MOTILITY SIGNAL CHARACTERIZATION

AND CLASSIFICATION

By

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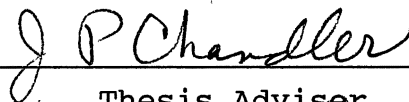Central State University

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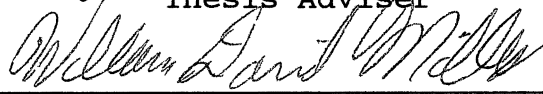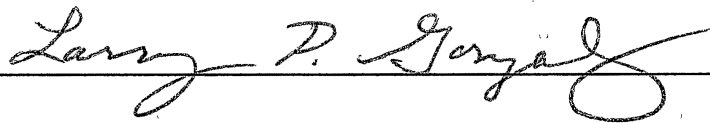MASTER OF SCIENCE
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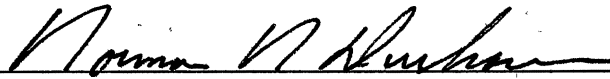
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GLOSSARY

ARMA model: Auto Regressive Moving Average model.

Adaptive segmentation: A technique by which a signal is broken into like parts. When the characteristics of the input signal significantly change the signal is segmented.

BAM: Bidirectional Associative Memory, a generalization of the Hopfield Associative Network. A type of network in which an input serves to retrieve a stored associated output.

Classifier: A mathematical model which assigns an element membership in a class according to its characteristics.

Connection weights: The value assigned to a connection between neurons, analogous to a synapse. The value of the connection weight determines how much of the incoming signal is passed to the connected neuron.

EEG: Electroencephalogram, electrical brain impulses caused by neuron firings.

Error back-propagation: A supervised learning method in which the error between the actual output and the target output is fed back through the network altering connection weights as it goes, in order to decrease the network error.

FFT: Discrete Fast Fourier Transform of a time function into a frequency domain to determine the individual frequency

components and relative power of each component.

Fixed-length segmentation: Breaking a signal into arbitrary fixed length portions.

Gradient: The maximum rate of change in a variable or a function.

Hanning: A pre-scaling or windowing function used to make a sampled waveform coherent with the window interval.

Hidden layer: Any of one or more neuron layers between the input and output neuron layers.

Hopfield network: This is a Content Addressable Memory Network capable of taking a partial input pattern and retrieving the entire associated pattern, also described as an autoassociator.

Input layer: The layer of neurons into which the input signal is initially propagated into the network.

Mapping continuity: A mathematical transformation in which similar input have similar outputs.

Motility signal: A sensor signal containing to animal movement data.

Neural network: A mathematical model of the brain's neurons. A system of neurons interconnected by synapses.

Neuron Normalized: An input value scaled from between the minimum and maximum possible input values to between 0 and 1, the neuron value range.

Neuron: A basic processing element in a Neural Network, also a nerve cell in a biological system. In either case it has a number of input signals which are summed and compared

against a threshold value. If the threshold is reached, an output signal is generated which is equal to the neuron's activation value.

No Power model: The simplest Neural Network Classifier model used in this project. The input pattern is Neuron Normalized and there is one input neuron per pattern data point.

Output layer: The layer of neurons from which Neural Network response is presented.

PA: Period Analysis.

Proportional Total Power model: A neural network Classifier model used in this project. The input pattern is preprocessed by replacing each data points value with its proportion of total power. This input pattern is then Neuron Normalized and there is one input neuron per pattern data point.

R^n: The set of all real numbers in n dimensional space.

Sigmoid function: A continuously differentiable transfer function, known for its S shape when plotted.

$$S(x) = \frac{1}{(1+e^{(-Gain*x)})}$$

Stereotype behavior: Standard repetitive animal behaviors.

Supervised learning: This is a method by which an external source tells the network the amount of output error present, so the neural network weights may be adjusted to reduce the error.

<u>Time series:</u> A Time Series is a set of numbers that are
assumed to be taken at an equally spaced time interval
measuring some ongoing activity.

<u>Total Power model:</u> A Neural Network Classifier model used in
this project. The input pattern is summed and added as an
additional last data point. This input pattern is then
Neuron Normalized and there is one input neuron per pattern
data point.

<u>Transfer function:</u> A function which determines what neuron
activation value is to be output. Typical transfer
functions are linear, sigmoidal, or threshold.

<u>Window:</u> A finite time slot wherein a sample group is derived
from a time function.

CHAPTER I

INTRODUCTION

The purpose of this project is to develop a motility
data analysis system for use by scientific researchers. The
software should run on a personal computer and identify the
different animal motor behaviors and their occurrence times,
from stored data files.

Background

Central nervous system disorders or drugs used in the
treatment of diseases affect the motor behavior of humans.
Laboratory animals are often used in experiments designed to
understand these effects better. Despite the importance in
experiments of monitoring motor behavior, most laboratory
animal motility data is gathered and analyzed manually by
either directly observing the animals or studying a video
tape. Unfortunately these methods are subjective and very
time consuming. An objective automated motility data
gathering and analysis system would be of great benefit to
researchers.

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While animal activity monitors have been developed that measure one or two behaviors, none exist that can monitor multiple behaviors simultaneously[9]. I have investigated the use of a modified Stoelting activity monitor system which is capable of recording multiple motor behaviors by using a radio-frequency capacitance field transducer that provides an output signal that varies with the movements within the field of the transducer. The frequency components of the movements that comprise a behavior and the amplitudes of these movements govern their effect on the output signal. Repeated head swings could generate a two hertz signal with a very large amplitude, while respiration generates a two hertz signal with a small amplitude. The output is a single DC analog signal composed of the multiple frequencies generated by the animal's different motor behaviors. This signal is stored as a time series, digitized at 128 integer points per second and stored onto a floppy disk. This data format is referred to as a time series.

The analysis method used to date [9,10,11] on the Stoelting monitor data consisted of a Fast Fourier Transform (FFT). The FFT was used to obtain power spectra for each 1-second segment of motility data, then the spectra were averaged across a large sampling period. Finally the log of the mean of the power spectra was taken. While this analysis method has demonstrated certain behaviorally

correlatable frequency signatures it has not been capable of producing a method of accurately characterizing different complex behaviors.

Problem Statement

The problem I am attempting to solve is to develop the analysis algorithms necessary to assess quantitatively the simultaneous occurrence of individual motor movements from the recorded motility data. For the system to be of practical use to scientific researchers the analysis algorithms should be capable of being executed on a relatively inexpensive Personal Computer system in a reasonable amount of time. With these constraints in mind a PC-80386/80387 system was chosen for system development. These analysis algorithms should be capable of cataloging the animal's motor behavior at all times into one of the following defined behavioral categories: sniffing, licking, gnawing, grooming and respiration, but should also allow for another category for undefined behavioral type. The general approach should also be applicable to other defined behaviors.

CHAPTER II

MODEL DEVELOPMENT AND METHODOLOGY

Introduction

A three fold approach to solving the motility analysis
problem was considered. First develop a method to segment
the signal into small portions of like behavior. Next
develop a technique to characterize each segment such that
individual behaviors have a unique, although variable,
identifiable signature. This can be viewed as feature
extraction or signal preprocessing to enhance
distinguishable features between behaviors. Finally develop
a method to correctly classify these signatures into
behavior categories.

A set of test data was obtained by recording motility
data and simultaneously videotaping the behavior of three
male Sprague-Dawley rats, 60 - 90 days old.

Animals were observed for 15 minutes and then received
a subcutaneous injection of apomorphine HCL (0.25 - 0.50
mg/kg). Observations continued for an additional 60
minutes. The drug injection resulted in an increase in the
occurrence of repetitive movements, and the recordings
obtained during this period provided the samples of motility

data which were analyzed during the remainder of this project. During this time the animals were also video taped. The videotape was recorded using a time code generator which puts a time stamp on every picture frame, 30 per second. These tapes were viewed by an animal behavior specialist who scored the tapes annotating the beginning and ending time of a segment and what behavior was observed. This manually scored data was used to determine the overall accuracy of the analysis algorithms.

Development Tools

I developed the graphical display, Fast Fourier Transform (FFT) and Period Analysis (PA) analysis software using the scientific software development package ASYST Version 3.01 scientific system by Macmillan Software Company. This package uses a very powerful stack-based fourth generation language, including a very large library of scientific and graphics functions. Due to certain ASYST limitations I used Turbo C Version 2.0 for both Neural Network implementations, data conversion utilities, and certain graphical display software.

Segmentation Methods

ARMA

One potential segmentation method involves using an Autoregressive Moving Average (ARMA) model [1,4,15,19] to segment the motility signal adaptively at points corresponding to a change in animal behavior. The autoregression technique involves adaptive segmentation of the signal using an autocorrelation function (ACF). An ACF is calculated for a fixed window at the beginning of the segment and for a window moving forward through the signal step by step. The Spectral Error Measure (SEM) is computed between the fixed window ACF and the moving window ACF. The SEM value reflects changes in the spectral characteristics of the signal. The moving window is stepped through the signal one data point at a time. At each step the moving window's ACF is updated and the SEM recalculated. A segment boundary is defined when the SEM remains above an arbitrary threshold for a given number of steps. At this point the entire procedure is repeated. Each one of the resulting signal segments would then be behaviorally characterized by another analysis method.

Fixed Length

The second analysis method considered involves segmenting the signal into arbitrary fixed length segments.

The segment length would be determined by the minimum
meaningful duration of the possible animal behaviors being
analyzed. Then each fixed length signal segment would be
behaviorally characterized by an analysis method to be
discussed later. Similarly categorized adjacent segments
would be grouped together as one continuous behavior
segment.

Segmentation Evaluation

Animal motor behavior activity segments of interest to
laboratory research last anywhere from several seconds to
several minutes at a time. It was judged that the increased
accuracy potential of adaptive segmentation as shown in
TABLE I would provide only a marginal improvement over a
fixed length segmenting technique, using a small fixed
length. The discriminant function analysis of the data was
performed by the statistical software package SAS.

TABLE I

DISCRIMINANT FUNCTION ANALYSIS OF MOTILITY
CHARACTERIZATIONS USING FFT ANALYSIS
PERCENT CORRECT CLASSIFICATIONS

	SIGNAL ANALYSIS TECHNIQUE	
Behavior	1-Second Segment	Adaptive Segment
Respiration	98%	100%
Sniffing	83%	100%
Stereotyped Sniffing with Head Swing	73%	88%
Stereotyped Paw Lick	80%	88%

Also an ARMA adaptive segmentation method would require
considerably more computational overhead than fixed length
segmenting. After considerable deliberation the fixed
length signal segmentation method was chosen as the
segmentation technique and a fixed segment length of 1-
second was selected for this project. The 1-second segment
length was a compromise between the greater expected
classification accuracy from a longer segment length and the
need to be able to identify short duration behaviors. This
selection allowed maximum concentration on the
characterization technique which is essential to either
segmentation method.

Characterization Methods

Two segment characterization methods were explored, Fast Fourier Transform (FFT) [2,17] and Period Analysis (PA) [5,6,17]. Variations on these methods were investigated in an attempt to find a technique that would provide a unique identifiable signature for each one of the behaviors to be characterized. The motility data was read in 30 second portions; the mean were calculated then subtracted from the data to remove the DC component.

FFT

In the FFT characterization technique [2,17] a complex signal can be analyzed and the contribution of each frequency component to the total signal power can be determined. Each 1-second data segment was Hanning Windowed [17] to reduce sidelobes, then the FFT was calculated. This magnitude was squared, giving the power, and finally the LOG of the power was computed; the LOG of the power was used in all FFT characterizations.

Upon visual inspection the 1-second FFT LOG of the power vector from 1 to 20 hertz appeared to give a behaviorally correlatable signature, but there was a considerable amount of variation between samples of the same behavior.

PA

In the PA characterization method [5,6,17] the motility data first were run through a 64 hertz low pass digital filter. Then, the total number of zero base line crosses of the signal segment was calculated, subtracted by one, and divided by two, giving the Major period component of the segment. Next the first derivative of the segment was taken and again the number of zero base line crosses of the signal segment was computed, subtracted by one, and divided by two, giving the Intermediate period. Last the second derivative of the segment was taken and again the number of zero base line crosses of the signal segment was computed, subtracted by one, and divided by two, giving the Minor period. These three values reflect the frequencies of the three most prominent components of the signal segment. This technique has been used by NASA in electroencephalogram (EEG) telemetry data compression [6].

Characterization Evaluation

Initial motility signal PA values appeared inconsistent with visual appearance of the signals. In an attempt to evaluate apparent PA characterization contradictions, two synthetic signal data files were created and analyzed by both FFT and PA. Since motility data signal components often have one or more orders of magnitude difference in

amplitude the two test files both contained signals with two
hertz and eight hertz frequency components, but different
amplitude ratios. For the purpose of mimicking the motility
data characteristics both test signals had two hertz
components that were the same amplitude. However, file
SIN28.3 had an eight hertz component one third the amplitude
of the two hertz and file SIN28.6 contained an eight hertz
component one sixth the amplitude. TABLE I shows the
results of the Period Analysis on the two test signals.

TABLE II

TEST SIGNAL PERIOD ANALYSIS

Test Signal	PERIOD		
	Major	Intermediate	Minor
SIN28.3	2.1099	8.0000	8.0000
SIN28.6	2.0645	4.4356	4.4356

After some analysis it was determined that the
erroneous PA values for test signal SIN28.6 were caused by
the large amplitude difference between the component
signals. This large amplitude difference caused the eight
hertz component contribution to be erratic in producing
turning points and points of inflection in the composite

signal as happened in the SIN28.3 signal. This is an inherent shortcoming of the Period Analysis method. Principal EEG component signal amplitudes are similar in magnitude. Thus, this error did not affect EEG uses of Period Analysis [5,6]. However, this flaw makes PA unsuitable for motility signal characterization.

These same two synthetic motility test signals were used to evaluate the 1-second FFT capability. Repeated 1-second FFTs of the test signals all had identical values for each signal and had no trouble correctly identifying the two frequency components, regardless of the power ratios. While the Hanning Windowing reduced sidelobes it caused a certain amount of spectral power leakage from the 2 and 8 hertz bins into neighboring frequency bins. In figures 1 and 2 the graphical displays of FFT patterns take the LOG of the power values between 0 and 15 and normalize them between 0 and 1. In view of the clearly superior accuracy of the FFT method over PA I chose the FFT method for signal characterization. The results of these two test signals are displayed in figures 1 and 2.
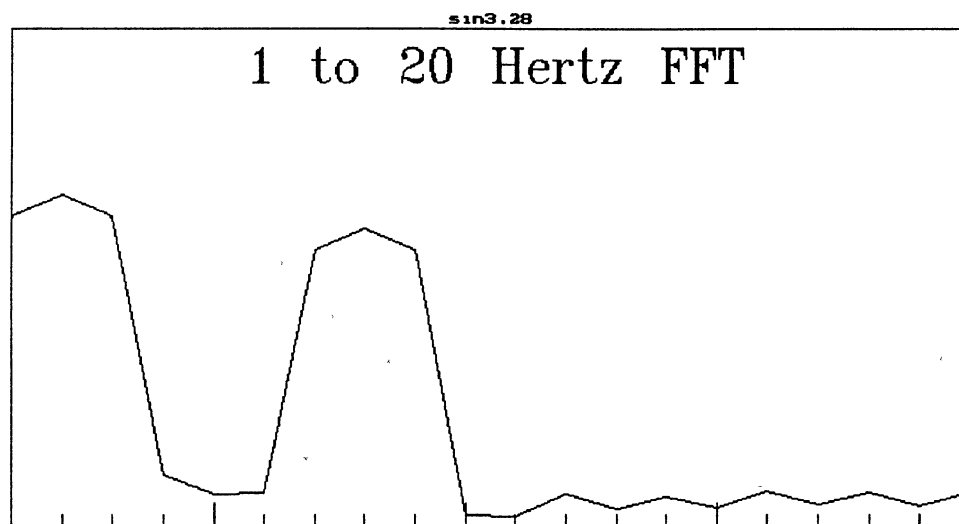
Figure 1. Neuron Normalized SIN3.28 FFT Pattern
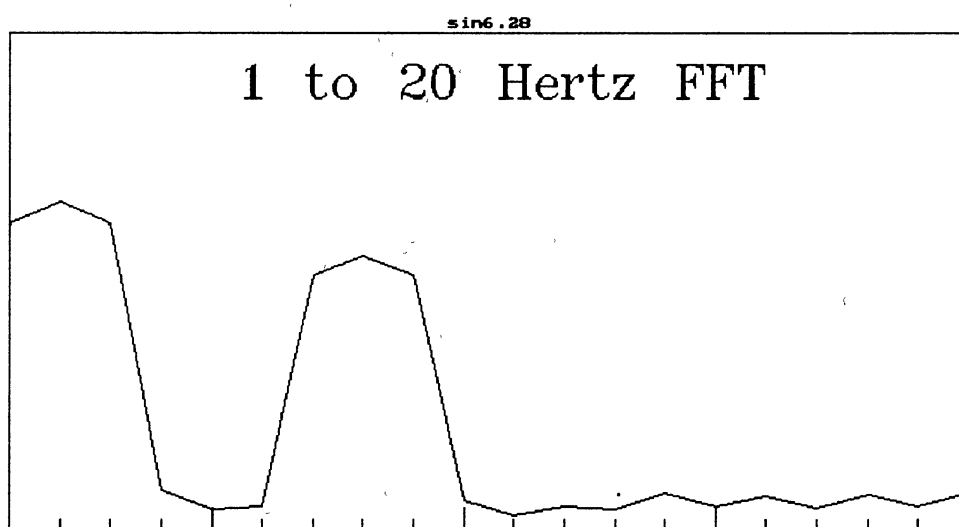
Figure 2. Neuron Normalized SIN6.28 FFT Pattern

Classification Methods

For the characterization classification problem the use of two different types of pattern recognition classifiers were investigated. The two pattern recognition classifiers are a Bidirectional Associative Memory (BAM) [12,13,14,16,18] Neural Network and a multi-layer non-linear Neural Network with error back-propagation [16,18].

BAM

The Bidirectional Associative Memory examined was a two-layer nonlinear feedback Neural Network [12]. A BAM is a generalization of a Hopfield network. This network is capable of bidirectional information flow allowing two-way associative search for stored associations (A_i, B_i) [12]. The associative information is encoded in a BAM by summing the correlation matrices of the associated pairs[12]. Passing information through the correlation matrix M gives one direction while passing it through its transpose M^T gives the other. A BAM's maximum storage capacity of m associated pairs for reliable recall from a matrix of dimensions n and p is limited to m<min(n,p) [12]. Therefore to classify five twenty-point patterns, a twenty by six BAM matrix is required. The identification code used was arbitrarily set in sequence for each pattern pair. Best

results are obtained when the associated vector pairs are encoded in a bipolar range {-1,1} [12]. I converted the integer data patterns and corresponding paired identifications to a bipolar floating point range using the following vector pair format (pattern(n dimension), identification(p dimension)). For the continuous transfer function a standard sigmoid function was used.

Neural Network with Error Back-Propagation

The other pattern classifier investigated was a feedforward nonlinear multilayer neural network using error back-propagation [18]. This type of network has been used as a pattern classifier in the past [16,18], with various types of data. The network architecture is made up of three layers of neurons; input, hidden and output. Every neuron is fully connected only to all neurons in the adjacent layer. Each input vector component value is normalized, between zero and one, and assigned to an input neuron. There are as many input neurons as input vector dimensions. Many neural network architecture modifications are possible and the following architecture variations were selected as the most appropriate for this project. The hidden layer contains the same number of neurons as the input layer. The output layer contains as many neurons as pattern classes. Although these are analog neurons in the 0 to 1 range, to

make classification unambiguous and easy to interpret, only
one output neuron is set to 1 for any given pattern. The
remainder of the output neurons are set to 0. Of course
these are the ideal class identification codes and a
classification criterion is used to determine if an output
vector is close enough to the ideal code to be included in
that class. A common classification criterion used is the
output vector's being within a set tolerance at every neuron
of the ideal class code. For the continuous transfer
function a standard sigmoid function was used.

This neural network uses supervised learning using
error back-propagation, essentially a gradient descent
procedure. The learning or training is accomplished by
varying the connection weights. The training of a neural
network with n weight coefficients can be viewed as a search
for a minimum of an error function over some subset of R^n.

First, the neural network is initialized with random
connection weights [18]. Second, the input pattern is
propagated through the network and the output neuron values
are computed. Next the output error is calculated, this is
the error between the output vector o and the target vector
t. The target vector is the correct classification code for
the input pattern. Each connection weight is modified by an
amount proportional to the product of the error signal.
This weight modification algorithm is known as the
generalized delta rule and for any input/output pattern pair

p is represented by the following equation [18].

$$\blacktriangle_p W_{JI} = \mu \; \delta_{pJ} \; o_{pI}$$

The parameter μ is a gain term that controls the rate of learning. The error term δ for any differentiable activation function is defined for the output and hidden units as follows. In the different error equations the j subsript corresponds to the current layer, while the k subsript corresponds to the previous layer.

$$net_{pJ} = \sum_k W_{JI} \; o_{pI}$$

Output Unit Error:

$$\delta_{pJ} = (t_{pJ} - o_{pJ}) \; \frac{\partial o_{pJ}}{\partial net_{pJ}}$$

Hidden Unit Error:

$$\delta_{pJ} = \frac{\partial o_{pJ}}{\partial net_{pJ}} \; \sum_k \delta_{pk} \; W_{kJ}$$

By taking the partial derivative of the sigmoid transfer function and substituting this result into the above equations the two error term expressions are derived:

Output Unit Error:

$$\delta_{pJ} = (t_{pJ} - o_{pJ}) \; o_{pJ} \; (1 - o_{pJ})$$

Input Unit Error:

$$\delta_{pJ} = o_{pJ} \ (1 - o_{pJ}) \ \sum_{k} \delta_{pk} \ W_{kJ}$$

In this way the error is propagated backwards through the network, one layer at a time. To improve network convergence an additional momentum term has been added [18]. This term contains a momentum parameter α which is multiplied times the previous connection weight delta. The complete network connection weight modification algorithm implemented in this project uses the following equation.

$$\blacktriangle_p W_{J1}(n+1) = \mu \ \delta_{pJ} \ o_{p1} + \alpha \ \blacktriangle_p W_{J1}(n)$$

If this procedure were a true gradient descent procedure it would take infinitesimal steps. Instead the size of the steps are determined by the learning rate and momentum rate, which are the constants of proportionality in this procedure. The learning rate and momentum rate parameters generally vary from 0.05 to 0.9 and are empirically determined according to the training set properties. The greater the values of the parameters the faster the coefficients change. In favorable circumstances this leads to network convergence, however if the values are set too high the network training process will be

overdriven and will oscillate randomly, never converging.
Generally the neural network continues iterating until the
euclidean distance between the output and target vectors for
all patterns decreases below a preset limit, at which point
the network is considered converged.   Since this network is
a pattern classifier, an output vector that is far off on
one neuron and matches on all other neurons is unacceptable.
Therefore a more stringent variation of this convergence
criterion was used. When the residual per neuron between
output and target vectors is below 0.1 for all neurons for
all patterns the network stops iterating and has reached
convergence.

Classification Evaluation

In this paper all graphical displays of FFT patterns
take the LOG of the power values between 0 and 15 and
normalize them between 0 and 1, referred to as neuron
normalized. This is the neuron value range, so the FFT
patterns are displayed in the same scale as they are
presented to the Neural Network.

After the BAM system was coded and tested on sample
data used by Kosko [12], it was tested on a group of five
sample FFT patterns. The first two pattern pairs were
stored and retrieved correctly, but after the third pattern
pair was stored the first pair could no longer be recalled.

When all five test pattern pairs were stored only three could be recalled correctly. Kosko [13] states that a BAM can be confused if like inputs are paired with unlike outputs or vice versa. Accurate BAM decoding [12] is based on a mapping continuity assumption of the training pairs. That is, if stored inputs are close their corresponding outputs are close. The complex nature of the behavior FFT patterns makes it unfeasible to make a mapping continuity assumption, thus ruling out using a BAM as a reliable pattern classifier.

The neural network with error back-propagation performed well when a simple classification evaluation was performed. It had no substantial difficulty in learning the test FFT pattern training set or classifying a few test patterns that were similar to the training set. Thus it was judged as a feasible pattern classifier for this project, unlike the BAM neural network. From this point on, when the Neural Network Classifier is discussed it refers to a Neural Network with error back-propagation.

Final Model Summary

After extensive investigation as described above the following signal analysis procedures were selected as a feasible analysis model for test trials. The analysis procedure processed one second of motility signal data at a

time. The data was Hanning Windowed, an FFT was performed
and the LOG of the power was calculated. The first FFT
value was the DC component which was discarded and the next
twenty floating point values corresponding to the signal
power contribution of the 1 to 20 hertz components were
retained. This 20-dimensional floating point vector was
then passed through the trained Neural Network. The segment
was classified according to the output neuron values. Then
the entire process was repeated on the next segment.

For proper evaluation of these analysis procedures the
development of graphical time series and FFT signal display
software was essential. The most crucial part of this
analysis method is the neural network training, which has
the greatest impact on the final signal classification
accuracy. The choice of the training set must be completely
representative of the behavior classes and unambiguous.
Meeting this training set criterion proved quite difficult
due to the large variability between signal samples of the
same behavior from the same animal. Various training
examples of each behavior class can be learned by the neural
network. However, there can be no ambiguity in the overall
training set. That is, there can be no intersection between
different behavior training sets, such as very similar
patterns in different behavior training sets.

When a fifty-second behavior segment that was expertly
scored as sniffing was analyzed for training examples a

problem arose. The FFTs from this single behavior segment were graphically displayed and superimposed, revealing a large variation of behavior signals. When this behavior segment video was viewed, one second at a time, it was observed that interspersed with the sniffing activity were random but repeated one second licking segments. Due to the subjective nature of motility behavior scoring, even when an animal was judged to be in a continuous grooming behavior stereotype segment, other different shorter behavior segments may actually be intertwined. Since this extremely complex interweaving of motor behaviors will cause an ambiguous training set if simple scored FFT samples are used for the behavior training sets, an alternative approach was needed. One possibility was a very difficult and time-consuming rescoring, at the frame level, of the motility data. Another possibility was that a series of behavior segment average FFTs, instead of raw FFTs, would provide a more accurate behavior pattern for training the Neural Network. The segment average patterns were found to be quite similar for each behavior class and no ambiguity was present.

Initially six behaviors were to be included in the study; however, the turning around behavior had to be eliminated. The recording instruments had been calibrated for maximum sensitivity to small motor activity for a previous experiment. There is a difference of several

orders of magnitude between sniffing and turning around.
Only after the animals had been run, during examination of
the data, was it discovered that all the turning around
segments were badly clipped. This problem can be remedied
easily in future work.

I chose to train a total of six different Neural
Network Classifiers. There were three basic classifier
types. For all the network models the number of output
neurons corresponded to the number of classes. The number
of classes equaled the number of animal behaviors plus the
unknown category. The FFT patterns had one value per hertz,
which ranged from 0 to 15 or from 0 to 20. First, the No
Power model which simply takes each normalized FFT hertz
value and assigns it to an input neuron. Second, the Total
Power model which is graphically displayed in figure 3. In
this model an extra input neuron is added to which the
normalized LOG of the total power of the signal between 1
and 20 hertz is input. This was done to make the classifier
extra sensitive to the total power of the signal.

FEEDFORWARD NON-LINEAR NEURAL NETWORK CLASSIFIER WITH ERROR BACK-PROPAGATION
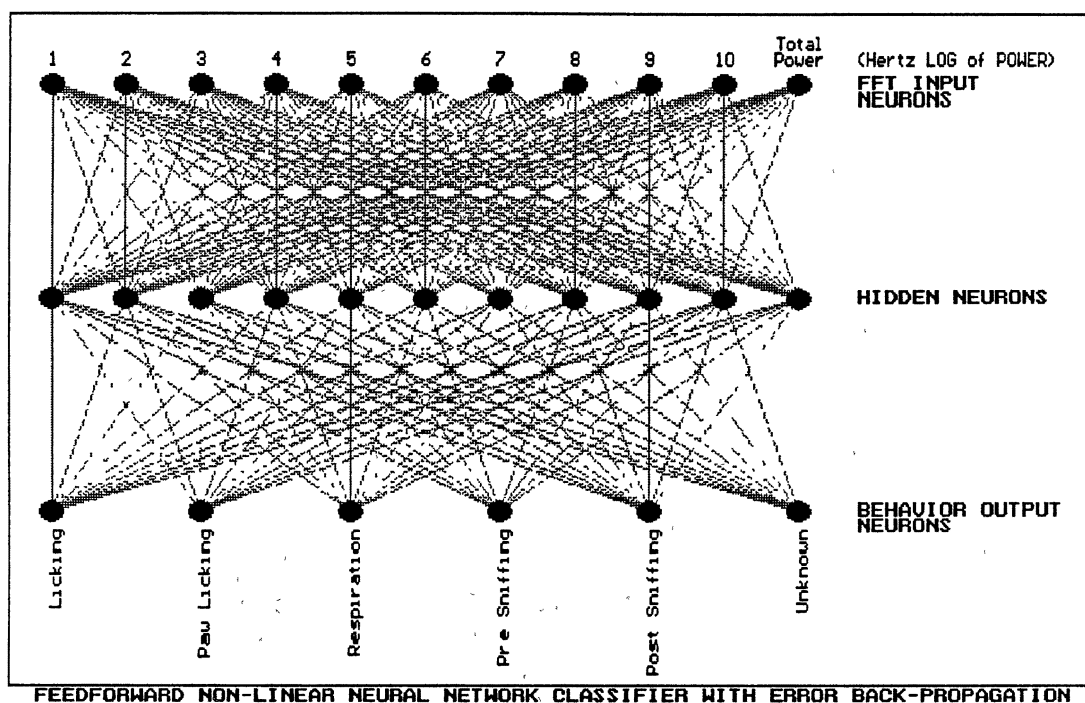
Figure 3. Total Power Neural Network

The third classifier model was Proportional Total Power which involved calculating the percent contribution of each individual FFT value, compared to the power of the whole pattern. This model was used to emphasize the shape of the FFT pattern.

Each of the three classifier models was trained and run with both 15-hertz and 20-hertz scored FFT pattern data, thus producing six sets of test data.

CHAPTER III

RESULTS AND DISCUSSION

FFT

The scored motility data were initially processed using
ASYST. A Hanning-Windowed FFT was performed on each second
of the data, the LOG of the power for 1 to 20 hertz was
calculated and written to an intermediate data file. This
initial processing required approximately 56 minutes for
every 1 hour of motility data. This is considered a
reasonable processing time. However, if required it could
be improved by a 'C' or even a hardware implementation.

Neural Network Classification

All six neural networks were trained to recognize the
same five different behaviors, using the same training sets.
The Networks were trained until they achieved convergence.
This required between 9,000 and 12,000 epochs. These
networks completed training on the 386/387 system in between
3.5 and 5.0 hours. This is an acceptable time, given that
this process would be executed infrequently. The network
training parameters used were a learning rate of 0.6 and a

momentum rate of 0.3. One epoch consisted of presenting each training pattern once to the network. Several example patterns of each behavior were used, these were segment average FFT patterns. The breakdowns of the numbers of examples per behavior in the total training set are listed in TABLE III.

TABLE III

NEURAL NETWORK TRAINING SAMPLE
SUBTOTALS PER BEHAVIOR

BEHAVIOR	SUBTOTAL
LICKING	15
PAW LICKING	12
RESPIRATION	8
PRE-SNIFFING	7
POST-SNIFFING	12
TOTAL	54

The Pre-sniffing and Post-sniffing classes denote two observably different sniffing behaviors. Pre-sniffing is the normal sniffing behavior prior to drug injection, while Post-sniffing is a drug-induced stereotyped sniffing behavior. Pre-sniffing FFTs show characteristic 5 to 6 hertz activity, while Post-sniffing FFTs show an activity shift into the 7 to 8 hertz range.

The scored motility behavior segments were processed by

behavior using ASYST. This resulted in one file per

behavior which contained all the 1-second FFTs that had been

scored for that behavior. These FFT behavior files were

then presented to the six different neural networks for

classification. The accuracy of the pattern classification

for each behavior was calculated for each Classifier and

listed in Appendix C. The Neural Network Classifier

processed data at the rate of about 1 hour of motility FFTs

per 2 minutes. This figure is well within the processing

time requirements for a feasible laboratory system. The

accuracy of both absolute and relative classification

criteria methods were calculated. The absolute

classification criterion represents a perfect class match,

while the relative classification criterion represents a

most likely class membership. Not surprisingly the relative

approach produced the highest accuracy and is used in all

the classification accuracy graphs in this section. The

classification accuracy of the three Neural Network models

using 15-hertz FFT patterns is displayed in figure 4.

The following abbreviations are used in certain graphs:

NP = NO POWER

TP = TOTAL POWER

PTP = PROPORTIONAL TOTAL POWER

Neural Network Pattern Classification
Percentage Correctly Classified 15 Hz
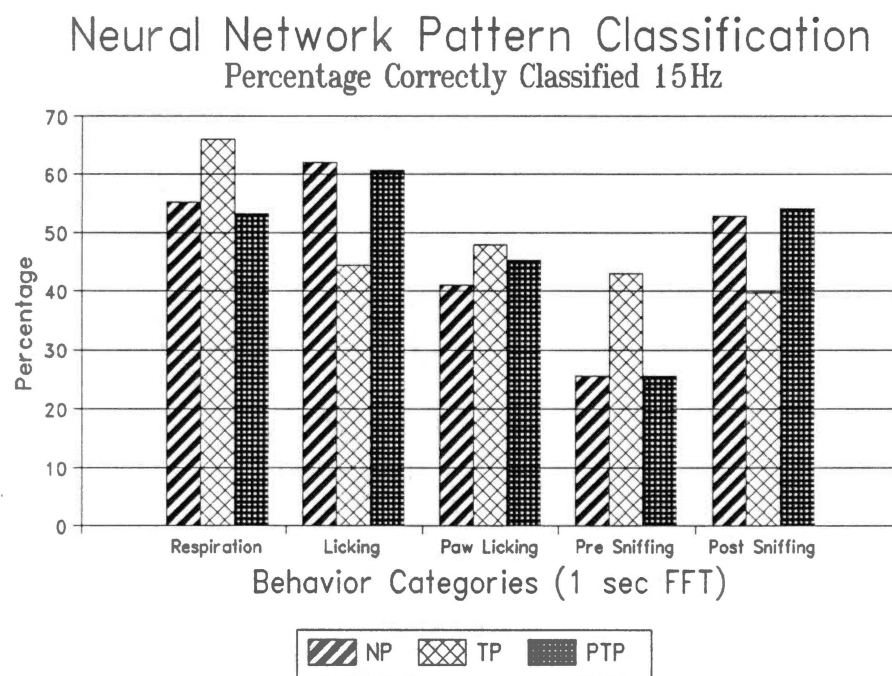
Figure 4. Neural Network Pattern Classification
Percenage Classified Correctly 15Hz

No single neural network model outperformed the other models in every behavior using 15-hertz FFT data.

The classification accuracy of the three neural network models using 20-hertz FFT patterns is displayed in figure 5.
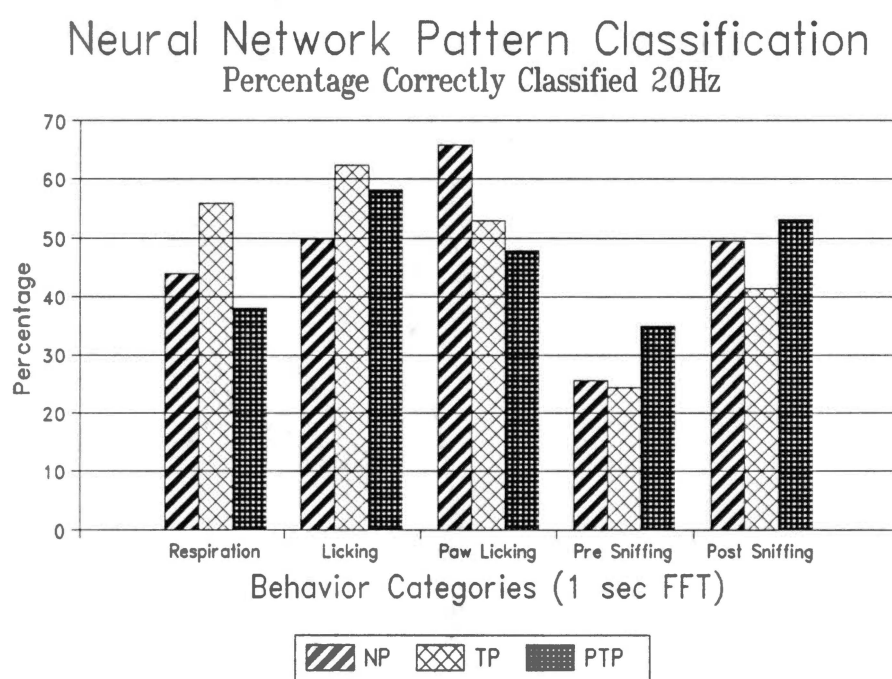
Figure 5. Neural Network Pattern Classification Percentage Correctly Classified 20Hz

Just as in the 15-hertz case none of the neural network models outperformed the other models in every behavior

category using 20-hertz FFT data.

The average accuracy, and the standard deviation of that average, of each of the six models is displayed in figure 6.
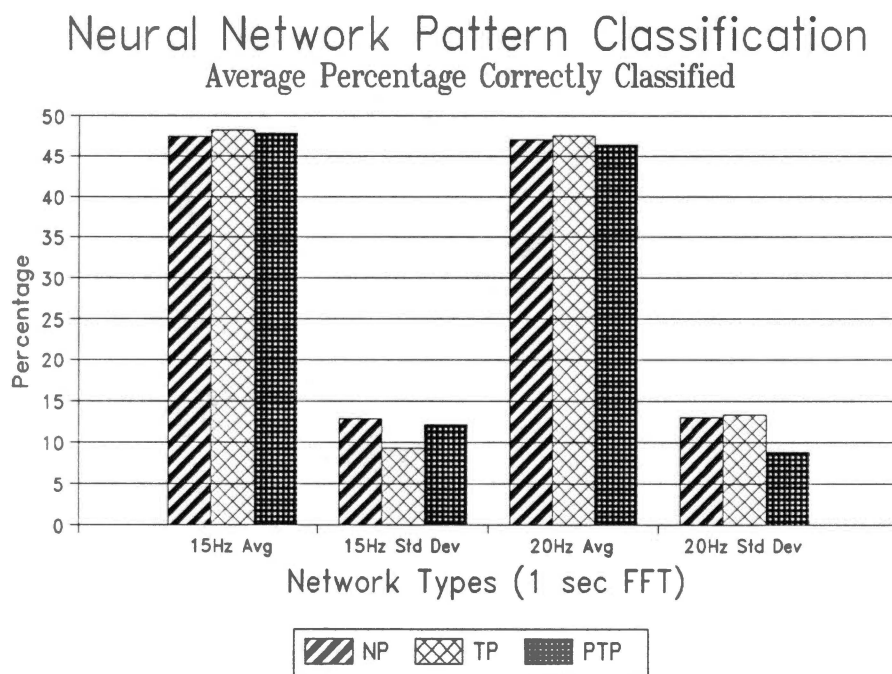
Figure 6. Neural Network Pattern Classification Average Percentage Correctly Classified

All the networks performed poorly and the highest average percent classified correctly was only 48.20%. There

are several possible contributing factors for this poor accuracy.

One factor, behavior intertwining, was discussed earlier in relation to choosing training set examples. This also affects the classification accuracy test. A ninety-second initially scored licking behavior segment was reinspected. Although when viewed at normal speed it appeared to be a long duration licking behavior segment, upon frame level inspection it was discovered that there were consistent and repeated sniffing behavior segments intertwined with the licking. It appeared that 15% of this scored licking behavior segment was made up of sniffing subsegments. However this still does not account for all the missed classifications.

The other likely explanation for this lack of accuracy is that the neural network total training set was not completely representative of the selected behaviors. Perhaps the behavior segment average FFTs do not accurately characterize the individual 1-second behavior FFTs. Each behavior seems to be made up of a group of distinct FFT pattern subsets, which apparently are not accurately represented by a segment average.

The ideal classifier should have a high average accuracy with a small standard deviation, or the best possible combination of the two. With these criteria in mind the Total Power 15-hertz model and the Proportional

Total Power 20-hertz were chosen as having the best overall performance for each pattern length. In an attempt to determine if the behavior segment average FFTs presented a more uniform behavior signature than the individual 1-second FFTs, these two top performing classifier models were tested by classifying all the scored behavior segment averages. The results are displayed in figure 7.

Neural Network Pattern Classification
Percentage Correctly Classified
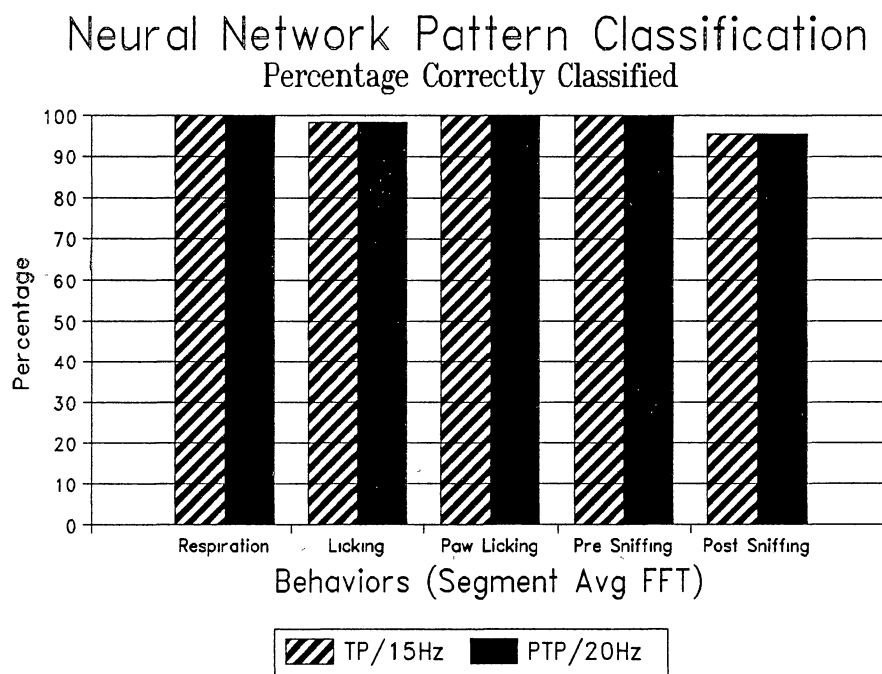
Figure 7. Neural Network Pattern Classification
Percentage Correctly Classified
(Segment Avg FFT)

These segment average classification results are listed
in TABLE XV. The overall average classification percentage
accuracy was identical for both models at 98.74%, and a
standard deviation of 1.78. While this result is not
conclusive, since of the 114 segment average FFT patterns
classified 54 were initially used for network training, it
supports the view that behavior segment averages are
behaviorally consistent.

CHAPTER IV

CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

Conclusions

The FFT characterization of the motility data signal
was found to be the best technique to enhance distinguishing
features between the different behaviors. However the 1-
second FFT classification method accuracy level was
unacceptably low, due to an unrepresentative behavior
training set.

A typical behavior segment seems to be composed of
several distinct 1-second FFT patterns randomly repeated but
with stable proportions, which produce a consistent segment
average FFT pattern. However, this behavior data segment
format makes segment average FFT patterns unrepresentative
of individual 1-second FFT patterns. To properly classify
1-second FFTs the training set must be made up of sample 1-
second FFT patterns and not segment average FFT patterns.

The segment average FFT classification method performed
very well. However this classification method cannot be
used with fixed segmentation, only adaptive or variable
segmentation.

The analysis methods used in this project processed data at a sufficiently rapid rate on the 386/387 system to be a feasible laboratory tool. Also, these analysis methods could be substantially speeded up if a production quality system were developed.

Future Research Directions

Two future research directions seem very promising, and are the logical next steps from this work.

One approach would use the overall analysis methods used in this project, but develop a new neural network training set, based on individual 1-second FFTs. This would require the frame by frame rescoring of a portion of the behavior data to improve the scored behavior accuracy, eliminating intertwined behavior inaccuracies. From this recorded data a new Neural Network training set would be built, comprising a representative sample of 1-second FFT patterns for each behavior, instead of segment average FFT patterns. In building these new behavior training sets particular importance must be placed on assuring that they are truly representative of all the FFT patterns making up each behavior and that no ambiguity exists.

The other logical research direction involves utilizing the high accuracy demonstrated in the behavior segment average classification method. The capability of adaptive

segmentation using an ARMA model to break a signal into segments containing a continuous behavior would be explored. If the ARMA model proved capable of accurately segmenting the signal, then the average 1-second FFT for the segment would be calculated. This behavior segment average FFT could then be classified using the same neural network method that achieved 98.74% accuracy in this project.

CHAPTER IV

MERITS OF RESEARCH

Both of these research directions hold the promise of producing a fast and accurate motility data signal analysis system. This final analysis system would be of tremendous benefit to animal research laboratories by automating the collection of animal behavioral data. This automated system could objectively gather enormous amounts of animal behavioral data, having far-reaching implications on both disease and drug animal research.

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APPENDIXES

APPENDIX A

SYNTHETIC MOTILITY TEST SIGNALS

FFT LOG OF POWER VALUES

TABLE IV contains the 1-second FFT LOG of power values from 1 to 20-hertz of the two synthetic motility test signals. Both test signals had two hertz components that were the same amplitude, however file SIN28.3 had an eight hertz component one third the amplitude of the two hertz and file SIN28.6 contained an eight hertz component one sixth the amplitude.

TABLE IV

TEST SIGNAL 1-second FFT

HERTZ	SIN28.3	SIN28.6
1	9.3623	9.3623
2	9.9644	9.9644
3	9.3623	9.3623
4	1.5906	1.2924
5	0.9982	0.6777
6	1.0482	0.7828
7	8.4080	7.8059
8	9.0100	8.4079
9	8.4080	7.8059
10	0.3648	0.9549
11	0.3138	0.4947
12	0.9947	0.7711
13	0.5566	0.6912
14	0.9282	1.2080
15	0.6104	0.7779
16	1.1023	1.1025
17	0.6677	0.7202
18	1.0331	1.1196
19	0.6356	0.7687
20	1.0308	1.2066

APPENDIX B

GRAPHICAL DISPLAY OF BEHAVIOR FFT

NEURAL NETWORK TRAINING SETS

The average FFTs of the individual behavior segments
were used as the Neural Network training sets. The
graphical display of the FFT patterns was found to be very
useful in pairing down the size of each individual behavior
training set by removing redundant patterns. Also by color
coding and superimposing different behavior training sets,
any erroneous set membership intersection between different
behaviors could be identified and avoided. This behavior
set intersection introduces ambiguity into the training
sets, thus preventing Neural Network convergence. The FFT
patterns in the graphical displays are the 1 to 20 hertz
portion of the FFT neuron normalized. This is the same
pattern presented to the Neural Network Classifier.
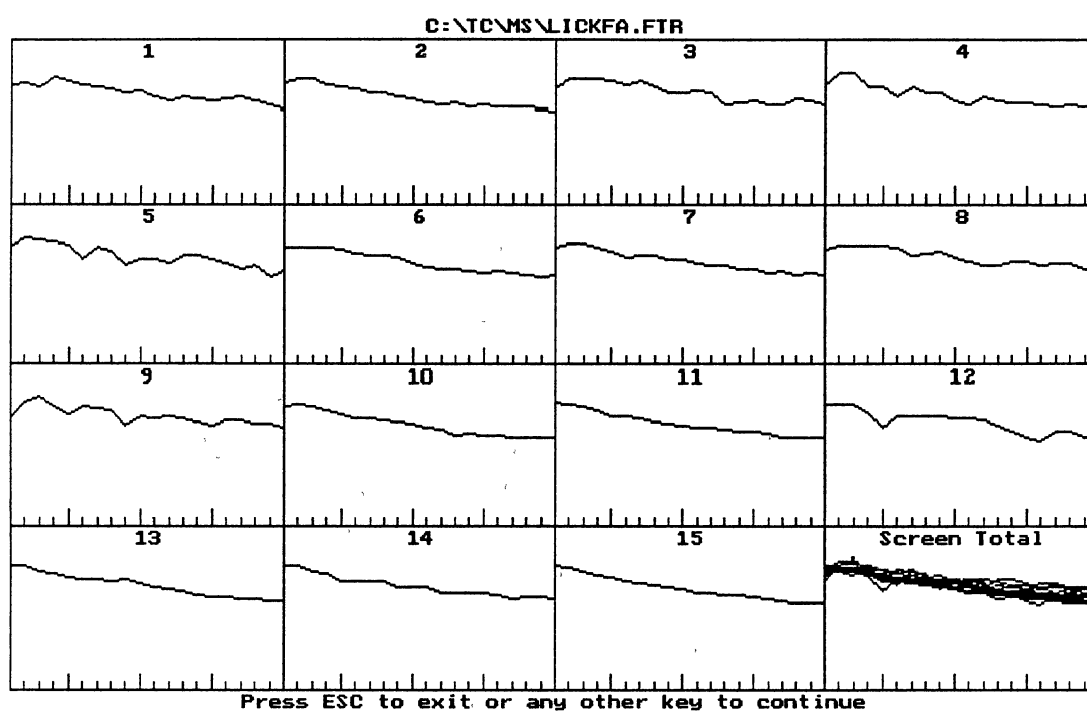
Figure 8. Licking Behavior Individual Training Examples
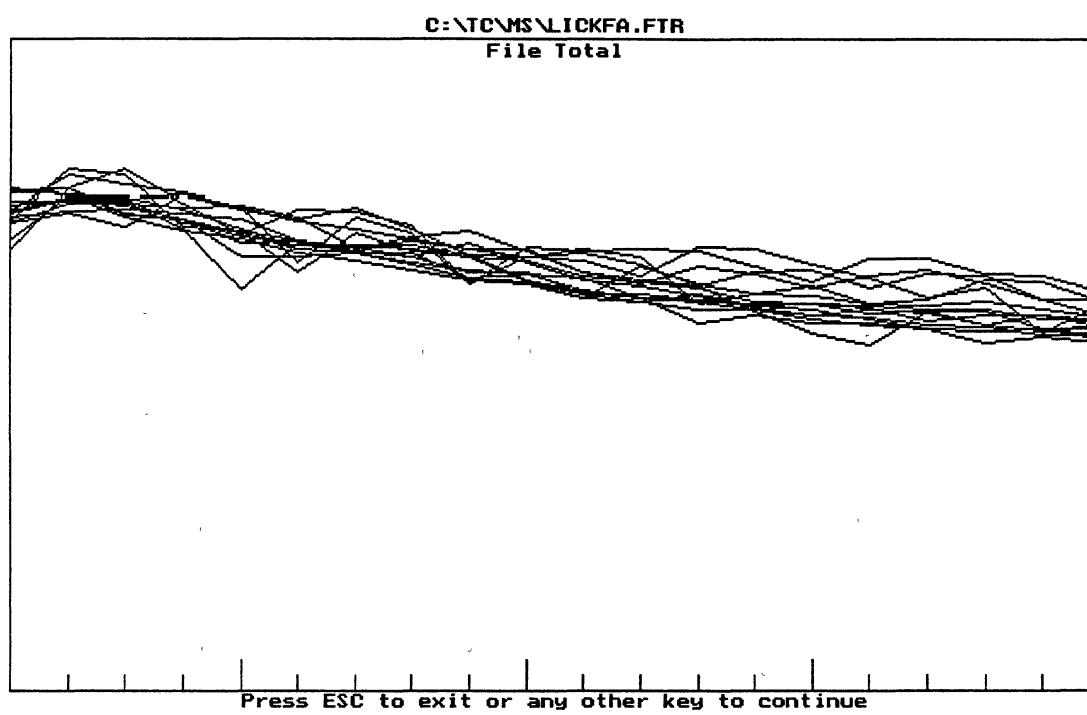
Figure 9. Licking Behavior Superimposed Training Set
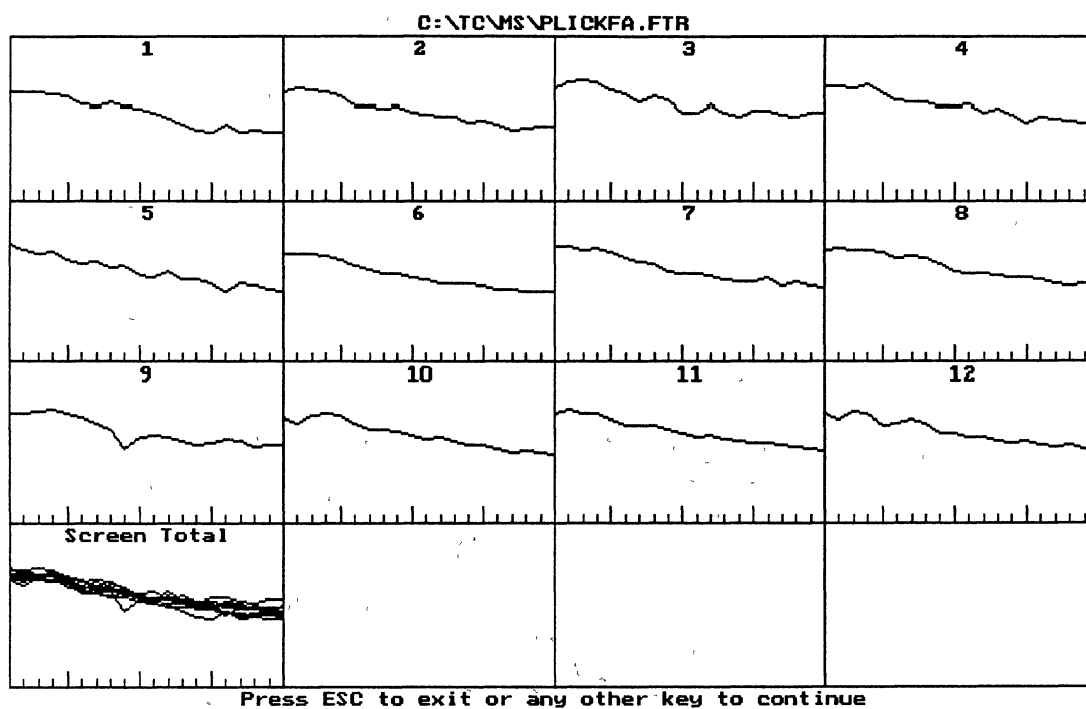
Figure 10. Paw Licking Behavior Individual Training Examples

C:\TC\MS\PLICKFA.FTR

File Total

Press ESC to exit or any other key to continue
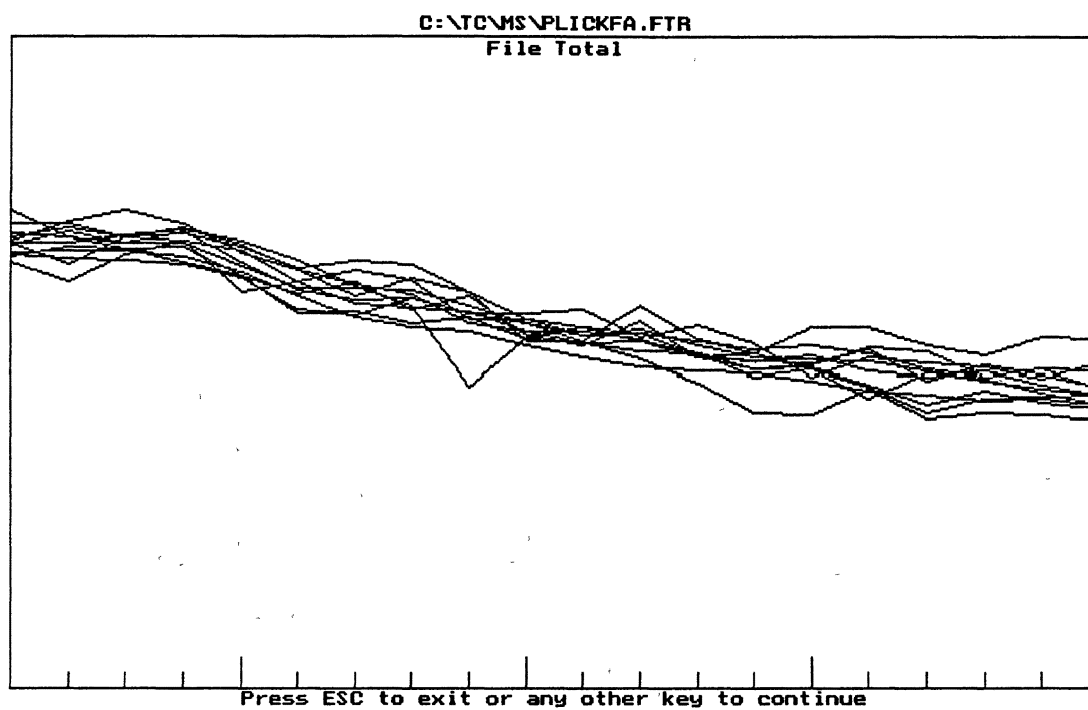
Figure 11. Paw Licking Behavior Superimposed Training
Set
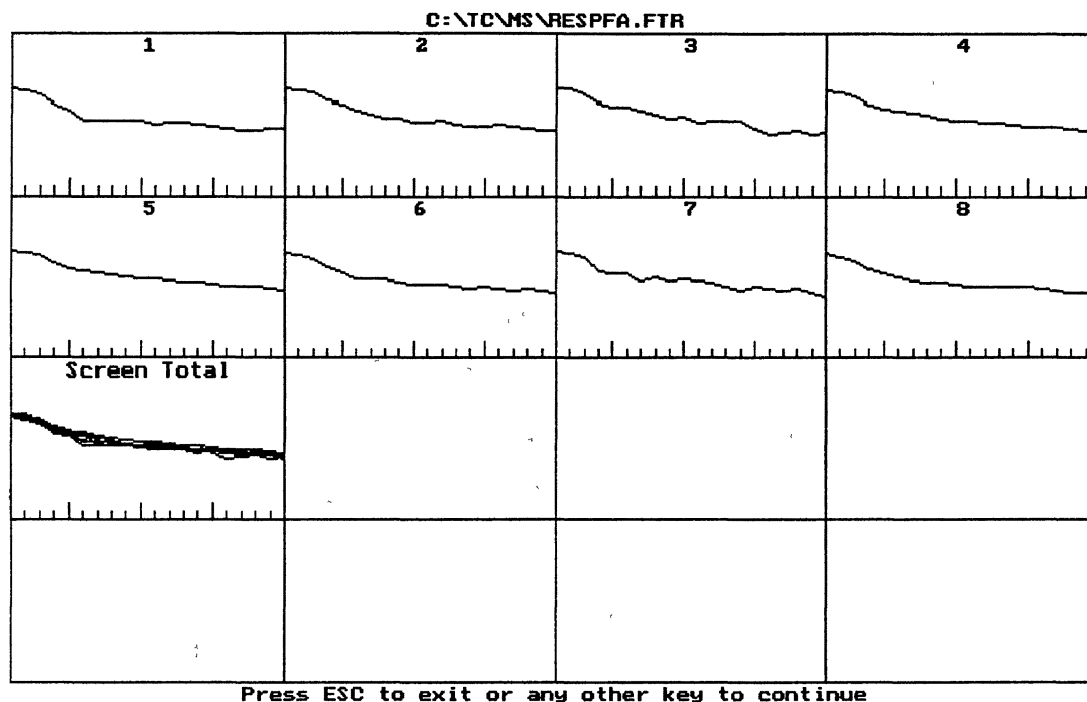
Figure 12. Respiration Behavior Individual Training Examples

C:\TC\MS\RESPFA.FTR

File Total

Press ESC to exit or any other key to continue
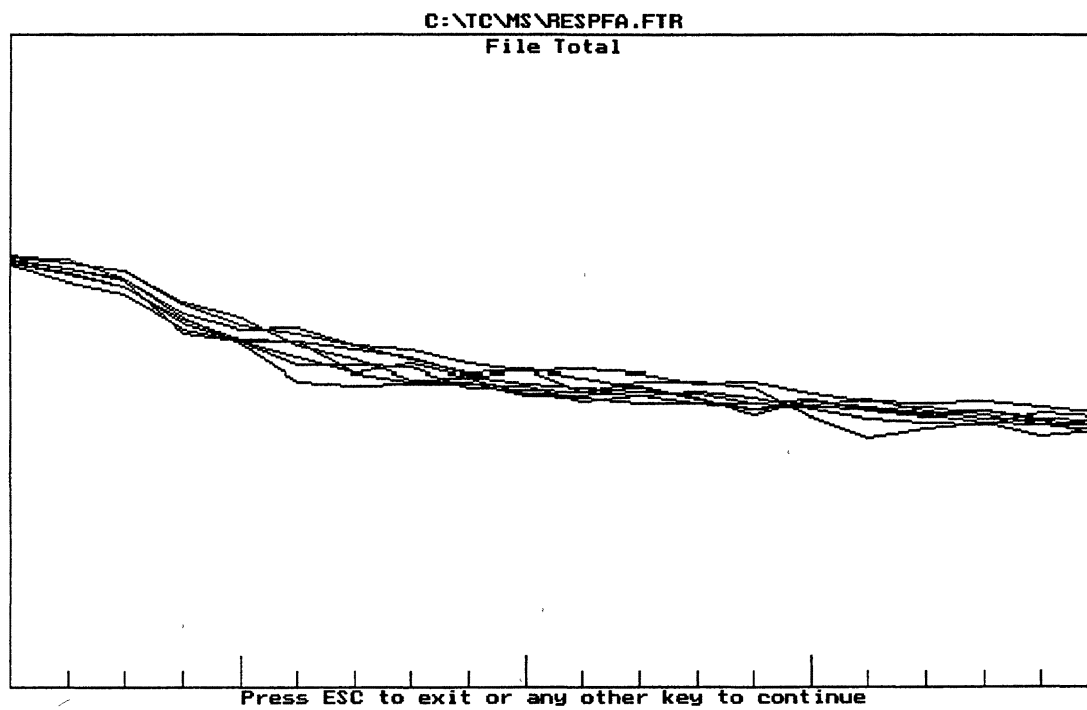
Figure 13. Respiration Behavior Superimposed Training
Set
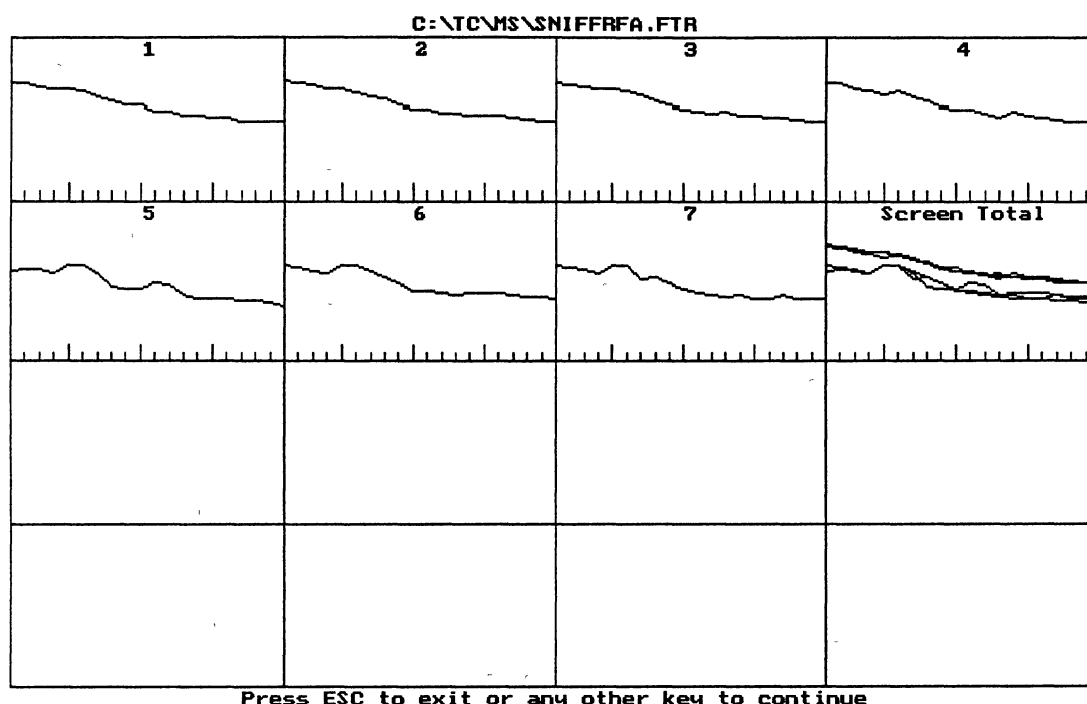
Figure 14. Pre-sniffing Behavior Individual Training Examples

C:\TC\MS\SNIFFRFA.FTR
File Total

Press ESC to exit or any other key to continue
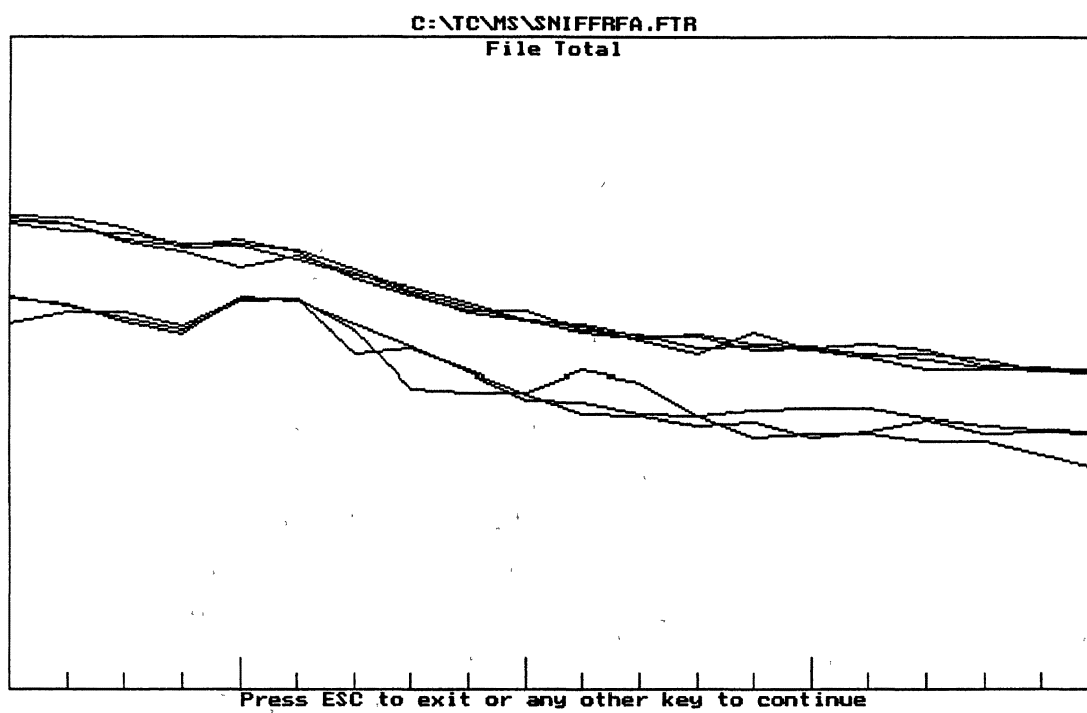
Figure 15. Pre-sniffing Behavior Superimposed Training Set
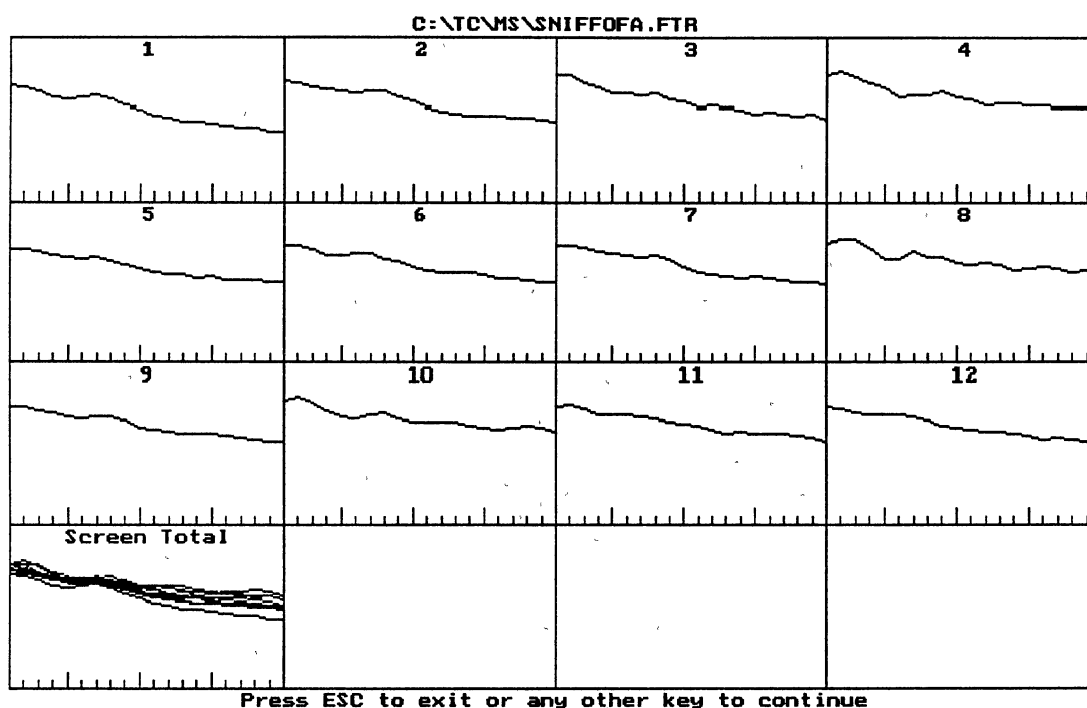
Figure 16. Post-sniffing Behavior Individual Training Examples
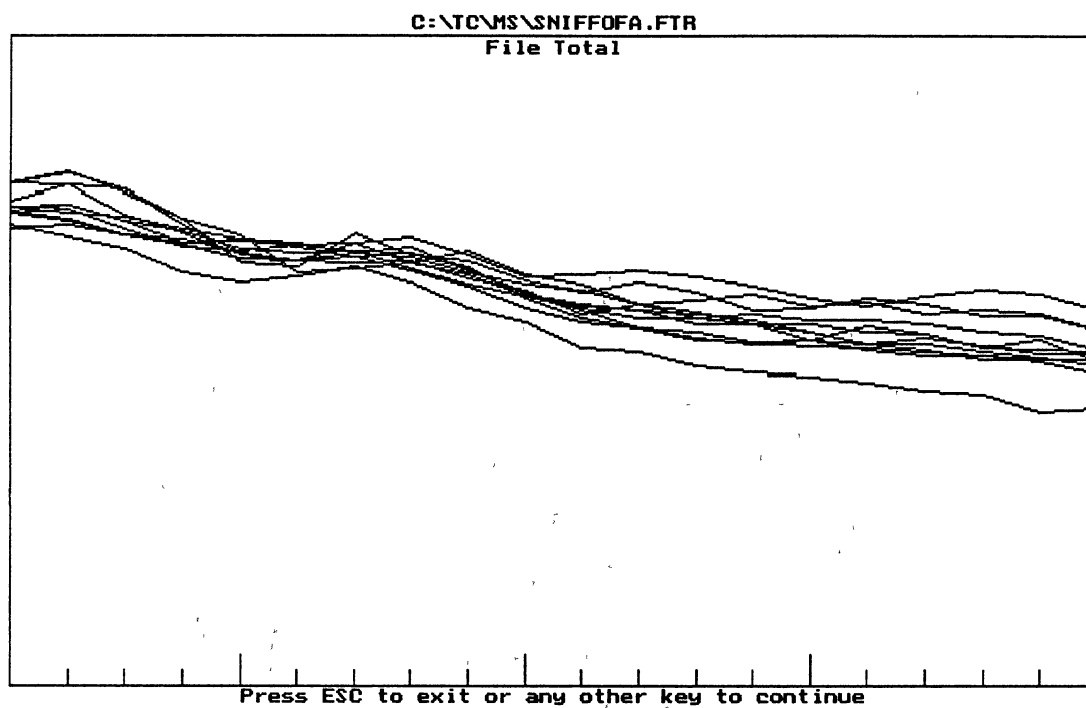
Figure 17. Post-sniffing Behavior Superimposed Training Set

APPENDIX C

PRELIMINARY TEST RESULTS ON ORIGINAL FFT DATA

USING ABSOLUTE AND RELATIVE

CLASSIFICATION CRITERIA

Two different methods of interpreting the Neural
Network results to assign class membership were tried. An
absolute match was achieved if the output pattern was within
0.3 tolerance for every neuron when compared to a behavior
identification pattern. A relative match consisted of the
largest valued output neuron being 0.2 above the second
highest neuron.

Three different types of Neural Network Classifiers
were tested on two different size FFT patterns. The two
pattern sizes were 15 and 20 hertz. When a pattern value is
assigned to an input neuron its value is normalized to
between zero and one. The No Power network assigns each
hertz value to one input neuron. The Total Power network
assigns each hertz value to one input neuron and the sum of
the hertz values are assigned to an extra input neuron. The
Proportional Power network calculates what percentage of
total power each hertz value represents and assigns this

percentage to a corresponding neuron. An asterisk preceding a behavior name in a table denotes the correct behavior classification for that scored data.

TABLE V

15-HERTZ NO POWER NEURAL NETWORK RESULTS

LICKING SCORED DATA 849 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
* LICKING	58.89%	61.96%
PAW LICKING	3.65%	5.06%
RESPIRATION	0.82%	2.24%
PRE-SNIFFING	2.47%	3.42%
POST-SNIFFING	16.37%	20.49%
UNKNOWN	17.79%	6.83%

PAW LICKING SCORED DATA 117 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	6.84%	11.11%
* PAW LICKING	34.19%	41.03%
RESPIRATION	7.69%	9.40%
PRE-SNIFFING	6.84%	9.40%
POST-SNIFFING	7.69%	11.11%
UNKNOWN	36.75%	17.95%

RESPIRATION SCORED DATA 150 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	1.33%	1.33%
PAW LICKING	1.33%	2.00%
* RESPIRATION	36.67%	55.33%
PRE-SNIFFING	0.67%	2.00%
POST-SNIFFING	6.00%	21.33%
UNKNOWN	54.00%	18.00%

PRE-SNIFFING SCORED DATA 86 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	10.47%	11.63%
PAW LICKING	12.79%	15.12%
RESPIRATION	5.81%	11.63%
* PRE-SNIFFING	18.60%	25.58%
POST-SNIFFING	12.79%	19.77%
UNKNOWN	39.53%	16.28%

POST-SNIFFING SCORED DATA 371 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	18.06%	19.41%
PAW LICKING	5.39%	8.09%
RESPIRATION	2.16%	4.58%
PRE-SNIFFING	7.82%	10.51%
* POST-SNIFFING	40.43%	52.83%
UNKNOWN	26.15%	4.58%

TABLE VI

15-HERTZ TOTAL POWER NEURAL NETWORK RESULTS

LICKING SCORED DATA 849 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
* LICKING	36.98%	44.52%
PAW LICKING	8.36%	10.95%
RESPIRATION	1.53%	2.47%
PRE-SNIFFING	3.30%	5.42%
POST-SNIFFING	17.67%	22.61%
UNKNOWN	32.15%	14.02%

PAW LICKING SCORED DATA 117 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	4.27%	5.98%
* PAW LICKING	39.32%	47.86%
RESPIRATION	8.55%	8.55%
PRE-SNIFFING	8.55%	8.55%
POST-SNIFFING	6.84%	8.55%
UNKNOWN	32.48%	16.24%

RESPIRATION SCORED DATA 150 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	3.33%	4.00%
PAW LICKING	4.67%	4.67%
* RESPIRATION	57.33%	66.00%
PRE-SNIFFING	5.33%	10.67%
POST-SNIFFING	0.67%	2.67%
UNKNOWN	28.67%	9.33%

PRE-SNIFFING SCORED DATA 86 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	8.14%	8.14%
PAW LICKING	13.95%	19.77%
RESPIRATION	6.98%	10.47%
* PRE-SNIFFING	29.07%	43.02%
POST-SNIFFING	5.81%	10.47%
UNKNOWN	36.05%	8.14%

POST-SNIFFING SCORED DATA 371 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	11.05%	13.48%
PAW LICKING	8.09%	10.51%
RESPIRATION	4.31%	5.93%
PRE-SNIFFING	9.70%	16.44%
* POST-SNIFFING	32.88%	39.62%
UNKNOWN	33.96%	14.02%

TABLE VII

15-HERTZ PROPORTIONAL TOTAL POWER NEURAL NETWORK RESULTS

LICKING SCORED DATA 849 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
* LICKING	55.59%	60.78%
PAW LICKING	5.06%	6.24%
RESPIRATION	0.59%	1.06%
PRE-SNIFFING	2.12%	3.42%
POST-SNIFFING	15.43%	20.73%
UNKNOWN	22.20%	7.77%

PAW LICKING SCORED DATA 117 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	9.40%	10.26%
* PAW LICKING	35.04%	45.30%
RESPIRATION	5.98%	7.69%
PRE-SNIFFING	5.98%	11.11%
POST-SNIFFING	7.69%	12.82%
UNKNOWN	35.90%	12.82%

RESPIRATION SCORED DATA 150 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	3.33%	3.33%
PAW LICKING	3.33%	7.33%
* RESPIRATION	36.00%	53.33%
PRE-SNIFFING	2.00%	4.00%
POST-SNIFFING	6.00%	16.67%
UNKNOWN	49.33%	15.33%

PRE-SNIFFING SCORED DATA 86 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	11.63%	17.44%
PAW LICKING	8.14%	16.28%
RESPIRATION	5.81%	9.30%
* PRE-SNIFFING	18.60%	25.58%
POST-SNIFFING	13.95%	19.77%
UNKNOWN	41.86%	11.63%

POST-SNIFFING SCORED DATA 371 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	15.90%	17.79%
PAW LICKING	4.31%	5.66%
RESPIRATION	2.70%	4.04%
PRE-SNIFFING	7.01%	10.78%
* POST-SNIFFING	39.93%	54.18%
UNKNOWN	33.15%	6.20%

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TABLE VIII

20-HERTZ NO POWER NEURAL NETWORK RESULTS

LICKING SCORED DATA 849 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
* LICKING	44.52%	49.82%
PAW LICKING	11.19%	13.78%
RESPIRATION	0.35%	0.59%
PRE-SNIFFING	1.18%	2.24%
POST-SNIFFING	18.73%	24.14%
UNKNOWN	24.03%	9.42%

PAW LICKING SCORED DATA 117 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	3.42%	3.42%
* PAW LICKING	56.41%	65.81%
RESPIRATION	1.71%	3.42%
PRE-SNIFFING	6.84%	11.97%
POST-SNIFFING	8.55%	10.26%
UNKNOWN	23.08%	5.13%

RESPIRATION SCORED DATA 150 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	2.00%	2.00%
PAW LICKING	12.00%	14.67%
* RESPIRATION	34.00%	44.00%
PRE-SNIFFING	0.67%	4.00%
POST-SNIFFING	10.00%	21.33%
UNKNOWN	41.33%	14.00%

PRE-SNIFFING SCORED DATA 86 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	6.98%	6.98%
PAW LICKING	17.44%	19.77%
RESPIRATION	3.49%	8.14%
* PRE-SNIFFING	15.12%	25.58%
POST-SNIFFING	13.95%	25.58%
UNKNOWN	43.02%	13.95%

POST-SNIFFING SCORED DATA 371 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	13.48%	13.75%
PAW LICKING	10.78%	13.21%
RESPIRATION	1.35%	2.16%
PRE-SNIFFING	6.47%	8.36%
* POST-SNIFFING	39.62%	49.60%
UNKNOWN	28.30%	12.94%

TABLE IX

20-HERTZ TOTAL POWER NEURAL NETWORK RESULTS

LICKING SCORED DATA 849 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
* LICKING	55.12%	62.31%
PAW LICKING	3.30%	4.36%
RESPIRATION	0.59%	1.18%
PRE-SNIFFING	1.18%	2.12%
POST-SNIFFING	14.13%	19.43%
UNKNOWN	25.68%	10.60%

PAW LICKING SCORED DATA 117 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	6.84%	7.69%
* PAW LICKING	47.86%	52.99%
RESPIRATION	7.69%	9.40%
PRE-SNIFFING	5.98%	10.26%
POST-SNIFFING	0.85%	3.42%
UNKNOWN	30.77%	16.22%

RESPIRATION SCORED DATA 150 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	2.67%	2.67%
PAW LICKING	1.33%	3.33%
* RESPIRATION	44.67%	56.00%
PRE-SNIFFING	0.00%	1.33%
POST-SNIFFING	3.33%	12.67%
UNKNOWN	48.00%	24.00%

PRE-SNIFFING SCORED DATA 86 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	11.63%	12.79%
PAW LICKING	11.63%	18.60%
RESPIRATION	6.98%	9.30%
* PRE-SNIFFING	15.12%	24.42%
POST-SNIFFING	5.81%	15.12%
UNKNOWN	48.84%	19.77%

POST-SNIFFING SCORED DATA 371 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	14.29%	16.17%
PAW LICKING	7.01%	8.36%
RESPIRATION	5.12%	6.20%
PRE-SNIFFING	7.01%	11.05%
* POST-SNIFFING	33.96%	41.51%
UNKNOWN	32.61%	16.71%

TABLE X

20-HERTZ PROPORTIONAL TOTAL POWER NEURAL NETWORK RESULTS

LICKING SCORED DATA 849 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
* LICKING	50.88%	58.30%
PAW LICKING	4.00%	5.42%
RESPIRATION	0.00%	0.35%
PRE-SNIFFING	2.36%	3.65%
POST-SNIFFING	16.61%	20.38%
UNKNOWN	26.15%	11.90%

PAW LICKING SCORED DATA 117 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	5.13%	6.84%
* PAW LICKING	41.03%	47.86%
RESPIRATION	2.56%	5.13%
PRE-SNIFFING	12.82%	17.95%
POST-SNIFFING	3.42%	10.26%
UNKNOWN	35.04%	11.97%

RESPIRATION SCORED DATA 150 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	2.00%	2.67%
PAW LICKING	4.00%	7.33%
* RESPIRATION	28.67%	38.00%
PRE-SNIFFING	7.33%	12.67%
POST-SNIFFING	10.67%	19.33%
UNKNOWN	47.33%	20.00%

PRE-SNIFFING SCORED DATA 86 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	8.14%	10.47%
PAW LICKING	12.79%	17.44%
RESPIRATION	5.81%	6.98%
* PRE-SNIFFING	25.58%	34.88%
POST-SNIFFING	10.47%	17.44%
UNKNOWN	37.21%	12.79%

POST-SNIFFING SCORED DATA 371 SEGMENTS

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	13.75%	16.17%
PAW LICKING	5.93%	8.36%
RESPIRATION	1.35%	1.89%
PRE-SNIFFING	6.74%	11.05%
* POST-SNIFFING	40.97%	53.10%
UNKNOWN	29.65%	9.43%

APPENDIX D

PRELIMINARY TEST RESULTS ON SEGMENT AVERAGE FFT

DATA USING ABSOLUTE AND RELATIVE

CLASSIFICATION CRITERIA

Each scored behavior segment had the average FFT
calculated by computing all the 1-second FFTs with in the
segment and taking the average. While only 54 segment
average FFTs were used in the Neural Network Classifier
total training set, a total of 114 scored behavior segments
existed. Since the behavior segment average FFTs showed
very little visual variability, they were chosen as an
alternate test set to be input into two of the Neural
Network Classifiers. An asterisk preceding a behavior name
in a table denotes the correct behavior classification for
that scored data.

TABLE XI

15-HERTZ TOTAL POWER NEURAL NETWORK

SEGMENT AVERAGE RESULTS

LICKING SCORED DATA 57 SEGMENT AVERAGES

BEHAVIOR	ABSOLUTE	RELATIVE
* LICKING	92.98%	98.25%
PAW LICKING	0.00%	0.00%
RESPIRATION	0.00%	0.00%
PRE-SNIFFING	0.00%	0.00%
POST-SNIFFING	1.75%	1.75%
UNKNOWN	5.26%	0.00@

PAW LICKING SCORED DATA 16 SEGMENT AVERAGES

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	0.00%	0.00%
* PAW LICKING	100.00%	100.00%
RESPIRATION	0.00%	0.00%
PRE-SNIFFING	0.00%	0.00%
POST-SNIFFING	0.00%	0.00%
UNKNOWN	0.00%	0.00%

RESPIRATION SCORED DATA 11 SEGMENT AVERAGES

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	0.00%	0.00%
PAW LICKING	0.00%	0.00%
* RESPIRATION	100.00%	100.00%
PRE-SNIFFING	0.00%	0.00%
POST-SNIFFING	0.00%	0.00%
UNKNOWN	0.00%	0.00%

PRE-SNIFFING SCORED DATA 8 SEGMENT AVERAGES

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	0.00%	0.00%
PAW LICKING	0.00%	0.00%
RESPIRATION	0.00%	0.00%
* PRE-SNIFFING	100.00%	100.00%
POST-SNIFFING	0.00%	0.00%
UNKNOWN	0.00%	0.00%

POST-SNIFFING SCORED DATA 22 SEGMENT AVERAGES

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	0.00%	0.00%
PAW LICKING	0.00%	0.00%
RESPIRATION	0.00%	0.00%
PRE-SNIFFING	4.55%	4.55%
* POST-SNIFFING	90.91%	95.45%
UNKNOWN	4.55%	0.00%

TABLE XII

20-HERTZ PROPORTIONAL TOTAL POWER NEURAL NETWORK

SEGMENT AVERAGE RESULTS

LICKING SCORED DATA 57 SEGMENT AVERAGES

BEHAVIOR	ABSOLUTE	RELATIVE
* LICKING	92.98%	98.25%
PAW LICKING	0.00%	0.00%
RESPIRATION	0.00%	0.00%
PRE-SNIFFING	0.00%	0.00%
POST-SNIFFING	1.75%	1.75%
UNKNOWN	5.26%	0.00@

PAW LICKING SCORED DATA 16 SEGMENT AVERAGES

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	0.00%	0.00%
* PAW LICKING	100.00%	100.00%
RESPIRATION	0.00%	0.00%
PRE-SNIFFING	0.00%	0.00%
POST-SNIFFING	0.00%	0.00%
UNKNOWN	0.00%	0.00%

RESPIRATION SCORED DATA 11 SEGMENT AVERAGES

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	0.00%	0.00%
PAW LICKING	0.00%	0.00%
* RESPIRATION	90.91%	100.00%
PRE-SNIFFING	0.00%	0.00%
POST-SNIFFING	0.00%	0.00%
UNKNOWN	9.09%	0.00%

PRE-SNIFFING SCORED DATA 8 SEGMENT AVERAGES

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	0.00%	0.00%
PAW LICKING	0.00%	0.00%
RESPIRATION	0.00%	0.00%
* PRE-SNIFFING	100.00%	100.00%
POST-SNIFFING	0.00%	0.00%
UNKNOWN	0.00%	0.00%

POST-SNIFFING SCORED DATA 22 SEGMENT AVERAGES

BEHAVIOR	ABSOLUTE	RELATIVE
LICKING	0.00%	0.00%
PAW LICKING	0.00%	0.00%
RESPIRATION	0.00%	0.00%
PRE-SNIFFING	4.55%	4.55%
* POST-SNIFFING	90.91%	95.45%
UNKNOWN	4.55%	0.00%

APPENDIX E

SUMMARY TEST RESULTS USING

RELATIVE CLASSIFICATION

CRITERIA

The tables in this appendix are a simplified summary of the data contained in appendix B. The three network types are represented by the following codes:

NP = NO POWER

TP = TOTAL POWER

PTP = PROPORTIONAL TOTAL POWER

TABLE XIII

ONE-SECOND SEGMENT FFT PATTERNS

15-HERTZ BEHAVIORAL CLASSIFICATION ACCURACY

BEHAVIOR	NP	TP	PTP
LICKING	61.96%	44.52%	60.78%
PAW LICKING	41.03%	47.86%	45.30%
RESPIRATION	55.33%	66.00%	53.33%
PRE-SNIFFING	25.58%	43.02%	25.58%
POST-SNIFFING	52.83%	39.62%	54.18%

20-HERTZ BEHAVIORAL CLASSIFICATION ACCURACY

BEHAVIOR	NP	TP	PTP
LICKING	49.82%	62.31%	58.30%
PAW LICKING	65.81%	52.99%	47.86%
RESPIRATION	44.00%	56.00%	38.00%
PRE-SNIFFING	25.58%	24.42%	34.88%
POST-SNIFFING	49.60%	41.51%	53.10%

TABLE XIV

OVERALL NEURAL NETWORK METHOD ACCURACY

BEHAVIOR	NP	TP	PTP
15Hz AVERAGE	47.35%	48.20%	47.83%
15Hz STD DEV	12.81	9.28	12.16
20Hz AVERAGE	46.96%	47.45%	46.43%
20Hz STD DEV	12.93	13.34	8.85

TABLE XV

BEHAVIOR SEGMENT AVERAGE FFT PATTERNS

BEHAVIORAL CLASSIFICATION ACCURACY

BEHAVIOR	TP/15Hz	PTP/20Hz
LICKING	98.25%	98.25%
PAW LICKING	100.00%	100.00%
RESPIRATION	100.00%	100.00%
PRE-SNIFFING	100.00%	100.00%
POST-SNIFFING	95.45%	95.45%
AVERAGE	98.74%	98.74%
STD DEV	1.78	1.78

VITA

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