



Detection and Analysis of Human Emotions Through Voice and Speech Pattern Processing

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ABSTRACT

The ability to modulate vocal sounds and generate speech is one of the features which set humans apart from other living beings. The human voice can be characterized by several attributes such as pitch, timbre, loudness, and vocal tone. It has often been observed that humans express their emotions by varying different vocal attributes during speech generation. Hence, deduction of human emotions through voice and speech analysis has a practical plausibility and could potentially be beneficial for improving human conversational and persuasion skills. This presents an algorithmic approach for detection and analysis of human emotions with the help of voice and speech processing. The proposed approach has been developed with the objective of incorporation with futuristic artificial intelligence systems for improving human-computer interactions. These systems aim to facilitate the natural interaction with machines by direct voice interaction instead of using traditional devices as input to understand verbal content and make it easy for human listeners to react. Some applications include dialogue systems for spoken languages such as call center conversations, onboard vehicle driving system and utilization of emotion patterns from the speech in medical applications. Emotion recognition from speech signals is an important but challenging component of HCI. In the literature of SER, many techniques have been utilized to extract emotions from signals, including many well-established speech analysis and classification techniques. Deep Learning techniques have been recently proposed as an alternative to traditional techniques in SER. This paper presents an overview of Deep Learning techniques and discusses some recent literature where these methods are utilized for speech-based emotion recognition. The review covers databases used, emotions extracted, contributions made toward speech emotion recognition and limitations related to it.

KEYWORDS: Deep learning, emotional analysis, human emotions, speech processing, voice processing.

Introduction

Deep Learning is continuously amusing us with its modern possibilities like self driving cars, fraud detection, and many more. Earlier we never imagined the things which are possible today and now we cannot even imagine a day without using it. Thus, in this blog, we are going to discuss this very interesting topic „Deep Learning“ in much more detail. Deep Learning is at the beginning of what machines can do and developers and business leaders totally need to comprehend what it is and how it functions. Deep learning models are sufficiently competent to focus on the exact features themselves by requiring a little direction from the programmer and are useful in taking care of the issue of dimensionality. Therefore, deep learning algorithms are used, particularly when we have a vast number of inputs and outputs. It is a kind of machine learning that prepares a computer to perform human-like errands, for example, perceiving speech, distinguishing pictures, or making forecasts. Rather than arranging information to go through predefined conditions, deep learning sets up essential boundaries about the information and trains the computer to learn on its own by perceiving designs using numerous layers of processing. Deep learning has networks worthy of learning unsupervised from information that is unstructured or unlabeled. In simple language, deep learning is a type of algorithm

LITERATURE REVIEW

One of the most important information that speech acoustics provide is the expression of emotions. The purpose of this research is to identify the pitch differences between two basic emotions: anger and joy. In order to find answers to this question vocal data have been collected from small group of participants. Results from Friedman's Two-Way Analysis of Variance by Ranks revealed difference in pitch levels when expressing anger and joy as well as jitter (rap). It is well known that speech is an acoustically rich signal that provides a lot of information about the speaker during vocal

interaction. The expression and recognition of emotions are extremely important steps for human communication process for this reason voice recognition is useful for detecting and identifying specific affective characteristics between the speakers.

PROPOSEDSYSTEM

Deduction of human emotions through voice and speech analysis has a practical plausibility and could potentially be beneficial for improving human conversational and persuasion skills. This paper presents an algorithmic approach for detection and analysis of human emotions on the basis of voice and speech processing. Three test cases have been examined, corresponding to the three emotional states: normal emotional state, angry emotional state, and panicked emotional state. Each case demonstrates characteristic associated vocal features which can help in distinguishing the corresponding emotional state. We examine the effectiveness of applying machine learning techniques to the sentiment classification problem. A challenging aspect of this problem that seems to distinguish it from traditional topic-based classification is that while topics are often identifiable by keywords alone, sentiment can be expressed in a more subtle manner. For example, the sentence "How could anyone sit through this movie?" contains no single word that is obviously negative. Thus, sentiment seems to require more understanding than the usual topic-based classification. So, apart from presenting our results obtained via machine learning techniques, we also analyze the problem to gain a better understanding.

Approach To Detection Of Human Emotions Algorithm

This section describes an algorithmic approach for deducing human emotions through voice- and speech-pattern analysis. In order to achieve this objective, three test cases have been examined, corresponding to the three emotional states: **Normal** emotional state, **Angry** emotional state, and **Panicked** emotional state. □ For carrying out the analysis, four vocal parameters have been taken into consideration: pitch, SPL, timbre, and time gaps between consecutive words of speech. In order to quantitatively represent timbre, its temporal envelope for advance and decay times has been considered. Its a different emotional states by analyzing the deviations in the aforementioned four parameters from that of the normal emotional state. The proposed analysis was carried out with the help of software packages such as MATLAB and Wavepad.

SYSTEM SPECIFICATIONS

HARDWARE REQUIREMENTS

Processor	: Intel processor 3.0 GHz
RAM	: 1GB
Hard disk	: 40 GB
Compact Disk	: 650 Mb
Keyboard	: Standard keyboard
Mouse	: Logitech mouse
Monitor	: 15-inch color monitor15

SOFTWARE REQUIREMENTS

Operating System	: Windows OS
System type	: 32-bit or 64-bit Operating System
IDE	: Python 3.5 and above
Install Dependency	: pip install pandas, pip install matplotlib, Pip install keras, pip install tensorflow

1. RESULT

```

28 elif n==8:
29     return "male_happy"
30 else:
31     return "male_sad"
32
33 json_file = open('model.json', 'r')
34 loaded_model_json = json_file.read()
35 json_file.close()
36 loaded_model = model_from_json(loaded_model_json)
37 loaded_model.load_weights('Emotion_Voice_Detection_Model.h5')
38 data, sampling_rate = librosa.load('test.wav')
39 X, sample_rate = librosa.load('test.wav', res_type='kaiser_fast', duration=2.5, sr=22050*2, offset=0.5)
40 sample_rate = np.array(sample_rate)
41 mfccs = np.mean(librosa.feature.mfcc(y=X, sr=sample_rate, n_mfcc=13), axis=0)
42 featurelive = mfccs
43 livedf2 = featurelive
44 livedf2 = pd.DataFrame(data=livedf2)
45 livedf2 = livedf2.stack().to_frame().T
46 twodim = np.expand_dims(livedf2, axis=2)
47 livepreds = loaded_model.predict(twodim, batch_size=32, verbose=1)
48 livepreds1=livepreds.argmax(axis=1)

```

```

PS C:\Users\Gnanavel.N\Documents> cd 'C:\Users\Gnanavel.N\Documents'; $(env:PYTHONENCODING)="UTF-8"; $(env:PYTHONUNBUFFERED)=
"1"; & 'C:\Users\Gnanavel.N\AppData\Local\Programs\Python\Python37\python.exe' 'C:\Users\Gnanavel.N\.vscode\extensions\ms-pytho
n.python-2020.2.82718\pythonfiles\ptvsd_launcher.py' --default --client --host localhost --port 58429 'C:\Users\Gna
navel.N\Documents\sema.py'
Using TensorFlow backend.
2020-02-13 12:05:56.593238: I tensorflow/core/platform/cpu_feature_guard.cc:142] Your CPU supports instructions that this Tens
oFlow binary was not compiled to use: AVX2
1/1 [=====] - 8s 38ms/step
male_angry
PS C:\Users\Gnanavel.N\Documents>

```

OUTPUT 1

```

24 elif n==6:
25     return "male_calm"
26 elif n==7:
27     return "male_fearful"
28 elif n==8:
29     return "male_happy"
30 else:
31     return "male_sad"
32
33 json_file = open('model.json', 'r')
34 loaded_model_json = json_file.read()
35 json_file.close()
36 loaded_model = model_from_json(loaded_model_json)
37 loaded_model.load_weights('Emotion_Voice_Detection_Model.h5')
38 data, sampling_rate = librosa.load('03-01-02-01-02-02-23.wav')
39 X, sample_rate = librosa.load('03-01-02-01-02-02-23.wav', res_type='kaiser_fast', duration=2.5, sr=22050*2, of
40 sample_rate = np.array(sample_rate)
41 mfccs = np.mean(librosa.feature.mfcc(y=X, sr=sample_rate, n_mfcc=13), axis=0)
42 featurelive = mfccs
43 livedf2 = featurelive
44 livedf2 = pd.DataFrame(data=livedf2)

```

```

PS C:\Users\Gnanavel.N\Documents> cd 'C:\Users\Gnanavel.N\Documents'; $(env:PYTHONENCODING)="UTF-8"; $(env:PYTHONUNBUFFERED)=
"1"; & 'C:\Users\Gnanavel.N\AppData\Local\Programs\Python\Python37\python.exe' 'C:\Users\Gnanavel.N\.vscode\extensions\ms-pytho
n.python-2020.2.82718\pythonfiles\ptvsd_launcher.py' --default --client --host localhost --port 58442 'C:\Users\Gna
navel.N\Documents\sema.py'
Using TensorFlow backend.
2020-02-13 12:08:19.797881: I tensorflow/core/platform/cpu_feature_guard.cc:142] Your CPU supports instructions that this Tens
oFlow binary was not compiled to use: AVX2
1/1 [=====] - 8s 38ms/step
male_calm
PS C:\Users\Gnanavel.N\Documents>

```

OUTPUT 2

```

File Edit Selection View Go Debug Terminal Help
sema.py - Visual Studio Code
C:\Users\Gnanavel.N\Documents> sema.py
24 elif n==6:
25     return "male_calm"
26 elif n==7:
27     return "male_fearful"
28 elif n==8:
29     return "male_happy"
30 else:
31     return "male_sad"
32
33 json_file = open('model.json', 'r')
34 loaded_model_json = json_file.read()
35 json_file.close()
36 loaded_model = model_from_json(loaded_model_json)
37 loaded_model.load_weights("Emotion_Voice_Detection_Model.h5")
38 data, sampling_rate = librosa.load('03-01-07-01-01-02-23.wav')
39 X, sample_rate = librosa.load('03-01-07-01-01-02-23.wav', res_type='kaiser_fast', duration=2.5, sr=22050*2, of
40 sample_rate = np.array(sample_rate)
41 mfccs = np.mean(librosa.feature.mfcc(y=X, sr=sample_rate, n_mfcc=13), axis=0)
42 featurelive = mfccs
43 livedf2 = featurelive
44 livedf2 = pd.DataFrame(data=livedf2)

OUTPUT TERMINAL DEBUG CONSOLE PROBLEMS
3: Python Debug Consc
PS C:\Users\Gnanavel.N\Documents> cd 'c:\Users\Gnanavel.N\Documents'; $(env:PYTHONIOENCODING='UTF-8'; $(env:PYTHONUNBUFFERED)=
'1'; & 'C:\Users\Gnanavel.N\AppData\Local\Programs\Python\Python37\python.exe' 'c:\Users\Gnanavel.N\vscode\extensions\ms-pytho
n.python-2020.2.62718\pythonFiles\ptvsd_launcher.py' '--default' '--client' '--host' 'localhost' '--port' '58479' 'c:\Users\Gna
navel.N\Documents\sema.py')
Using TensorFlow backend.
2020-02-13 12:12:44.893852: I tensorflow/core/platform/cpu_feature_guard.cc:142] Your CPU supports instructions that this Tens
orFlow binary was not compiled to use: AVX2
1/1 [-----] - 0s 39ms/step
male_fearful
PS C:\Users\Gnanavel.N\Documents>

```

OUTPUT 3

```

File Edit Selection View Go Debug Terminal Help
sema.py - Visual Studio Code
C:\Users\Gnanavel.N\Documents> sema.py
24 elif n==6:
25     return "male_calm"
26 elif n==7:
27     return "male_fearful"
28 elif n==8:
29     return "male_happy"
30 else:
31     return "male_sad"
32
33 json_file = open('model.json', 'r')
34 loaded_model_json = json_file.read()
35 json_file.close()
36 loaded_model = model_from_json(loaded_model_json)
37 loaded_model.load_weights("Emotion_Voice_Detection_Model.h5")
38 data, sampling_rate = librosa.load('03-01-04-01-02-02-23.wav')
39 X, sample_rate = librosa.load('03-01-04-01-02-02-23.wav', res_type='kaiser_fast', duration=2.5, sr=22050*2, of
40 sample_rate = np.array(sample_rate)
41 mfccs = np.mean(librosa.feature.mfcc(y=X, sr=sample_rate, n_mfcc=13), axis=0)
42 featurelive = mfccs
43 livedf2 = featurelive
44 livedf2 = pd.DataFrame(data=livedf2)

OUTPUT TERMINAL DEBUG CONSOLE PROBLEMS
3: Python Debug Consc
PS C:\Users\Gnanavel.N\Documents> cd 'c:\Users\Gnanavel.N\Documents'; $(env:PYTHONIOENCODING='UTF-8'; $(env:PYTHONUNBUFFERED)=
'1'; & 'C:\Users\Gnanavel.N\AppData\Local\Programs\Python\Python37\python.exe' 'c:\Users\Gnanavel.N\vscode\extensions\ms-pytho
n.python-2020.2.62718\pythonFiles\ptvsd_launcher.py' '--default' '--client' '--host' 'localhost' '--port' '58456' 'c:\Users\Gna
navel.N\Documents\sema.py')
Using TensorFlow backend.
2020-02-13 12:09:44.076591: I tensorflow/core/platform/cpu_feature_guard.cc:142] Your CPU supports instructions that this Tens
orFlow binary was not compiled to use: AVX2
1/1 [-----] - 0s 39ms/step
male_sad
PS C:\Users\Gnanavel.N\Documents>

```

OUTPUT 4

CONCLUSION

Building the model was a difficult undertaking as it included parcel of trail and mistake strategies, tuning and so on. The model is very much prepared to recognize male and female voices and it recognizes with 100% exactness. The model was tuned to recognize feelings with over 70% precision. Exactness can be expanded by including more sound records for preparing.

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