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A LIMITED SPEECH RECOGNITION SYSTEM

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ACKNOWLEDGEMENTS

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ABSTRACT

LISPER, a program designed for limited speech recognition, learns
to identify utterances as one of a limited input message set.
Functions of the raw spectral data are transformed into sequences
of states (features) in order to normalize for word onset time,
speaking rate, and speaking rhythm. State transition thresholds
are normalized for speaking level, and a hysteresis region is
employed about decision thresholds to reduce the sensitivity of
the system to noise. A feature sequence need not be consistently
correct because the recognition algorithm makes use of redundancy
to identify the most probable message. Features related to tense-
lax, sibilant, fricative, continuant, several place-of-articulation
features and a stress feature are included in a set of "linguistic"
features used for recognition. Another set of non-linguistic
features was also tested. Recognition scores approach 97% correct
after three rounds of training on a 54 word vocabulary for both
sets of features.

I. INTRODUCTION

This report describes the results of a successful study for the
National Aeronautics and Space Administration on the feasibility
of a voice link with a computer. LISPER, a prototype Limited
Speech Recognition system, was built to demonstrate and experiment
with the set of techniques for speech recognition described below.
The goals of the implementation were to provide a system which
would:

1) be able to identify an utterance as one of a limited set
   of possible input messages. Different message sets used
   contain approximately 50 to 100 items and consist of
   words or phrases less than 2 seconds long spoken in iso-
   lation.

2) allow an individual user to "train" the system. LISPER
   learns separately the characteristics of an input message
   set as spoken by each individual to use the system.

3) allow maximum flexibility for data access and system
   modification. For this reason LISPER was built in an
   extended LISP system (McCarthy, 1964) (Bobrow, Murphy
   and Teitelman, 1968). This decision allowed an easy
   transfer of the system from a DEC PDP-1 to an SDS 940
   computer.

This LISPER system has been used as both a research tool for
exploring characteristics of speech, and a prototype of a train-
able speech pattern recognition system.

Any pattern recognition system must have three basic components:
preprocessing hardware to extract a representation of the input;
programs utilizing this raw data to compute properties of the un-
known input (data reduction); and a recognition or decision algo-
rithm.   Figure 1 shows a block diagram of the organization of the
LISPER system.   The input speech signal may be obtained from either
a microphone or tape recorder.   The basic parameters of the input
are extracted by a spectrum analyzer which consists of a pre-emphasis
network followed by nineteen bandpass filters.   Bandpass filter
outputs are rectified, low-pass filtered, sampled, converted into
logarithic units, and stored on digital tape, or in the memory of
the computer.

The spectral representation of a word as derived from our input
system consists of 200 spectral samples, corresponding to 2 sec-
onds of speech material.   A spectral sample consists of the out-
puts of the 19 bandpass filters, all sampled at a particular
instant of time.   A filter output, in log units, is an integer
ranging from 0 to 63, covering a 45 decibel range of intensity.
Design considerations for the input system are discussed in Sec-
tion II.

The use of the logarithm of the short-time spectrum is well estab-
lished as one approach to speech analysis (see, for example,
Flanagan, 1965), and has often been used as the basis for recog-
nition programs.   The principal contributions of this research
have been the development of a set of algorithms for extracting
features which characterize speech utterances, and coupling this
set with a recognition algorithm capable of high quality word
identification in the presence of redundant, inconsistent, or
incorrect information from these properties.   The recognition
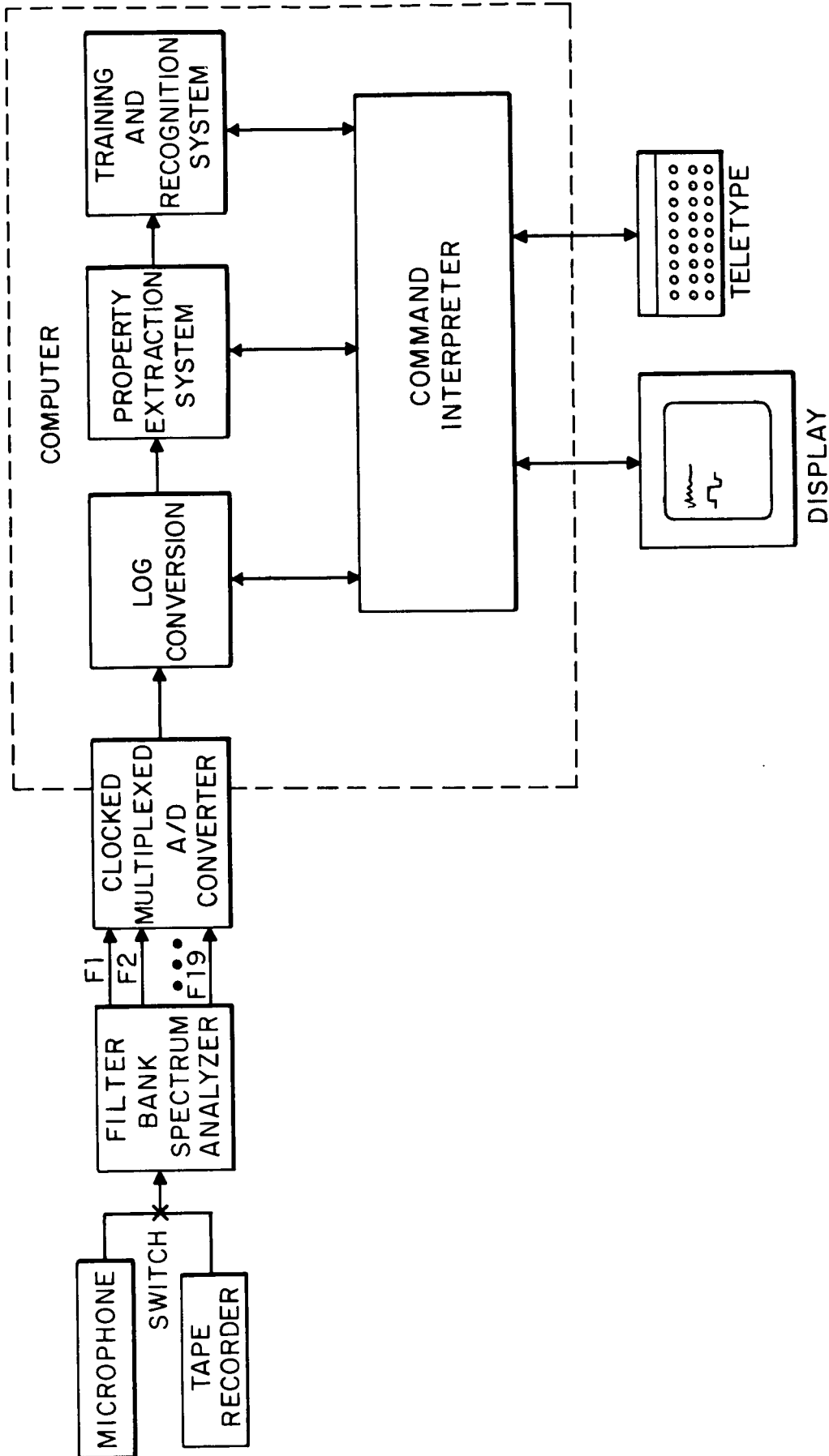algorithm does not directly utilize the spectral data, nor is an

FIG. 1   BLOCK DIAGRAM OF THE LISPER SYSTEM

intermediate phonetic (or phonemic) transcription of the word pro-
duced. We discuss below some problems of these two approaches and
indicate how a number of these problems have been circumvented by
techniques used in LISPER.

Our system has been extensively tested, and recognition scores
have been obtained on three vocabularies with three different
speakers. Typical of our results is attainment of recognition
scores that approach 97% correct on a 54 word vocabulary after
three rounds of training for a single speaker. Experiments indi-
cate that our recognition system is very successful in handling a
moderate amount of additive noise. Our recognition scores compare
favorably with those of other investigators (Gold, 1966; Denes and
Mathews, 1964; Dudley and Balashek, 1958; Davis et al., 1952).
However, unlike some of these, the LISPER system is not intended
to be used simultaneously by multiple speakers, and a new speaker
must train the system to the characteristics of his voice.

The techniques used in LISPER can best be appreciated by first
exploring some problems involved in identifying a speech utterance
on the basis of the 19 x 200 array representing a 2 second sampling
of its energy spectrum. Pattern recognition schemes operating on
data of this dimensionality are theoretically tenable (Sebestyen,
1960), but only if repetitions of words cluster properly in the
resultant vector space. It is by now well-known that speech spectral
patterns as initially stored in a computer do not cluster accord-
ing to the word spoken. Some of the reasons for this are:

1. The range of intensities encountered will vary because
    the overall recording level is not fixed. Recording
    level depends on vocal effort and the distance of a
    speaker from the microphone.

2. An unknown word is difficult to register at the same
    place within 200 spectral samples because word onset
    time is not a simple feature to detect reliably. For
    example, initial voiceless fricatives may be missed,
    prevoiced stops are hard to treat consistently, etc.

3. The total duration of a word is highly variable. An
    increase in speaking rate is not manifested by a linear
    compression of the time dimension. Final syllables are
    often prolonged. Some transitions (for example, the
    release of a stop consonant) are not as greatly affected
    by changes in speaking rate as the steady-state portions
    of vowels. If shortened enough, vowels are likely to be
    reduced and consonants may not be carefully articulated,
    with resultant losses in spectral distinctiveness.

4. A speaker attempts to generate an utterance so that it
    has a particular set of perceptual attributes (or features).
    We do not know in detail what the acoustic correlates of
    these attributes are. There is a great deal of variation
    allowed in the acoustic properties of the signal that will
    still give rise to the same utterance. There is also
    sufficient redundancy in the message to permit a speaker
    to leave out certain attributes entirely. For example,
    the degree of stress placed on a syllable will determine
    the extent to which the vowel may be reduced (Lindblom,
    1963). Consonants in unstressed syllables may contain
    less frication noise, a weak stop burst release, or in-
    complete stop closure. Vowels may be nasalized in nasal
    environments. The substitution of one incomplete gesture
    for a consonant cluster is also common in unstressed
    syllables of natural speech. None of these effects would

necessarily produce word recognition difficulties if they appeared consistently in the data. Unfortunately, they do not.

5.   If a speaker is instructed to speak distinctly and not rapidly, some surprising and unfortunate variability in speaking habits has been experimentally detected. In an attempt to help the system, our speakers released final stops, increased the length of some syllables, and articulated unstressed syllables more carefully than they would normally. Unfortunately, our speakers appear to have found these speaking habits unnatural, and could not remember from repetition to repetition exactly what they had done to help. For example, final voiced stop releases gave trouble by producing short vowel segments that varied greatly in amplitude, and the words "four" and "core" were sometimes pronounced as if they had two syllables.

6.   Individual speakers have vocal tracts of different sizes and shapes. It is physically impossible for two speakers to produce identical spectra for a given phone or word. A speaker makes an articulatory gesture that we, as listeners, interpret, possibly with respect to our knowledge of the spectra that he is capable of producing (Gerstman, 1967). The nature and importance of the normalization process of a listener are not well understood.

7.   Different speakers have articulatory habits (idiolects) that may be quite distinct. Habits include the timing and dynamics of articulatory movements and the features that a particular speaker employs to manifest a phonemic distinction. Whether recognition difficulties can be

attributed to individual speech habit structures is not
known. Very little quantitative data are available on
the characteristics that distinguish speakers (Kersta,
1962).

The variability of the spectrum of a word has led to the search
for data reduction techniques to eliminate irrelevant information.
An approach favored by several investigators has been to develop
rules for detecting phonemes (Fry and Denes, 1958; Martin et al.,
1966; Reddy, 1967). We believe that phoneme recognition is a much
more difficult problem than word recognition because it presupposes
a good understanding of the cues that distinguish phonemes in arbi-
trary phonetic environments. For example, allophones of the
phoneme /p/ may be:

1. normally aspirated, as in the word "peak" $[p^hik]$
2. weakly aspirated, as in the word "supper" $[s\wedge p\eth]$
3. non-aspirated, as in the word "spin" $[sp\mathrm{I}n]$
4. non-released, as in the word "top" $[t^hap^\lnot]$

There is no need for a word recognition program to attempt to
group this disparate set of physical signals together into one
phoneme. However, to the extent that algorithms for deriving
a detailed phonetic-feature description of an utterance can be
found, they can be of considerable help to a practical word recog-
nition system. Examples of feature approaches that are relevant
include the work of Hughes (1961), Hemdal and Hughes (1964), and
Gold (1966).

We have implemented a number of programs which characterize
phonetic features of words. These features are defined and com-
pared with the work of other investigators in Section III. Fea-
tures that have been implemented include (1) voiced, (2) strident,

(3) fricative, (4) stop-burst, (5) nasal, (6) [r]-like, (7) stri-
dent-stop, (8) [i]-like, (9) [a]-like, (10) [u]-like. For our
purposes, a feature is defined to be a function of sampled time
having a range limited to a small number of distinguishable states.
State transition thresholds are normalized for speaking level, and
a hysterisis region about the threshold reduces the sensitivity
to noise. The time dimension is removed by transforming the time
function into the sequence of states that is produced by the un-
known word. This reduces the information content in the represen-
tation of the word, automatically has the effect of normalizing
for speaking rate and defines word onset as the first change of
state. Several properties are used exclusively to describe the
stressed syllable. We have been able to segment words into syl-
lables, primarily on the basis of changes in total signal energy.
The stressed syllable has been identified with the aid of a func-
tion that computes an approximation to the perceived loudness of
a vowel. The features of the stressed syllable are less likely
to be affected by the natural variability that characterizes the
speech process (Stevens, 1968), and therefore are good properties
for use in recognition.

For each new utterance, the recognition algorithm decides which
previously seen message this one is most like. The algorithm is
related to a maximum likelihood decision in which the state se-
quences for each feature independently suggest for recognition
those input messages which have been previously characterized by
that sequence during training. The details of this decision pro-
cedure are described in Section V. The recognition algorithm
is capable of high quality word identification in the presence of
incorrect or inconsistent characterizations from many of the fea-
tures.

It should be emphasized that all of our feature definitions are
relatively simple-minded. They do not produce results that corres-
pond to a phonetic transcription of a linguist. Some features
work reliably in some phonetic environments, and not at all in
others. The features have the single purpose of providing suffi-
cient information about the invariant characteristics of the input
message for the recognition algorithm to operate successfully.

It should be clear that we believe a pattern recognition algorithm
cannot succeed with data of the type provided by the input system
unless the algorithm deals explicitly with some of the problems
mentioned previously. In particular, amplitude normalization,
word onset time, and speaking rate problems are likely to produce
more variability than any naive pattern learning program can
successfully treat. Pattern recognition programs that attempt to
overcome these difficulties have been described in the literature
(Schroeder, 1968; Shearme and Leach, 1968; Denes and Mathews, 1961;
Dudley and Balashek, 1958; Davis et al., 1952).

The feature approach that we have taken provides a good working
solution to these three problems. In the latter stages of the
research, we formulated a set of non-linguistic features to be
used as a basis for comparison with the features described in
Section IV. The non-linguistic properties involved simple sums
and differences of filter outputs. The results of the comparison
show that, for a single speaker, pattern detecting properties
that are unmotivated by linguistic considerations (but carefully
chosen) work very well, approaching 97% correct in a 54 word
vocabulary after 3 training rounds. These scores are roughly
equivalent to our previous results. The reasons for this success
are discussed in Section VI.

II. THE INPUT SYSTEM

A block diagram of the hardware that is employed to convert acoustic waveforms into a digital representation is shown in Fig. 2. Up to two seconds of speech is entered into the computer from a live microphone or tape recorder. A pre-emphasis filter having a frequency response that increases by 6 db/octave (3 db up at 740 Hz) is introduced so that the full dynamic range of each bandpass filter can be utilized. This network is similar to the inverse of the long-term average spectra for a male speaker.

The 19 channel filter bank of Fig. 2 approximates the short-time power spectrum of the speech signal. The filter characteristics have been selected to preserve the significant acoustic properties of an adult male speaker. In the frequency range up to 3000 Hz, 15 filters are arranged to be spaced uniformly and to have equal bandwidths. This is the approximate frequency range encompassed by the first three resonances of the vocal tract (Peterson and Barney, 1952). An even spacing of filters on a linear frequency scale was chosen to enable the hardware to share poles from adjacent filters.

During normal utterances of male speakers, the fundamental frequency rarely exceeds 180 Hz, and is usually in the range 80-150 Hz (Fairbanks, 1940). For voiced sounds, the spectrum analyzer should provide a representation of the spectral envelope, and this representation should be relatively uninfluenced by changes in fundamental frequency. These considerations led to the selection of 360 Hz as an appropriate filter bandwidth in the range up to 3000 Hz. With such a bandwidth there are always at least two harmonics of the fundamental within a given filter, and no more than four such harmonics. Thus changes in the pattern of
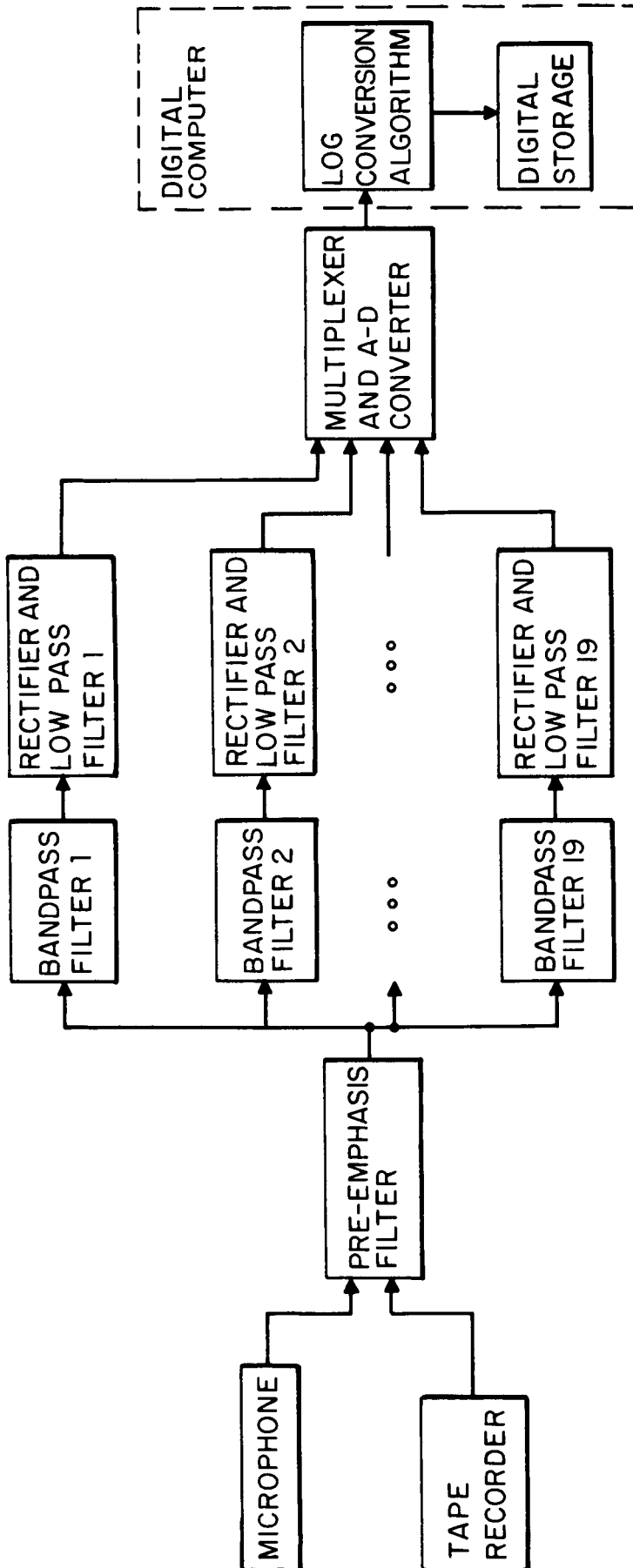
FIG. 2   A BLOCK DIAGRAM OF THE INPUT SYSTEM

filter outputs for a voiced sound due to changes in fundamental frequency are small.

In order to provide an adequate representation of the spectrum envelope, it was decided to space the filters every 180 Hz in the frequency range up to 3000 Hz. Once the desirability of filters with 360 Hz bandwidths has been established, it becomes clear that relatively few filters are required to cover the speech band. If filters were placed every 90 Hz instead of every 180 Hz, it would not be possible to locate the centroid of an energy concentration with significantly greater precision because outputs from adjacent filters have energy from several harmonics in common.

The frequency range above 3000 Hz is of importance primarily for carrying information about the noise-like components of speech-- the frication noise for stop and fricative consonants. Fine frequency resolution is not as important (Heinz and Stevens, 1961). The frequency range from 3000 to 6500 Hz is covered by four wide bandwidth filters. Filter center frequencies and bandwidths are listed in Table 1.

Four-pole Lerner filters (Lerner, 1963) are used to realize the bandpass characteristics because (1) adjacent filters can share poles, (2) the phase response is linear over the passband of the filter, and (3) the slope of the phase response, i.e., the delay time, is the same for each of the filters so that spectral components of a signal appear simultaneously at the outputs of the filter channels. It has been shown by Stevens (1968) that the relative timing of energy onsets in different frequency regions may be an important cue for the differentiation of place-of-articulation for stops. The set of Lerner filters will preserve this type of information. Fig. 3 plots the measured frequency response of each bandpass filter.

Filter No.	Center Freq.	Lower Cut-Off	Higher Cut-Off	Band Width
	cps	cps	cps	cps
1	260	80	440	360
2	440	260	620	360
3	620	440	800	360
4	800	620	980	360
5	980	800	1160	360
6	1160	980	1340	360
7	1340	1160	1520	360
8	1520	1340	1700	360
9	1700	1520	1880	360
10	1880	1700	2060	360
11	2060	1880	2240	360
12	2240	2060	2420	360
13	2420	2240	2600	360
14	2600	2420	2780	360
15	2780	2600	2960	360
16	3260	2960	3560	600
17	3980	3560	4400	840
18	4940	4400	5480	1080
19	6020	5480	6560	1080

TABLE 1. List of Filter Center Frequencies and Bandwidths
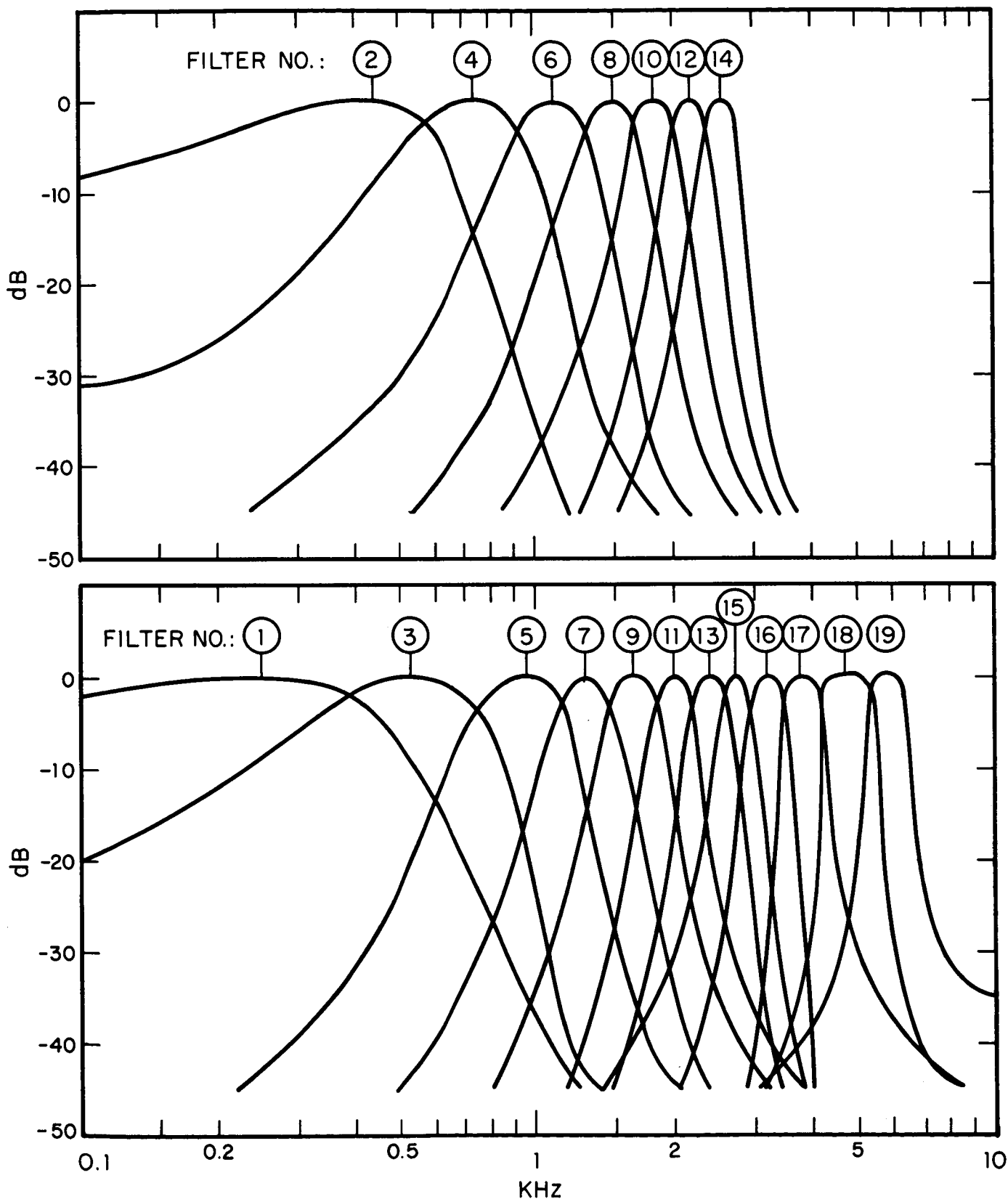
FIG.3   MEASURED FREQUENCY RESPONSE OF FILTER BANK.
RATIO OF DC OUTPUT TO AC INPUT IN dB

The output of a bandpass filter is first full-wave rectified and
then low-pass filtered. The averaging time for the low-pass filters
should be sufficiently long that there are no appreciable fluctua-
tions in the outputs of the channels within a period of the funda-
mental frequency because fluctuations are not easy to distinguish
from significant spectral changes. On the other hand, the aver-
aging time should be sufficiently short so that rapid changes in
level and spectral shape associated with stop and nasal consonants
can be detected. These considerations led to the selection of a
compromise averaging time on the order of 10-20 msec.

The weighting function (i.e., the impulse response) associated with
the low-pass filter should have as short a tail as possible so that
only events over the 10-20 msec interval are averaged. The Bessel
filter provides a non-ringing impulse response with a tail that
is relatively short. A four-pole Bessel low-pass filter with the
characteristics indicated in Fig. 4 terminates each of the 19 fil-
ter channels.

The output of a filter is sampled every 10 msec, using the multi-
plexer and analog-to-digital converter of the computer. Thus,
each 10 milliseconds the computer extracts 19 numbers (integers
ranging from 0 to 1023) which represent the average energy in
19 frequency bands for the previous 10 milliseconds. In the com-
puter, the logarithm of this energy is computed. Each sample is
transformed to an integer between 0 and 63, covering a 45-decibel
range of intensity.

An example of the spectrum of the word "store", as derived by the
input system, is shown in Fig. 5. Note that the resolution of
individual formant peaks is poor with these filters (e.g., the
first and second formants of [o^w] in "store" do not produce

FREQUENCY RESPONSE

IMPULSE RESPONSE
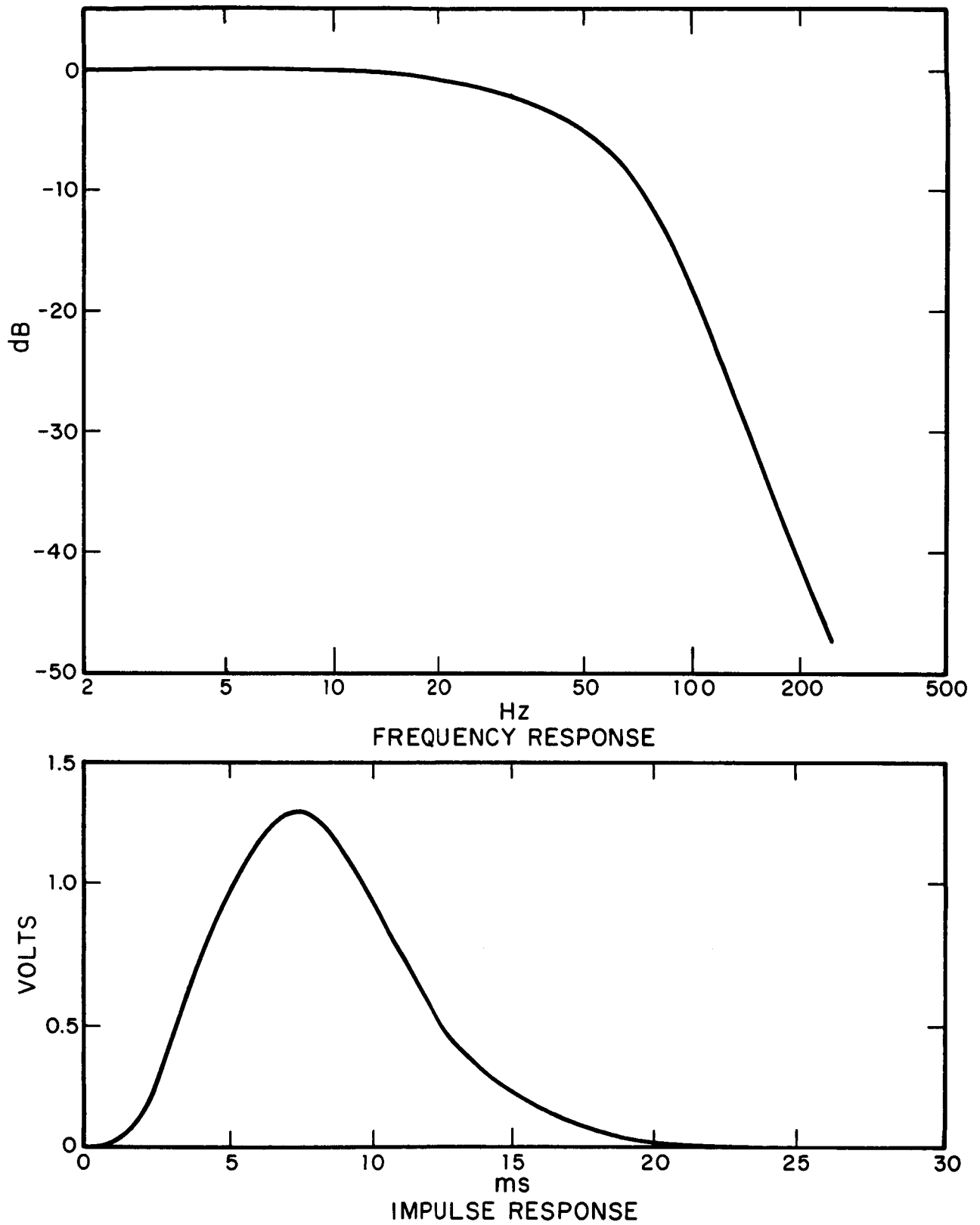
FIG. 4   CHARACTERISTICS OF THE FOUR-POLE
BESSEL LOW-PASS FILTER

```
word 12     speaker 2    repetition 1
      1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19  total
 1   12  3  0  0  0  0  0  1  0  0  0  0  0  0  0  0  0  0  0   16
 2   11  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0   11
 3    7  1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0    8
 4   10  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0   10
 5   17  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0   17
 6   12  1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  1  0  2   16
 7    9  0  0  0  0  0  0  0  0  0  0  0  0  0  0  1  4  2  8   24
 8   16  2  0  0  0  0  0  0  1  0  0  0  0  0  0  2 10  7 15   53
 9   15  0  0  0  0  0  0  1  0  0  0  0  1  0  0  6 15 12 19   69
10   12  0  0  0  0  0  0  1  1  0  0  0  2  0  0  6 17 20 24   83
11   18  3  2  0  1  1  1  2  2  0  2  1  7  0  2 11 28 25 36  142
12   16  0  1  1  1  1  0  2  1  1  2  0  2  0  3 17 28 27 32  135
13   17  5  2  0  1  0  0  1  1  0  1  1  4  0  3 26 29 29 39  159
14   13  2  2  1  2  0  1  2  2  1  3  2  7  2  6 30 32 36 43  187
15   12  2  2  1  2  0  1  2  3  1  4  5  7  3  7 33 32 34 42  193
16   22  3  2  1  2  0  1  2  2  1  4  4  7  3  6 29 29 32 39  189
17   15  1  1  0  1  0  1  1  2  1  2  1  4  0  5 26 25 27 35  148
18   10  3  0  0  0  0  0  0  0  0  1  0  2  0  2 21 20 23 29  111
19   21  0  0  0  0  0  0  0  0  0  0  0  0  0  1 17 14 17 24   94
20   14  1  0  0  0  0  0  0  0  0  0  0  0  0  0 12  9 13 19   68
21   20  2  0  0  0  0  0  0  0  0  0  0  0  0  0  8  6  9 14   59
22   21  2  0  0  0  0  0  0  0  0  0  0  0  0  0  6  4  5  9   47
23   16  3  0  0  0  0  0  0  0  0  0  0  0  0  0  2  2  2  5   30
24   14  0  0  0  0  0  0  0  0  0  0  0  0  0  0  1  0  1  2   18
25   18  4  0  0  0  0  0  0  0  0  0  2  3  0  3  3  1  1  2   37
26   22 14 15 12 10  7  6 10  6  3  8 18 22 20 18 19  7  6 19  242
27   19 11  9  7  6  4  3  8  5  3  8 14 17 15 14 19  8  9 17  196
28   32 26 18  8  5  5  4  6  2  1  4  6  9  5  8 15  5  5 11  175
29   48 46 39 28 19 18  9  6  3  5  6  9  8  5  6 10  3  1  7  276
30   47 48 43 33 29 27 18 10  2  2  2  3  4  0  3  8  2  1  4  286
31   48 50 46 36 35 32 20 11  6  5  4  2  3  0  2  6  1  0  3  310
32   48 52 48 42 40 36 22 12  6  7  5  3  3  0  1  5  1  0  2  333
33   48 53 50 44 40 34 20 11  7  7  5  1  2  0  0  3  1  0  1  327
34   48 53 51 46 40 33 19 12  7  9  5  0  1  0  0  2  0  0  0  326
35   48 54 52 47 42 33 18 14  9 11  5  1  1  0  0  1  0  0  0  336
36   49 55 53 49 44 33 17 15 12 14  7  2  1  0  0  0  0  0  0  351
37   48 55 54 50 45 33 17 17 13 15  9  2  2  0  0  1  0  0  1  362
38   47 55 54 51 45 33 17 17 14 17 10  5  2  0  0  0  0  0  0  367
39   49 56 55 51 46 34 18 19 16 19 12  5  2  0  0  0  0  0  0  382
40   50 57 56 52 47 35 19 21 18 20 14  5  2  0  0  0  0  0  0  396
```

(Continued)

41	51	58	58	53	47	35	21	23	20	22	17	6	3	0	0	0	0	0	2	416
42	50	58	58	52	45	35	21	22	18	21	15	5	3	0	0	0	0	0	2	405
43	49	57	56	52	46	36	21	21	18	21	16	5	3	0	0	0	0	0	2	403
44	49	56	56	52	46	36	20	21	18	21	17	7	4	0	0	0	0	0	3	406
45	48	56	56	52	47	38	22	23	19	22	19	8	4	0	0	0	0	0	1	415
46	49	56	56	52	47	39	22	23	20	22	18	8	6	0	0	1	0	0	1	420
47	47	56	56	52	49	42	24	25	22	23	20	13	8	0	1	1	0	0	1	440
48	47	54	54	52	49	43	28	26	23	24	19	13	8	1	1	2	1	0	3	448
49	46	53	54	52	50	46	30	27	24	24	19	14	9	3	2	1	1	0	1	456
50	45	52	52	51	50	46	33	28	24	23	16	11	7	2	2	0	0	0	0	442
51	44	51	51	50	49	45	33	28	24	22	17	14	9	4	3	1	0	0	0	445
52	42	50	50	49	48	45	34	30	25	22	16	14	9	4	4	2	0	0	1	445
53	40	49	50	48	47	45	35	31	26	21	16	14	9	4	5	1	0	0	1	442
54	39	49	50	48	47	45	36	33	27	21	14	12	8	3	3	1	0	0	0	436
55	36	48	49	47	46	45	38	35	29	20	12	11	7	2	3	1	0	0	0	429
56	40	49	49	46	45	45	39	36	28	19	10	9	6	0	2	1	0	0	0	424
57	42	50	50	46	44	44	40	36	28	18	10	9	7	1	2	2	1	0	0	430
58	42	50	50	46	43	43	40	36	28	19	9	9	7	1	3	3	1	0	0	430
59	42	48	48	44	40	42	38	36	28	17	7	8	4	0	1	1	0	0	0	404
60	40	46	46	41	36	38	36	34	24	13	4	2	2	0	0	0	0	0	0	362
61	40	45	45	40	35	36	35	34	24	14	3	1	1	0	0	0	0	0	0	353
62	40	43	43	36	32	33	33	32	23	12	2	0	1	0	0	0	0	0	0	330
63	39	43	42	36	29	31	32	32	23	13	2	0	0	0	0	0	0	0	0	322
64	38	42	42	35	27	29	30	30	22	10	2	0	0	0	0	0	0	0	0	307
65	39	41	39	33	24	26	27	28	19	10	1	0	0	0	0	0	0	0	0	287
66	39	36	33	28	20	21	24	25	17	9	1	0	0	0	0	0	0	0	0	253
67	32	32	29	24	17	17	20	23	14	8	1	0	0	0	0	1	0	0	1	219
68	30	29	25	20	13	12	17	19	12	7	2	0	0	0	0	1	0	0	2	189
69	32	24	21	17	10	8	13	17	10	5	1	0	0	0	0	1	0	0	0	159
70	31	22	18	14	9	9	12	17	9	4	0	0	0	0	0	0	0	0	0	145
71	30	24	14	10	7	5	8	12	6	2	0	0	0	0	0	0	0	0	0	118
72	25	15	8	6	5	3	5	7	3	0	0	0	0	0	0	0	0	0	0	77
73	16	13	5	5	5	3	4	6	2	0	0	0	0	0	0	0	0	0	0	59
74	18	10	5	3	3	2	3	6	1	0	0	0	0	0	0	0	0	0	0	51
75	14	6	3	3	3	2	2	3	1	0	0	0	0	0	0	0	0	0	0	37
76	13	6	2	2	2	1	1	2	0	0	0	0	0	0	0	0	0	0	0	29
77	12	2	1	1	2	3	1	1	0	0	0	0	0	0	0	0	0	0	0	23
78	13	4	2	2	2	1	1	1	0	0	0	0	0	0	0	0	0	0	1	27
79	17	3	2	1	2	1	1	1	1	0	0	0	0	0	0	1	0	0	1	31
80	17	3	2	1	2	1	0	1	0	0	0	0	0	0	0	0	0	0	0	27

FIG. 5.　　THE SPECTRUM OF THE WORD "STORE" AS DERIVED BY THE INPUT SYSTEM.

individual peaks). The choice of filters represents a commitment
to a non-formant-tracking approach to speech processing. It is
based on the hypothesis that the human perceptual apparatus does
not attempt to resolve individual formant tracks, but rather is
sensitive to gross changes in energy concentrations. Thus, when
two formant frequencies come close, as in a back vowel, only one
broad energy concentration is seen by our input system and, pre-
sumably, by the peripheral auditory system as well. An approxi-
mation to the frequency locations of formants could be recovered
from the spectral data through an analysis-by-synthesis procedure
(Bell, et al., 1963) if desired.

In working with the input system, it has become evident that two
qualifications should be made concerning its design. A finer fre-
quency resolution would be of some help in the frequency region
from about 300 Hz to 1200 Hz. Additional filters (or a modifica-
tion in the spacing of the maximum of 19 filters to which we are
limited by the multiplexer hardware) would hopefully improve the
ability of the system to detect sudden movements in energy con-
centrations more reliably. The second design improvement that we
would include in a second-generation input system would be a
shortening of the averaging time of the low-pass filters by about
30-40 percent. At present, sudden changes in energy concentrations
are indicated with insufficient temporal resolution. This latter
improvement might be accompanied by an increase in the digital
sampling rate from 100 spectra per second to about 200 spectra
per second.

A detailed description of the electronic circuits of our input
system is contained in Appendix A. This system was designed and
built by K. N. Stevens and G. von Bismarck (1967).

III. PROPERTY EXTRACTION SYSTEM

An unknown word is represented in the computer by a matrix of in-
tegers (filter number vs. sampled time vs. log-amplitude). The
purpose of a property or feature extraction system is to reduce
the information content of the input signal to a level that makes
it possible for the decision or recognition algorithm to operate
reasonably. The critical thing is that the information eliminated
should be information which is irrelevant to the decision that the
recognition algorithm must make.

The principal result of this research has been the development of
a set of feature definitions which characterize speech spectra in
a way that makes recognition possible. The feature definitions
have evolved through the course of the research and represent a
gradual learning by the researchers of the relevant characteris-
tics of speech as seen by the input system. The approach has
been to make use of the present day body of knowledge about acous-
tic phonetics and the distinctive feature approach to phonological
description (Jakobson, et al., 1963; Chomsky and Halle, 1968). A
similar orientation is exemplified by the work of Hughes and Hem-
dal (1965).

The properties of speech which are used by the recognition program
are based on the energy measures derived from the input system.
The output of each filter is an elementary function of the speech
input signal. We use the notation $F_n(i)$ for the output of filter
n at sample interval i; that is $F1(i)$, $F2(i)$, ... , $F19(i)$ are
used for the output of filters 1 through 19 at sample interval i.
The filter number n ranges from 1 for the low frequency filter to
19 for the high frequency filter; and $i=1$ for the first sample
interval to $i=200$ for the last time sample of a two second utter-
ance.

More complicated functions of the speech input signal can then be defined in terms of these elementary (base) functions, F1, ... F19, in the LISP system. For example, the following function has been found to correlate with perceived loudness, independent of vowel quality.

$$Loud(i) = F1(i) + F2(i) + F3(i) + F4(i) + F12(i) - F7(i)$$

The output of the seventh filter is subtracted from the sum of the first four filters and filter 12 to compensate for the fact that low vowels are inherently more intense when produced with the same vocal effort. We will indicate later how a modified version of this function Loud(i) can be used to correct for differences in recording level between repetitions of the same word.

Loud(i) is useful in reducing the information that must be processed by the decision algorithm, since it helps to normalize the input with respect to a variable which is not important to recognition, namely, the recording level of the input signal. We describe in this section a number of techniques which are used to reduce the information content of the incoming signal in ways that preserve the invariance of message identity over ranges of parameters which are irrelevant to the decision about the identity of the message.

One important way we have found to reduce the information content of a function is to reduce its range of values. Thus, for example, we may define a reduced information property Amp2(i) based only on the output of filter F2.

$$\text{Amp2(i)} = +1 \text{ if } F(2) > 40$$
$$0 \text{ if } F(2) > 20$$
$$-1 \text{ otherwise}$$

Amp2(i) is thus a 3 valued function, where we ascribe no significance to the names of the three values. As described later, a set of non-linguistic threshold properties similar to Amp2 can be used as a basis for recognition. However, we note the following problem. If the signal in F2 were varying around either of the thresholds, 20 or 40, then there would be little significance to the changes of state between -1 to 0, or 0 to 1; they probably would be caused more by noise than a real (significant) variation in the input signal.

To make such properties less sensitive to noise, we introduce a hysteresis region around the thresholds. This helps to insure that a change of state is significant. A revised definition of Amp2(i) is

$$\text{Amp2(i)} = +1 \text{ if } [F2(i) > 40] \text{ or } [F2(i) > 37 \text{ and } F2(i-1) = 1]$$
$$0 \text{ if } [F2(i) > 20] \text{ or } [F2(i) > 17 \text{ and } F2(i-1) \neq -1]$$
$$-1 \text{ otherwise}$$

Most of the features we use are functions of sampled time having a range limited to a small number of distinguishable states. These functions are very sensitive to slight changes in time scale and origin; however, these variations in the data are irrelevant for recognition. Therefore, time dimension is removed from a feature by transforming the time function into a sequence of transitions of states, as is illustrated in the following example:

```
i           1 2 3 4 5 6 7 8 9 ...
Voice(i)    0 0 1 1 1 1 1 1 0 ...
Voice =     0 1 0 ...
```

This transformation reduces the amount of data that must be manipulated by the program. Due to the nature of spoken language, the exact time when features change value will vary from repetition to repetition of the same word, but the essence of the word remains in the sequence of state transitions of an appropriate set of features.

No information about the word onset time, speaking rate, and speaking rhythm can be recovered from the sequence unless these parameters have an effect on the actual states that are reached. To this extent, recognition will be unperturbed by variations in word onset time, speaking rate, and speaking rhythm.

A problem that arises from collapsing the time dimension is an inability to tell whether two features were in specific states at the same time. Time removal assumes that features independently characterize a word. This is obviously false. A clear example is provided by the words "sue, zoo" which can only be distinguished by knowing whether the strident is simultaneously voiced, or not. It is possible to retain some timing information by the inclusion of features containing states which are entered only upon simultaneous satisfaction of two conditions, or features that count the number of time samples between temporal landmarks in the data and change state if the count exceeds a threshold.

For example, the state "-1" corresponds to voiceless segments in the definition of the spectral quality [r]-like(i). This is used to indicate in which voiced segment an [r]-like phone occurred.

The sequence produced for the word "ratio" should be -1, 1, 0, -1, 0, -1. A more detailed localization of the [r] is probably not necessary and would certainly be more difficult. We found that very gross timing information is satisfactory for recognition. Two features are used to make a preliminary division of a word or message into one or several segments. One feature divides a word into voiced and voiceless segments and the other divides it into syllables. Voice(i) and Syllable(i) are then used to introduce time markers in the definitions of other features.

Time removal achieves the most significant reduction in the information content of the raw data. Information content is also reduced when the intensity and filter number (frequency) dimensions are transformed into changes of state of selected functions. The information retained by these transformations can be increased by (1) an increase in the number of distinguishable states, or (2) an increase in the number of feature detectors.

Information manipulable by the recognition algorithm can also be obtained by mapping the value of a function at a particular time interval into a small range of values. For example, features which classify the vowel quality of the stressed syllable of an utterance into one of 10 categories have been found to be very useful in recognition. The stressed syllable is identified with the aid of a function Loud(i) that computes an approximation to the perceived loudness of a vowel. These features of a stressed syllable are less likely to be affected by the natural variability that characterizes the speech process (Stevens, 1968).

Three types of information are available for evaluating and re-defining features. The primary data source is a set of computer print-outs of the spectra produced by the 54 word vocabulary of Gold (1967) repeated once by 2 speakers. The word list appears

in Table 2; an example of the computer printouts is shown in
Fig. 5 earlier.

A feature definition that appears to work for this data is tested
on 9 other recordings of the same word list by the two speakers.
One result of this test is a set of recognition scores: X percent
correct identification for each repetition of the word list. This
is usually not a sufficiently sensitive measure of feature perfor-
mance, so we also obtain a printout of the feature characterization
of each word in each repetition of the vocabulary for all feature
definitions. Examples of feature characterization for the Gold
vocabulary are contained in Appendix B.

From this information we might find that, for example, the feature
Voice(1) produces a sequence 01010 for some repetitions of the
word "divide". Each "1" represents a voiced segment and each "0"
represents an unvoiced segment. Reference to the original spec-
tral printout for "divide" suggests that the problem is a weakly
voiced [v]; sometimes the voicing in [v] falls below our threshold
setting, sometimes not.

At this point we would lower the voicing threshold and observe the
results. We might find that a vocabulary item with two voiced
segments (e.g. "compare") now sometimes produces the incorrect
sequence 010, indicating only one voiced segment. A simple solu-
tion, threshold adjustment, is incapable of making the voicing
definition conform to our linguistic intuition. More importantly,
the simple adjustment does not produce consistent results.

However, our recognition algorithm is powerful enough to deal
with ambiguity in the voicing assignment of some vocabulary items,
and thus we did not develop a more sophisticated voicing algorithm.

We made no attempt to use rate of voicing onset, offset, time be-
tween burst and energy build-up for stops, etc., as additional
cues to a better feature definition. In all the features used,
the ambiguity remains at a level tolerable to the recognition algo-
rithm. The redundancy of the feature definitions allows recog-
nition of variations of the same message.

IV.   RECOGNITION ALGORITHM

Our recognition algorithm is a program that learns to identify a
word by associating the outputs of various property extractors
with that word. During learning, the vocabulary of words is pre-
sented a number of times, and information is accumulated about the
different ways that the speaker may pronounce each word. For
example, the result of the training procedure applied to the
feature sequence Voice after 5 presentations of the 4-word vocabu-
lary "one, two, subtract, multiply" might be:

Word	Sequence	Number of times sequence occurred
one	010	5
two	010	5
subtract	01010	5
multiply	0101010	3
multiply	01010	2

The two versions of the word "multiply" exemplify a common problem.
No matter where we place threshold boundaries, there are some words
that are treated inconsistently by the feature detectors. Another
way of putting it is to say that there appear to be no absolute
boundaries along the dimensions we have chosen. The recognition
algorithm takes this fundamental limitation into account and makes
a best guess given the imperfect nature of the properties.

The program first reorganizes the training data for each property
into a list of these sequences (or other outputs) that have
occurred. The list for Voice of our example is shown below:

Sequence	(Word, frequency)
010	one 5, two 5
01010	subtract 5, multiply 2
0101010	multiply 3

If a new utterance is presented to the program for recognition and the feature Voice(i) produces the sequence 01010, then Voice will register one vote for the word "subtract" and one vote for the word "multiply". The unknown word is identified as the vocabulary word eliciting votes from the most features. Typically, the identified word received a vote, signifying a perfect match, from only about 80 percent of the features.

In case of ties, the program makes use of information concerning the number of times a word appears at a node. Thus, if "subtract" and "multiply" tie for first place in the voting from all the features and Voice=01010, then Voice will register 5 votes for "subtract" and 2 votes for "multiply" in the run-off between these two candidates.

The final decision procedure is an attempt to find the message from the set of possible inputs which is most similar to the current input message. Because there is a wide variation in the way people say things, the decision procedure does not insist that the current input must be like one of the prototype input strings in all ways that it was categorized; that is, it need not be suggested by all properties. In this sense, the decision procedure allows a generalization of the original training learning by looking for a best fit without putting a bound on the goodness of this fit.

The property sequences have been considered as independent characterizations of the input message. In this case, by independent we do not mean that the computations themselves are necessarily independent, but that these descriptors of the input message are treated independently in the decision process. With the assumption of independence, the voting procedure is similar to a maximum likelihood estimate.

The a priori probabilities of all messages are the same. Therefore, the most likely message is the one for which the product of the a posteriori probabilities (or the sum of their logarithms) is a maximum. For each property, every message, M_i, previously associated with the current input sequences S_i is given a (scaled) log probability of $100+N_i$, where $N_i \geq 1$ is the frequency with which M_i was seen for S_i. Messages not associated with S_i in training are given log-probability $\emptyset$ and can therefore be ignored in the summation. These assignments of probabilities achieve in one step a score which allows a single search to determine the most likely message.

It has been experimentally determined that this voting scheme works as well or better than a number of other measures that make use of the same information. For example, we tried the adjusted weight used by Teitelman (1964) in ARGUS, a hand printed character recognizer (a similarly structured pattern recognizer); and a weight of $\log(1+N_i)$ which is a good small sample probability estimate of the a posteriori probability of S_i.

V. FUNCTIONS AND PROPERTIES USED IN RECOGNITION

The principal results of this research have been the development
of properties which characterize speech input signals in a way
to make recognition possible. These properties have evolved over
the course of the research, and represent a gradual learning by
the researchers of characteristics of speech as seen through the
"ear" of our input spectrum analyzer filter bank. Two different
sets of recognition properties are included here. The first is a
set of properties and functions which tend to describe the speech
signal in more linguistic terms. Transitions of these properties
describe features of the input message which can be understood
in terms of the ordinary linguistic descriptions of such messages.
In this way, they tend to be more speaker independent than the second
set of properties which are described.

The second set of properties used for recognition described below
extract features of the spectral shape of a message. Their ex-
treme simplicity makes them seem ideal for hardware implementation,
and their high accuracy in recognition testifies to the uniform
way that people tend to say a particular message. At least there
seems to be a fair uniformity as seen through our spectrum analyzer.

A. Linguistic Features

We distinguish functions, such as Loud(i), which have a domain
equal to the input spectral representation of an unknown word;
features, such as Voice(i), which are functions that are used in
recognition and have a range limited to a small number of states;
and feature sequences, such as Voice, which are the result of
removing the time dimension from a feature. The following functions
are used in the definitions of a set of 15 features. All functions

have a single variable, i, which represents an index over time. The notation F6(i) will be used to denote the output of filter 6 at time sample i.

Functions

1. Loud(i) =F1(1) + F2(i) + F3(i) + MAX [F2(i), F4(i)]

         + MAX [2(F3(i) - F4(i)), 0].
         This function is intended to provide a measure of the
         perceptual loudness of vowels. Perceptual loudness is
         related to vocal effort whereas the acoustic energy in a
         vowel depends in part on the vocal tract configuration as
         well as vocal effort. For example, the low vowel, [a],
         for which the vocal tract is relatively open will have a
         greater natural intensity than the high vowel, [i], for
         which the vocal tract is more closed (Lehiste and Peterson,
         1959; Fant, 1960). The function is intended to compensate
         for the reduced level associated with a low first formant.

2. ah(i) = F3(i) + F4(i) - F1(i) - F2(i).
         This function and the following two functions are used to
         characterize the spectral quality of the vowel nuclei of
         a word. The vowels [i, a, u] represent limiting articu-
         latory positions for the tongue body. The vowel [a], as
         in "pot", is produced by placing the tongue as far back
         and as low as possible without producing a constricted
         vocal tract (and therefore a consonant). An acoustic
         correlate of this articulation is a high first formant,
         resulting in a greater output in filters 3 and 4 than in
         filters 1 and 2. The function ah(i) will therefore be a
         maximum when vowels with a high first formant similar to
         [a] are produced.

3. $ee(i) = F9(i) + F10(i) + F11(i) + F12(i) - 2F6(i) - 2F7(i)$.

The vowel [i] as in "beet" is produced by positioning the tongue body as high and as forward in the mouth as possible. An acoustic correlate of this articulation is a low first formant and a high second and third formant, resulting in an energy minimum in filters 6 and 7, and an energy concentration between filters 9 and 12. The function $ee(i)$ will therefore be a maximum for vowels similar to [i].

4. $oo(i) = F3(i) + F4(i) + F5(i) - F8(i) - F10(i) - F12(i)$
   $-F14(i) - F16(i)$.

The vowel [u] as in "boot" is produced by positioning the tongue body as high and as far back in the mouth as possible. An acoustic correlate of this articulation is a low first and second formant, resulting in a major energy concentration below F7 and reduced energy above F7. The function $oo(i)$ will therefore be a maximum for vowels similar to [u].

5. $er(i) = F7(i) + F8(i) - F4(i) - F12(i)$.

This function is similar to the vowel functions in form, but has the task of detecting spectra characteristic of the consonantal and syllabic allophones of [r]. The low third formant characteristic of [r] and [ɚ] (as the vowel in Bert) produces a distinct spectral shape with an energy concentration centered in filters 7 and 8, a dip in energy at filter 4 between the first and second formants, and an absence of energy above F10 due to the low third formant. The function $er(i)$ will therefore be a maximum when phones similar to [r, ɚ] are produced.

6. $str(i) = F16(i) + F17(i) + F18(i) + F19(i)$.

   This function is a maximum when high frequency frication energy is present. The strident phones produce intense high frequency energy, whereas a non-strident fricative produces a small energy peak in filter 19. The function $str(i)$ will therefore be a maximum for many allophones of [s, z, š, ž, č, ǰ, t, k], which are the first consonants in [sin, zen, shin, azure, chin, gin, tin, kin] respectively.

7. $dspect(i) = |ah(i) - ah(i-1)| + |ee(i) - ee(i)|$
   $+ |oo(i) - oo(i-1)|$

   This function is a computationally inexpensive approximation to a spectral derivative. The function will be a maximum when the spectrum is changing rapidly, as for example in a consonantal transition. Dspect(i) is used as an aid in delimiting syllable boundaries. It is also used to distinguish ee-like vowels from some consonant-vowel transitions that produce a momentary peak in the function ee(i).

8. $cv(i)$ = sum of $F1(i)$ through $F16(i)$.

   This function tends to be greater for vowels than for adjacent consonants. This is because a constricted or closed vocal tract configuration results in a reduced acoustic output in the frequency range spanned by these filters. The function is used to detect syllable boundaries.

9. damp(i) = sum of F1(i) through F19(i) minus sum of
                   F1(i-1) through F19(i-1).
         This function indicates a sudden increase in energy in
         all filters. It will be a maximum for stop releases and
         sudden voicing onsets. It is used to detect stop bursts.

Features

The preceding functions are used in the computation of the following
features. The usual interpretation of the three feature values
(states) is: "-1" implies that the property is irrelevant for this
time interval; "0" means that the property is relevant but not
present; and "1" means that the property is relevant and present.

1. Voice(i) = 1 if [F2(i)>t1] or [F2(i)>t1-5 and Voice(i-1) = 1]
                  0 otherwise
                  t1 = 34

A hysteresis region of 5 units is employed about the threshold,
t1, to ensure that a change of state is significant and not due to
random fluctuations in level. The effect of the second conditional
part of the definition is to keep Voice(i) in its current state
for values of F2(i) between 30 and 34, the hysteresis region.

An unknown word may vary considerably in overall recording level
if the speaker moves with respect to the microphone or changes his
vocal effort. It is much easier to compensate for recording level
by modifying the threshold, t1, than by attempting to modify the
raw data. The maximum value attained by the time function Loud(i)
is used for this normalization:

    Maxloud = Max_i [Loud(i)]

Loud(i) attains its maximum value near the midpoint of the stressed
vowel nucleus. For a speaker positioned correctly in front of a
microphone and speaking at a comfortable level, a typical value for
Maxloud is 200. Threshold normalization is accomplished by com-
puting a new threshold, tl', for each unknown word according to the
following formulae:

$$tl' = tl* (200/Maxloud)$$

The method fails if the recording level increases to saturation
or decreases below background noise. The effective range for
recording level sensitivity is somewhat less than the full 45
decibel range of the input system.

The fundamental voice frequency of a male speaker will vary from
about 90 to 180 Hz. The greatest energy due to voicing will appear
in the low frequency filters because energy in the harmonics of
the laryngeal source falls off at about 12 db per octave. Voice(i)
looks at the energy in filter 2. If this energy exceeds a threshold,
voicing is present, otherwise not. This simple definition has
worked surprisingly well. The greatest difficulty has been in
treating final voiced stop releases consistently, and in detecting
voicing energy in some voiced fricatives.

2. Syllable(i) = 1 when the function Cv(i) is significantly
                    increasing
                  0 when the function Cv(i) is significantly
                    decreasing
                    otherwise, set to same value as in previous
                    time sample.

The precise computation is most easily stated in terms of a program segment. Peak and Valley are variables indicating the local maximum and minimum in the function Cv(i). Time is a variable that counts the number of time samples during which Syllable(i) has remained in the same state.

```
        Syllable(0) = 0, Valley = 0, Peak = 0,
        Time = 6, Cv(0) = 0
        Do for i = 1 in steps of 1 to 200:
        Time = Time + 1
        if [Syllable(i-1) = 0], Go To 1
        if [Cv(i-1)>Peak], Peak = Cv(i-1)
        Syllable(i) = 1
        if [[Time<6] or [[Cv(i)>Peak - 70] and [Dspect(i)<35]] or
        [Cv(i)>Peak - 20]], Go To 2
        Syllable(i) = 0, Valley = 1000, Time = 0
        Go To 2
    1   if [Cv(i-1)<Valley], Valley = Cv(i-1)
        Syllable(i) = 0
        if [[Time<6] or [Voice(i) = 0] or [[Dspect(i)<35] and
        [Cv(i)<Valley + 40]] or [Cv(i)<Valley + 20]],
        Go To 2
        Syllable(i) = 1, Peak = 0, Time = 0
    2   Continue
```

The times at which this feature changes state do not delimit precise syllable boundaries. The feature usually gives an accurate count of the number of syllables in a word and provides a rough segmentation. Examples of difficulties with Syllable(i) include a frequently missed third syllable in "binary" and the segmentation into two syllables of some repetitions of the words "four" and "core".

3.   Stress(i) = 1 if Loud(i) = Maxloud for the first time.

                0 if Syllable(i) = 1

             -1 otherwise

             Maxloud = Max$_i$ [Loud(i)]

This feature is designed to indicate which syllable of a word is
the one which has the maximum loudness and is therefore the
stressed syllable. Stress assignment has worked very well. The
only word for which stress assignment has not consistently agreed
with the expected stress assignment is "óverflow", and this may
be due to variations in the actual stress given the word by our
speakers.

4.   [a]-like(i) = -1 if Voice(i) = 0

                    1 if [ah(i)>1] or [ah(i)>-2 and

                         [a]-like(i-1)= 1]

                    0 otherwise

This feature indicates the presence of the vowels [a, o^{w}, ɔ ,æ , ʌ]
in many phonetic environments, the vowels in [pot, boat, bought,
bat, but] respectively.

5.   [i]-like(i) = -1 if Voice(i) = 0

                     1 if [[ee(i)>16] or [[i]-like(i-1) = 1 and ee(i)>8]]

                        and F19(i)<25

                        and Dspect(i)<30

                     0 otherwise

This feature indicates the presence of the vowels [i,ɪ , e^{y},ɛ]
(the vowels in [beat, bit, bait, bet) in many phonetic environments.
The two additional clauses involving F19(i) and Dspect(i) are

utilized to eliminate false responses to stridents and consonantal
transitions which are momentarily [i]-like.

6. [u]-like(i) = -1 if [Voice(i) = 0]
                    1 if [oo(i)>t2 or [[u]-like(i-1) = 1
                      and oo(i)>t2-7]] and F2(i)>F1(i)
                    0 otherwise

                    t2 = 32

This feature indicates the presence of the vowels [u, ʊr, oʷ, ɔ]
(the vowels in [boot, book, boat, bought]) in many phonetic
environments. The additional clause involving F1(i) and F2(i)
is intended to eliminate responses to consonants such as
[m, n, l, w]. It has been found necessary to ignore any transi-
tions to the "1" state in the features [i]-like(i) and [u]-like(i)
if they last less than 6 time samples. Even with this additional
constraint, a number of consonants are assigned one of these vowel-
like qualities. In addition, there appear to be no natural
threshold boundaries in the vowel-quality space so that a certain
percentage of the vocabulary is treated inconsistently by each
feature.

7. [r]-like(i) = -1 if [Voice(i) = 0]
                    1 if [[er(i)>18 and F3(i)-F4(i)>5]
                      or [er(i)>14 and [r]-like(i-1) = 1]]
                    0 otherwise

This feature indicates the presence of [r, ɚ] in many phonetic
environments. The clause involving F3(i) and F4(i) is intended
to ensure that the first formant frequency is not high. The low

-38-

third formant of these phones produces a spectrum that is distinct
and relatively easily differentiated from all other speech spectra.
The feature works consistently except following voiceless stops
and in some unstressed intervocalic positions.

8. Strident(i) is most easily defined in terms of a program
    segment:

```
        Maxstr = 0      t3 = 70
        Do for i = 1 in steps of 1 to 200
        if not [[[str(i)>t3] or [[str(i)>t3-20] and
                [Strident(i-1) = 1]]] and [str(i)>Maxstr-30] and
                [[str(i)>str(i-1)] or [Strident(i-1)= 1]]]
                Go To 1
        Maxstr = Max [Maxstr, str(i)]
        Strident(i) = 1
                Go To 3
    1   Maxstr = 0
        if Voice(i) = 1  Go to 2
        Strident(i) = 0
                Go To 3
    2   Strident(i) = -1
    3   Continue
```

This feature indicates the presence of [s, z, š, ž,] and also
[t, d, k, g] in certain phonetic environments (generally in
stressed position and followed by a front vowel). The floating
threshold, Maxstr, is employed to divide a sequence of two
successive stridents (e.g., [st]) into two strident segments
separated by the state "-1".

9.   Strid-stop(i) = 0 if Lstrident(i) = 1
                     1 if Strident(i) = 1
                     -1 otherwise

where Lstrident(i) is the same as Strident(i) except that the
state "+1" must occur for more than 6 time samples or it is trans-
formed to the state -1. This property computes the length of a
strident segment and places it in one of two categories. In
general, a long strident is a continuant and a short strident is
a stop. However, in many phonetic environments, voiceless stops
may have an aspiration duration that is longer than the frication
duration of an intervocalic fricative.

10.   Fricative(i) = 1 if [[F19(i)>t4] or [[F19(i)>t4-4]
                     and [Fricative(i-1) = 1]]
                     and [Loud(i)<120]]
                   0 if Voice(i) = 0
                  -1 otherwise

                  t4 = 6

This feature looks for the high frequency energy characteristic
of [f, v, θ, γ], (the initial consonants of [fin, vend, thin, then]).
Strident phones generally exceed the threshold and are also detected
by Fricative(i). The upper bound on Loud(i) is used to prevent a
response to a loud vocalic sound in which energy is spread over
the entire spectrum. A feature like Fricative(i) or Strident(i)
sends a great deal of information about a word to the recognition
algorithm, but neither feature is as consistent in its analysis
of an unknown word as a simple feature such as Voice(i).

11.　Stop-burst(i) = 1 if [[damp(i)>75] and [F19(i-1)<30] and
　　　　　　　　　　　[[F2(i)<20] or [F2(i)-F2(i-1)<1]]]
　　　　　　　　0 if Voice(i) = 1
　　　　　　　-1 otherwise

This feature detects the sudden onset of energy in all filters
that is characteristic of the release of a stop. The stop burst
is distinguished from a rapid voicing onset by requiring the
energy in F2(i) to either be low or not increasing. The "-1"
state following a burst is removed if it is less than 3 time
samples long. This transformation is an only partially successful
attempt to signal voiced stops by the sequence "1,0" and voiceless
stops by the sequence "1,-1,0."

12.　Nasal(i) = -1 if Voice(i-2) = 0
　　　　　　　1 if [Loud(i)-Loud(i-1)>5
　　　　　　　　or [Nasal(i-1) = 1
　　　　　　　　and Loud(i)-Loud(i-1)>1]]
　　　　　　　　and [ah(i) -ah(i-1)>5
　　　　　　　　or　ah(i) = ah(i-2)]
　　　　　　　0 otherwise

This feature looks for a voiced segment followed by a sudden
increase in loudness and a rising first formant frequency. A
nasal followed by [i] does not satisfy this criterion, but nasals
in many other environments are detected. Initial [l] is frequently
also detected by the feature. Features that look for dynamic
properties of the input spectra are not easy to define efficiently.
This relatively simple algorithm does not give a very satisfactory
definition of nasality.

13-15. There are three other features of a somewhat different
type. These features are intended to give a fairly precise
characterization of the stressed vowel in the unknown word. The
features, called [a]-stress, [i]-stress, and [u]-stress respectively,
characterize the spectrum at a single time sample, that point
during the stressed vowel when Loud(i) reaches a maximum for the
word.

The ranges of the functions ah(i), ee(i), and oo(i) have been
divided into 10 regions corresponding to the 10 possible states
of the three special features:

<p align="center">UPPER BOUND ON REGION</p>

State:	1	2	3	4	5	6	7	8	9	10
ah(i)	none	14	9	4	0	-3	-6	-11	-16	-27
ee(i)	none	80	60	40	20	0	-20	-40	-60	-80
oo(i)	none	80	60	40	20	0	-20	-40	-60	-80

A typical stressed [i] phone might be characterized by the
states [a]-stress=9, [i]-stress=1, and [u]-stress=6. It has been
found that this characterization is relatively stable for a given
word. Most words fall into two or at most three states for each
of the features.

B.   Non-Linguistic Properties

A set of abstract non-linguistically oriented properties was
defined near the end of the research project in order to test the
performance of the linguistically oriented features just described.
The properties are intended to take advantage of some of the
constraints that apply to speech spectra, but to be unaware of
the detailed phonetic content of the words.

There are two distinct types of spectral shape properties that
were used in this set. The first nineteen properties crudely
categorize the shape over time of the output of each of the
nineteen filters, individually, with no attention paid to
correlation between filters. There are three regions of "interest"
in the output. The spectral property is given the value "-1"
if the output is in the lowest region, "0" in the middle region,
and "1" in the highest region. A hysteresis region around the
transition threshold is used to prevent many transitions when the
filter output is near the border of these regions.

Formally, we define a set of 19 spectral amplitude properties,
$Sn(i)$, as follows, where the notation $Fn(i)$ denotes the output
of filter n at the ith sample interval:

$$Sn(i) = 1 \text{ if } [Fn(i)>B] \text{ or } [[Fn(i)>B-8] \text{ and } [Sn(i-1)=1]]$$
$$0 \text{ if } [Fn(i)>A] \text{ or } [[Fn(i)>A-8] \text{ and } [Sn(i-1)\neq -1]]$$
$$-1 \text{ otherwise}$$

A and B, as a function of the filter number, are given in the
following table:

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
A	37	34	30	25	20	30	25	20	15	25	21	18	15	20	15	17	20	17	13
B	50	47	44	40	35	45	40	35	30	38	34	31	27	35	30	30	30	25	30

The threshold values in this table should be modified if there
is a change in recording level. This can be done in the same
way as previously described for thresholds involving linguistic
features.

Another ten properties are used which roughly describe the
correlation between adjacent filters for the lower ten filters.
These properties categorize the differences between energies in
adjacent filters. The three alternatives are: the next higher
band has significantly more energy, significantly less energy,
or about the same energy, as its lower neighbor. These properties
are given values "1", "-1", and "0" respectively in these cases.
Formally, we define a set of 10 spectral difference properties,
$D_n(i)$, as follows, where $n=1, 2, \ldots , 10$ and $m=n+1$:

$$D_n(i) = 1 \text{ if } [[F_m(i)-F_n(i)>4]$$
$$\text{or } [[F_m(i)-F_n(i)>-1]$$
$$\text{and } [D_n(i-1)=1]]$$
$$-1 \text{ if } [[F_m(i)-F_n(i)<-4]$$
$$\text{or } [[F_m(i)-F_n(i)<1]$$
$$\text{and } [D_n(i-1) = -1]]$$
$$0 \text{ otherwise}$$

A change of state for one of these properties indicates that the
spectral shape of the current time sample differs from the spectral
shape of the previous time sample. A change of state is not pro-
duced by a simple change in level. This is because the large
hysteresis region around the thresholds prevents a property from
changing state for the equal energy case.

The thresholds for the two types of properties were selected so
that each state could be reached by at least some of the vocabu-
lary items. The 29 properties produce sequences of states used
in recognition. We can compare directly these recognition scores
with those produced by state sequences from the 15 linguistic
features.

VI.   RESULTS

The results of this research are best described in three parts.
We first describe the experimental procedure and the results of
the recognition system in an optimal (quiet) environment. We then
describe an experiment which indicates the behavior of the system
when degraded by added noise. Finally, we discuss a technique by
which we evaluate individual properties when the recognition rate
gets so high that improvements can only be measured indirectly.

A.   Recognition Experiments

As benchmark experimental data, we recorded a word list, Table 2,
used by Ben Gold in other speech recognition experiments. This
list was recorded in a quiet room (S/N ratio > 35 db) as spoken
10 times by two speakers, KS and CW. Both had been used as sub-
jects by Gold. KS and CW were also recorded 5 times each on two
other lists, an augmented International Word Spelling alphabet,
Table 3, and a message list typical of one that might be used in
a NASA mission context, Table 4.

The messages were recorded on high quality magnetic tape at
7 1/2 ips, with approximately two seconds gap between words. For
almost all experiments we used a digital tape containing the 6 bit
logarithms of the filter bank output sampled every 10 milliseconds.
Only in the noise degradation experiment was the analog input used
directly.

insert	name
delete	end
replace	scale
move	cycle
read	skip
binary	jump
save	address
core	overflow
directive	point
list	control
load	register
store	word
add	exchange
subtract	input
zero	output
one	make
two	intersect
three	compare
four	accumulate
five	memory
six	bite
seven	quarter
eight	half
nine	whole
multiply	unite
divide	decimal
number	octal

TABLE 2. Word List From Ben Gold

zero	hotel
one	India
two	Juliet
three	kilo
four	Lima
five	Mike
six	November
seven	Oscar
eight	papa
niner	Quebec
affirmative	Romeo
negative	Sierra
alpha	tango
bravo	uniform
Charlie	Victor
delta	whiskey
echo	x-ray
foxtrot	yankee
golf	zulu

TABLE 3.   International Word Spelling
Alphabet and Numbers

one	distance to dock
two	fuel tank content
three	time to sunrise
four	time to sunset
five	orbit apogee
six	orbit perigee
eight	revolution time
nine	closing rate to dock
point	midcourse correction time
plus	micrometeoroid density
stop	radiation count
zero	what is attitude
seven	remaining control pulses
minus	alternate splashdown point
pressure	weather at splashdown point
negative	sea and wind at splashdown point
what is yaw	visibility at splashdown point
what is pitch	temperature at splashdown point
end repeat	skin temperature
affirmative	power consumption
inclination	fuel cell capacity
distance to earth	repeat at intervals

TABLE 4.   Message List From NASA Context

A training round consists of one repetition of the entire word
list in which the computer makes an identification attempt, is
told the correct response, and stores the characterization of this
message for use in future identification. With four rounds of
training utilizing the linguistic properties, the system recognized
correctly (gave as unambiguous first choice) 51 and 52 out of
54 words of the Ben Gold list for KS and CW respectively. Early
experiments indicated that additional training would not increase
the recognition scores after reaching its asymptote, and these
95 +% correct scores were available after only 3 rounds of training.
Further experiments gave speaker KS 38 out of 38 correct on the
International Word Spelling Alphabet and 43 out of 44 correct on
the NASA message set, indicating the usefulness of these linguistic
properties on other message sets. Typical recognition rates for
the Gold list as a function of training rounds are shown in
Table 5. Note the lack of improvement (and oscillation of scores)
with more than 4 rounds of training. Part of the difficulty is
that these later rounds were recorded at a different time. This
indicates that some degradation in performance may be expected
under less well controlled conditions.

Some incorrect responses are listed in Table 6 (for KS on the Gold
list after 4 training rounds). These confusions give an indication
of the types of phonetic information that is not well represented
by the non-linguistic features. For example, the "four-core"
confusion suggests that frication noise often falls below the
lower thresholds of the filters, and that formant transitions are
not sufficiently distinct to trigger different state transitions
for this word pair. It is expected that some improvements could
be made in the threshold settings by studying the data of Table 6.

TABLE 5.

Typical Recognition Scores (KS)

Previous Training	1	2	3	4	5	6	7	8	9	Perfect
Ben Gold List	43	44	49	51	47	45	52	49	51	54
Alphabet	30	36	34	38						44
NASA List	35	37	43	43						38

TABLE 6.

Typical Mistakes

Guess	Correct Answer
Alternate Splashdown Point	Weather at Splashdown Point
Core, or Whole	Four
Memory	Binary
One	Load

These asymptotic recognition scores also indicate the separability of this 54 word vocabulary with these linguistic properties. The three vocabularies were combined into a single vocabulary of 114 distinct messages (duplications between vocabularies were considered only one message). On this larger vocabulary, the recognition score was a remarkable 110 out of 114 forks. All those messages identified correctly in the individual lists were also identified in this larger context after the same four training rounds. This indicates very little interference between words on these different lists; and implies that fairly large non-interfering (phonetically balanced) vocabularies might be constructed while maintaining this high recognition rate. It should be emphasized that while messages were repeated in training and testing, the same speech utterance was never seen more than once by the system.

To test the consistency of speakers uttering messages, we devised the spectral threshold properties described earlier. We tested these properties for recognition only on the Ben Gold word list. After four rounds of training, the system was able to identify correctly 52 out of the 54 input messages presented to it for KS; and 51 out of 54 for CW. This rate is as good as that discussed for the linguistic features; however, the cross speaker correlation was higher for the linguistic property set. For the second speaker (using the first speaker's training) 26 out of 54 messages were identified correctly on the first round, whereas using the spectral properties only 15 out of 54 were correctly identified.

B. Performance of the System with Added Noise

Speech-shaped random noise, (i.e., white random noise filtered by
a bandfilter whose frequency response is identical to the long-
term RMS speech spectrum) was added to the speech signal to test
the degradation of the system under adverse conditions. It was
prefiltered in order to (1) obtain approximately equal noise levels
in all filter channels and (2) avoid overloading of the filter-
networks. This would occur for a white noise input at low S/N
ratios, due to the high frequency pre-emphasis in the filter bank.
The set up used to add noise to the speech input is shown in
Fig. 6.

The S/N ratio at the input to the filter networks (B) is determined
by the constant S/N ratio of the speech input and by the noise
level as set on the calibrated attenuator. The noise level of the
speech input was measured at points A, B, C and found to be
35 db, 36 db* and 34 db respectively, below the speech peaks with
speaker DB. (speech peaks measured with a ballantine-true-RMS-
meter, VU-METER damping) The noise level of the speech-noise
generator was set so that the overall level was 0 VU at point D.
(attenuator in ODB position) With the attenuator set at -36 db
and a speech S/N ratio of 36 db, the effective S/N ratio at
point B would be 33 db.

---

*The noise level at point (B) is 1db lower than at point (A)
because of the low frequency cut off (120 HZ) in the input
amplifier.
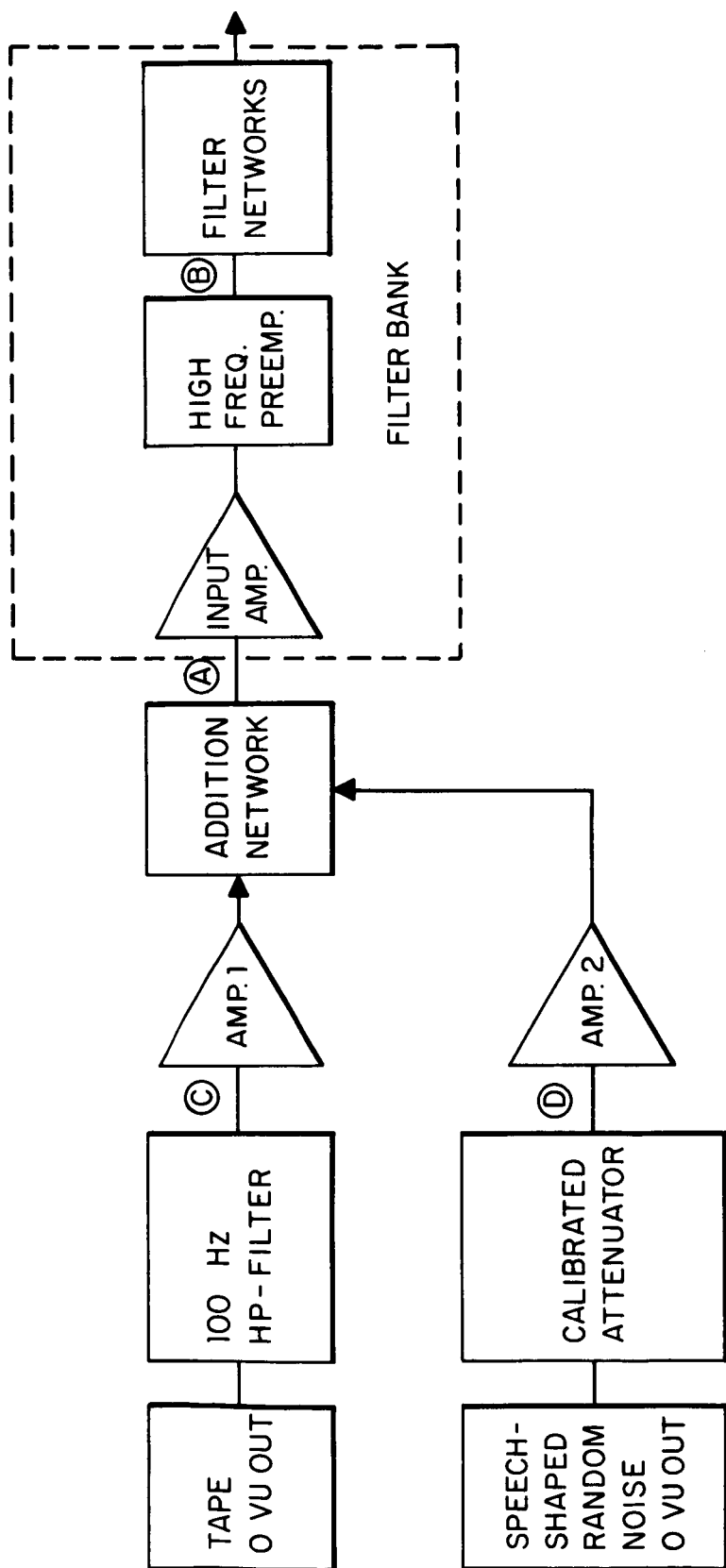
FIG. 6   SET UP USED TO ADD NOISE TO THE SPEECH INPUT

The system was trained for four rounds with no noise added. The same set of utterances with different levels of noise added were used to test the system. The recognition rates are shown in Fig. 7. Note that DB is a less consistent speaker than the other two, or the properties need to be tuned for him, because the asymptotic recognition rate is only about 80%. The shape of the rate of recognition curve under noise degradation is identical to that for humans, falling off almost completely in 20 db. However, the break for humans is 10 to 20 db lower, and the asymptotic rate much higher.

C. Evaluation of Properties

As recognition scores of the system get better and better, it becomes more difficult to evaluate the individual properties. A measure of information content has been used as an aid in the evaluation of individual features. This measure of the information contained in a feature tree has provided some insight into the desirable and undesirable properties of a feature. The measure will be defined, applied to some examples, and then discussed.

Let: J be an index over the nodes of a tree

         I be an index over the words in the vocabulary

         n_{IJ} be the number of times word I appears at node J

         NV be the total number of words in the vocabulary

         NT be the number of rounds of training

         R be a measure of the information contained in the tree about the identity of an unknown word.

         $P(I)$ probability of Ith word (assumed equal to $1/NV$)

         $R = H(I) - H_J(I)$

where $H(I) = -\sum_I p(I) \log [p(I)] = \log NV$

and $H_J(I) = -\sum_{IJ} p(I,J) \log [p_J(I)] = -\sum_{IJ} \frac{n_{IJ}}{(NV)(NT)} \log [\frac{n_{IJ}}{\sum_I n_{IJ}}]$.

Effective S/N Ratio	34	31	25	20	15	10
Number Correct	42	44	43	38	31	23
Percent Correct	78	81	80	70	59	44
Log (%-Correct)	1.89	1.91	1.90	1.85	1.77	1.65
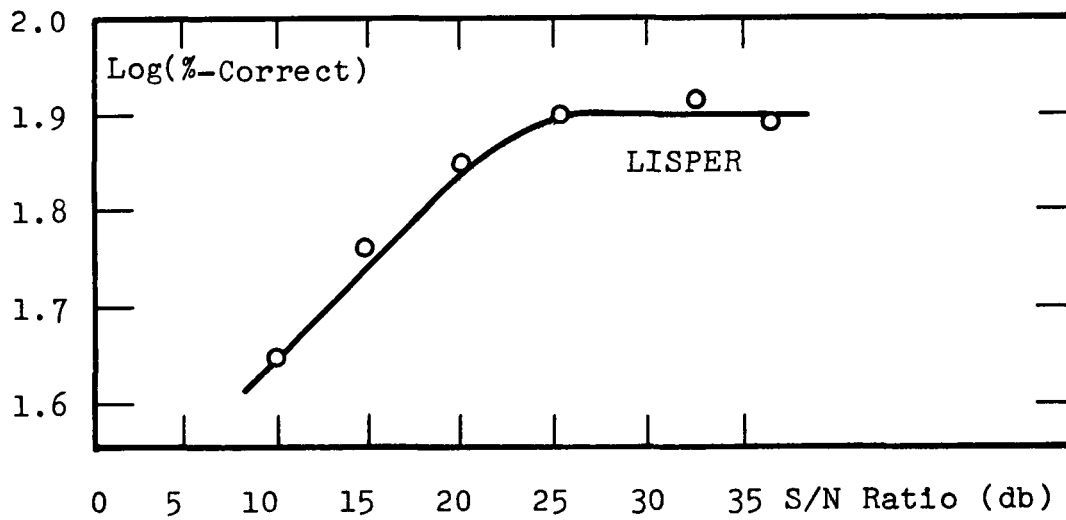
Fig. 7 Recognition Rate With Added Noise

Example 1:

```
                              /|\
                           /  | \  \
                        /    |   \    \
                     /      |     \       \
                  add 4   subtract 4   multiply 4      divide 4
```

R = H(I) = 2 bits

This is an example of the perfect tree, one that assigns a unique node to each vocabulary word.

Example 2:

```
                        /\
                      /    \
                    /        \
                 add 4      multiply 4
              subtract 4     divide 4
```

R = 2 - 1 = 1 bit

This is an example of a tree that consistently assigns a word to the same node, but does not completely separate the vocabulary words from one another.

Example 3:

```
                        /|\
                     /  | \  \
                  /    |   \    \
               add 2  subtract 2  divide 2   add 2
                                             subtract 2
                                             multiply 2
                                             divide 2
```

R = 2 - 1 = 1 bit

This is an example of a tree with more nodes (greater possible separability), but with an inconsistent assignment of words to nodes.

There is always the possibility that the unknown word will be
assigned to a new node of the tree, one that was not present during
training. The tree can provide no information about the identity
of the word in this case. The measure of information, R, does not
account for this possibility because it assumes incorrectly that
the frequencies, n_{IJ}, are accurate estimates of the underlying
probabilities.

R may be a biased measure because of this fact. When training
grows a large tree, there is, initially, a greater chance of a
word producing a novel node than when training grows a smaller
tree. The difference between large and small trees in growth
of novel nodes after about three rounds of training is not very
great. Therefore, we have not attempted to correct for the
potential bias in the information measure R.

There are some intuitive measures of the goodness of a feature we
have found interesting. The number of nodes N (different input
sequences found in training) gives a measure of the range of
separation that can be expected of the property. The number of
messages M, or average number of variations per input message M',
gives a measure of the consistency of the property. The ratio
N/M', of separability to consistency, seems intuitively to be a
quantity one would want to maximize.

The intuitive measures and the computed information provided by
each of the linguistic features is tabulated in Table 7. There
seems to be a reasonable correlation between R and N/M'. It should
be obvious that the features are highly redundant and that there
may be pairs of words that we are unable to differentiate with
this feature set. The latter question can only be answered by
testing additional repetitions of the vocabulary and noting both
error frequencies and the degree of similarity of feature assign-
ments for pairs of words.

		N=# Nodes	M=# Messages	Average # of variations M'=M/54	N/M'	R Information Measure
1.	Voice	3	64	1.19	2.5	1.4
2.	Syllable	4	70	1.30	3.1	1.5
3.	Stress	7	72	1.33	5.3	2.1
4.	[a]-like	33	110	2.02	16.3	3.0
5.	[i]-like	37	126	2.34	15.8	3.0
6.	[u]-like	36	127	2.35	15.3	2.6
7.	[r]-like	21	91	1.68	12.5	2.4
8.	Strident	45	110	2.02	22.2	3.2
9.	Strid-stop	11	92	1.71	6.4	2.5
10.	Fricative	55	139	2.57	21.4	3.2
11.	Stopburst	50	167	3.09	16.2	2.7
12.	Nasal	19	110	2.02	9.4	1.8
13.	[a]-stress	10	158	2.92	3.4	2.3
14.	[i]-stress	10	166	3.07	3.3	2.5
15.	[u]-stress	10	189	3.50	2.9	1.8

TABLE 7.   Evaluation of Linguistic Properties
After Ten Rounds of Training - Speaker KS

The trees grown by the non-linguistic features are quite large.
Most words are assigned to more than one node during training.
Even with this inconsistency, the information provided by each
feature is relatively high. As a comparison figure, consider the
fact that a feature detecting the presence or absence of voicing,
functioning with no errors, provides less than 2 bits of informa-
tion to the recognition algorithm. (The vocabulary words
contain 1, 2, 3, or 4 voiced segments and this results in a
feature tree with only four nodes.)

There are two conclusions to be drawn from these results. One is
obvious, that there is a trade-off between the separability of
words provided by a large tree and the consistency with which a
word is analyzed; see Example 2 vs. Example 3. The information
measure, R, gives a good idea of what that trade-off is.

Another, non-obvious, conclusion is that the information measure
accounts for the comparable recognition scores using non-linguistic
and linguistic features. The linguistic feature set was derived
with a strong emphasis on consistency. The linguistic features
condense a number of acoustic measurements to a binary decision,
the presence or absence of some attribute. Both of these strategies
are bad given the nature of the recognition algorithm. This
algorithm is designed to make efficient use of all of the clues
provided by the features. The emphasis on consistency and minimal
binary distinctions reduces the information flowing to the recog-
nition algorithm. Errors in feature assignment are then more
likely to be fatal. A general observation is that more features
with greater redundancy almost invariably led to higher recognition
scores.

VII. DISCUSSION

We have outlined the reasons why word recognition based on spectral
input data is not a straightforward problem in pattern recognition.
The invariants in the speech code appear to be relatively complex
functions of the spectral input. We have also outlined the reasons
why phoneme recognition is not an appropriate intermediate step in
a word recognition algorithm. Unsolved problems include the segmen-
tation of speech spectra into phoneme sized chunks and the deriva-
tion of rules for recognizing all of the allophones of a given
phoneme. Our approach is intermediate between pattern recognition
and phoneme recognition; it combines some of the advantages of
both.

A set of acoustic feature detectors have been defined. The time
dimension is removed from each feature so that the learning pro-
gram deals only with the sequences of states produced by the fea-
ture definitions. The feature sequence characterization of an
input message is sufficiently redundant so that the recognition
algorithm is able to deal successfully with errors and inconsis-
tencies in some fraction of the features.

The advantages of this approach are:

> (1) No precise segmentation of the utterance is required;
>   features can change state in arbitrary time segments
>   because the time dimension is removed from a feature
>   in a way that is independent of the changes of state
>   of other features.

> (2) A word need not be registered at exactly the same
>   place in the 2 second speech sample; state sequences
>   are independent of time origin.

(3) Feature definitions can be made insensitive to the re-
cording level by adjusting threshold settings according
to a measure of the loudness of the unknown word.

(4) Feature definitions can be made less sensitive to noise
by employing hysteresis regions about thresholds.

(5) State transition sequences weight changes in spectra as
the important cues to word recognition.(simple pattern-
matching schemes will give undue weight to a sustained
vowel).

(6) Features may be defined to take advantage of natural
acoustic boundaries between phones (Stevens, 1968b)
and thereby minimize the variability in state transition
sequences produced by a feature.

(7) Features may be added to the system to provide redundancy
for those decisions that are difficult. There is a
direct control over the amount of redundancy sent to the
recognition algorithm.

(8) The feature approach permits the introduction and testing
of linguistic hypotheses, such as placing greater em-
phasis on the properties of the stressed syllable.

The disadvantages of this approach are:

(1) Removal of the time dimension discards all information
concerning the simultaneous occurrence of specific
states for two or more features. We have used the
voicing feature to reintroduce some timing information.

There exist pairs of English words for which this "time
with respect to the voiced segments" is not enough to
disambiguate the pair. Special features can always be
defined to treat special cases, but our approach is not
easily generalized to yield segmentation of an utterance
into phone-sized chunks.

(2)   The features currently implemented are not speaker
        independent. Each speaker will have to train the system
        and this requires approximately 3 or 4 repetitions of
        the vocabulary.

(3)   Our system will degrade in performance as the length of
        the vocabulary is increased or as the number of speakers
        that it can simultaneously recognize is increased. This
        property is of course true of any recognition program;
        however, it should be noted that, with our current sim-
        ple-minded set of features, there is a high error rate
        in any feature characterization and we rely heavily on
        redundancy to select the most likely input message.

(4)   For our limited objectives, the current implementation
        is computationally fast and gives satisfactory results.
        However, more sophisticated and more reliable features
        would be desirable. The exponent in the function re-
        lating computation time and feature performance is not
        known, but may be restrictively large.

A set of simple sum-and-difference properties was compared with
the linguistically motivated features in the latter stages of re-
search. The comparable performance of this set of properties has
led to several conclusions concerning the desirable attributes of
features that operate within this framework.

(1) A good feature includes a maximum amount of information
     in the sequences that it produces. Factors that in-
     fluence information content are consistency of charac-
     terization and the number of vocabulary items that can
     be differentiated on the basis of the feature. A voicing
     feature that works perfectly does not contain as much
     information about the unknown word as any of the relatively
     inconsistent spectral properties. In other words, a
     moderate amount of inconsistency is tolerable if accom-
     panied by increased word separability (and additional
     features to provide redundancy).

(2) Another reason why the spectral properties compared
     favorably on the basis of recognition scores is that the
     linguistic features are fewer in number and computationally
     similar in form to the spectral properties. We believe
     that, even for limited vocabulary word recognition, a
     set of phonetically oriented features exist which are
     better in some sense than simple pattern features. The
     reasons for this faith consist of arguments:

     (a) that there exist natural acoustic boundaries
          between phones (Stevens, 1968b),

     (b) and that there exist invariant attributes in
          acoustic waveforms from different speakers; these
          invariants, when incorporated into feature defini-
          tions, will produce recognition scores that are
          less sensitive to the individual speaker.

(3) The arguments in favor of phonetically oriented features
     are offset by the computational simplicity of the spec-
     tral properties. Not enough is currently known in
     acoustic phonetics to take advantage of these theoretical
     benefits without additional basic research. We argue
     that a carefully selected set of properties like our
     spectral properties represent a practical word recognition
     solution that may not be superseded for some time to come.

The research described in this report does not consistute a com-
pleted investigation. There are many open questions that can
profitably be pursued. The list of linguistic features described
in this report is biased in favor of features that seemed easiest
to define and implement. A glaring deficiency is in the area of
place-of-articulation features for stop and nasal consonants. The
primary reason for not including features of this type is that the
feature definition will depend in part on the specified vowel
following the stop. The result must be a fairly complex definition
in terms of parameters that are not well understood.

We hope to study this and related problems of context dependent
features by implementation of recent proposals of K. N. Stevens
that place-of-articulation for stops may be identified by the
timing of energy build-up in high and mid-frequency regions rela-
tive to the time of build-up in the low-frequency region. Other
features to be developed are Aspiration, Tense-lax, Front-glide,
and Back-glide. Several of the current features can be substan-
tially improved by context-dependent definitions (e.g., nasal).

We wish to investigate further the reasons for the success of the
non-linguistic features. Of help would be a measure of the infor-
mation about the identity of a word that one feature gives

conditional to the fact that we know the sequence of states gene-
rated by another feature, i.e., independent additional information
that a new feature provides. Such a measure can be defined in the
same general way as was described in section VI. With this measure
and the results obtained from the development of new linguistic
features, we may be able to modify the spectral property set to
give even better results.

APPENDIX A   CIRCUITS OF FILTER BANK

Input Stage

The circuit diagram of the input stage is shown in Fig. 7.
The output from a conventional tape recorder is fed into
an input amplifier (Type BBN-DE-200) whose variable feedback
resistor provides the common gain adjustment for all filter
channels. The gain adjustment procedure is facilitated by
a VU-meter connected to the output of the input amplifier.
By means of a separate potentiometer this VU-meter may be
adjusted such that speech peaks exceeding +3VU will indicate
clipping in the filter channels and/or overloading of the
A/D converter.

The RL-network in the feedback path of the first driver
amplifier provides the high frequency pre-emphasis. By
means of a switch this network may be replaced by a resistor
for gain calibration of the filter channels.

Since the bandpass filter networks require inputs of opposite
phase, a second inverting driver amplifier is used as
shown on the lower right of Fig. 7. A potentiometer in the
feedback path provides for adjustable amplitude balance of
the two input signals.

Band-Pass Filters

The pole pattern yielding the frequency responses of Fig. 8 is shown in Fig. 9. Poles associated with one filter are connected by converging lines. Each filter shares two poles with each neighboring filter.

According to the Lerner synthesis procedure, poles of an individual filter are spaced at equal intervals (240 Hz) in the pass-band and at half intervals (120 Hz) at the band edges. Since the frequency responses of neighboring filters have their 3 dB crossover points at a frequency mid-way between the shared poles, all 4-pole filters (no. 1-15) have bandwidths of 360 Hz. The number of the poles for the remaining filters are selected such that bandwidths as given in Table 1 resulted.

Each pole of Fig. 9 is realized by a series resonant circuit as shown in Fig.10 for filters no. 1 through 15. The proper pole residue is achieved by resistor weighting of the currents from each resonant circuit into the summing node of an operational amplifier as described by Drouilhet and Goodman(1960). Identical inductor values were used for all resonant circuits and the capacitors were calculated by $C = 1/4\pi^2 L f^2$, where f is the frequency of a pole. (Approximately 1% of the C value was realized by a trimmer capacitor to compensate for slight inaccuracies and variations of the filter components.) For a chosen value of L = 0.5 mh, R = 1.66 k was obtained from the relation $L/R' = 1/2\pi \cdot 360$, where $R' = 2/3$ R, the parallel resistance of R and 2R.

Filters no. 16 though 19 were realized by the same circuit
structure as shown in Fig.10, with poles in the passband
and at the band-edges. (Fig. 9) weighted by R and 2R respect-
ively. The highest pole at 6620 Hz was tied over R to
ground to simulate the input impedance of an additional
neighboring summing amplifier as is also shown for the lowest
pole in Fig. 9.

Rectifiers and Low-Pass Filters

The circuitry containing the summing amplifiers, rectifiers,
low-pass filters and output amplifiers is shown in Fig. 11.
(All operational amplifiers: Union Carbide type H6010).
The circuit for filter channel no. 1 is shown in the upper
portion of the figure. The summing amplifier is followed
by a full wave rectifier circuit. Full wave rectification
was necessary for filter channel no. 1 only, in order to
reduce the ac-components passed by the low-pass filter of
this channel. (At 80 Hz the rms level of the ac-component
in the output of filter channel no. 1 is 35 dB below the
dc level and decreases with a slope of 22 dB/octave.)

The circuit in the lower portion of Fig.11 is used for filter
channels no. 2-19. The first amplifier (1) sums the current
components from the band-filter, (2) half-wave rectifies that
signal and (3) provides a signal of adjustable amplitude to
drive the low-pass filter. The gain of these amplifiers is
adjusted such that all dc channel outputs are equal for white
noise input to the spectrum analyzer (pre-emphasis network
not used).

The output of the low-pass filters is fed into output amplifiers
which provide low impedance sources to drive the A/D converter.

APPENDIX B   Examples of the sequences produced by selected features
              for ten repetitions of the Gold vocabulary by speaker
              KNS.

1. Voice

     The sequence 010 indicates the presence of one voiced segment,
01010 indicates two voiced segments, and 0101010 indicates
three voiced segments. The initial portion of any sequence
is not repeated and is implicit in the columns in the printout.
A ten bit (octal) code follows each vocabulary word. This
code indicates which repetitions of the word produced the
sequence. For example, the first 9 repetitions of the word
"bite" produced an indication of one voiced segment, and the
10th repetition produced an indication of two voiced segments;
intense prevoicing of the [b] appears to have triggered the
extra segment in this case.

     Voice

     0   1   0   (373 BITE 1776 SEVEN 1336 UNITE 1777 WHOLE 1777 HALF
1777 QUARTER 77 MEMORY 1777 MAKE 1777 EXCHANGE 101 WORD 1777
POINT 1777 JUMP 1777 SKIP 1777 SCALE 1777 END 1777 NAME 1777
NUMBER 377 NINE 1775 EIGHT 1777 SIX 1777 FIVE 1777 FOUR 1777
THREE 1777 TWO 1777 ONE 1777 ZERO 1777 ADD 1777 STORE 1777
LOAD 1777 LIST 1777 CORE 1777 SAVE 1777 BINARY 1777 READ 1777
MOVE 1777 DELETE 1777)
             1   0   (222 NUMBER 1400 QUARTER 1700 EXCHANGE 1676
(NINE) 2 OCTAL 1777 DECIMAL 1777 BITE 1 ACCUMULATE 777 COMPARE
1737 INTERSECT 33 OUTPUT 1777 INPUT 1777 CONTROL 1777 OVERFLOW
35 ADDRESS 1777 CYCLE 1777 DIVIDE 1777 SEVEN 441 SUBTRACT 1777
DIRECTIVE 1777 REPLACE 1777 INSERT 1777)
             1   0   (123 ACCUMULATE 1000 COMPARE 40 INTERSECT
1744 OVERFLOW 1742 REGISTER 1777 MULTIPLY 1777)

2.   Strident

Strident is an example of a feature that is relatively incon-
sistent in assigning sequences to vocabulary items. Neverthe-
less, Strident sends a great deal of information to the recog-
nition algorithm because there is good separation of words in
this tree and, after a few rounds of training, much of the
possible inconsistency has been learned and is represented in
the tree.

STRIDENT

    0 -1   (210 END 1400 THREE 300 ADD 500 HALF 1770 WORD 1770
LOAD 1774 WHOLE 1777 QUARTER 77 MEMORY 1777 MAKE 713 NAME 1777
NUMBER 377 NINE 1775 FIVE 1777 FOUR 1777 ONE 1777 CORE 1777
BINARY 1777 READ 301 MOVE 1773)
        0 -1   (110 NUMBER 1400 DIVIDE 720 NINE 2 COMPARE 1737
OVERFLOW 31)
            0 -1   (104 COMPARE 40 OVERFLOW 1742)
            1 -1   (124 REPLACE 1700 ADDRESS 1724 BITE 1 OUTPUT
1777 INPUT 1777 DIVIDE 1051)
        1 -1   (106 ADDRESS 52 REPLACE 77)
        1 -1   (154 MAKE 1064 MOVE 4 BITE 1776 READ 1476 UNITE
1777 HALF 7 WORD 7 POINT 1777 END 377 EIGHT 1777 ADD 1277 LOAD
3 DELETE 701)
            0 -1   (117 DIRECTIVE 720 DECIMAL 210 OVERFLOW
4 OCTAL 1767 CONTROL 1777)
                0 -1   (104 MULTIPLY 1321)
                    1 -1   (100 ACCUMULATE 1000)
                1 -1   (104 INSERT 320 ACCUMULATE 451)
            1 -1   0 -1   1 -1   (100 INTERSECT 400)
                0 -1   1 -1   (100 INTERSECT 1000)
        1 -1   (100 LIST 100)
            0 -1   0 -1   (100 MULTIPLY 400)
                1 -1   (107 EXCHANGE 1676)
        0 -1   (99 OCTAL 10 DIRECTIVE 1)
            1 -1   (106 ACCUMULATE 326 ADDRESS 1 INSERT
453)
                0 -1   (101 REGISTER 1200)
                1 -1   0 -1   (100 REGISTER 400)
            1 -1   0 -1   (101 REGISTER 140)
                1 -1   (103 INTERSECT 344)
                1 -1   0 -1   (102 REGISTER 32)
                0 -1   (101 REGISTER 5)
        1 -1   0 -1   (105 QUARTER 1200 DECIMAL 1526)
            0 -1   (101 MULTIPLY 42)
            1 -1   (103 INSERT 1004 INTERSECT 33)
        1 -1   (108 LIST 1677)
        0 -1   (101 QUARTER 500)
            0 -1   (101 MULTIPLY 14)
    1 -1   0 -1   (121 SCALE 600 SAVE 574 SEVEN 206 THREE 1477 TWO
1777 ZERO 1041)
            0 -1   (108 CYCLE 773 SEVEN 441)
                1 -1   (101 DIVIDE 6)
            1 -1   (104 SIX 1446)
                0 -1   (102 DIRECTIVE 40 SUBTRACT 541)
                    1 -1   (105 SUBTRACT 1236)
            0 -1   (100 DIRECTIVE 4)
                1 -1   (100 DIRECTIVE 1000)
        1   0 -1   (123 SKIP 1777 SCALE 1177 STORE 1777)
                1 -1   (101 EXCHANGE 101)
        0 -1   (118 SEVEN 1130 ZERO 736 JUMP 1777 SAVE 1203)
            0 -1   (101 CYCLE 1004)
            1 -1   (108 DELETE 1076 SIX 331)
                0 -1   (100 DECIMAL 40)
            0 -1   (101 DIRECTIVE 12)
        1 -1   0 -1   (100 DECIMAL 1)

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