AUTOMATIC CLASSIFICATION AND FORMANT ANALYSIS OF FINNISH VOWELS USING NEURAL NETWORKS

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ABSTRACT
In this paper we report results from a study of using feedforward neural networks with error back-propagation in order to see their inherent ability to learn speech independent classification and formant analysis of Finnish vowels.

1. INTRODUCTION
The recognition and analysis of vowels is an important problem in the field of speech recognition and phonetics. Neural networks [5] are shown to give excellent performance in many speech recognition subtasks [1],[2]. They can be described as "black-boxes" that when given an input and desired output can actually learn to associate the input with the output. The performance levels achieved with neural nets can be very high and their use is an attractive method when performing vowel recognition or analysis [5].

In our study we used feedforward nets with error back-propagation. Figure 1 shows a possible network topology where data flows from the input layer to the output layer via a hidden layer. Each layer is fully connected with the next one. The dimensionality of the net can be stated as the number of nodes in each layer (10-6-2 in figure 1).

This paper describes the application of neural networks to vowel recognition and analysis. Experimental results of vowel recognition and formant analysis are presented along with a summary regarding the usefulness of neural nets in this problem domain.

2. VOWEL RECOGNITION
For our vowel recognition experiments we used speech taken from 12 female and 24 male speakers. Static auditory spectra (288 in total) each consisting of a 48 point real-valued vector were used as the input representation [2]. The topmost curve in figure 2 shows the auditory spectrum of the vowel /a/. The 0-24 Bark critical-band scale corresponds to approximately 0-15 kHz.

We defined a criterion for when a neural net had learned all of the input material: 1) all of the inputs had to be correctly classified; and 2) a 0.75 minimum level had to be measured for the correct output layer node. The target values during training were 0.0 or 1.0.

In the first experiment we determined how many nodes were required in the hidden layer as well as which spectral representation performed best to correctly learn 8 vowels from a single male speaker. What is meant by spectral representation is the scale or resolution of the input data. We applied a Gaussian band-pass filter to the original auditory spectra to obtain a fine-scale representation that would emphasize formant-like local structures in the spectrum. A higher level of smoothing was also applied to yield a coarse-scale representation that emphasized more global spectral trends. The fine and coarse representations for the vowel /a/ can also be seen in figure 2.

We then trained 100 separate nets with similar initial parameters of dimension 48-3-8 (48 input nodes, 3 hidden nodes, and 8 output nodes each corresponding to one of the eight Finnish vowels). We repeated this test for 4 to 9 hidden nodes, and for all three representations. The results which can be seen in figure 3 indicate that the fine spectral representation learned the 8 vowels most frequently, followed by the original and coarse representations. This result is explainable since emphasized formants help to distinguish each of the eight vowels of a single speaker.

For a larger input set (24 male speakers, 192 vowel spectra) these results changed somewhat and are shown in figure 4. Here the number of nodes was varied between 3 and 14 and only the original and fine spectral representations were compared. The ability of learning the input set perfectly when using the fine resolution was always lower than for the original representation. A possible explanation for this is that in general the fine representation will emphasize formants, and since several examples of each vowel exist in the training set with different formant frequencies, the variability of the input representation increases making it more difficult for the net to learn the differences. For this reason we decided to use only the original spectral representation in the remaining tests.

We then repeated this test for the male+female set (36 speakers), and for all three representations. The results which can be seen in figure 5 indicate that the fine spectral representation learned the 8 vowels most frequently, followed by the original and coarse representations. This result is explainable since emphasized formants help to distinguish each of the eight vowels of a single speaker.
training set test, i.e., no significant improvement or degradation of learning frequency was found by including pitch information.

3. FORMANT ANALYSIS
The second main topic of this study was to investigate the usefulness of neural networks in analyzing continuous parameters or features of vowels. Specifically, we wished to teach nets to be able to identify the location of the first two formant frequencies of vowels in the auditory spectrum. A traditional method to perform this task automatically is to calculate formant frequencies of vowels in the auditory spectrum. A traditional method to perform this task automatically is to calculate formant frequencies of vowels in the auditory spectrum. A traditional method to perform this task automatically is to calculate formant frequencies of vowels in the auditory spectrum. A traditional method to perform this task automatically is to calculate formant frequencies of vowels in the auditory spectrum. A traditional method to perform this task automatically is to calculate formant frequencies of vowels in the auditory spectrum. A traditional method to perform this task automatically is to calculate formant frequencies of vowels in the auditory spectrum. A traditional method to perform this task automatically is to calculate formant frequencies of vowels in the auditory spectrum.

We trained networks of dimensions 48–X, X ∈ [2,15] to estimate the two first formant frequencies F1 and F2 of vowels. These estimates were based on the auditory spectrum input and we hypothesized that the network could be more robust to the traditional methods to find and label the formant frequencies. The output level nodes of the net were modified by removing the sigmoid non-linearity thus allowing continuous valued output values to be realized. As a training set we selected 64 vowels and diphthongs from a single male speaker. The formant frequencies were located by hand by an experienced speech scientist.

Figure 6 shows the average F1 and F2 errors as a function of the number of hidden nodes. F2 exhibits a larger error since a larger input variation exists for it but drops down to 0.15 Bark when the number of hidden nodes is seven or higher. This error corresponds to approximately 35 Hz at 1.5 kHz. The F1 error being considerably smaller was found to be 0.08 Bark which corresponds to 10 Hz at 400 Hz.

4. COMPUTATIONAL ENVIRONMENT
These experiments were carried out on an object-oriented signal processing environment called QuickSig [3], developed in our laboratory. QuickSig, which is an extension to the Symbolics Common Lisp environment runs on Symbolics Lisp Machines. To speed up the tests by a factor of 150 over the Symbolics Lisp Machines a Texas Instruments TMS320C30 digital signal processor was used.

5. SUMMARY
This study has shown that neural networks are very useful tools in the classification and analysis of vowels. The ability of a neural network to generalize is an attractive feature since this means that a trained net, even if it has not seen a certain input before, can make an intelligent decision.

Specifically we found that F0 does not help in achieving better performance levels for vowel recognition. This confirms earlier work [4]. The number of nodes in the hidden layer was found to affect the learning potential. With too many nodes the net will learn but will not generalize (it will learn each training element individually). On the other hand, given too few nodes all the inputs will not be classified correctly. We also found that the preferred spectral representation to choose from a set of representations derived from the auditory spectrum was the unmodified auditory spectrum itself.

In the formant frequency analysis experiments more spectra need to be used to verify the accuracy and potential of the approach. Eventhough performance may not reach the levels of other well established methods such as LPC, neural networks may provide a useful general indication of formant locations for later, more detailed analysis, or rule-based combination of multiple methods.

6. REFERENCES