

# Recognition of emotions in speech: overview and implementation

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## Abstract

In this paper will be considered studies on recognition of emotions in speech, distinguished their techniques, advantages and disadvantages. Then will be offered own simple implementation of the recognition system.

## 1 Introduction

Speech emotion recognition has many application areas. More evident of them: robots and improving the quality of customer service.

If robot has ability to emotional speech generating, it will help him to interact with people better. Because understanding of speech emotion recognition gives understanding how to generate emotional speech. And robots with emotional speech are more people-friendly. Also, speech emotion recognition can improve the robot's decision-making system. Because there are situations when a robot needs to take into account human emotions.

Closer to reality application of this system is within an estimation of customer service quality. For example, call-centers have records of conversations. And for operator's work estimation we can identify expressive conversations and analyze them.

There are many research where described dependencies between human emotions and acoustic characteristics. Main differences between them in using different:

- Acoustics characteristics
- Features
- Classification techniques
- Recognizable emotions

The main goal of this study is to consider these differences and implement own simple solution.

## 2 Overview

### 2.1 Acoustic characteristics

Before we consider a few studies, let's consider some acoustic characteristics:

- Pitch or fundamental frequency
- Loudness or intensity
- Formants
- MFCC (Mel-frequency cepstrum coefficients)

#### 2.1.1 Pitch

Human speech frequency is approximately in the range of 300 to 3400 Hz. The fundamental frequency of speech for male from 85 to 185 Hz, for female from 165 to 255.

The fundamental frequency, often referred to simply as the fundamental, is defined as the lowest frequency of a periodic waveform. In terms of a superposition of sinusoids (e.g. Fourier series), the fundamental frequency is the lowest frequency sinusoidal in the sum [1].

#### 2.1.2 Formant and MFCC

The most frequently in studies used only pitch and loudness. Although formant and MFCC characteristics also useful.

Formant is a range of frequencies of a complex sound in which there is an absolute or relative maximum in the sound spectrum". In speech science and phonetics, however, a formant is also sometimes used to mean an acoustic resonance of the human vocal tract.[2]

In sound processing, the mel-frequency cepstrum (MFC) is a representation of the short-term power spectrum of a sound, based on a linear cosine transform of a log power spectrum on a non-linear mel scale of frequency[3].

## 2.2 Features

For emotion classifying from acoustic characteristics is necessary extract some features of these characteristics for every emotion. We extract and compute emotion features from training set to use it for classification. And classification is as follows:

1. Extract features from processed speech
2. Compare extracted features with emotion's features

Features can be divided to two types by how to compute and how to compare them:

- speaker-dependent
- speaker-independent

### 2.2.1 Speaker-dependent features

At first, with speaker-dependent features we need a divided training set for every person. And compute features for every person. When classifying we need to compare extracted features with personal features. Advantages of this technique: can be more precisely and much features are not needed. These features based on some average values. For example: average pitch, average intensity, pitch range, intensity range. And they are different for every person. That is why it is not a universal technique because requires statistics keeping for each person. And it is can be applied only in a few cases.

### 2.2.2 Speaker-independent features

Unlike a previous technique here divided training set is not required. But the accuracy of classifying depends on number of speech records and number of speakers represented in the training set. Features based on speech signal dynamics, also some average values. For example, pitch DDS (explanation further), intensity DDS, average phrase duration, etc.

## 2.3 Classification

Classification techniques described in detail in the paper

[Speaker Emotion Recognition Based on Speech Features and Classification Techniques].

So let's consider some of them.

### 2.3.1 Binary Decision Tree

Decision Tree is a stream design drawing like structure in which inward hub talks to check on a quality, every extension talks to deduction of check and every leaf hub talks to class title (choice taken in the wake of registering all traits). A way from root to leaf speaks to arrangement runs the display. In alternative examination a conclusion tree and the almost identified influence journal is utilized as a visual and scientific choice support device, where the usual qualities (or required utility) of arguing options are computed.

*Advantages:* easy implementation, easy explanation of input and output relationship Can handle high dimensional data Easy to interpret for small sized trees The learning and classification steps of induction are simple and fast Accuracy is comparable to other classification techniques for many simple data sets Convertible to simple and easy to understand classification rules.

*Disadvantages:* decision-tree learners can create overcomplex trees that do not generalize the facts and figures well. Decision trees can be unstable because small variations in the facts and figures might outcome in a absolutely different tree being developed. This difficulty is mitigated by using decision trees inside an ensemble. The difficulty of discovering an optimal decision tree is known to be NPcomplete under several facets of optimality and even for easy concepts. Consequently, functional decision-tree learning algorithms are founded on heuristic algorithms such as the greedy algorithm where locally optimal decisions are made at each node. Such algorithms will not assurance to return the globally optimal decision tree. There are concepts that are hard to discover because decision trees do not articulate them effortlessly, such as XOR, parity or multiplexer troubles. conclusion tree learners conceive biased trees if some categories dominate. It is thus suggested to balance the dataset prior to fitting with the conclusion tree

### 2.3.2 Artificial Neural Network

An Artificial Neural mesh (ANN) is a facts and figures organising standard that is inspired by the way biotic anxious structures, for example the cerebrum, process facts and figures. The key constituent of this ideal model is the innovative structure of the facts and figures handling structure. It is made out of countless interconnected changing components (neurones) employed as one to tackle specific issues. ANNs, for demonstration persons, study by illustration. An ANN is designed for a specific provision, for demonstration design acknowledgement or information characterization, through a revising method. revising in living structures includes acclimations to the synaptic associations that exist between the neurones. This is accurate of ANNs besides.

*Advantages:* they can both about any convoluted conclusion supplied that enough nodes are utilised. Neural systems are rather easy to implement (you do not need a good linear algebra solver as for examples for SVNs). Neural networks often exhibit patterns alike to those exhibited by humans. although this is more of interest in cognitive sciences than for functional examples.

*Disadvantages:* long preparing time The VC measurement of neural systems is indistinct. This is extremely critical when you need to think about how exceptional an answer could be. Neural systems can't be retrained. Provided that you include information later, this is just about difficult to add to an existing system. Taking care of time arrangement information in neural systems is an exceptionally confounded point.

### 2.3.3 Naïve Bayes classifier

The Naive Bayes Classifier procedure is reliant upon the purported Bayesian hypothesis and is particularly suited when the dimensionality of the inputs is high. Notwithstanding its effortlessness, Naive Bayes can frequently outflank more refined grouping strategies.

*Advantages:* fast to train (single scan). Fast to classify Not sensitive to irrelevant features Handles real and discrete data Handles streaming data well.

*Disadvantages:* assumes independence of features

For example, at the Figure 1 showed some features of emotions. And we can see that some emotions very similar(anger-joy,sadness-boredom). Although number of emotions is not so large. But with increasing number of emotions, also increases intersections between emotions on features. So it's important to define emotions which is needed for particular task

## 3 Implementation

### 3.1 The goal in general

The main goal is to implement simple recognition system. The program should have ability to recognize emotions from sound file or microphone. Also, it should be resistant to interference and noise. Implementation will be carried out using C# programming language.

Implementation can be divided to four steps:

1. Extracting sound characteristics from sound file or microphone
2. Speech splitting to phrases or words
3. Feature extraction and analyzing
4. Classification

#### 3.1.1 Extracting sound characteristics

At first, is important to note that we need only voice characteristics and to avoid wrong results sound should be filtered. At first, is important to note that we need only voice characteristics and to avoid wrong results sound should be filtered. Filtering is important not only because is needed correct voice characteristics, also because it provides ability distinguish voiced and unvoiced intervals of speech.

To retrieve sound characteristics using C# one can use these libraries:

- NAudio (<http://naudio.codeplex.com>)
- Bass Audio library (<http://naudio.codeplex.com>)

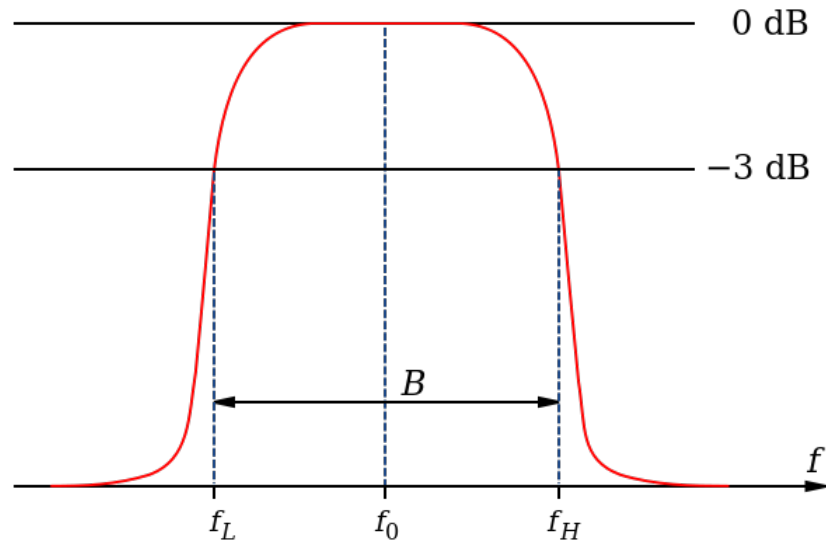


Figure 1: Pass-band filter

But these libraries provide only sound signal receiving from file or microphone. And to get sound characteristic, for example pitch, we have to implement also Fast Fourier Transform function. Also, we have to implement filtering function. For example, simplest filtering can be implemented as pass-band filter.

Pass-band filter just establish range of signal values, and if signal values go beyond they will be ignored.(Figure 2)

There is also software package which fits our goals - PRAAT. It is often used for speech analyzing and contains all needed functions:

- Get fundamental frequency (pitch)
- Get loudness
- Get spectrogram
- Get formant
- Filtering function

That are functions that we will use, but package contains a lot more functions. And for using all function it has own script language.



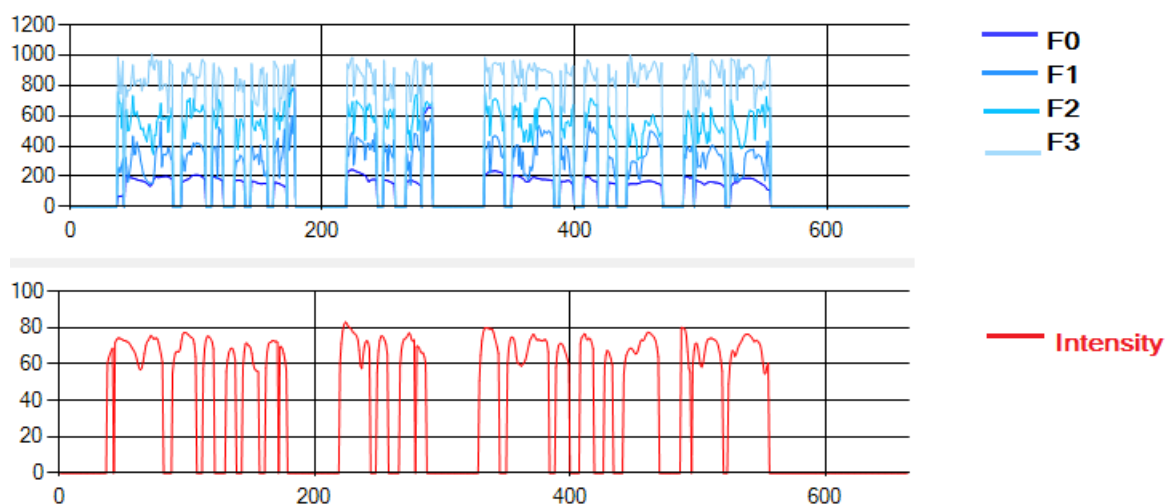


Figure 2: Extracted sound characteristics

For filtering in the package is using *Remove noise* function. Which consists of pass-band filter and special functions for white noise removing.

Eventually, using PRAAT we will get from sound file these characteristics:

- Pitch, or F0
- Loudness, or intensity
- Formant (F1, F2, F3)
- Center of gravity of spectrogram

Graphics for these characteristics represented in the Figure 2. We can see that there are intervals where values are equal to zero. It is the result of filter working. When pitch (F0) goes beyond human speech frequency range, all values are assigned to zero.

### 3.1.2 Dividing speech to phrases

Because when people are speaking, they express emotions by changing some characteristics of phrases or words. And for accurate recognition is needed to divide speech to phrases and analyze them separately.

It is worth noting, that precise dividing is impossible without filtering. That is why successfulness of this step very strong related with previous

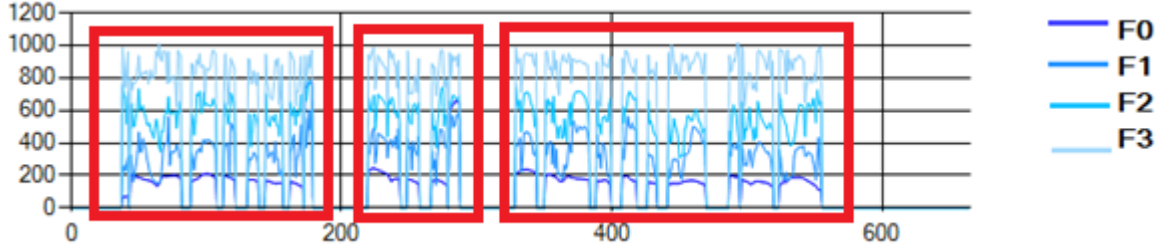


Figure 3: Speech divided to phrases

step. In output from previous step we get set of characteristics where silence intervals marked as zeros. So, algorithm can be as follows:

- Until zero value, collect phrase values
- After zero value, ends with this phrase and go to the next

But problem with this in that a few zeros can appear in the middle of the phrase. And to solve this problem we should set the minimum length of zeros between phrases. At the Figure 3 is shown speech divided to phrases, and within phrase exist intervals of zeros but they are slight.

So after two steps in the output is received set of sound characteristics and phrase pointers. It is now necessary to extract features for classification.

### 3.2 Features extraction

*Variance.* It can be calculated by standard deviation of set:

$$V = \sqrt{\sum_{i=0}^n (x_i - \bar{x})^2}$$

where  $\bar{x}$  is average of set

Pitch (F0)	Variance
	Range
	DDS
Formant 1 (F1)	DDS
Formant 2 (F2)	DDS
Formant 2 (F3)	DDS
Loudness (Intensity)	Variance
	Range
	DDS
Time	mean phrase duration
	mean silence duration
Spectrogramm	Center of gravity (centroid)

Table 1: Using features

*Range.* It is difference between maximum and minimum

*DDS (Difference-Distance-Slope)* The idea of this feature taken from [Real-time automatic emotion recognition from speech]

It is calculating for each phrase (Example in the Figure 4)

- Find local *maximum* and *minimum* elements for phrase
- $difference = maximum - minimum$
- $distance = maximum_{position} - minimum_{position}$

Phrase duration and silence duration are calculating by phrase pointers. Also, center of gravity of spectrogram for all speech provides PRAAT.

### 3.3 Features from training data set

As a training data set we use [EmoDB]. It is emotional database which consist of speech records of 10 different actors. For classification we use only four basic emotions: anger, happiness,sadness,neutral. And from EmoDB we use 107 records with these emotions and different texts. Results of features extraction represented in Table 3.

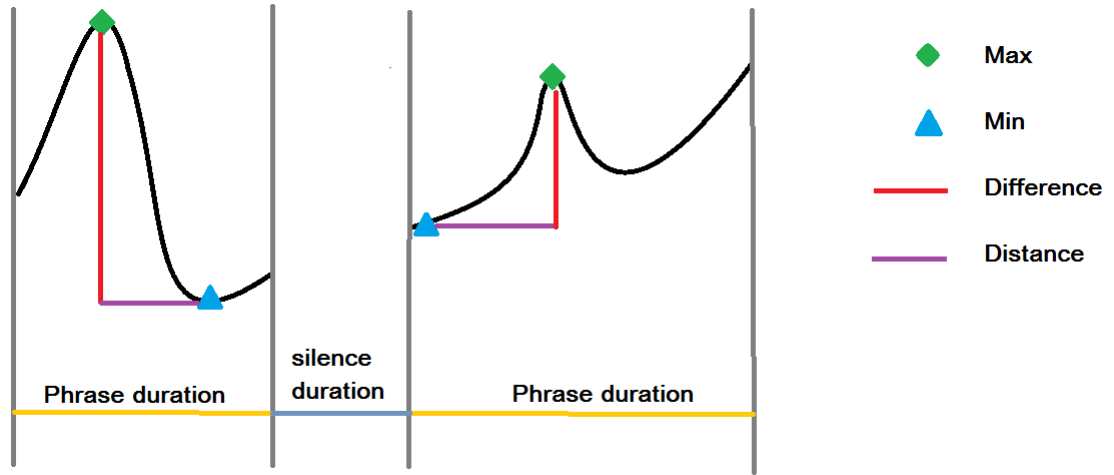


Figure 4: DDS

### 3.4 Classification

So we have got some feature values for each emotion, and is needed to build classifier using them. There are impossible to set strict confines for features values for each emotion. Because emotion feature value is median for all analyzed speech records and some values very different from this value. In addition, some feature values are very similar and it's difficult divide them to four classes. But often among these 4 values exist two high and two low values. It caused by fact that some emotion very similar with some features, but they have some distinct features. For example: angry-happy, sadness-neutral. It can be seen on the Table 3, most of the features of angry and happiness are similar, there are some features which distinct for them. For example, phrase duration is lower for angry.

That is why was decided to use fuzzy sets for classifying each feature to two classes: *high* and *low* triangle membership function. Because classification to 2 classes will be more precise. And fuzzy sets allow to set intersection between them.

#### 3.4.1 Fuzzy sets construction

So we have to construct two fuzzy sets from 4 feature values. In addition, for each feature is necessary determine *min* and *max* values. Each set represented as a triangle. At the top of the triangle membership probability is

Feature/Emotion	anger	happy	sadness	neutral
PitchDff	137,08	211,55	67,32	64,63
PitchDis	-6	-10,125	-19,33	-8
IntDif	22,22	22,92	19,63	18,76
IntDis	6,44	-5,83	-7,41	-3,2
F1Dif	239,44	228,16	210,52	193,49
F1Dis	-1,71	-5,87	-9	-1,66
F2dif	349,82	318,56	340,58	299,02
F2Dis	-1,42	-3,15	-2,32	0,66
F3Dif	355,51	359,38	449,35	425,46
F3Dis	-0,4	-2,28	-0,33	2,6
PitchRange	465,16	406,37	150,065	457,2
IntRange	31,36	28,95	28,865	27,61
PitchVariance	7253,96	10823,92	1737,46	6720,77
IntVariance	46,19	41,20	35,10	36,24
PhraseDuration	28,9	38,16	39,58	24,66
SilenceDuration	5,2	4,45	5,375	5,4
Centroid	580,3	519,54	359,08	350,02

Table 2: Extracted features from training data set. Dif-Difference, Dis-Distance, Int-Intensity

equal to 100%.

Algorithm is as follows:

1. Sort numbers
2.  $mean1$  = average value of two first values,  $mean2$  = average value of two last values
3.  $intersection$  = 20% of maximum element (first element)
4. first set is=  $\{(min, 0), (mean1, 100), (mean2 - intersection, 0)\}$ , second set is=  $\{(mean1 + intersection, 0), (mean2, 100), (max, 0)\}$

eventually for each feature we can define two characterizing functions:  $IsLow$  and  $IsHigh$ , which will return probability. And based on this model from training data set each emotion can be described as in the Table 4. So,

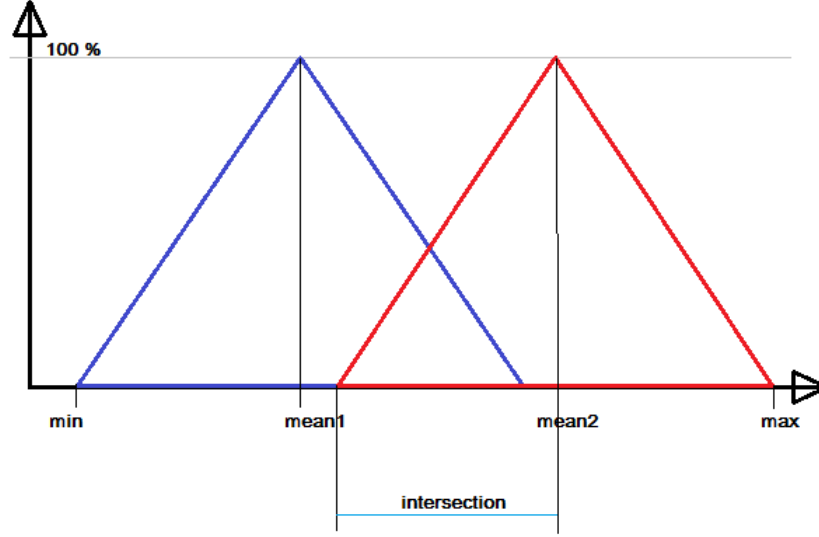


Figure 5: Fuzzy sets

accuracy of classification depends on properly selected fuzzy sets boundaries.

And the emotion probability computing will look like:

$$anger = PitchDif.IsHigh() + PitchDis.IsLow() + IntDif.IsHigh() + \dots$$

### 3.5 System as whole

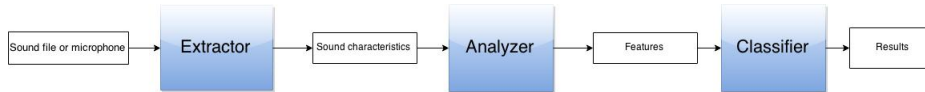


Figure 6: System as a whole

System's work as whole shown in the Figure 6. Extractor receives sound from file or microphone and extracts sound characteristics using PRAAT. Then Analyzer computes features for sound characteristics for further classification. Classifier using fuzzy sets computes probability for each emotion.

Feature/Emotion	anger	happy	sadness	neutral
PitchDff	High	High	Low	Low
PitchDis	High	Low	Low	High
IntDif	High	High	Low	Low
IntDis	High	Low	Low	High
F1Dif	High	High	Low	Low
F1Dis	High	Low	Low	High
F2dif	High	Low	High	Low
F2Dis	High	Low	Low	High
F3Dif	Low	Low	High	High
F3Dis	Low	Low	High	High
PitchRange	High	High	Low	Low
IntRange	High	High	Low	Low
PitchVariance	High	High	Low	Low
IntVariance	High	High	Low	Low
PhraseDuration	Low	High	High	Low
SilenceDuration	Low	Low	High	High
Centroid	High	High	Low	Low

Table 3:

## 4 Testing

## 5 Conclusions

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