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SPEECH RECOGNITION BASED ON CONVENTIONAL NEURAL NETWORKS

Abstract. In this research work, the problem of speech recognition is considered in the form of an analysis of the numbers from 1 to 10 recorded by the speaker on the dictaphone. The paper uses the method of recognizing the spectrogram of an audio signal using convolutional neural networks. Also written and implemented an algorithm for processing input data, and an algorithm for recognizing spoken words. In this work, the quality of recognition was assessed for a different number of convolutional layers. A comparison of the recognition quality is made in cases when the input data for the network are the spectrogram of the audio signal or the first two formants extracted from it. The recognition algorithm was tested using examples of male and female voices with different pronunciation lengths.

Keywords: spectrogram, formant, algorithm for learning neural networks.

Аннотация. В данной исследовательской работе рассматриваются способы распознавания речи в виде анализа записанных диктором на диктофон цифр от 1 до 10. В работе используется метод распознавания спектрограммы звукового сигнала с помощью сверточных нейронных сетей. Так же написан и реализован алгоритм для обработки входных данных, и алгоритм распознавания произнесенных слов. В работе была дана оценка качества распознавания для разного количества сверточных слоев. Произведено сравнение качества распознавания в случаях, когда входными данными для сети являются спектрограмма звукового сигнала или выделенные из нее первые две форманты. Тестирование алгоритма распознавания произведено на примерах мужского и женского голоса с разной длительностью произношения.

Ключевые слова: спектрограмма, формант, алгоритм обучения нейронной сети.

Аңдатпа. Бұл зерттеу жұмысында сөйлеуді тану мәселесі диктофонға дикторға жазып алған 1-ден 10-ға дейінгі сандарды талдау түрінде қарастырылады. Қағазда convolutional нейрондық желілері арқылы

дыбыстық сигнал спектрограммасын тануәдісі қолданылады. . Сондай-ақ, енгізілген деректерді өңдеу алгоритмі жәнеайтылған сөздерді тану алгоритмі жазылған және енгізілген. Бұл жұмыста конволюциялыққабаттардың басқа саны үшін тану сапасы бағаланды. Тану сапасын салыстыру желіүшін кіріс деректері аудио сигналдың спектрограммасы немесе одан алынған алғашқыекі формант болған жағдайда жасалады. Тану алгоритмі әр түрлі айтылу ұзындығыбар ерлер мен әйелдер дауыстарының мысалдары арқылы тексерілді.

Түйін сөздер: спектрограмма, формант, нейрондық желініоқыту алгоритмі.

Introduction

In this work, a convolutional neural network (CNN) is used, since such networks currently show one of the best results in the field of image recognition [8]. This feature of the CNN allows us to consider not the temporal realization of an audiosignal (speech), but it's spectrogram, which is recognized as an image. An important feature of the CNN is its resistance to changes in scale and image displacements, which, obviously, takes placein the case of spectrograms of speech signals [9, 10]. Supervised neural networks require data onwhich the network will train. In our case, the input data library will contain the spoken words recordedon the dictaphone. To improve the quality of recognition, it is advisable to processthesesignals - to highlight the most important characteristics and present them in a form suitablefor feeding to the CNN input. Thus, the problem can be formulated as follows: the implementationof a human word recognition algorithm using a convolutional neural network, aswell as a data preprocessing algorithm for recognition.

Aim and objectives of research

The aim of this research work was to study a synthesizedspoken number recognition algorithm based on convolutional neural networks. Recognizeand test the realizations of several numbers in a female voice, as well as those pronounced bythe main speaker quietly and loudly, at a slow and fast pace.

Background of Literature Review

Research in the field of automatic speech recognitionand speech synthesis has received a lot of attention over the past fifty years, given that theinterest in automation in general began even earlier - more than sixty years ago. The idea of creating artificial intelligence (AI) appeared in the 50s of the twentieth century, when computer scientistsasked the question: "Can a computer think?" It began to be actively investigated in the1980s [1]. One of the proposed methods for implementing AI was artificial neural networks (ANNs), the use of which was focused, among other things, on the task of speech recognition, includingrecognition of phonemes or several words [2]. Research in the field of speech recognitioncontinues to this day [3–6], and the creation of AI in the human sense is still a lot of science fiction literature [7].

Discussion

Input processing.

Processing of input data Digits from 1 to 10 recorded on a dictaphone were used as examples of speech. The neural network was trained not on the time realization of signals, but on the images of their spectrograms. Speech signals were recorded using a dictaphone with a sampling rate of 44.1 kHz. To construct spectrograms on the time signal realization, segments with a length of 1024 samples were selected. From these segments, the calculation of the fast Fourier transform was made. In order to reduce the recognition error, preliminary processing was carried out (Fig. 1), including the following stages:

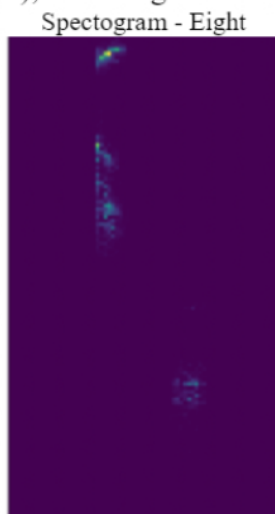


Figure 1. (Spectrogram of word “Eight”)

- limiting the signal in the time domain to highlight the informative part of the signal;
- limiting the frequency range of the signal. In [11], it is shown that the frequency range up to 3.4 kHz (the frequency range for the transmission of telephone conversations) is not enough for high-quality recognition, since two similar words can have the same spectral components in this area and differ at higher frequencies. Therefore, the frequency range of spectrograms was used up to 8 kHz;
- normalization of the spectrum intensity. To work with signals of different loudness, it is advisable to normalize the brightness of the spectrograms;
- decreasing the image resolution. The quality of recognition strongly depends on the amount of data on which the network will be trained. If there is a lot of data (the images will have a high resolution), then a lot of computing power will be required to train the neural network. To increase the speed of performing operations in the experiments carried out, the images of the spectrograms were reduced to a size of 50×50 pixels;

- increasing the contrast in order to highlight the informational components of the signal against the background of noise (the speech was recorded not in a studio environment).

Convolutional neural network synthesis. In order for the implemented CNN to produce the correct results, you need to create three directories in which data about audio signals will be stored:

- directory of training data (train), which will be used to train the neural network;

- directory of verification data, which will check the quality of training during the training itself;

- directory of test data (test), which can be used to test the trained network. In order to minimize the recognition error, network training must be carried out on a large data array - from 1000 to 10000 [1]. But since it takes a lot of time and a lot of computing power to prepare such a volume of data and training, a much smaller sample of data was used in this work: 100 images of spectrograms (10 realizations for 10 digits) for training and 50 images each for checking and testing (5 implementations for 10 digits). The network has been trained over 30, 40 and 50 eras. Sigmoid and ReLU were used as an activation function in different layers (Fig. 2). It is also known that the complexity and quality of a neural network depends on the number of layers [7]. Therefore, to optimize the algorithm, experiments were carried out with sequential build-up of layers up to four. The initial structure of the SNA (Fig. 3) contained the following elements:

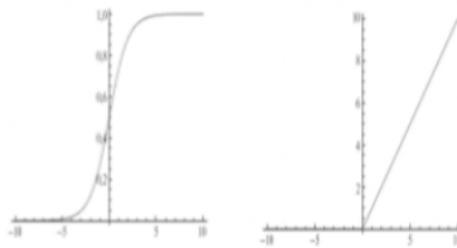


Figure 2. Activation functions of the “sigmoid” and ReLU

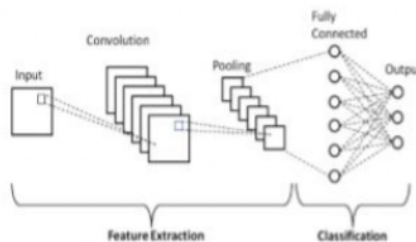


Figure 3. CNN structure

- a convolutional layer that highlights 32 features; core 3×3 ; ReLU activation function;
- subsampling layer (MaxPooling) with a 2×2 core;
- a layer for transforming a two-dimensional array into a vector;
- fully connected layer of 32 neurons; ReLU activation function;
- Dropout layer against overfitting;
- fully connected layer of 10 neurons; activation function "sigmoid".

Recognition results

To obtain statistical data, experiments were carried out in which 5 neural networks were created for 30, 40, 50 epochs with the number of convolutional layers from 1 to 4. Then the recognition quality was assessed. A different approach to recognition was also implemented. There is a known method for recognizing spoken numbers by teaching a neural network not on spectrograms, but on images of formants (narrow sections of the highest spectrum intensity) of speech signals [1]. Often, the first two formants are clearly visible on spectrograms, and their shape can be used as a feature for recognition. The implemented formant extraction algorithm made it possible, after additional processing of the input data, to obtain binary images. Testing the CNN trained on formant images (Fig. 4) showed that the recognition quality decreased in comparison with the recognition of spectrogram images directly (Table 1.).

layers	30		40		50	
	Formants	Spectrograms	Formants	Spectrograms	Formants	Spectrograms
1	85,2%	80,5%	87,6%	90%	88,4%	90,8%
2	88,8%	89,6%	88%	90%	87,6%	90,8%
3	82%	92%	78,8%	93,2%	82%	98%
4	83,2%	89,6%	80,8%	84%	85,6%	94%

Table 1.

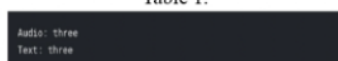


Figure 4. (Result)

Thus, of the two considered applications of the CNN, it is preferable to use the recognition of spectrograms or set more stringent requirements for the formant extraction algorithm (up to the extraction of 4 or 5 formants). Although, having analyzed the appearance of the spectrograms, it is pertinent to note that not only the formants determine the general picture of the spectrogram, but also extended sections that occupy a large area.

Conclusion

The synthesized algorithm for the recognition of spoken numbers based on convolutional neural networks showed an accuracy of about 80–98% of the recognized signals in the test sample. Realizations of several numbers in a female voice were successfully recognized, as well as those pronounced by the main speaker quietly and loudly, at a slow and fast pace. The following facts

about the work of neural networks have been investigated and confirmed:

- an increase in the number of learning epochs increases the quality of recognition;
- the complication of the network structure, that is, the introduction of additional layers for the selection of features, leads to an increase in the quality of recognition.

On the other hand, if the structure is too complex, the recognition worsens, as the neural network is retrained. The advantages of the chosen algorithm can be attributed to its relative simplicity, since the synthesis of the CNN structure was carried out in Python using the Keras library for working with neural networks. The advantages of the method used are due to the properties of the CNN: the stability of the algorithm to signal stretching in time and the automatic extraction of characteristic features of the image, which are then used for recognition.

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