information for all combinations of the different predator species

Species classified	Accuracy (%)	Training sessions
Humans, dogs	87	2000
Humans, coyotes	89	1500
Humans, hawks	95	1500
Dogs, coyotes	88	2000
Dogs, hawks	96	2000
Coyotes, hawks	90	2500
Humans, dogs, coyotes	79	3000
Humans, dogs, hawks	85	3500
Humans, coyotes, hawks	86	2500
Dogs, coyotes, hawks	85	3500
Humans, dogs, coyotes, hawks	79	5000

tion embodied in the network. Weight adjustment was scheduled to continue iteratively until either no error occurred when classifying input vectors or until the training algorithm no longer improved the classification accuracy of the network. In none of the classification experiments did the network reach 100% accuracy. Therefore, in each test the iterative training regime stopped itself when no further improvement was seen in three consecutive training sessions.

3. Results

Table 1 provides a summary of information for all the classification tests run. Each row represents a classification experiment for a specific combination of target species. For example, the second row of Table 1 represents the classification test that trained a backpropagation neural network to distinguish between alarm call barks issued in the presence of humans and alarm call barks issued in the presence of coyotes. The network was able to distinguish between the alarm calls with an accuracy of 89%. Furthermore, it took 1500 training sessions to achieve this accuracy.

A contingency table showing the results of the classification of alarm calls associated with all four species of predators is given in Table 2. The column labels represent the species that were 'guessed' by the neural network to be associated with the alarm calls tested. The row labels represent the actual species associated with the alarm calls tested. For example, the cell associated with row 'dog' and column 'hawk' gives data related to the number of times the neural network incorrectly associated a hawk with alarm calls vocalized in the presence of a dog. The diagonal cell in row 'human' and column 'human' gives data related to the number of times the neural network correctly associated a human with alarm calls vocalized in the presence of a human. Each cell in Table 2 contains two values. The first value gives the observed count for that cell and the parenthesized value gives the expected count for that cell if the neural network had been selecting randomly among the four species. The values show that the classification results are highly significant ($\chi^2 = 793$, df = 9, $P < 0.005$).

Table 2
Contingency table for classification of alarm calls for all the four predator species[a]

Actual species associated with alarm calls	Species associated by neural network with alarm calls			
	Human	Dog	Coyote	Hawk
Human	154 (70)	12 (31)	10 (41)	2 (36)
Dog	18 (34)	62 (15)	4 (20)	3 (18)
Coyote	14 (54)	14 (24)	99 (32)	10 (28)
Hawk	13 (42)	1 (19)	4 (24)	88 (21)

[a] Each cell contains the observed value and the expected value in parentheses. These results are highly significant ($\chi^2 = 793$, df = 9, $P < 0.005$).

4. Discussion

The results presented above show highly accurate classifications of species-specific alarm calls. The highest classification accuracy of 96% was obtained between dog and hawk calls. The lowest accuracy of 79% was obtained when classifying all four species together and when classifying humans, dogs, and coyotes. All other classification tests were between 85 and 95% accurate.

The classification system described in this study provides strong corroboration that Gunnison's prairie dogs have different alarm calls for different species of predators. The corroboration is strong because it comes through the use of an entirely different analysis technique than that used in the original research by Slobodchikoff et al. (1986) or in subsequent study done by Slobodchikoff et al. (1991). The study described here also is more completely automated than earlier study in this area. This automation allowed a large volume of field data to be processed where all measurements of relevant parameters were performed through software control. Previous study processed a smaller data set and utilized manual measurement techniques. A further advantage of the new system of analysis is that it utilizes powerful tools of artificial intelligence: fuzzy logic and neural networks. Neural networks in particular help to establish a plausible link between what prairie dogs are actually experiencing or capable of experiencing, and what the research tool (a neural net) is demonstrating. If a simple primitive artificial neural network can distinguish, with high accuracy, alarm calls issued in the presence of different species of predators, it seems to be reasonable to assume that the organic neural networks of Gunnison's prairie dogs are capable of making the same discrimination.

It is surprising that the experimental results presented in this study demonstrated such high accuracy. The original alarm call field recordings were made over a period of years in outside locations at two different prairie dog colonies. There were various sources of noise (including wind, trains, etc.) encountered during the taping sessions which resulted in recordings of varying quality. Additional degradation in sound quality came from the fact that the digitized alarm calls were made from copies of the original field recordings and these copies were played into a PC using a low-quality tape recorder. Thus, no extraordinary measures were taken to assure high fidelity sound reproduction. In addition to using noisy field data digitized with low quality audio equipment, it should be pointed out that no data filtering was done. The automated classification system utilized all the individual alarm call barks that were selected for a given classification test; no data was thrown out. Not only can one assume that some of the alarm call barks were of poor quality due to noise etc. but it is entirely possible that not all alarm call barks were intended primarily to specify the species-specific information. For example, it was mentioned earlier that prairie dog alarm calls have been shown to possess other types of information such as size, shape, and color of individual predators as well as direction and approach of a predator.

The use of a large number of alarm call barks recorded over a period of several years in varying conditions at two separate prairie dog colonies helped to guard against training the neural network to recognize something other than species specific information. For example, if the same external sounds or noise were present each time alarm call barks were recorded in the presence of dogs, the neural network might be recognizing that external noise and not be identifying predator specific information related to dogs. Another possible source of non-species specific information could be the characteristics of the vocalizations of specific prairie dog individuals. Reby et al. (1997) showed this capability of neural networks when they trained them to recognize the individual vocalizations of four fallow deer. Given the data set used for the work described in this study, it is unlikely that recognition of individual prairie dog vocalizations could explain the high accuracy of the classification results.

It is interesting, and not entirely surprising, that frequency ratios have been found to be an important factor in classifying predator-specific prairie dog alarm calls as described in this study. In music, the ratio of the frequencies of musical notes is highly significant because it defines a relationship between those notes that is immediately recognizable when one hears the notes. Striking examples of this are the notes of the same name, which differ in frequency by powers of two. Consider also that two chords, for example, the sixth and seventh chords of a given key, can contain several identical notes but differ only in one specific note and yet still produce clearly distinct harmonies. It seems quite possible that certain combinations of frequency ratios might form patterns that could be used to identify the distinguishable units or phonemes of an acoustic communication system.

The work presented in this study strongly suggests that frequency ratios are related in some way to the manner in which information is encoded in Gunnison's prairie dog alarm calls. Establishing the importance of this parameter was one of the major outcomes of the work described here. However, the exact way in which the information is encoded in Gunnison's prairie dog alarm calls and the level of linguistic complexity of these calls are clearly not addressed in this study. Additional work is needed to address these difficult issues. Nonetheless, part of the significance of the classification system presented in this study is that, it provides a system of analysis that can be used to investigate these more difficult questions. This system draws on powerful techniques of artificial intelligence that can be expanded to examine the issue of how and at what level of complexity information is encoded in animal alarm calls.

Acknowledgements

We thank Anne Epstein for her work in digitizing a large library of Gunnison's prairie dog alarm calls.

References

Beynon, R., Rasa, O.A.E., 1989. Do dwarf mongooses have a language? Warning vocalizations transmit complex information. S. Afr. J. Sci. 85, 447–450.

Greene, E., Meagher, T., 1998. Red squirrels, *Tamiasciurus hudsonicus*, produce predator-class specific alarm calls. Anim. Behav. 55, 511–518.

Gyger, M., Marler, P., Pickert, R., 1987. Semantics of an avian alarm call system: the male domestic fowl. Behaviour 102, 15–40.

Kiriazis, J., 1991. Communication and sociality in Gunnison's prairie dogs. Ph.D. dissertation, Northern Arizona University.

McCulloch, W.S., Pitts, W., 1943. A logical calculus of the ideas imminent in nervous activity. Bull. Math. Biophys. 5, 115–133.

Owings, D.H., Virginia, R.A., 1978. Alarm calls or California ground squirrels. Z. Tierpsychologie 44, 58–70.

Pereira, M.E., Macedonia, J.M., 1991. Response urgency does not determine antipredator call selection by ring-tailed lemurs. Anim. Behav. 41, 543–544.

Reby, D., Lek, S., Dimopoulos, I., Joachim, J., Lauga, J., Aulagnier, S., 1997. Artificial neural networks as a classification method in the behavioral sciences. Behav. Processes 40, 35–43.

Ross, T., 1995. Fuzzy Logic with Engineering Applications. McGraw-Hill, New York.

Rumelhart, D.E., Hinton, G.E., Williams, R.J., 1986. Parallel Distributed Processing: Explorations in the Microstructure of Cognition, vol. 1. MIT Press, Cambridge, MA.

Seyfarth, R.M., Cheney, D.L., Marler, P., 1980. Vervet monkey alarm calls: semantic communication in a free-ranging primate. Anim. Behav. 28, 1070–1094.

Slobodchikoff, C.N., Coast, R., 1980. Dialects in the alarm calls of prairie dogs. Behav. Ecol. Sociol. 7, 49–53.

Slobodchikoff, C.N., Fischer, C., Shapiro, J., 1986. Predator-specific alarm calls of prairie dogs. Am. Zool. 26, 557.

Slobodchikoff, C.N., Kiriazis, J., Fischer, C., Creef, E., 1991. Semantic information distinguishing individual predators in the alarm calls of Gunnison's prairie dogs. Anim. Behav. 42, 713–719.

Slobodchikoff, C.N., Ackers, S., Van Ert, M., 1998. Geographic variation in alarm calls of Gunnison's prairie dogs. J. Mammal. 79, 1265–1272.

Zadeh, L., 1965. Fuzzy sets. J. Inf. Contr. 8, 338–353.