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Identifying the Behavior of the Dogs Using Their Barks

T. Raj Kumar

Abstract

In recent years, dogs have become more close to humans that they were like a family. Each individual would like to know their behavior. In order to make this possible we are going analyze the barks of the dogs. This study helps us to identify the behavior of the dogs using their vocalization. In this paper, we are going to compare the sounds of the dogs bark and find their behavior. Generally the barks of the dogs vary according to the different situations. Sometimes the dog barks due to some disturbances, sometimes while it plays, and some other times it barks when it is isolated. The frequency and the pitch of the bark sound vary to different situations. Also the bark sound varies according to their gender, age and their breed. To analyze all these we have collected 2000 bark sounds which were recorded in four different contexts. These sounds are converted to machine language. This helps to identify the behavior of the dogs.

Keywords: dogs bark, candies, vocalization.

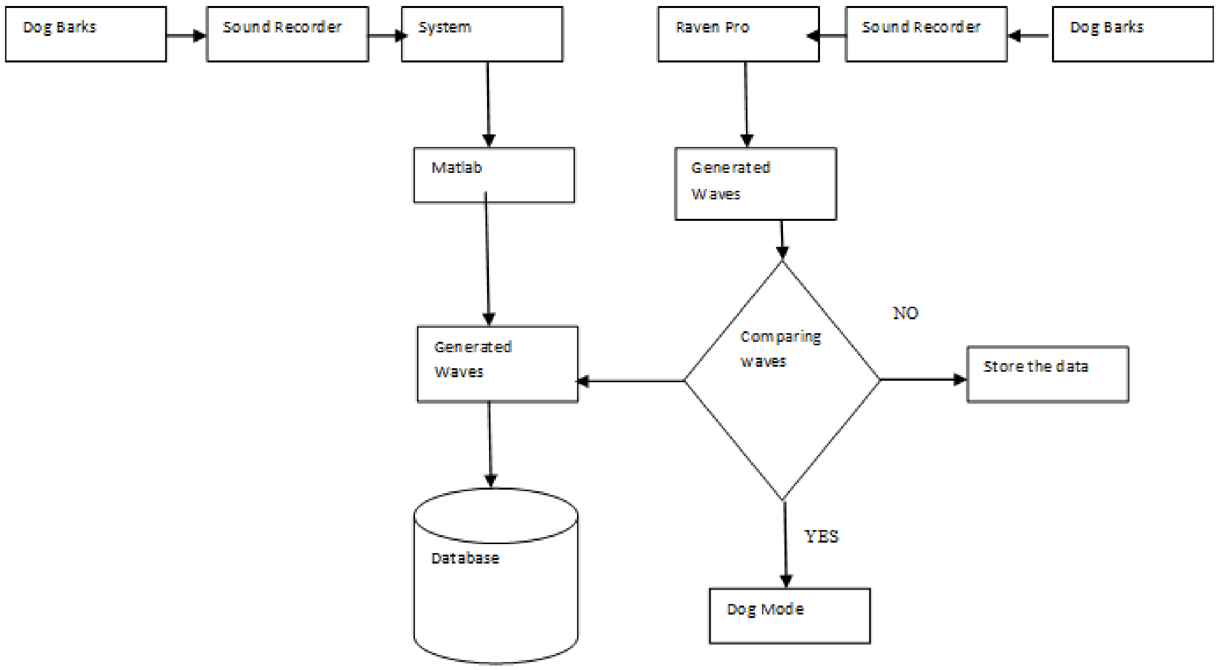
Introduction

Wild and domestic canids are well known for their rich vocal signals. Though barking is connected to most of the canids, it is more seen in dogs. Almost all the canine acoustics signals are related to some special situation. But barking which is the most characteristics vocalization of dogs does not have any specific communicative role. Dogs barking are well known when compared to other sounds by the canids. Other canids bark only in their puppyhood and during defending territory when the dogs bark does not relate to any specific context. It barks of various situations: Sometimes without any intention just to interact with other dogs. However dogs barking play a special role between dogs and humans. Sincedogs have strong attachments to humans. Dog's response to human in various ways depending on the different human activities. At present, there are many researches going on that investigates whether dog barks a play a vital role in dog-human communication. This depends on how the human understands and react to various (or) different acoustic sounds created by the dogs. The dog barks help humans to know their mode of behavior.

This can be identified by deeply listening to the different vocalization of the dogs. The dogs bark vary depending on various situations like play , fight, stranger, walk, etc.., to identify the mode of the dog more than nearly 2000 barks were recorded at various situations using a sound recorder and saved in a system.

Then the individual bark sounds were separated from the saved recordings which possibly contain three to four barks. These individual barks are separated from the continuous barks that are one bark followed by the other without any interval silences or break. This is done to the clearance of the dogs bark and also to reduce the background noise, these isolated barks are saved in a device (chips or memory card). Then these barks are converted into waves using mat lab. Then the converted waves are stored in a database which specifies different modes of behavior of the dogs. On the other side the dog barks are recorded using recorder and then converted into waves using a Raven pro tool. Raven pro is a software tool which generates waves based on the given sound. This generates wave checks for the matching wave that is already stored in a database. If the wave matches then the mode or behavior of the dog is displayed. If the wave does not matches with any of the waves that is stored in a database, then the wave can be saved to the database with a new mode of behavior of the dog. By doing this we will be able to understand the mode of the dog better and behave with them according to their mode. This improves the better communication between dogs and human.

Architecture



Methods and materials:

Source and collection of sound recordings

We collected bark recordings in seven different levels according to their surrounding or environment. Now we are going to see about how the training school was handing their monkey behavioral in different situations

The seven situations are as follows:

1. Stranger: The unknown person was handling the monkey's position and appeared in the garden of the owner or at the front door of his apartment in the absence of owner. The person who handling the experiment recorded the barking of the monkey during his appearance for 2-3minutes.
2. Fight: For monkeys to perform in this situation,the trainer encourages the monkey to bark to attack the stranger. And to bite the give on the trainer's arm,meanwhile the owner keeps the monkey's leg rope.
3. Walk: The owner was asked to behave as if she was preparing to go for a walk with the monkey.
   For example: The owner took the rope of the monkey in her hand and told the monkey "we are leaving now"
4. Alone: The owner tied the monkey to a tree with a rope in a park and walked away, out of sight of monkey
5. Ball:The owner held a ball at a height of approximately 1.5m in front of the monkey.
6. Play:The owner was asked to play with the monkey a usual game such as,
   Tug of war (rope war,rope pulling)
   Chasing
7. Wrestling: For some monkey wrestling is a favorite gamemonkey's use wrestling to communicate with each other as well as to burn off extra energy. It can be a sign of friendship or a means to move up in the

pack's peaking order the unknown person recording the backing sound during this interaction.

Recording and preparing sound material

The recordings of the dog barks wee made manually. The experimenter recorded the barks using a microphone at a maximum distance of 4-5m .The experimenter tried to stand in front of the dog at most cases while recording(Pongráczet al. 2006). They used a song TCD-100DAT tape recorder and song ECM-MS907 microphone on song PDP-65C DA7 tapes to record the dogs barks. The recorded material was then transferred to a computer, where it was digitalized. The recordings vary in an efficient manner for each dog and each situation. To avoid or minimize the background noise, it is important to separate the individual bark sounds of the dog. Each recording contained minimum 4-5 barks. From these barks individual barks sounds ere manually separated and extracted. While separating, the interval silences between two barks were excluded (Monceaux et al. 2005; Cabral et al. 2005).This process resulted in a final collection of 6000 sound files containing only single bark sound.

Analyzing process

Phase 1: Generation of a large number of descriptors adapted to a specific classification problem using EDS.

The large number of descriptors is required during this process. To perform this EDS which is an audio signal processing system is used. If produces descriptors to a particular audio classification problem. FDS contains a library of acoustic features which combines evolutionary algorithm that produces descriptors that are more specific to the problem use want to solve using mathematical composition of functions. EDS combines the basic operators. The composition of basic operators is expressed as a space of all functions such function space is potentially huge. Hence searching for "interesting functions is a highly combinatorial process.

EDS implements various artificial intelligence techniques to cope with this issue. First, a type system prevents the creation of malformed descriptors. Second, a library of weighted heuristics for operator composition is used to guide the elaboration of new descriptors. Finally, the descriptor creation is based on a genetic algorithm: EDS iteratively creates generations of descriptors; only the most efficient descriptors, according to their Witness, of one generation are kept as seeds for the next one, i.e. they are combined together according to "genetic mutations" to create new descriptors (Koza 1992). The Witness used to assess descriptor's performance is based on class membership. For a given descriptor, a nearest-neighbor classifier is created that is trained and tested on non-overlapping datasets. The Witness of the descriptor is the performance of the associated classifier. This process goes on until very efficient descriptors have been devised by the system. Eventually, the best descriptors are fed into a machine-learning algorithm to produce classifiers. For this study, we started with a set of basic signal processing operators and explored their combinations using EDS. A large number of descriptors adapted to the classification problem were generated this way.

Phase 2: Creation of an optimal subset of descriptors

To evaluate a feature set and to search the space of feature sets we create an optimal subset of descriptors. This involves two approaches, filter and wrapper approach. The machine language techniques are used for the reduction of the feature space. Two approaches are commonly used. In the "filter" approach, a feature subset is selected based on the properties of the data itself and is independent of the chosen classifier algorithm. In the "wrapper" approach, the classifier algorithm is used during the search of the feature subset. The method used in this study belongs to the "wrapper" approach. To evaluate the feature subset, we used a simple Bayesian method trained over a part of a data set (roughly2/3) and tested over another (1/3) (Witten and Eibe 1999). For the situation classification problem, the test set did not contain any samples from dogs present in the train set. Respectively, for the dog classification problem, the train set did not contain any samples with situations present in the classification set. This prevents possible over fitting of the classification method to particular individuals, contexts or recording conditions. The choice of the Bayesian classifier was motivated by its good compromise between efficiency and simplicity and by the fact that it is mathematically well defined (Kohavi and SommerWeld 1995). This is a simple and classical method in statistical modeling, with clear semantics. However, it is possible that other classification methods outperform these classifiers for the twotasks considered. The search stopped when the addition or deletion of any remaining attributes resulted in a decrease in evaluation. With this method, for both classification problems considered, we reduced the space to a small number of very relevant features. During this phase, each classifier was trained over a part of a data set and tested over another for evaluating rapidly the quality of the attribute space. For the situation classification problem, the test set did not contain any samples for dogs present in the train set.

Phase 3: Complete evaluation of recognition

The Bayesian classifier was conducted once an adapted attribute set was created for each classification problem. For the context recognition problem, 14 train/test sets were created, each of them corresponding to a test on the data of a single individual and training on all others. Similarly, for the individual recognition problem, 6 train/test sets were created, each of them corresponding to a test on a particular

Context and training on all others. Results were then aggregated and compared. Once again, this method prevents biases linked with particular recording conditions.

Result

Experiment 1: Categorization of barks into contexts

Here categorization algorithm is used for classification of barks into context. To construct the attribute space, a training set was constituted with recordings from nine dogs (d05, d08, d09, d10, d12, d14, d16, d18, d20—4,059 samples in total, 61% of the total number of samples) and a test set with recordings from Five dogs (d23, d24, d25, d26, d27—2,587 samples in total, 39% of the total number of samples). Using the EDS algorithm and the optimal feature subset search method described above, the system converged on a set of seven features. Itpresents the results of each independent individual test set as well as the overall performance and overall confusion matrix. The overall recognition rate is 43%. A random classification algorithm would have guessed only 18%. The overall recognition rate was significantly higher than the recognition rate using a random algorithm. In order to correct for agreement that occurs by chance, we can calculate the kappa statistic by deducting the number of corrected predictions obtained by the random algorithm from the ones obtained by the Bayesian classifier and comparing it. This results in an overall kappa of 30%. The best recognition rates were achieved for the barks recorded in the "Fight" (74%, kappa = 68%) and "Stranger" (63%, kappa = 49%) contexts and poorest rate was achieved when categorizing the "Play" barks (6%, kappa = 6%). We compared the recognition rates for barks in different contexts to each other and to the recognition level of the random algorithm as well. We found that the success rate of the algorithm was significantly higher in cases of "Stranger" (one-sample t-test: $t12 = 4.08$; $P < 0.01$), "sFight" ($t9 = 5.45$; $P < 0.001$), and "Ball" ($t9 = 3.55$; $P < 0.01$) situations, and we found no significant difference in cases of "Walk" ($t10 = 0.43$; $P = 0.67$), "Alone" ($t4 = 0.06$; $P = 0.95$), and "Play" ($t5 = 1.63$; $P = 0.16$) contexts. We compared the recognition rates of the algorithm for barks in different contexts with each other. We found that the algorithm was significantly more successful in categorizing "Stranger" and "Fight" barks than the others ($F4, 49 = 10.20$; $P < 0.001$) for recognition rates in all the situations and confusion matrix. The confusion matrix shows the proportions of the correctly and incorrectly categorized barks in each situation. In the case of barks recorded in "Play" context, a relatively high proportion of erroneously classified barks were considered as "Walk" barks (40%). "Alone" barks are also confused with "Stranger" barks (43%). Important differences in the recognition rate can be observed in the individual dog test sets (maximum for d08, 89% and minimum for d20, 25%) Experiment 2:

Recognition of dogs Symmetrically with the previous experiment, for constructing an attribute space adapted to the recognition of individual dogs, we First separated the whole dataset into a training set with recordings corresponding to "Ball", "Stranger" and "Fight" barks (3,921 recordings, 59% of the whole dataset) and a test set corresponding to the "Alone", "Play" and "Walk" barks (2,725 recordings, 41% of the whole dataset) and vice versa. With such separation, dogs will have to be recognized in situations that the classifiers have not encountered before. Using the ED's algorithm and optimal feature subset search method described above, the system converged on a set of eight features. The results of each independent situation test set (classifiers trained to recognize dogs on all situations but one and tested on the remaining one), as well as the overall performance (global and per context) and global confusion matrix. For this task, the overall recognition rate is 52% (3,463 correctly classified instances over 6,646, kappa = 45%). We compared the recognition rates of the 14 individuals to the chance level (100/14 = 7.14), and found that the success rate of the algorithm was significantly higher than chance level (one-sample t-test: t12 = 3.21; P < 0.01). Important differences exist between dogs. Some dogs were easily recognized, as with d23 (733 recordings, kappa = 75%) or d24 (1,524 recordings, kappa = 69%), others were very poorly recognized, possibly because of the comparatively small number of recordings available as with d08 (75 recordings, kappa = ¡1%) or d10 (85 recordings, kappa = ¡1%). We should note that in the analyzed set of barks not every individual was represented by the same amount of collected barks. This can explain some of the differences of recognition rates between individual dogs (classes with too few training examples are poorly recognized). Looking more precisely at the comparative performance of the different situation test sets, we compared the recognition rates of the algorithm for barks recorded in different situations. We did not Find significant differences among them (ANOVA: F5,49 = 2.37; P = 0.056), however it seems that recognizing a dog in the "Ball" (65%), "Alone" (64%), "Walk" (64%) and "Play" (60%) is easier than in the"Fight" (49%) and "Stranger" (30%). This is unlikely to be an effect of the particular separation of the train and test set used during the construction of the attribute space ("Ball", "Stranger", "Fight" for training, "Alone", "Play", "Walk"for testing) but we cannot discard this effect completely. This suggests the "Fight" and "Stranger" situations are indeed special contexts, both easier to recognize as context type but more difficult than other contexts for the recognitionof individual dogs.

Discussion

Context classification

We have found that barks can be categorized into situationsand different individuals' barks are distinguishable using acomputerized method. The relative efficiencies of the softwarewere comparable to human performance in the situationsof "Stranger" and "Fight". In thesituations of "Walk" and "Ball", the program outperformedhumans, but in the "Play" and "Alone" contexts humanshowed better performance. The algorithm could categorizethe barks into the correct contexts in 43% of the barks onaverage (kappa = 30%).We have found earlier that humans could categorize the"Stranger", "Fight", and "Alone" barks with a relativelyhigh accuracy rate. Whereas in the"Play", "Walk" and "Ball" situations, their performance was less efficient, the "Stranger", "Fight" and "Alone" barks were categorized with a success rate of 45–50% while "Walk", "Ball" and "Play" barks were successfully categorized in 30% of cases. We concluded the reason for these Findings might be that in the latter contexts the barks of different individuals are less similar to each other because there was not a strong selection affecting their acoustic features or that during the vocalization the motivational states of dogs in these situations varies very rapidly.In contrast, the "Stranger" and "Fight" barks, which could be dominated by agonistic tendencies, and the "Alone" (perhaps fearful) barks are more uniform among different individuals. First to point out that in some contexts barks are acoustically different which means that the acoustic features of the bark depend either on the motivational/emotional state and/or on the actual context. The achievements of the program clearly show that barks have the acoustic potential for being context-specific calls. The different motivational states of dogs in aggressive, friendly or submissive contexts could result in acoustically different barks. This showed that several mammalian and bird species emit harsh, low frequency sounds in aggressive situations, and, in contrast, tonal, high frequency ones in submissive or friendly contexts. But these differences occur among qualitatively different vocalization types. Here in barks, dogs could modify their sounds within the same vocalization type, which suggest that barks are very easy to modify, so they could be an effective tool to communicate inner states in a flexible way. From this point of view, the dog's barks are different from wolf's barks since wolves bark only in very distinct contexts. These modifications could have happened as a result of evolutionary changes in the dog's vocalization system but another option is that dogs vary their barks according to their learned experiences.

Individual classification

The other important result was that the software was able to categorize the barking individuals with an efficiency of 52% (kappa = 50%). We found that the software categorized individuals at a higher level of success if they were barking in "Walk", "Alone", "Ball" and "Play" contexts, but the difference was not significant. This was very surprising because there was no previous evidence that barks may contain individual-specific information. Actually, applying a very similar task we have found that humans are not able to discriminate reliably between barks of different individuals recorded in the same context and their task was to guess if those two barks were recorded from the same or different dogs. The reasoning of this argument is that the formant characteristics are better detectable if the call is more tonal which means that the power is concentrated in the harmonic pattern. Unpublished data collected by us suggest that barks in the situations "Alone", "Ball" and "Play" are more tonal. In an individual-recognition task, the algorithm could recognize the dog with a higher efficiency when it was barking in "Ball", "Alone", "Walk" and "Play" situations in contrast to "Stranger" and "Fight" contexts where the success rate was lower. In a context-categorization task, the algorithm was most successful in categorizing "Stranger" and "Fight" barks and was relatively less successful in categorizing "Alone", "Play" and "Walk" barks. These two Findings suggest that "Stranger" and "Fight" barks are less individual-specific and barks in the other situations are more distinguishable among individuals. Comparisons of the performances of the humans and computerized algorithm could be useful to understand the effects in the background of human performances when categorizing the barks, although their performances can be compared at only a limited level due to methodological differences between the two experiments. Because of these differences unfortunately we cannot compare directly the performances of the algorithm and humans using statistical analyses. One important difference between this computerized analysis and a human perceptual test is that humans were exposed to several barks in sequence coming from the same context but the software used only "one" isolated bark to make its decision. Since in a previous study we found that the intervals between the barks have an effect on the decisions of listeners about the dog's motivational state (the barks with shorter intervals were considered more "aggressive" while barks with longer intervals were considered more "fearful", "desperate" and "happy"), one could presume that this acoustic feature might be different among various individuals' barks and in different contexts. In cases of "Alone" and "Play" barks the humans significantly outperformed the computer. A reason for this performance could be that in these situations the human listeners use the intervals between barks more extensively while the computer did not have the opportunity to use this feature for categorization. Another difference between the human and computer tests is that the computerized algorithm was exposed to massive training on dog barks in the First phase of the experiment. Whereas humans could rely only on their previous experience of hearing dog barks and they did not have the opportunity to listen to training sound samples. The prior training could increase the success rate of listeners in case of barks recorded in "Ball", "Play" and "Walk" contexts because these contexts seemed to be less uniform. A future experiment should clarify whether the human performance levels can be enhanced by specific training on dog barks. According to our Findings the computer significantly outperformed the humans in individual categorization task while in situation classifying tasks its performance was at a similar level to that of humans'. This suggests that prior training could have a significant effect on individual categorization abilities. The main difference between performances of the computer algorithm and humans was that the software could reliably discriminate among individuals while humans could not. It might mean that there are individual differences in barks of dogs but humans are not able to recognize them easily. In another study, we found that dogs can differentiate barks of different individuals. From the Findings of these three studies, we hypothesized that there are individually distinctive features of barks butthese characteristics are recognizable only by con specifics and not by humans. However, that study was designed according to the "habituation-dishabituate paradigm", so the task of dogs was simpler than categorizing the barks. In our opinion, the performance of the computer must have been based on distinct context-specific and individual specific acoustic features of the barks. If these features emitted in a given situation had varied randomly they would not have been recognizable above chance level either for humans or a computer algorithm. This raises the question of what kind of information could be encoded in barks. During early domestication of dogs people might have preferred more vigilant dogs, which could alarm them when a stranger approached, defending the camp against intruders. If the dogs could recognize the barks of others, which were emitted in certain situations, it might improve the success and reliability of alerting. Hence there might have been a strong positive selection for dogs, which barked frequently especially if they could distinguish among barks of others. It should be noted that the features we propose in this paper are the result of a particular experiment, with a particular database of dog bark sounds. The features found using the EDS system are better than the "conventional" features used in the audio classification literature. However, these features are not easily interpretable. Also, we cannot assess precisely how robust they are to changes in the testing set. Note that this last remark (robustness) is also applicable to results using conventional features, by definition: the capacity of classifiers to generalize is always demonstrated to a certain extent, determined by the "testing" database. From a methodological perspective, the use of advanced machine learning algorithms to classify and analyze animal sounds opens new perspectives for the understanding of animal communication. This study offers only a First illustration of this potential. It is important to stress that the method used in this study is fully automatic (except the segmentation of barks). No information linked with the particular problem of bark classification was included at any stage of the process. This means that the process can be applied indiscriminately to any other audio classification problem. This also guarantees that the process is unbiased that limits the number of potential preconceptions that researchers may introduce into the construction of good descriptors of the data and permits discovery of structure that they may have otherwise missed. This study illustrates how such type of automatically discovered structure may be interpreted in a specific context and how this type of experiment can complement, in a useful manner, other approaches to the study of animal communication. The promising results obtained strongly suggest that the advanced machine learning approaches deserve to be considered as a new relevant tool for ethnology.

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Author's details

1Manjusha Kulkarni, Asst Prof., CSE, T John Institute Of technology,Karnataka,India, manjushakulkarni@tjohngroup.com

2Annie S Asst Prof., CSE, T John Institute Of technology, Karnataka, annies@ tjohngroup.com