# VILNIUS UNIVERSITY FACULTY OF MATHEMATICS AND INFORMATICS MODELLING AND DATA ANALYSIS MASTER'S STUDY PROGRAMME

Master's thesis

# Applications of Changepoints Analysis for Speech Signal and Fundamental Frequency

# Pasikeitimo taškų analizės taikymas šnekos signalui ir pagrindiniam dažniui

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#### Abstract

The goal of this study is to separate the letters of Lithuanian words that are recorded in audio files. In other words, split audio file tracks into intervals, where the beginning and end of each interval indicate to the beginning and end of the letter. Two methods were used to do this: application of changepoints analysis for speech signal and application of changepoints analysis for fundamental frequency. First, all the letters of the words were marked manually in "Audacity" program. The changepoints obtained using both methods were compared with the points of the manually marked letters. Comparing the signal and the fundamental frequency, it can be said that more accurate changepoints are determined in the signal.

Key words: changepoints analysis, the speech signal, the fundamental frequency, audio files.

# Pasikeitimo taškų analizės taikymas šnekos signalui ir pagrindiniam dažniui

#### Santrauka

Šio darbo tikslas yra atskirti lietuviškų žodžių raides, kurie yra įrašyti į garso failus. Kitaip sakant, padalinti garso failų įrašus į intervalus, kur kiekvieno intervalo pradžia ir pabaiga atitinka raidės pradžią ir pabaigą. Tam atlikti buvo naudojami du metodai: pasikeitimo taškų analizės taikymas šnekos signalui ir pasikeitimo taškų analizės taikymas pagrindiniam dažniui. Pirmiausia, visos tiriamų žodžių raidės buvo sužymėtos rankiniu būdu "Audacity" programoje. Taikant abejus metodus, gauti pasikeitimo taškai buvo palyginti su rankiniu būdu sužymėtų raidžių taškais. Atlikus signalo ir pagrindinio dažnio palyginimą, galima teigti, kad signale nustatomi tikslesni pasikeitimo taškai.

Raktiniai žodžiai: pasikeitimo taškai, šnekos signalas, pagrindinis dažnis, garso įrašai.

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# **1** Introduction

In the modern world of technology, voice technology is becoming increasingly important, such as speech recognition, speech signal synthesis, and their combined variants.

There are two main applications of language technology:

- Speech signal synthesis the computer speaks words according to the available word sound patterns.
- Speech recognition the computer recognizes alleged words according to the specified dictionary.

Speech synthesis programs are relevant for users who prefer to listen to text rather than read ebooks from a monitor screen. For those who preserve their vision, who want to hear how words and phrases sound in different languages.

Speech recognition systems identify words spoken by humans and convert them into text. These systems cover a wide range of areas, such as: voice-guided user interfaces, dictation tools, automatic telephone call processing, automatic voice translation from one language to another, and stenography.

One of the many steps in the speech signal recognition process is speech signal segmentation. The speech signal can be interpreted as the output of a linear system with abruptly changing parameters. Speech segmentation can be applied to different languages but words recorded in Lithuanian language will be used in this work. The Lithuanian language is little researched and for example the methods used for English words are not suitable for Lithuanian words, therefore this language is chosen for research. The aim of my work is to divide (segment) the audio signal into certain intervals. Each of those subdivided intervals indicates the transition from one letter to another.

In order to present the information clearly and comprehensibly, the work is divided into two parts. One of them provides theoretical descriptions of speech signal, the fundamental frequency, changepoints analysis. The next part is the research part, which describes the data used. Also there are presented, analyzed and interpreted two different methods. At the end of the work, the obtained results and conclusions are presented.

## 2 Signal and fundamental frequency

## 2.1 Signal

A **signal** - can be defined as an abstraction of any quantity that can be measured, which is function of at least one independent variable (time or space). A signal is the functional representation of a physical quantity or variable, and it contains information about the behavior of the physical quantity.

Mathematically, a signal is represented as a function of an independent variable t. Most of the time t stand for time. The mathematical notation of a signal is x(t). Depending on the continuity of the contained information signals can be:

- Continuous time
- Discrete time

A **continuous-time signal** has a value for all instants in time or space. Mathematically, these signals can be described by the functions of a continuous variable. As such signals an example is the microphone output signal, temperature sensor signals, the voltage of a battery or the position of a pendulum.



Fig. 2.1. Continuous - time signal

A **discrete-time signal** has a value only at discrete moments in time. It can be obtained from the analog signal by subtracting its values only at certain points in time. We can consider a discrete signal as a sequence of numbers. An example of such a signal could be the weight of a human measured early or the daily average temperature measure in a specific area.



Fig. 2.2. Discrete - time signal

In this work there is analyzing **speech signal**. The speech signal, as it emerges from a speaker's mouth, nose and cheeks, is a one-dimensional function (air pressure) of time. Microphones convert the fluctuating air pressure into electrical signals, voltages or currents, in which form we usually deal with speech signals in speech processing. Perception of speech signal is influenced by three factors: volume, pitch and timbre. Volume is a measure of sound intensity and corresponds with the amplitude of the signal. Pitch is given by the fundamental frequency of the speech signal and represents a measure of how a specific subject is perceiving the sound. Timbre is determined by the harmonics of the sound and corresponds with frequency components of the signal spectrum.



The analysis of speech signals can be defined as the process of extracting relevant information from the speech signal (i.e., from a recording). This process is mainly based on the speech production mechanism, whose study involves multiple disciplines from linguistics and articulatory phonetics to signal processing and source coding. In mathematics, Fourier transform method is the most popular for speech signal analysis. Expression for Discrete Fourier Transform is:

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-n2\pi k/N}, k = 1, 2, ..., N,$$

where X(k) is the value of spectral component k, x(n) represents the signal sample n and N is number of samples.[5] Each component X(k) is characterized by two real values: amplitude  $A_k$  and phase  $\varphi_k$  because the calculus is made in complex domain. Real values are described like:

$$A_k = |X(k)|, \varphi_k = \arg(X(k)).$$

#### 2.1.1 The fundamental frequency

The **fundamental frequency** (often denoted by F0) – is defined as the lowest frequency of periodic waveform. Typically, fundamental frequencies lie roughly in the range 80-450Hz, where males have lower voices than females. The fundamental frequency is closely related to pitch, which is defined as our perception of fundamental frequency. That is, the F0 describes the actual physical phenomenon, whereas pitch describes how our ears and brains interpret the signal, in terms of periodicity.

F0 is described by simply formula

$$F0 = \frac{1}{T}$$

where T is periodic.[8]

The fundamental frequency from audio file looks like:



Fig. 2.1.1. The fundamental frequency (F0)

Analyzing **Fig. 2.1.1.** there we can see that F0 is stable and random. Its help to identify vowels (when F0 - stable) and consonants (when F0 - random).

## **3** Literature Review

Analyzing the sources, an attempt was made to search for information about speech signal research, sound and letter separation in words or audio files. The information found in the sources shows that researches were performed using various methods, such as: Functional principal components analysis, empirical mode decomposition(EMD), classification, BeBe system method, ect.

Speaking about EMD, it was used as a new tool for the analysis of nonlinear and nonstationary data. This method was first time introduced by N.E. Huang (1998). The technique adaptively splits the signal into oscillating components which correspond very well to the signal and can be used to extract the resonant frequencies of the vocal tract.[9] Another method used classification algorithms (Gausian Mixture Models, Support Vector Machines, Multiplayer Perception) which is compared in order to detect the phonemes based on a manually established music phoneme database. In the course of the study, 2244 phonemes from vocal popular music were manually marked and using them was performed melody detection algorithms for reducing influences from accompanying sounds.[10] One of the more interesting methods was using the Bebe system. BeBe's activity concerns what is traditionally termed the preprocessing stage of speech recognition, in which the original sound waveform is converted to a phonemic digital representation. One of advantages that Computation can be performed in real time and recognition is robust enough to adapt to different speakers and changes in talking speed. The subjects were 4 male adults, all native American English speakers. Each of them was given a page containing 5 lines of text. BeBe0 was tested on its recognition of 4 phonemes: /@/ as in bat, /R/ as in stir, /I/ as in fit, and /U/ as in should. The results show that 83-100% of the assigned phonemes were identified correctly.[11]

Other authors used functional data analysis methods. One of most cmmonly used method is Principal Components Analysis. In one work, functional data analysis is used as a tool to analyze dynamic speech signal transitions. The aim of the work was to investigate whether two clusters sand t can be distinguished by removing the vowel e from the word "sets". Using principal components analysis, it was found that the main st clusters are statistically significant, but it was not determined whether they could be distinguished by removing the vowel e.[6] Methods of functional data analysis were used to analyze the emotional language of a man and a woman when the following emotions are neutral, sad, angry, happy. There was developed an "aperture function" computation program which computes cross-sectional distances between the lower and upper boundaries of the vocal tract in the midsagittal plane from the larynx to the lips. Two methods are distinguished: 1) functional time alignment and 2) functional principal components analysis, which were used to show that the tip of the tongue tip and rapid movements are the main parameters of modulation related to emotional expression and trajectories of form are similar in terms of emotions.[7]

The articles show that speech analysis is very popular among researches, but there are still a lot opportunities to explore it further. Therefore, the goal of my work is to separate the letters in an audio file. Lithuanian language words are used for this purpose, as this language is little researched and the methods discovered and used in English language are not suitable for Lithuanian language.

## 4 Changepoints analysis

Changepoint analysis for time series is an increasingly important aspect in both applied and theoretical statistics. A changepoint is an instance in time where the statistical properties before and after this time point differ. The first published article concerning changepoints was in 1954 by E.S. Page. Over the decades, changepoint analysis has developed rapidly with multiple changepoints, different types of data and other assumptions being considered. Changepoints includes segmentation, structural breaks, break points, regime switching and detecting disorder.[4] Changepoints analysis are considered from:

- Single changepoint method
- Multiple changepoint method

To define changepoint methods there are used time-series data  $y_{1:n} = (y_1, ..., y_n)$ . For simplicity the observation at each time t and  $y_t$  is univariate data. Also there are number of changepoint (which is marked *m*) and their positions:  $\tau_{1:m} = (\tau_1, ..., \tau_m)$ . Each changepoint position is an integer (1,..., n-1). Then  $\tau$  is define like:  $\tau_0 = 0$  and  $\tau_{m+1} = n$  and assume that the changepoints are ordered so that  $\tau_i < \tau_j$  if i < j. The *m* changepoints split data into *m*+1 segments and then the *i*th segment consist of data  $y_{\tau_{i-1}+1:\tau_i}$ . For each segment there is a set of parameters which are associated with *i*th segment and it is denoted  $\theta_i$ . So the likelihood function is

$$L(m, \tau_{1:m}, \theta_{1:m+1}) = p(y_{1:n}|m, \tau_{1:m}, \theta_{1:m+1}),$$

where  $p(\cdot|\cdot)$  is a general conditional density function.

In order to understand the single changepoints method, there is close correspondence between the likelihood-ratio test and the penalised likelihood approches. Both involve comparing the maximum log-likelihood of the two models corresponding to one and no changepoint. A changepoint is detected if the increase in log-likelihood under the one changepoint model is greater than some threshold. The differences lie only in how this threshold is calculated.

The analysis of multiple changepoint models is computationally much more challenging, as the number of possible positions of *m* changepoints increases quickly with *m*. For instance, with 1000 data points there are just 999 possible positions of a single changepoint, but  $2x10^{23}$  sets of possibilities for 10 changepoints. To understand multiple changepoint detection there were suggested some of algorithms like: Binary Segmentation, Segment Neighbourhood Search, Minimum Description Length and Bayesian Methods.

For Bayesian analysis there is needed to specify a prior for a number and position of changepoints. Therefore, there are two suggestion. The first is to specify a prior on the number of changepoints and then the prior for their position given the number of changepoints. The second is to specify the prior for the number and position of changepoints indirectly through a distribution for the length of each segment. The second suggestion is more natural in useful applications.[3]

# 5 Case study

## 5.1 Description of available dataset

Records collected by the Image and Analysis group of Data Science and Digital Technologies institute were used for the research and it can be called "set of Lithuanian words". The file of words looks like:

1.	Būti
2.	Kuris
3.	Galėti
4.	Visas
5.	Kaip
6.	Lietuva
7.	Kitas
8.	Turėti
9.	Savas
10.	Darbas
11.	Žmogus
12.	Metai
13.	Labai
14.	Vienas
15.	Nebūti
16.	Reikėti
17.	Žinoti
18.	Didelis
19.	Tačiau
20.	Teisė
21.	Laikas
22.	Diena
23.	Dabar
24.	Pagal
25.	Valstybė
26.	Jeigu
27.	Respublika
28.	Nustatyti
29.	Dalis
30.	Įstatymas
31.	Straipsnis
32.	Įmonė
33.	Žodis
34.	Norėti
35.	Kalba
36.	Šalis
37.	Sudaryti
38.	Asmuo
39.	Naujas

40.	Sistema
41.	Sakyti
42.	Todėl
43.	Kartas
44.	Gauti
45.	Áukštas
46.	Žemė
47.	Metas
48.	Vieta
49.	Niekas
50.	Įvairus
51.	Lietuviai
52.	Svarbus
53.	Vaikas
54.	Gerai
55.	Prieš
56.	Tarp
57.	Dažnai
58.	Skirti
59.	Veikla
60.	Eiti
61.	Atlikti
62.	Pasakyti
63.	Gyventi
64.	Priimti
65.	Valstybinis
66.	Mokslas
67.	Akis
68.	Geras
69.	Atvejis
70.	Dirbti
71.	Antras
72.	Mažas
73.	Miestas
74.	Ranka
75.	Bendras
76.	Istaiga
77.	Mokykla
78.	Teismas

79.	Kalbėti
80.	Forma
81.	Bankas
82.	Tada
83.	Kultūra
84.	Sąlyga
85.	Viskas
86.	Tyrimas
87.	Vanduo
88.	Matyti
89.	Grupė
90.	Priemonė
91.	Vyriausybė
92.	Būdas
93.	Naudoti
94.	Medžiaga
95.	Nors
96.	Procesas
97.	Pasaulis
98.	Ūkis
99.	Kiek
100.	Rašyti
101.	Nulis
102.	Du
103.	Trys
104.	Keturi
105.	Penki
106.	Šeši
107.	Septyni
108.	Aštuoni
109.	Devyni
110.	Pradžia
111.	Pabaiga

Fig. 5.1. Data set

There are 111 different words and each of them was recorded in audio files. To make it clearer there is presenting word "labai" scheme (**Fig. 5.2.**):



Fig. 5.2. Word scheme

The audio file of word "labai" was recorded by 36 women and 26 men. Each woman and man repeated it in 60 files (just one man repeated it in 78 files). These files were without noise and with noise. As we can see for one word there was recorded 3738 files. Therefore, data set are collected from 414918 audio files (111 words x 3738 files).

### 5.2 Methods

To reach my goal there were used two methods in this thesis.

- First method: changepoints analysis in signal
- Second method: changepoints analysis in the fundamental frequency

## 5.2.1 Changepoints

In practical part, there were used two different changepoints analysis functions:

- Changepoint variance (cpt.var) from *changepoint* package in R
- Envcpt from *Envcpt* package ir R

Changepoint variance function is used to find changes in variance for data using the test statistic specified in the test.stat parameter. The changes are found using the method supplied which can be single changepoint (AMOC method), multiple changepoints (PELT or SegNeigh methods) or approximate (BinSeg method). In this function there are used the main parameters like: *penalty* 

(Choice of "None", "SIC", "BIC", "MBIC", AIC", "Hannan-Quinn", "Asymptotic", "Manual" and "CROPS" penalties), *pen.value* (for instance 0.05 value when using "Asymptotic" penalty or a vector of length 2(min,max) if using the CROP penalty), *method* (mentioned above).[1] For this thesis was used "PELT" method, penalty "CROPS", and pen.value which depends on the length of the word. Changing the values of pen. value allows to most accurately segment the audio file.

Envcpt fits 12 models often used to represent climate and environmental time series and selects which one provides the best fit to represent the time series. The simplest models for the time series assume that the series is well represented by either a constant mean or a linear trend in addition to a background white noise. Envcpt function can detect changepoints in mean and variance (not separately), slopes (,,trends"), and AR(1)/AR(2), as well as conveniently fitting various models without changepoints. It automatically infers the number of changepoints. In this thesis was used ,,trendcpt" model. A trend with multiple changepoints in the regression parameters (Trend cpt), represent the intercept and trend in each segment.[2]

The main reason why for signal and fundamental frequency are applied two different functions is that changes in variance are clearly visible in the signal (there used changepoint variance function) while F0 does not have such fluctuations in variance but one can observe fluctuations in trend, therefore there used envcpt function with trend model.

#### 5.3 Results

For this research there was used R-studio and Audacity programs. There was decided to choose five words of different length like: "darbas", "labai", "akis", "mokykla", "du". For each word was choose 36 audio files. (**Fig. 5.3.1.**)



Fig. 5.3.1. Word scheme

Graphics of all audio recordings will be presented in the following order:

• Letters marked in Audacity program (Fig. 5.3.2.):



Fig. 5.3.2. Audio file in Audacity program

• Changepoints in signal (red lines mean changepoints) (Fig. 5.3.3.):



Fig. 5.3.3. The signal graph in R

• Changepoints in F0 (yellow lines mean changepoints) (Fig. 5.3.4.):



Fig 5.3.4. The fundamental frequency graph in R

All these graphs have different x-axis values: there are seconds in audacity program, there are numbers of sample in signal and there are centiseconds in fundamental frequency. However, all results (changepoints) are given in seconds.

It is important to mention that in many files there are more changepoints that do not mean any letters. This is because the word does not always start to be uttered from the beggining, only the sound of audio records are heard in those place. Also, some of the graphs of the analyzed words are given below, other graphs are given in the appendices.

Firstly, analyze word "akis":



Fig. 5.3.5. Changepoints by woman (without noise)



Fig. 5.3.6. Changepoints by woman (without noise)



Fig. 5.3.7. Changepoints by woman (with 20dB noise)







Fig. 5.3.9. Changepoints by man (without noise)



Fig. 5.3.10. Changepoints by man (without noise)



Fig. 5.3.11. Changepoints by man (with 20dB noise)



Fig. 5.3.12. Changepoints by man (with 100dB noise)

In the signal, the vowels "a" and "i" are separated without reproaches. There are no dipthongs, so there is no difficulty. The consonants "k" and "s" is unvoiced, however it can also be separated. Changes were observed in audio recordings with 100dB noise. The consonants "k" and "s" are the made of several changepoints and "s" merges with the end of the sound recording.

In the fundamental frequency, the first letter "a" is separated with one changepoint, however other letters are more difficult to distinguish and it has several changepoints.

Secondly, analyze word "darbas":



Fig. 5.3.13. Changepoints by woman (without noise)



Fig. 5.3.14. Changepoints by woman (without noise)



Fig. 5.3.15. Changepoints by woman (with 20dB noise)



Fig. 5.3.16. Changepoints by woman (with 100dB noise)



Fig. 5.3.17. Changepoints by man (without noise)



Fig. 5.3.18. Changepoints by man (without noise)



Fig. 5.3.19. Changepoints by man (with 20dB noise)



Fig. 5.3.20. Changepoints by man (with 100dB noise)

In the signal, it can be seen that the mixed diphthong "ar" merges and it is inseparable or it can be separated, however a vowel "a" and a consonant "r" have several changepoints. Also it is important to mention that the consonant "s" is made of several changepoints in part of files.

In fundamental frequency, the first letter ,,d" is separated with one changepoint, the mixed diphthong ,,ar" also difficult to separate and it have some of changepoints.

Thirdly, analyze word "labai":



Fig. 5.3.21. Changepoints by woman (without noise)



Fig. 5.3.22. Changepoints by woman (without noise)



Fig. 5.3.23. Changepoints by woman (with 20dB noise)



Fig. 5.3.24. Changepoints by woman (with 100dB noise)



Fig. 5.3.25. Changepoints by man (without noise)



Fig. 5.3.26. Changepoints by man (without noise)



Fig. 5.3.27. Changepoints by man (with 20dB noise)



Fig. 5.3.28. Changepoints by man (with 100dB noise)

Voiced consonant "l" is prounced very similar to vowels. In the signal, changepoints are set inaccurately because the sounds of consonant "l" and vowel "a" merges. There is also diphtongs "ai" in the word, so the sounds of the vowels "a" and "i" are difficult to separate. Specifically,

changepoints are found and the letters are separated but the points do not coincide with the points of marked letters.

In the fundamental frequency, there is the same situation like in the signal. However, it is important to mention that more changepoints are needed to separate letters.

Fourthly, analyze word "mokykla":



Fig. 5.3.29. Changepoints by woman (without noise)



Fig. 5.3.30. Changepoints by woman (without noise)



Fig. 5.3.31. Changepoints by woman (with 20dB noise)



Fig. 5.3.32. Changepoints by woman (with 100dB noise)



Fig. 5.3.33. Changepoints by man (without noise)



Fig. 5.3.34. Changepoints by man (without noise)



Fig. 5.3.35. Changepoints by man (with 20dB noise)



Fig. 5.3.36. Changepoints by man (with 100dB noise)

In the signal, the consonant "m" and the vowel "o" do not separate or innacurately separate. The reason is that the consonant "m" like the consonant "l" is pronounced in the same way as vowels and sounds merge. The same situation is with the consonant "l" and the vowel "a" – the sounds merge and the letters are separated inaccurately. It is also important to mention that the consonant "k" is inaccurately separated or has several changespoints because "k" is unvoiced consonant.

In the fundamental frequency, here is the same situation as in the signal but even more changepoints are needed to separate the letters.

Fifth, analyze word "du":



Fig. 5.3.37. Changepoints by woman (without noise)



Fig. 5.3.38. Changepoints by woman (without noise)



Fig. 5.3.39. Changepoints by woman (with 20dB noise)



Fig. 5.3.40. Changepoints by woman (with 100dB noise)



Fig. 5.3.41. Changepoints by man (without noise)



Fig. 5.3.42. Changepoints by man (without noise)



Fig. 5.3.43. Changepoints by man (with 20dB noise)



Fig. 5.3.44. Changepoints by man (with 100dB noise)

In the signal, the consonant "d" and the vowel "u" are separated but the meanings of the points do not coincide at all with the points of the marked letters. Also it was quite difficult to mark the letters accurately in the "Audacity" program, as the sounds merge when listening records. It can be argued that when a word is momosyllabic, then it is difficult to accurately determined changepoints of the letters.

In the fundamental frequency, there is the same situation like in the signal. However, it is important to mention that more changepoints are needed to separate letters.

## 6 Conclusion

In conclusion, it can be said that vowels and consonants can be separated when there are no diphthongs and mixed diphthongs in the word. Letters are more difficult to distinguish when there are diphthongs because then the sounds of both vowels merge or mixed diphthongs because then the vowel and the consonant can be separated but their changepoints ar not exact. Much attention is also allocated to unvoiced consonants as more than one changepoint is required to separated them or for voiced consonants "l" and "m" because the rules prevails that such consonants are pronounced similarly as vowels in Lithuanians language.

These trends can also be seen in the graphs in the appendices, but there are individual cases sometimes where the effect of noise on the separation of letters is felt in certain files. However, it can be firmly stated that gender does not influence the achievement of the set goal.

Comparing the signal and the fundamental frequency, it can be said that more accurate and clear changepoints are determined in the signal.

# 7 References

[1] R.Killick and I.A. Eckley. An R Package for Changepoint Analysis, 2014.

[2] C.Beaulieu and R.Killick. *Distinguishing Trends and Shifts from Memory in Climate Data*, 2018.

[3] I. A Eckley, P. Fearnhead and R. Killick, Analysis of Changepoint models, 2011.

[4] <u>http://members.cbio.mines-paristech.fr/~thocking/change-tutorial/RK-CptWorkshop.html</u>

[5] O. Buza, G. Toderean. Voice Signal Processing for Speech Synthesis, 2006.

[6] M.Gubian, F. Torreira, H.Strik, L.Boves. *Functional Data Analysis as a Tool for Analyzing Speech Dynamics A Case Study on the French Word c 'était*, 2009

[7] S.Lee, E.Bresch, Sh.Narayanan. An Exploratory Study of Emotional Speech Production using Functional Data Analysis Techniques, 2006.

[8] T.Backstrom, 2020. https://wiki.aalto.fi/pages/viewpage.action?pageId=149890776

[9] A.Bouzid, N.Ellouze. EMD Analysis of Speech Signal in Voiced Mode, 2007.

[10] M.Gruhne, Ch.Dittmar. Phoneme Detection for Lurics Synchronization, 2015.

[11] L.Sweeney, P.Thompson. Speech Perception Using Real-Time Phoneme Detection: The BeBe system, 1997.
# Appendices

A R codes

# #Audio files reading

```
require(readxl)
require(tidyverse)
library(tuneR)
library(writexl)
setwd("D:/Users/Desktop/Magistras/Magistras_II_semestras/Magistro darbas/Data_wav")
pathName <- "D:/Users/Desktop/Magistras/Magistras II semestras/Magistro darbas/Data wav"
topicName <- list.files(path = pathName)</pre>
for(i in 1:length(topicName)) {
 topicPath <- paste(pathName, topicName[[i]], sep = "")</pre>
 files_to_read = list.files(
  pattern = '*.wav',
  recursive = TRUE,
  full.names = TRUE
 )
 data_lst <- list()</pre>
 for(k in 1:length(files_to_read)){
  data_lst[[k]] <- readWave(files_to_read[k])</pre>
  z <- attributes(data_lst[[k]])$left</pre>
  x \le as.data.frame(z)
  write.csv(x,
                         paste0("D:/Users/Desktop/Magistras/Magistras_II_semestras/Magistro
darbas/Data_excel/", topicName[[k]], ".csv"))
 }
}
#Application of changepoints functions for speech signal and fundamental frequency
require(readxl)
library(changepoint)
library(EnvCpt)
#For speech signal
                        read.csv("D:/Users/Desktop/Magistras/Magistras II semestras/Magistro
Duom2
              <-
darbas/Data_excel/M001_03_010.wav.csv")
cpt variance1 <- cpt.var(Duom2$z,method="PELT",penalty="CROPS",pen.value=c(100,5000))
plot(cpt_variance1, ncpts=5, xlab= "Number of sample")
#For fundamental frequency(f0)
#Excel files for f0 were exported from Python program with "crepe" function
Duom1 <- read.csv("D:/Users/Desktop/Magistro zodziai/Data excel f0/ M001 03 010.F0.csv")
cngpoint <- envcpt(Duom1$frequency, models="trendcpt")</pre>
```

plot(cngpoint)

# **B** Graphics

# 1. Word "akis":

By women without noise:















# By women with 20dB noise:







# By women with 100dB noise:







# By men without noise:

















#### By men with 20dB noise:







# By men with 100dB noise:







# 2. Word "darbas":

By women without noise:

















#### By women with 20dB noise:









By women with 100dB noise:







# By men without noise:





59













# By men with 20dB noise:







By men with 100dB noise:







### 3. Word "labai":

### By women without noise:

















# By women with 20dB noise:







### By women with 100dB noise:






By men without noise:





73













#### By man with 20dB noise:







By man with 100dB noise:







# 4. Word "mokykla":

By women without noise:

















#### By women with 20dB noise:







#### By women with 100dB noise:







#### By men without noise:

















#### 0.10 6.20 0.30 0.40 0.50 0.00 0.60 0.70 1.0 0.5 ahishikikika LILLIN !! 0.0 CHALLER OF (TRAFPITATION) -0.5 -1.0 K m 20000 ılli ull Trend cpt 0 1000 -30000 Data 2000 0 4000 6000 8000 80 20 40 60 0 Number of sample 0.070 0.020126 0.078182 0.17000 m 0.020126 0.078182 170 0.230000 m 0.019609 0.075442 0.078182 0.197390 0.197390 0.330532 m o k 3.230 0.320000 0 0.075442 0.194369 3.320 0.330532 0.417229 y 0.197390 k 0.194369 0.332089 k 0.330532 0.417229 y k 0.330532 y k 1 0.417229 0.550371 0.332089 0.418970 y k 0.550371 0.417229 0.550371 0.664161 0.664161 1 0.547157 0.550371 0.801947 0.547157 0.786102 1-a a 0.664161 0.801947 Letters points marked in Changepoints in signal Letters points marked in Changepoints in Audacity program Audacity program fundamental frequency



## By men with 20dB noise:



By men with 100dB noise:







# 5. Word "du":

By women without noise:















By women with 20dB noise:





By women with 100dB noise:







By men without noise:

















# By men with 20dB noise:







By men with 100dB noise:



