

**BENCHMARK FOR NASAL CONTINUANTS
IN TELUGU FOR SPEAKER
IDENTIFICATION**

LAKSHMI PRASANNA, P.

Register No: 09SLP011

A Dissertation Submitted in Part Fulfillment of Final Year

Master of Science (Speech-Language Pathology)

University of Mysore, Mysore

ALL INDIA INSTITUTE OF SPEECH AND HEARING,

MANASANGOTHRI, MYSORE – 570006

June-2011



CERTIFICATE

This is to certify that this dissertation entitled “*Benchmark for Nasal Continuants in Telugu for Speaker Identification (SPID)*” is the bonafide work submitted in part fulfillment for the Degree of Master of Science (Speech-Language Pathology) of the student with Registration No.: 09SLP011. This has been carried out under the guidance of a faculty of this institute and has not been submitted earlier to any other University for the award of any other Diploma or Degree.

Mysore
June, 2011

(Dr. S. R. Savithri)

Director

All India Institute of Speech and Hearing,
Manasagangothri,
Mysore -570006.

CERTIFICATE

This is to certify that the dissertation entitled “*Benchmark for Nasal Continuants in Telugu for Speaker Identification (SPID)*” has been prepared under my supervision and guidance. It is also certified that this has not been submitted earlier in any other University for the award of any Diploma or Degree.

Mysore,
June, 2011

Dr. S. R. Savithri
Guide

Professor in Speech Sciences
Department of Speech-Language Sciences
All India Institute of Speech and Hearing,
Manasagangothri,
Mysore-570006

DECLARATION

This is to certify that this Master's dissertation entitled "*Benchmark for Nasal Continuants in Telugu for Speaker Identification (SPID)*" is the result of my own study under the guidance of Dr. S. R. Savithri, Director, All India Institute of Speech and Hearing, Mysore, and has not been submitted in any other University for the award of any Diploma or Degree.

**Mysore
June, 2011**

Register No. 09SLP011

Acknowledgement

My humble and heartfelt gratitude to Dr. S. R. Savithri, Director and Prof. in Speech sciences, All India Institute of Speech and Hearing, for all her patience, guidance and constant support throughout this study. Without you this study wouldn't have been a success. You are my source of inspiration and you have fortified my interest in forensic field/ acoustics of speech.

I thank Late. Dr. Vijayalakshmi Basavaraj, Ex - Director, of All India Institute of Speech and Hearing for permitting me to do this study. I offer my prayers to her, may her soul rest in peace.

Heartfelt thanks to my beloved parents, grandma for your love, trust, & constant motivation. I know that you are there with me in all my happiness & sorrows.... Luv u lot ♥☺, God bless u with all happiness.

My Dearest Ajay, you are my support and life. Without you I wouldn't have been in this position, thank you so much for your love, care and concern towards me. I'm lucky to have you, I will be thankful to god by giving me such a wonderful person as my husband.....you are the best, where you sacrificed everything just to make me happy ♥☺ god bless u, may all ur wishes and dreams come true.

Dear Dr. M. V. Apparao & family. Thank you so much for your kindly help and support throughout my education where you showed the path for my life by giving me an opportunity to seek higher education. God bless u all...♥☺

My dearest father-in-law & mother-in-law, for their understanding & allowing me to continue my education though not as per tradition.... Harsha and Sharma for their love and help ...god bless u all....♥☺

I thank my Sisters and brother-in-laws for all their love and concern for me. God bless u all...♥☺

I bless my cute little sister's children Abhi and Siddu where I spent happy moments with them, May god bless them with a wonderful future ahead.....♥☺

Aacharya devo bava... I express my sincere gratitude to all my teachers from school to college who have imparted knowledge, moral values and taught to travel on right path in life.

I thank all my lecturers at AIISH for their help and efforts to make a student as best...♥☺

Hmmm ... coming to friends I've spent lots of happy moments here with padma, bhuvana, nahaveni akka, mahi, sangu, ranju, nirmal, sneha, nayu, madhu, varun & priyanka endless..... at AIISH where I enjoyed each and every moment and felt homely with you people. At hostel...b'day celebrations, friendship parties, festival celebrations, movies etc.. enjoyed a lot...☺

I thank Sweekaar- Upakaar institute where I learned ABC's in audiology and speech- language pathology...especially my teachers Aparna mam and Swathi mam.

I thank AIISH where I learned many things that have helped me hold my head high & helped me stand high in life....

I thank Dr. Y. V. Geetha, HOD of Speech Sciences Department for allowing me to use instruments for the study.

I thank all my Bsc and Msc classmates who made me feel happy, each and every moment I had with them

I thank bhuvana, nagender and sunil kumar for their help in perceptual judgement.

I thank my hubby, parents, suresh anna and shyamala for their help in data collection. Thank you so much for your help, without you it wouldn't have been easy for me.

I thank all my subjects who participated and co-operated for the recordings with utmost patience.

Something that has puzzled me all my life is why, when I am in special need of help, the good deed is usually done by somebody on whom I have no claim. I thank god almighty for being with me and giving me a chance to help others....

List of contents

Sl. No.	Chapter	Page No.
	List of contents	i
	List of tables	ii
	List of figures	iii
I	Introduction	1- 5
II	Review of literature	6- 20
III	Method	21- 26
IV	Results	27- 31
V	Discussion	32 - 34
VI	Summary and conclusions	35- 42
V	References	43- 44
VI	Appendix I – List of words (test material)	iv
	Appendix II - Euclidean distance for males	v-xix
	Appendix III - Euclidean distance for females	xx-xxxiv

Sl. No	List of tables	Page. no
1	Table 1: Nasal continuants of Telugu with its occurrence in various positions in the word.	22
2	Table 2: Illustration of comparing unknown speaker (USP1) with known speakers (1 to 10) on nasal continuant /ŋ /.	24
3	Table 3: Euclidean distances of unknown speaker (USP1) with known speakers (1 to 10) on nasal continuant /ŋ /.	25
4	Table 4: Percent correct identification in males and females in group A.	27
5	Table 5: Percent correct identification in males and females in group B.	29
6	Table 6: Percent correct identification in males and females in group C.	30
7	Table 7: Benchmarking for nasals in three groups and context of vowels.	33
8	Table 8: Benchmarking for all nasals in three groups.	34

Sl. No	List of figures	Page no.
1	Figure 5: Extraction of formant frequencies and bandwidths from spectrogram.	23
2	Figure 6: Correct identification of USP1 with SP1 (male speaker) for / <u>n</u> /.	28
3	Figure 7: False identification of USP1 with SP4 (male speaker) for / <u>n</u> /.	28
4	Figure 8: Correct identification of USP1 with SP1 (male speaker) for / <u>n</u> /.	29
5	Figure 9: False identification of USP1 with SP5 (male speaker for) / <u>n</u> /.	29

CHAPTER I

INTRODUCTION

Personal identity verification is an essential requirement for controlling access to protected resources. Personal identity is usually claimed by presenting a unique personal possession such as a key, a badge, or a password. However, these can be lost or stolen. Further, a simple identity claim is not sufficient if the potential for loss is great and the penalty for false identification is severe. Hence verification of that claimed identity is necessary. This can be attempted by examining an individual's biometric features, such as finger prints, hand geometry, or retinal pattern, or by examining certain features derived from the individual's unique activity such as speech or hand writing. In each case, the features were compared with previously stored features for the person whose identity is being claimed. If this comparison is favorable, based on decision criterion, then the claimed identity is verified.

Among these methods, identity verification based on a person's voice has special advantages for practical deployment. Speech is our most natural means of communication and therefore user acceptance of the system would be very high.

Speaker verification means determining whether an unknown voice matches the known voice of a speaker whose identity is being claimed. Or it is defined as deciding if a speaker is whom he claims to be. This is different than the speaker identification problem, which is deciding if a speaker is a specific person or is among a group of persons. The speaker verification is also termed as voice verification, speaker authentication, voice authentication, talker authentication, and talker verification. Rose (2002) reported that one major difference between automatic speaker

verification/identification and forensic speaker identification is that in verification and identification the set of speakers that constitutes the reference sample is known, and therefore the acoustic properties of their speech are known.

The performance of the two tasks, speaker identification and verification, is further determined by the type of speech material used to claim an identity. Fixed-text systems require the recitation of a predetermined text, thereby maintaining a high degree of user cooperation, whereas free-text systems accept speech utterance of unrestricted text. Fixed-text systems typically require 2-3s of speech for training and for verification. Free-text systems require 10-30 s of speech for training and 5-10 s of speech for verification. Speech samples used in the speaker verification is of two types Contemporary and Non-contemporary where Non-contemporary refers to speech samples, which are obtained at different points of time and Contemporary refers to speech samples obtained at same points of time.

The classification of speaker identification (SPID) methods according to Bricker and Pruzansky (1976) is as follows:

1. Speaker identification by listening: A person hears a voice and then attempted to match it to a particular individual, i.e., the one whose speech they heard.
2. Speaker identification by visual method: Spectrogram is a three dimensional (time, amplitude, and frequency) display of speech sounds. These were used in attempts to identify unknown speakers by matching their speech/ voice patterns with those of known speakers (or suspects).
3. Speaker identification by machine: In the *Semi Automatic Speaker Identification (SAUSI)* the examiner selects unknown and known samples (similar phonemes, syllables, words and phrase) from speech samples, which have to be compared, i.e.

computer processes these samples, extracts parameters and analysis them according to a particular program. The interpretation is made by the examiner. In the *Automatic Speaker Identification (AUSI)*, the computer does all the work and the participation of the examiner is minimal. For the purpose of automatic identification, special algorithms are used which differ based on the phonetic context. This method is used very often in forensic sciences but factors such as noise and distortion factors of voice and other samples need to be controlled. In such case a combination of subjective and objective methods should be used.

In the past, all three methods have been used. As regard to the second method – Speaker identification by visual method – Kersta (1962) reported identification rate of above 95%. However, Young & Campbell (1967) reported 78.4% and 37.3 % identification in training and experimental tasks, respectively. Stevens, Williams, Carbonell, & Woods (1968) reported an error rate of 21%. Using semi-automatic methods, researchers have reported speaker identification using several acoustic parameters in contemporary, non-contemporary, field, lab, and disguised conditions. Luck (1969) used cepstral measurements to characterize vowels. Results indicated that identification was impossible for non-contemporary speech samples. Schafer & Rabiner (1970) automatically estimated the lowest 3 formants and pitch period of voiced speech. Results indicated good performance. The results of the study by Enders, Bambach & Flosser (1971) indicated (a) shift in formants with increase in the age of speakers, and (b) inability of the imitators to match formants and pitch. Two vectors – time-energy distribution and voiced-unvoiced speech time contrast yielded 100 % speaker identification scores in normal condition (Johnson, Hollien & Hicks, 1984). Bachorowski

& Owren (1999) used the frequencies of the first three formants, F0, jitter, shimmer, and duration and reported that the formant frequencies were in the first factor (factor analysis) in differentiating talkers' gender. Pamela (2002) extracted some spectral and temporal measures in Hindi speaking normal subjects and reported that two speech samples can be considered to be belonging to two different speakers if 67% of measures were different. In an experiment on acoustic similarities and differences Savithri (2008) attempted benchmarking for temporal and spectral measures in normal and 45 disguised speaking conditions in direct and telephone recordings. The benchmarking for formant frequencies were 68%, 50%, and 40% in direct recording and 76%, 68%, and 58% in telephone recording.

Glenn & Kleiner (1968), describe a method of automatic speaker identification based on the physiology of the vocal apparatus and essentially independent of the spoken message. Power spectra produced during nasal phonation are transformed and statistically matched. Initially, the population of 30 speakers was divided into three subclasses, each containing 10 speakers. Subclass 1 contained 10 male speakers, Subclass 2 contained 10 female speakers, and Subclass 3 contained an additional 10 male speakers. For each speaker, all 10 samples of the spectrum of /n/ from the test set were averaged to form a test vector. The test vectors were compared, with the stored speaker reference vectors for the appropriate subclass. The values of the cosine of the angle between the reference and the test vectors were correlation values between the test vector for a given speaker and the reference vector for each speaker in the subclass. The maximum correlation value for each test vector was used and 97% over all correct identification was attained. Next, the effect of a larger population was tested by

correlating each speaker's averaged test data with the reference vectors for all 30 speakers and an average identification accuracy of 93 % was reached. Finally, the effect of averaging speaker samples was tested as follows. The same speaker reference vectors based on all 10 training samples were used. However, the test data were subjected to varying degrees of averaging. First, single-speaker samples were correlated with the 30 speaker reference vectors. The average identification accuracy for all 300 such samples (10 per speaker) was 43%. Then, averages of two speaker samples from the test data were taken as test vectors. The average identification accuracy for 150 such vectors was 62%. Next averages of five speaker samples from the test data were taken as test vectors. The average identification accuracy for 60 such vectors was 82%. The procedure developed to exploit this information provides a basis for automatic speaker identification without detailed knowledge of the message spoken. This study was focused on the nasal phonation using power spectra, used reference and test vectors. This is the only study using spectra of nasal continuants. Given the physiology of nasal continuant production one needs to explore on the possibility of using nasal continuants for SPID. Further, the frequency of the occurrence of the nasal continuants is 10.06% [/m/ = 0.01%, /n/ = 6.35%, /ɳ/= 0%, /ŋ/= 0.36% and /ŋ/= 0.01% in Telugu¹, (Ramakrishna, Nair, Chipplunkar, Atal, Ramachandran, & Subramanian, 1962). However, till date there are no studies on benchmarking of nasal formants and bandwidths. In this context, the present study was planned. The objective of the present study was to obtain a benchmark for SPID using nasal continuants in Telugu.

1. Telugu is hypothetically classified as a Dravidian language with heavy Indo-Aryan influence and is native to the Indian subcontinent. It is the official language of Andhra Pradesh. It is also one of the twenty-two scheduled languages of the republic of

Indian and was conferred the status of a classical language by the Government of India. The mother tongue of the majority of people of Andhra Pradesh, it is also spoken in neighboring states like Chhattisgarh, Karnataka, Maharashtra, Odysa and Tamil Nadu. Telugu is the third most- spoken language in India (74 million native speakers according to the 2001 census) and is 15th in the Ethnologue list of most spoken languages worldwide.

CHAPTER II

REVIEW OF LITERATURE

“Forensic voice identification is a legal process to decide whether two or more recordings of speech are spoken by the same speakers” (Rose, 2002). The importance of voice identification was first noted during the period of World War II related to the assassination of Adolf Hitler; it occurred on July 21, 1944 at Wolf’s Lair, his field headquarters in East Prussia. At that time, no one knew if he had been killed or just escaped out of Germany. There were still some speeches said to be from Hitler but their authentication was questioned. Fortunately, some of his past speeches were recorded and stored. Groups of scientists comprising phoneticians and engineers then decided to compare the old and new recordings. A series of analysis led to the conclusion that Adolf Hitler was still alive (Hollien, 2002).

The voice identification technique was first adopted by the Michigan State Police in 1966 and introduced in the American court in the mid 1960’s. Such method was used widely in different states including California, Florida and New York since then. However, different admission standards and interpretation methods were used among courts resulting in a lack of consistency (McDermott & Owen, 1996). Forensic voice identification had already been used in various crime cases, including murder, bomb threats, rape, political corruption and kidnapping (Cain, Smrkovski & Wilson, 1990). Some witnesses of these cases could see the criminals but some could not, for example, the voices were heard over a telephone line or when the witness was blindfolded.

Forensic speaker identification

Expert opinion is increasingly being sought in the legal process as to whether two or more recordings of speech are from the same speaker. This is usually termed forensic speaker identification, or forensic speaker recognition. As the examples above show- and many more could be cited – forensic speaker identification can be very effective, contributing to both conviction and elimination of suspects. Equally important, the examples also demonstrate the necessity for expert evaluation of voice samples, since three of them show how the truth actually ran counter to the belief of naïve listeners. The aim of speaker identification is, not surprisingly, identification: ‘to identify an unknown voice as one or none of a set of known voice’ (Naik, 1994).

The voice identification technique was first adopted by the Michigan State Police in 1966 and introduced in the American court in the mid 1960’s. Such method was used widely in different states including California, Florida and New York since then. However, different admission standards and interpretation methods were used among courts resulting in a lack of consistency (McDermott & Owen, 1996). Forensic voice identification had already been used in various crime cases, including murder, bomb threats, rape, political corruption and kidnapping. Some witnesses of these cases could see the criminals but some could not, for example, the voices were heard over a telephone line or when the witness was blindfolded.

It might seem that recognizing someone by their voice is a simple notion, but there are many different circumstances under which this can happen. Your voice could be recognized by your friend when you ring them up, for example, or it might need to be

automatically recognized by a computer in order for you to have access to your bank statement over the phone. There thus many different types of speaker recognition, of which forensic SPID is one.

Speaker recognition

Forensic speaker identification can often be found classified as a kind of speaker recognition (Nolan, 1997). The kind of activity covered by term speaker recognition is conceptually straight forward, and definitions abound. Hecker (1971) suggests that speaker recognition is “any decision-making process that uses the speaker-dependent features of the speech signal,” and Atal (1976) offers the formulation “any decision-making process that uses some features of the speech signal to determine if a particular person is the speaker of a given utterance.” The discussion on the likelihood ratio it can be appreciated that, in forensic speaker identification the decision as to whether or not an utterance was spoken by a particular speaker is properly the domain of the court, this characterization is not appropriate. Another aspect wherein Aral’s characterization is not totally correct for forensic speaker identification is that it strongly suggests that an unambiguous, categorical outcome is expected: the person is either determined to be or determined not to be the speaker of a given utterance. In the forensic case the outcome should be a ratio of probabilities. Despite these shortcomings, it is clearly still helpful to persevere with the idea of forensic speaker identification as a kind of speaker recognition (Rose, 1990). Figure 1, shows the schematic representation of speaker recognition.

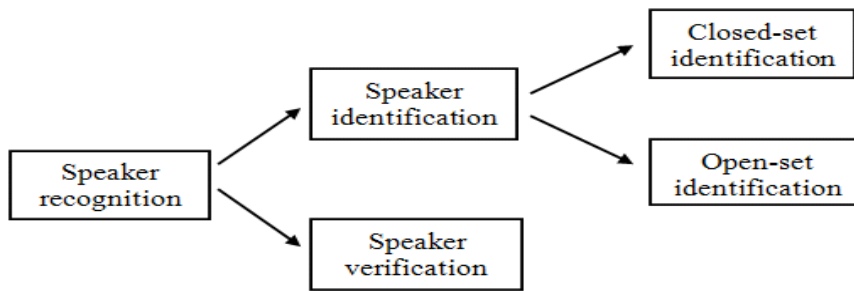


Figure 1: Schematic representation of speaker recognition.

Speaker identification and verification

There are two main classes of speaker recognition task, called identification and verification (Furui, 1994; Nolan, 1997). The distinction between them rests firstly on the type of question that is asked and secondly on nature of the decision-making task involved to answer that question.

Speaker identification

The aim of speaker identification is, not surprisingly, identification: ‘to identify an unknown voice as one or none of a set of known voice’ (Naik, 1994). One has a speech sample from an unknown speaker, and a set of speech samples from different speakers the identity of whom is known. The task is to compare the sample from the unknown speaker with the known set of samples, and determine whether it was produced by any of the known speaker (Nolan, 1983).

Figure 2 shows a schematic representation of simple speaker identification. The speaker identification experiment is represented with a reference set of 50 known speaker samples. In Figure 2, the unknown sample on the left is compared with that from known speaker 1(A), then known speaker 2 (B), and so on. The question mark represents the question: are these two speech sample from the same speaker? If it is

decided that the unknown sample is the same as one of the known speaker, say known speaker 4, then that identifies the speaker of the unknown sample as D.

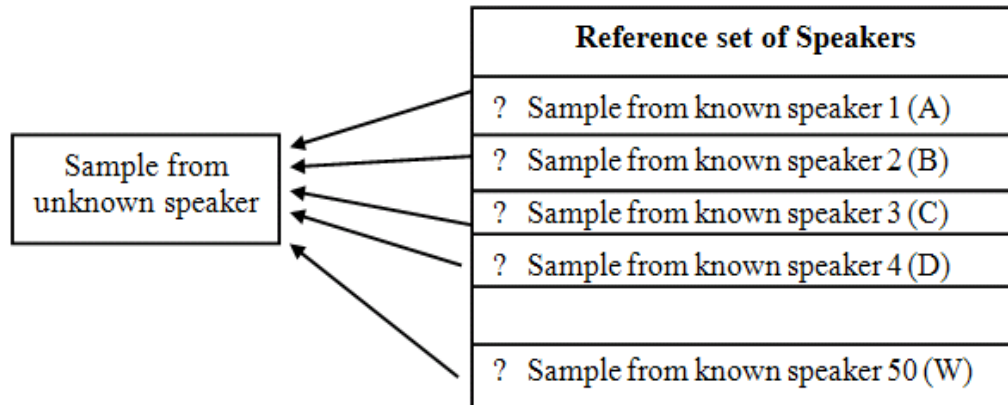


Figure 2: Schematic representation of speaker identification.

Speaker verification

Speaker verification is the other common task in speaker recognition. This is where ‘an identity claim from an individual is accepted or rejected by comparing a sample of his speech against a stored reference sample by the individual whose identity he is claiming’ (Nolan, 1983). The schematic representation of speaker verification is shown in Figure 3. The speaker D wants to access and verified. The system has samples of speaker D’s voice in storage, which it retrieves and compares with that of the sample tendered by speaker D. If the two voice samples are judged similar enough, speaker D’s claim is verified and he is given access.

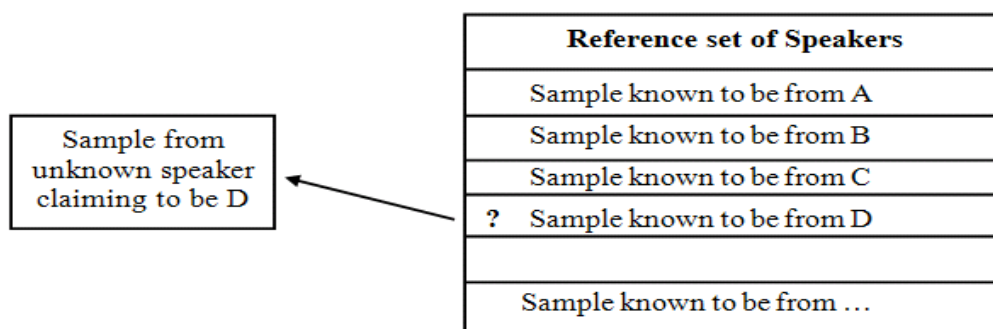


Figure 3: Schematic representation of speaker verification.

Open and closed set identification

In speaker identification, the reference set of known speakers can be of two types: closed or open. A closed reference set means that it is known that the owner of the unknown voice is one of the known speakers. An open set means that it is not known whether the owner of the unknown voice is present in the reference set or not. Closed set identification is usually a much easier task than open set identification. Since it is known that the unknown speaker is one of the reference set, the closed set identification task lies in (1) estimating the distance between the unknown speaker and each of the known reference speakers, and (2) picking the known speaker that is separated by the smallest distance from the unknown speaker. The pair of sample separated by the smallest distance is then assumed to be from the same speaker (Nolan, 1983). *Because the nearest known speaker is automatically selected in a closed set identification, no threshold is needed.* Both closed and open sets can occur in forensic case-work, although the latter, where we do not know if the putative offender is among the suspects or not, is usually far more common. Since the task usually becomes very much simpler with a closed set, the distinction between open and closed set tasks is an important one in forensic speaker identification.

Type of decision

In identification, only two type of decision are possible. Either the unknown sample is correctly identified or it is not. Verification is more complicated, with four types of decision. The decision can be correct in two ways: the speaker is correctly identified as being who they say they are, or not being who they say they are. And it can be incorrect in two ways: the identity claim of the speaker can be incorrectly rejected (the speaker is who they say they are but rejected), or incorrectly accepted (the speaker is an impostor but is nevertheless accepted).

Type of errors in speaker identification

In the open set speaker identification task three types of errors were possible. Figure 4 shows the schematic representation of classification of errors.

- (1) Error A: a match did exist but the examiner selected the wrong one (false identification).
- (2) Error B: a match did exist but the examiner failed to recognize it (false elimination).
- (3) Error C: a match did not exist although the examiner selected one (false identification).

In the closed set speaker identification, since a match always existed, only one kind of error was possible: false identification or wrong identification. This error from closed set identification is labeled as Error D.

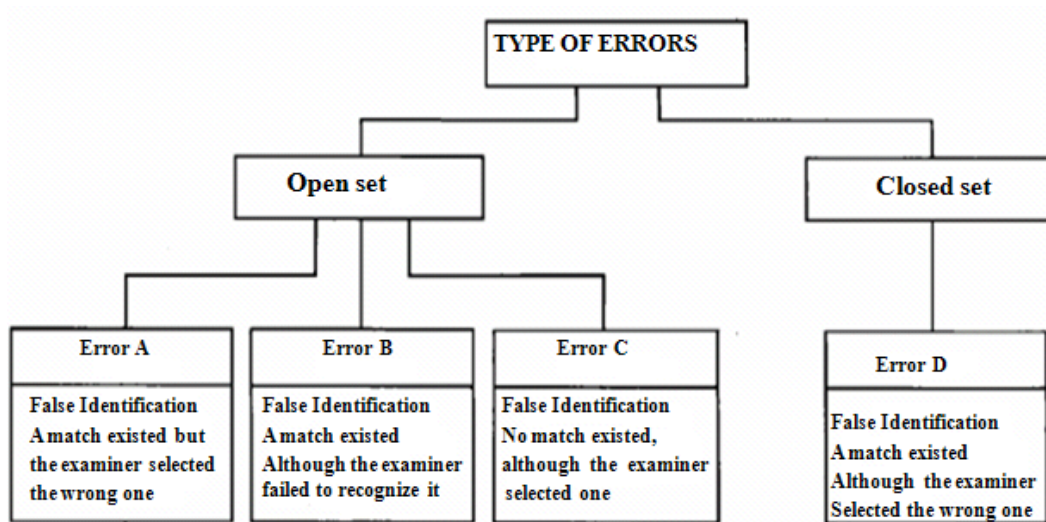


Figure 4: Classification of errors.

Problems in speaker identification

There are many problems in carrying out a speaker identification task. Some of them are as follows:

Uniqueness

The identification task might involve an open set of trials. Specifically, the unknown must be detected from within a large to very large population of ‘possibilities’. But this can be overcome to some extent that we can reduce the number of possibilities by taking in to consideration, the gender, dialect, language, some common phrases used and style of speaking by the speaker.

Distortion

It becomes very difficult to identify a speaker by his/her voice, especially when they are talking in an environment which distorts or masks their utterances (channel distortions) or when they are excited or stressed (speech distortions). The distortions are broadly classified into two types.

- (1) System distortion and

(2) Speaker distortion.

(1) System distortion

This category includes several kinds of signal degradation. One is reduced frequency response, i.e., the signal pass band can be limited when someone talks over a telephone line or mobile phone, poor quality tape recorders are used to 'store' the utterances and / or microphones of limited capability are employed. In these cases, the important information about the talker is lost and these elements are not usually retrievable. Such limited signal pass band can reduce the number of helpful speaker specific acoustic factors. Second, noise can create a particularly debilitating type of system distortion as it tends to make the talker's voice and, therefore, can obscure elements needed for identification. Examples of noise included those created by wind, motors, fans, automobile movement and clothing friction. The noise itself may be intermittent or steady state saw tooth or thermal and so on. Third, any kind of frequency or harmonic distortion can also make the task of identification more difficult. Examples include intermittent short circuits, variable frequency response, and harmonic distortion and so on.

(2) Speaker distortion

The speaker themselves can be the source of many types of distortions. Fear, anxiety or stress like emotion can occur when the perpetrator is speaking during the commission of crime. They often will degrade identification as the speech shifts triggered by these emotions can markedly changed one or more the parameters within the speech signal. The effects of ingested drugs or alcohol; and even a temporary health state

such as a cold can affect the speech. The suspect may sometimes attempt to disguise their voice. All those affect the speaker identification process horrendously.

II. Methods of speaker identification

The problem of identifying individuals from their speech is a complex one exhibiting many facets, levels, and parameters. With respect to the current state of the art, even the selection of the particular methods to be used is a difficult, and often confusing, process. Hecker (1971) classifies the methods of speaker identification into three general categories.

- (1) Speaker identification by listening (subjective method)
- (2) Speaker identification by visual examination of spectrograms (subjective method)
- (3) Speaker identification by machine (objective method)

All have demonstrated some success in the laboratory but none have been particularly successful under field like conditions. Of these approaches, the third method (semi automatic and automatic) appears to be the most promising for the future, primarily because (1) specific parameters within the speech signal can be selected and analyzed serially or simultaneously, (2) the selected vectors may be used in various combinations, and (3) subjective analysis by human is eliminated.

(1) Speaker identification by visual examination of spectrograms (subjective method)

In the mid 1940's, the scientists of the Bell Telephone Laboratories in USA developed the first sound spectrograph (the Sonagraph), a visual record of speech

including frequency, intensity and time (McDermott & Owen, 1996). In the Fifties, Lawrence Kersta, an engineer from the Bell Telephone Laboratories, developed “voiceprint identification” (Hollien, 2002). Studies using the spectrograph were carried out in the 1950s and 1960s in USA (Hollien, 2002).

Kersta (1962) introduced the term *voiceprint* and studied identification methods of visually matching spectrograms. High school girls were trained for five days to identify talkers from spectrograms on the basis of eight “unique acoustic cues”. Results revealed that high rate of identification accuracy that was inversely related to the number of talkers. For 5, 9, and 12 talkers, identification rate were 99.6%, 99.2% and 99%, respectively.

Young & Campbell (1967) conducted a study on the ability to identify talkers from monosyllables spoken in context. In this study Kersta's method of visually comparing spectrograms was employed. Ten observers were trained to identify five talkers from spectrograms of two words spoken in isolation. The experimental task then required the observers to identify the same talkers from the same words spoken in different contexts. The correct rates for the training task (78.4%) could not be reproduced in the experimental task (37.3%). The results were interpreted to indicate that different contexts decrease the identification ability of observers because: (a) the shorter stimulus durations of words in context decreases the amount of acoustic information available for matching, and (b) the different spectrographic portrayals introduced by different phonetic contexts outweighs any intra-talker consistency.

Stevens (1968) compared spectrographic and auditory presentation of speech samples using open set and closed set experiments. The results for the closed tests indicated that, after about 4 h of exposure to the test situation, the percent error in identification of speakers from isolated speech samples (words or phrases) was 6 % for aural presentation and 21 % for visual presentation. These scores depended upon the talker, the subject, and the phonetic content and duration of the speech material. For the open visual tests, appreciable numbers of false acceptances (incorrect authentications) were made. The results suggest procedures that might be used to minimize error scores in practical situations.

(2) Semi-automatic/ automatic methods

In the years following identification by the aural mode, voice processing technology became quite popular and the simplest approach used was to generate and examine amplitude and frequency, time matrices of speech samples. The other approach was to extract speaker dependent parameter from the signals and analyze them by machines.

In an attempt to identify acoustic correlates of talker sex and individual talker identity in a short vowel segment produced in running speech Bachorowski and Owren (1999) extracted *fundamental frequency (F0), jitter, shimmer, duration, formant frequencies (F₁ F₂ F₃), vocal tract length and amplitude*. Factor analysis was used in this study, which indicated that the formant frequencies were in the first factor and they were helpful in differentiating talker's sex. The results support a theoretical approach to indexical attributes in speech.

Savithri (2008) studied the acoustic similarities and differences within and between speakers in speech disguised conditions (disguise like 70-80 yr old, severe hoarse voice, hyper nasal, and slow rate). Fifty normal English speakers (25 males and 25 females) spoke five sentences in which six words were embedded. Two types of recordings live and telephone were used. Results indicated 68% similar for first formant, 50% for F_2 and 40% for F_3 in live recording. In telephone condition, F_1 was similar 71% of times, F_2 68% and F_3 58% of times. Comparison of live and telephone recordings showed very poor benchmarking. Percent similarity for word duration, closure duration, burst duration and transmission duration were above chance level in live and telephone conditions.

Glenn & Kleiner (1968), describe a method of automatic speaker identification based on the physiology of the vocal apparatus and essentially independent of the spoken message. Power spectra produced during nasal phonation are transformed and statistically matched. Initially, the population of 30 speakers was divided into three subclasses, each containing 10 speakers. Subclass 1 contained 10 male speakers, Subclass 2 contained 10 female speakers, and Subclass 3 contained an additional 10 male speakers. For each speaker, all 10 samples of the spectrum of /n/ from the test set were averaged to form a test vector. The test vectors were compared, with the stored speaker reference vectors for the appropriate subclass. The values of the cosine of the angle between the reference and the test vectors were correlation values between the test vector for a given speaker and the reference vector for each speaker in the subclass. The maximum correlation value for each test vector was used and 97% over all correct identification was attained. Next, the effect of a larger population was tested by

correlating each speaker's averaged test data with the reference vectors for all 30 speakers and an average identification accuracy of 93 % was reached. Finally, the effect of averaging speaker samples was tested as follows. The same speaker reference vectors based on all 10 training samples were used. However, the test data were subjected to varying degrees of averaging. First, single-speaker samples were correlated with the 30 speaker reference vectors. The average identification accuracy for all 300 such samples (10 per speaker) was 43%. Then, averages of two speaker samples from the test data were taken as test vectors. The average identification accuracy for 150 such vectors was 62%. Next averages of five speaker samples from the test data were taken as test vectors. The average identification accuracy for 60 such vectors was 82%. The procedure developed to exploit this information provides a basis for automatic speaker identification without detailed knowledge of the message spoken. This study was focused on the nasal phonation using power spectra, used reference and test vectors. This is the only study using spectra of nasal continuants. Given the physiological of nasal continuant production one needs to explore on the possibility of using nasal continuants for SPID.

Ying-Yong Qi & Robert (1989) have studied the acoustic features of the nasals [m, n] in CV syllables and [m, n, ŋ] in VC syllables in English. They were analyzed and compared using cepstrally smoothed running FFT spectra. Clear differences between nasals in CV and VC syllables were obtained. For example, the spectral energy transitions from vowel to nasal in VC syllables were found to be much less dramatic than in CV transitions. Next, given the recent interest in the efficacy of auditory representations in speech recognition schemes, the nasals in VC contexts were examined in terms of auditory transformed running spectra. Several features of interest were

obtained: The spectra were generally dominated by the second formant and, when the preceding vowel was a low vowel, nasal place of articulation was distinguished by the second formant transition, which converged to 16–17 ERB for [m] and 19–20 ERB for [n]; [ŋ] was characterized by little formant movement. Consistent nasal place features were not found in the context of the vowels [i] and [u]. Finally, since the antiresonances of a nasal may provide place of articulation information, the system zeros of the nasals were analyzed using parametric spectral analysis based on the autoregressive moving average (ARMA) process. Results indicated that the antiresonances of nasals in a VC syllable could be consistently estimated by a two-step AR approximation method that could be used to distinguish reliably between [m] and [n].

Ying-Yong Qi & Robert (1992) has done study on nasal consonants using perceptual linear predictive (PLP) method. Six speakers produced 300 CV syllables with initial nasal consonants /m/and /n/. Results indicated that the frequencies for the transformed poles, particularly for the second pole, were significantly lower for /m/ than for/n/and were independent of factors such as vowel context and gender of the speaker. A nasal identification rate of 86% was obtained based on the frequency of the second pole. The use of the PLP method clearly has overcome difficulties associated with the anti resonance in analyzing nasal consonants.

The review indicates that earlier studies were used aural and visual methods for SPID and in semi/automatic SPID studies were analyzed benchmarks for formants in various conditions, used power spectra for nasal phonation and perceptual linear predictive (PLP) methods were also used. There has been no particular research done till date using nasal formants and bandwidths. In this context the present study was planned

to provide “*benchmark for nasal continuants in Telugu for speaker identification*”.

The aim of the study was to establish benchmarking for SPID in Telugu using formant frequencies (F_1 , F_2 , and F_3) and bandwidths (B_1 , B_2 and B_3) of nasal continuants.

CHAPTER III

METHOD

Subjects: Twenty Telugu speaking normal males (10) and females (10) in the age range of 21-40 yrs participated in the study. Subjects had passed 10th standard. None of the subjects had (a) any history of speech, language and hearing problems, (b) abnormal oral structure, (c) any other associated psychological or neurological problems, and they were reasonably free from cold or other respiratory illnesses during recording. Hearing screening was done for all subjects using Ling's sound test.

Material: Phonemically there are three nasals in Telugu – (a) /m/ a bilabial, (b) /n/ has four allophones [ṇ] [n] [ñ] and [ŋ]. Before a dental stop it is a dental nasal. Before a palatal stop it is a palatal nasal. Before a velar stop it is a velar nasal. In all other positions it is an alveolar nasal, and (c) /ŋ/, a retroflex.

These six nasal continuants (bilabial, dental, alveolar, retroflex, palatal and velar) in the context of vowels /a/, /i/, /u/ in bisyllabic and trisyllabic meaningful Telugu words were selected for the study. A total of 90 words with the nasal continuants in initial, medial, and final positions were selected. The nasals m, n, ŋ were followed by vowel whereas nasals ṇ, ñ, ṅ, were preceded by vowels. The word list is given in appendix I. Table 1 shows the nasal continuants of Telugu with the position that they occur.

Nasal continuant	Place of Articulation	Position in the word		
		Initial	Medial	Final
/m/	Bilabial	+	+	+
/n/	Alveolar	+	+	-
/ɳ/	Retroflex	-	+	-
/ɲ/	Palatal	+	+	-
/ŋ/	Velar	-	+	-
/ɳ̪/	Dental	-	+	-

Table 1: Nasal continuants of Telugu with its occurrence in various positions in the word.

Procedure: The words were written three each on a card. Subjects were instructed to read the words one after another four times. These were recorded by using Olympus voice recorder.

Analysis: Before analysis the key words were judged by a qualified Speech-Language Pathologist in order to check the accuracy of the production of nasal continuants in words. The data was transferred onto the computer memory using Adobe Audition Software and was sampled at 8000 kHz. Wide band bar type of spectrograms of the words was displayed using the analysis program of PRAAT (Boersma & Weenink, 2009). Two recordings of words were used as trace (training set) and the remaining two as test set. The formant frequencies (F_1 , F_2 , and F_3) and bandwidths (B_1 , B_2 , and B_3) of nasal continuants were extracted in the steady part of the nasal using the wide band bar type of spectrograms. Figure 5 shows the extraction of formant frequencies and bandwidths from PRAAT software.



Figure 5: Extraction of formant frequencies and bandwidths from spectrogram.

Formants and bandwidths were added and averaged to get two vectors X and Y which were calculated as follows:

$$X = \frac{F1 + F2 + B1 + B2}{4} \qquad Y = \frac{F3 + B3}{2}$$

X and Y of the three positions were averaged and normalized using the following formula:

$$\text{Normalization of variable} = \frac{\text{Variable} - \text{Minimum variable}}{\text{Maximum value} - \text{Minimum value}}$$

The purpose of normalization is to convert a data derived from any normal distribution with mean (0) and variance (1). For example, if X= 437, minimum and maximum values are 405 and 870, then N= (437-405) / (870-405) = 0.06. The normalization was done using Microsoft Excel.

Averaged X and Y of the first two recordings in all positions were considered as training set and those of the last two recordings in all positions were considered as test

data. In this study all the voice samples were contemporary, as all the recordings were carried out in one sitting (field recording). Closed-set speaker identification tasks were performed, in which the examiner was aware that the “unknown” speaker was among the “known” ones.

The obtained normalized data of both sets was used to calculate Euclidean distance. The Euclidean distance is an ordinary distance between two points and is a measure of similarity or dissimilarity. The unknown speaker with a least or minimum threshold distance is chosen as known speaker with respect to group of known speaker population. If the distance between the unknown speaker and respective known speaker is less, then speaker identification will be deemed to be correct or otherwise if Euclidean distance is large then it is identified as incorrect or false identification. An illustration is provided in the table 2.

Unknown speaker			Known speakers		
	X1	Y1		X2	Y2
USP1	0.329032	1.100671	SP1	0.632432	1
			SP2	0.183432	0
			SP3	1	0.485981
			SP4	0.247748	0.372014
			SP5	0.586957	0.43554
			SP6	0.906832	0.130045
			SP7	0.761194	0.271795
			SP8	0.675676	0.123123
			SP9	0.367647	0.212644
			SP10	0.173913	0.163701

Table 2: Illustration of comparing unknown speaker (USP1) with known speakers (1 to 10) on nasal continuant /ŋ /.

Euclidean distance was calculated by using the formula given below

$$\text{Euclidean Distance} = \text{Square root } \{(X_2 - X_1)^2 + (Y_2 - Y_1)^2\}$$

Where (X_2, Y_2) , (X_1, Y_1) are training and test data points in scatter plot. In the same way the measurements were done for all 10 unknown speakers separately for each nasal

continuant. Speakers were grouped in to 10, 5, and 2. Euclidean distance between the known and unknown speaker from a closed set was performed. Unknown speaker having the least Euclidean distance with one of the ten known speaker was identified as that speaker. If the same speaker had the least Euclidean distance, then it was deemed to be correct identification. If Euclidean distance was least between two different speakers then it was deemed to be a false identification. An illustration is provided in the table 3.

Unknown speaker			Known speakers			Euclidean distance (ED)
X1	Y1		X2	Y2		
USP1	0.329032	1.100671	SP1	0.632432	1	0.319666
			SP2	0.183432	0	1.11026
			SP3	1	0.485981	0.909968
			SP4	0.247748	0.372014	0.733177
			SP5	0.586957	0.43554	0.713389
			SP6	0.906832	0.130045	1.129588
			SP7	0.761194	0.271795	0.934773
			SP8	0.675676	0.123123	1.037189
			SP9	0.367647	0.212644	0.888867
			SP10	0.173913	0.163701	0.949724

Table 3: Euclidean distances of unknown speaker (USP1) with known speakers (1 to 10) on nasal continuant /ŋ/.

Percentage of correct identifications was determined using the following formula.

$$\text{Percentage of correct identification} = \frac{\text{No. of correct identification}}{\text{Total no. of identifications}} \times 100$$

In the present study, three variables were considered i.e., number of “known” speakers, nasals, and vowels. The effect of these three variables on the percentage of correct speaker identification was examined as outlined below.

1. **Number of “known” speakers:** Percentage of correct identification for three groups of different number of “known” speakers was examined. All the twenty speakers (10 males and 10 females) were randomly listed as speaker 1 to speaker 10. Three groups of speakers were examined - Group A, Group B and Group C. In group A (10 speakers), Group B (5 speakers) and Group C (2 speakers) were considered
2. **Nasals:** percentage of correct identification of six nasals /m/ /n/ /ŋ/ /ɲ/ /ɳ/ and /ɳ̄/ were examined.
3. **Vowels:** Percentage of correct identification for three vowels /a:/, /i:/, and /u:/ preceded/followed by nasal were examined.

CHAPTER IV

RESULTS

Percentage of correct identification was calculated under three groups (Group A, Group B and Group C). Both males and females ten speakers in each were randomly listed as speaker 1 to speaker 10. In group A, one “unknown” speaker was compared with all the ten “known” speakers and the Euclidean distance was calculated. In group B, one “unknown” speaker was compared with all the five “known” speakers and the Euclidean distance was calculated, and finally in the group C one “unknown” speaker was compared with one “known” speaker and the Euclidean distance was calculated. If the distance between unknown speaker and the corresponding known speaker was less, then the speaker was deemed to be correctly identified, if the distance between unknown speaker and the corresponding known speaker was large, then the speaker was deemed to be false.

Group A showed poor benchmarking on all the ten speakers in both males and females of all nasals. The percent correct identification is given in the table 4. Figures 5 and 6 show correct and false identification, respectively.

Nasals	Males			Average	Females			Average
	a	i	u		a	i	u	
m	10	10	20	13	0	20	0	7
n	0	0	0	0	20	0	20	13
ɲ	0	0	0	0	40	0	30	23
ɲ̃	20	10	20	17	30	10	20	20
ɳ	0	30	10	13	30	30	10	23
ɳ̃	20	10	10	13	0	20	30	18
Average	8	10	10		17	13	18	

Table 4: Percent correct identification in males and females in group A.

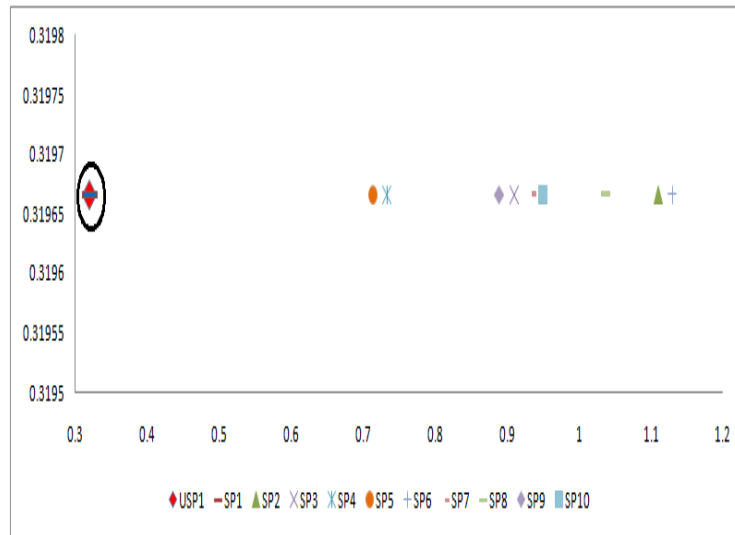


Figure 6: Correct identification of USP1 with SP1 (male speaker) for /ŋ/.

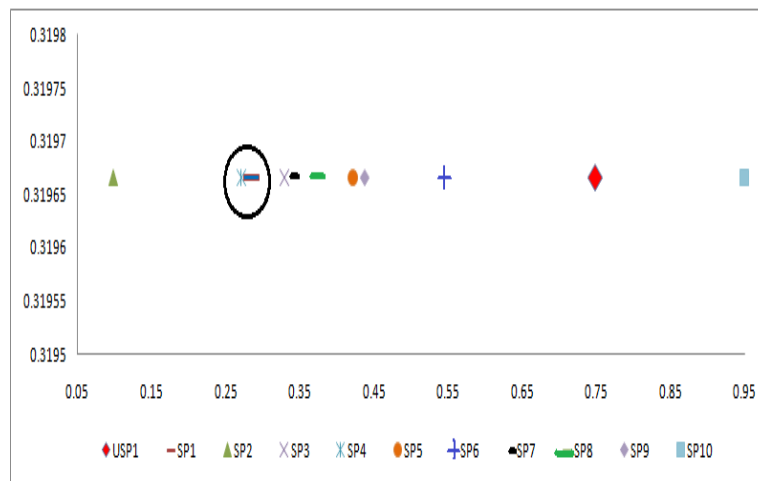


Figure 7: False identification of USP1 with SP4 (male speaker) for /ŋ/.

In a group of five speakers the SPID was poor except for /ñ/ in males (60%) and /n/ and /ŋ/ in females. Table 5 shows percent correct identification and figures 7 and 8 show correct and false identification, respectively.

Nasals	Males			Average	Females			Average
	a	I	u		a	i	U	
m	30	40	40	37	50	30	0	27
n	20	20	30	23	50	30	60	47
ɲ	30	10	10	17	40	30	40	37
ɱ	60	60	50	57	50	40	40	43
ɳ	50	50	50	50	60	60	50	57
ɽ	30	50	20	33	40	50	40	43
Average	35	38	33		48	40	38	

Table 5: Percent correct identification in males and females in group B.

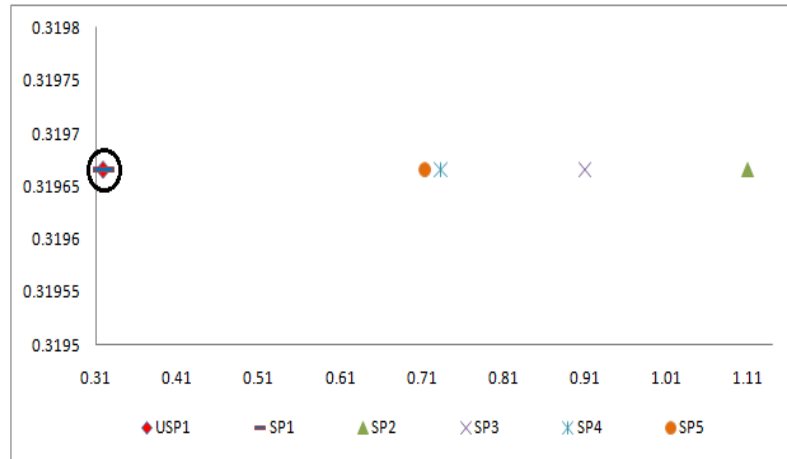


Figure 8: Correct identification of USP1 with SP1 (male speaker) for /ɲ/.

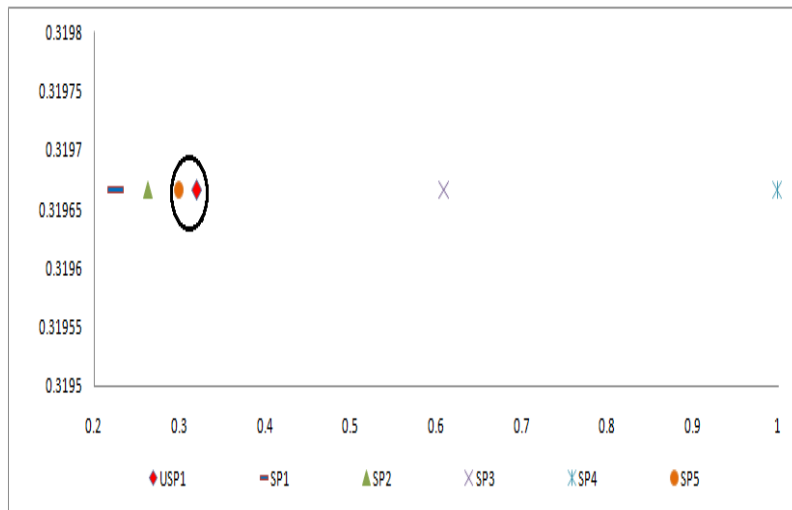


Figure 9: False identification of USP1 with SP5 (male speaker) for /ɲ/.

In a group of two speakers, the percent correct identification was better than those in groups of five and ten speakers. Of the nasals, palatal / \tilde{n} /, retroflex / η / and dental / \underline{n} / had higher percent correct identification than others. Nasals followed by vowels /a/ and /i/ had better identification than others. Tables of Euclidean distance of males and females are given in appendix II and appendix III respectively. Table 6 shows the percent correct identification.

Nasals	Males			Average	Females			Average
	a	i	U		a	i	u	
m	50	50	50	50	50	40	20	36
n	40	60	60	53	60	30	60	50
η	50	20	30	33	60	70	60	63
\tilde{n}	60	90	60	70	60	60	60	60
\underline{n}	70	70	40	60	70	80	50	66
\underline{n}	60	60	40	53	60	60	70	63
Average	56	58	46		60	56	53	

Table 6: Percent correct identification in males and females in group C.

To summarize, the results in group A showed poor percent correct identification in both males and females for all the nasals. In group B, benchmark obtained was poor, except for / \tilde{n} / which had 60 % of identification in males; in females, /n/, and / η / showed 60 % of correct identification and the benchmarking for other nasals were below chance level. Finally, group C showed higher benchmarking for the nasals /n/ / η / / \underline{n} /and / \tilde{n} / for males and the benchmarking for other nasals were below chance level. The nasal / \tilde{n} / showed 90% of benchmarking when it was preceded by a vowel /i/ in males. Female speakers showed better benchmarking for nasals / η / / η / and / \underline{n} / and the benchmarking for other nasals were below chance level. The nasal / η / had 80% correct identification when it was followed by vowel /i/ and 70% for the nasal / \underline{n} /when it was followed by vowel /u/ in females.

All the nasals showed poor benchmarking in a group of ten speakers for both males and females. The benchmarking of the nasals in a group of five speakers was better for /ñ/ (50-60%) in males and /n/ and /ŋ/ (60%) in females, whereas benchmarking for other nasals were below chance level. The benchmarking of the nasal /n/ /ŋ/ /ɲ/ and /ñ/ was better in a group of 2 speakers for males; in females, the nasals /ŋ/ /ɲ/ and /ɳ/ showed better benchmarking than for other nasals. In males, the nasal /ñ/ had highest benchmarking (90%) whereas in females /ŋ/ had highest benchmarking (80%).

Within vowels following/preceding nasals, poor benchmark was obtained for all the vowels in a group of ten speakers for both males and females. Nasals in the context of Vowel /a/ had 20 %, 60% and 70 % in group A, B and C, respectively in males; in females it was 40 %, 60 % and 70 %. Nasals in the context of Vowel /i/ had 30 %, 60 % and 90 % in a group A, B, and C, respectively in males; in females it was 30 %, 60 % and 80 %. Nasals in the context of Vowel /u/ had 20 %, 50 % and 60 % in a group A, B and C, respectively in males; in females it was 30 %, 60 % and 70 %.

The benchmarking depended on the number of speakers, nasals and vowels. Percent correct identification increased with decrease in the number of speakers.

CHAPTER V

DISCUSSION

The present study obtained a benchmark for nasal continuants in Telugu for speaker identification. This was the first attempt to obtain a benchmark for nasal continuants by using formants (F1, F2 & F3) and bandwidths (B1, B2, & B3) as there is a limited research on these parameters of the nasals. The results revealed several points of interest.

Firstly, group A showed poor benchmark for both males and females for all the nasals. In group B, benchmark obtained was poor for both males and females for all nasals, except /ñ/ which had 60 % correct identification in males, and /n/, and /ŋ/ which had 60 % correct identification in females. Benchmarking for other nasals were below chance level. In group C, benchmarking was better for nasals /n/ /ŋ/ /ɳ/ and /ñ/ in males and the benchmarking for other nasals were below chance level. Nasal /ñ/ showed 90% of correct identification when preceded by vowel /i/ in males. Female speakers showed better benchmarking for nasals /ŋ/ /ɳ/ and / ɳ/ and the benchmarking for other nasals were below chance level. Nasal /ŋ/ showed 80% correct identification when followed by a vowel /i/ and 70% for the nasal /ɳ/when followed by vowel /u/ in females.

Second, all the nasals showed poor benchmarking in group A and B. The benchmarking for nasals /n/ /ñ/ /ŋ/ and /ɳ/ was better than the other nasals. In males, nasal /ñ/ had 90% correct identification and /ŋ/ had 70% correct identification. In females /ŋ/ had 80% correct identification and /ŋ/ and /ɳ/ had 70% correct identification. Palatal nasal continuant /ñ/ had the highest percent correct identification.

Thirdly, nasals in the context of vowels had poor benchmarking in group A and B. Nasals in the context of vowel /a/ had 20%, 60%, and 70% correct identification in group A, B, and C, respectively in males. In females, nasals in the context of vowel /a/ had 40%, 60% and 70% correct identification in group A, B and C, respectively. Nasals in the context of vowel /i/ had 30%, 60% and 90% correct identification in group A, B, and C, respectively in males; in females it was 30%, 60% and 80%. Nasals in the context of vowel /u/ had 20%, 50% and 60% correct identification in group A, B, and C, respectively in males; in females it was 30%, 60% and 70%. Of the vowel contexts, context of /i/ in group C was the best with 90% correct identification. Contexts of vowels /a/ /i/ and /u/ in group A had the poorest benchmarking.

Glenn & Kleiner (1968) derived a benchmark of 43% for 300 vectors, 62 % for 150 vectors and 82 % for 60 vectors using power spectra of nasal phonation /n/. However, in the present study palatal nasal /ɲ/ had the best correct percent identification in the context of vowel /i/. The results of the present study are also not in consonance with those of Ying-Yong Qi & Robert (1992) who used perceptual linear predictive method (PLP) for the initial nasal consonants /m/ and /n/ and derived 83 % of benchmark. Jakhar (2009) and Srividya (2010) used cepstra of vowels and reported a benchmarking of more than 80%. In the present study, even with two subjects the benchmarking was 70-90%. The results suggest the benchmarking as in tables 7 and 8.

Groups	Males			Females		
	/a/	/i/	/u/	/a/	/i/	/u/
A	20	30	20	40	30	30
B	60	60	50	60	60	60
C	70	90	60	70	80	70

Table 7: Benchmarking for nasals in three groups and context of vowels.

Groups	Males						Females					
	m	n	ŋ	ñ	ɳ	ɳ̣	m	n	ŋ	ñ	ɳ	ɳ̣
A	13	0	0	18	13	13	7	13	23	20	23	18
B	37	23	17	57	50	33	27	47	37	43	57	43
C	50	53	33	70	60	53	36	50	63	60	66	63

Table 8: Benchmarking for all nasals in three groups.

The results suggest that the benchmarking will be best in the context of vowel /i/ for the palatal nasal / ñ/. Hence, it is recommended that the palatal nasal /ñ/ be used for speaker identification.

The results of the present study have contributed to the field of forensic speaker identification. In general it could be concluded that nasals /ñ/ and / ɳ / in the context of vowels /a/ and /i/ could be used for speaker identification as their benchmarking is \geq 70% when two speakers are compared. The present study is restricted to three vowels, and the language Telugu, field recording, words, and reading. The results can't be generalized to other vowels, other languages, telephone recording and disguise conditions. Future studies in these areas are warranted.

CHAPTER VI

SUMMARY AND CONCLUSIONS

“Forensic voice identification is a legal process to decide whether two or more recordings of speech are spoken by the same speakers” (Rose, 2002). Though it is general assumption that different speakers have different voice, no-one-ever speaks the same word/sentence in exactly the same way (Rose 1996).

Personal identity verification is an essential requirement for controlling access to protected resources. Personal identity is usually claimed by presenting a unique personal possession such as a key, a badge, or a password. However, these can be lost or stolen. Further, a simple identity claim is not sufficient if the potential for loss is great and the penalty for false identification is severe. Hence verification of that claimed identity is necessary. This can be attempted by examining an individual’s biometric features, such as finger prints, hand geometry, or retinal pattern, or by examining certain features derived from the individual’s unique activity such as speech or hand writing. In each case, the features were compared with previously stored features for the person whose identity is being claimed. If this comparison is favorable, based on decision criterion, then the claimed identity is verified.

Among these methods, identity verification based on a person’s voice has special advantages for practical deployment. Speech is our most natural means of communication and therefore user acceptance of the system would be very high.

Speaker recognition can be divided into speaker identification and speaker verification. Speaker identification can be done through close set or open set

identification. Speaker recognition can again be divided into naïve and technical recognition.

There are three methods of speaker identification by listening/perceptual method, by visual method and by machine. There have been several measures for speaker identification, first and second formant frequencies (Stevens, 1971; Atal, 1972; Nolan, 1983; Hollien, 1990; Kuwabara & Sagisaka, 1995 and Lakshmi & Savithri, 2009), higher formants (Wolf, 1972), fundamental frequency (Atkinson, 1976), pitch contour (Atal, 1972), Linear Prediction Coefficients (Markel & Davis, 1979; Soong, Rosenberg, Rabiner, & Juang, 1985), Cepstral Coefficients & Mel Frequency Cepstral Coefficients (Fakotakis, Anastosios & Kokkinakis, 1993; Atal, 1994; Reynold, 1995; Rabiner & Juang, 1993), Long Term Average Spectrum (Kiukaaniemi, Siponen & Mattila, 1982), and Cepstrum (Luck, 1969; Atal, 1974; Furui, 1981; Li & Wrench, 1983; Higgins & Wohlford, 1986; Che & Lin, 1995; Jakkar, 2009) have been used in the past.

Glenn & Kleiner (1968), describe a method of automatic speaker identification based on the physiology of the vocal apparatus and essentially independent of the spoken message. Power spectra produced during nasal phonation are transformed and statistically matched. Initially, the population of 30 speakers was divided into three subclasses, each containing 10 speakers. Subclass 1 contained 10 male speakers, Subclass 2 contained 10 female speakers, and Subclass 3 contained an additional 10 male speakers. For each speaker, all 10 samples of the spectrum of /n/ from the test set were averaged to form a test vector. The test vectors were compared, with the stored speaker reference vectors for the appropriate subclass. The values of the cosine of the angle between the reference and the test vectors were correlation values between the test vector for a given speaker and the reference vector for each speaker in the subclass. The

maximum correlation value for each test vector was used and 97% over all correct identification was attained. Next, the effect of a larger population was tested by correlating each speaker's averaged test data with the reference vectors for all 30 speakers and an average identification accuracy of 93 % was reached. Finally, the effect of averaging speaker samples was tested as follows. The same speaker reference vectors based on all 10 training samples were used. However, the test data were subjected to varying degrees of averaging. First, single-speaker samples were correlated with the 30 speaker reference vectors. The average identification accuracy for all 300 such samples (10 per speaker) was 43%. Then, averages of two speaker samples from the test data were taken as test vectors. The average identification accuracy for 150 such vectors was 62%. Next averages of five speaker samples from the test data were taken as test vectors. The average identification accuracy for 60 such vectors was 82%. The procedure developed to exploit this information provides a basis for automatic speaker identification without detailed knowledge of the message spoken. This study was focused on the nasal phonation using power spectra, used reference and test vectors. This is the only study using spectra of nasal continuants. Given the physiology of nasal continuant production one needs to explore on the possibility of using nasal continuants for SPID. Further, the frequency of the occurrence of the nasal continuants is 10.06% [/m/ = 0.01%, /n/ = 6.35%, /ñ/= 0%, /ŋ/= 0.36% and /ŋ/= 0.01% in Telugu, (Ramakrishna, Nair, Chipplunkar, Atal, Ramachandran, & Subramanian, 1962).

Ying-Yong Qi & Robert (1989) have studied the acoustic features of the nasals [m, n] in CV syllables and [m, n, ŋ] in VC syllables in English by using cepstrally smoothed running FFT spectra. Results indicated that the antiresonances of nasals in a

VC syllable could be consistently estimated by a two- step AR approximation method that could be used to distinguish reliably between [m] and [n].

Ying-Yong Qi & Robert (1992) studied nasal consonants using perceptual linear predictive (PLP) method. Six speakers produced 300 CV syllables with initial nasal consonants /m/and /n/. Results indicated that the frequencies for the transformed poles, particularly for the second pole, were significantly lower for /m/ than for/n/and were independent of factors such as vowel context and gender of the speaker. A nasal identification rate of 86% was obtained based on the frequency of the second pole. The use of the PLP method clearly has overcome difficulties associated with the anti resonance in analyzing nasal consonants.

The review indicates that earlier studies used aural and visual methods for SPID using formants, power spectra and perceptual linear predictive (PLP). There has been no particular research done till date using nasal formants and bandwidths. In this context the present study was planned to provide ***“benchmark for nasal continuants in Telugu for speaker identification”***.

Twenty normal Telugu speaking males (10) and females (10) in the age range of 21-40 years participated in the study. Six nasal continuants (bilabial, dental, alveolar, retroflex, palatal and velar) with vowels /a/, /i/, /u/ in bisyllabic and trisyllabic meaningful Telugu words and a total of 90 words with the nasal continuants in initial, medial, and final positions formed the material. The participants were instructed to read the words one after another four times. These were recorded by using Olympus voice recorder. Before analysis the key words were judged by a qualified speech-language pathologist in order to check the accuracy of the production of nasal continuants in

words. The data was transferred on to the computer memory using Adobe Audition Software and was sampled at 8000 kHz. Wide band spectrograms of the words were displayed using the analysis program of PRAAT (Boersma & Weenink, 2009). Two recordings of words were used as trace (training set) and the remaining two as test set. The formant frequencies (F_1 , F_2 , and F_3) and bandwidths (B_1 , B_2 , and B_3) of nasal continuants were extracted using the wide band spectrograms. In this study all the voice samples were contemporary, as all the recordings were carried out in one sitting (field recording). Closed-set speaker identification tasks were performed, in which the examiner was aware that the “unknown” speaker was among the “known” ones. All the positions (initial, medial and final) were combined and the average was taken for each nasal. The average of formants (F_1 & F_2) and bandwidths (B_1 & B_2) of recordings A and B (training set) was considered as X_1 and the average of formants and bandwidths (F_3 & B_3) was considered as Y_1 . Similarly the average of formants (F_1 & F_2) and bandwidths (B_1 & B_2) of recordings C & D (test set) was considered as X_2 and the average of formants and bandwidths (F_3 & B_3) were considered as Y_2 . The average of formant frequencies and bandwidths of both sets were normalized using the following formula:

$$\text{Normalization of variable} = \frac{\text{Variable} - \text{Minimum variable}}{\text{Maximum value} - \text{Minimum value}}$$

Euclidean distance was calculated by using the formula given below:

$$\text{Euclidean Distance} = \text{Square root } \{(X_2 - X_1)^2 + (Y_2 - Y_1)^2\}$$

Where (X_2, Y_2) , (X_1, Y_1) are training and test data points in scatter plot. In the same way the Euclidean distances were measured for all 10 unknown speakers separately for each nasal continuant. Speakers were grouped in to 10, 5, and 2. Euclidean distance between the known and unknown speaker from a closed set the speaker identification task was performed. Percentage of correct identifications was determined using the formula.

$$\text{Percentage of correct identification} = \frac{\text{No. of correct identification}}{\text{Total no. of identifications}} \times 100$$

In the present study, three variables were considered i.e., number of “known” speakers, nasals, and vowels. The effect of these three variables on the percentage of correct speaker identification was examined.

Firstly, group A showed poor benchmark for both males and females for all the nasals. In group B, benchmark obtained was poor for both males and females for all nasals, except /ñ/ which had 60 % correct identification in males, and /n/, and /ŋ/ which had 60 % correct identification in females. Benchmarking for other nasals were below chance level. In group C, benchmarking was better for nasals /n/ /ŋ/ /ɲ/ and /ñ/ in males and the benchmarking for other nasals were below chance level. Nasal /ñ/ showed 90% of correct identification when preceded by vowel /i/ in males. Female speakers showed better benchmarking for nasals /ŋ/ /ɲ/ and / ɲ/ and the benchmarking for other nasals were below chance level. Nasal /ŋ/ showed 80% correct identification when followed by a vowel /i/ and 70% for the nasal /ɲ/when followed by vowel /u/ in females.

Second, all the nasals showed poor benchmarking in group A and B. The benchmarking for nasals /n/ /ñ/ /ŋ/ and /ŋ/ was better than the other nasals. In males, nasal /ñ/ had 90% correct identification and /ŋ/ had 70% correct identification. In females /ŋ/ had 80% correct identification and /ŋ/ and /ŋ/ had 70% correct identification. Palatal nasal continuant /ñ/ had the highest percent correct identification.

Thirdly, nasals in the context of vowels had poor benchmarking in group A and B. Nasals in the context of vowel /a/ had 20%, 60%, and 70% correct identification in group A, B, and C, respectively in males. In females, nasals in the context of vowel /a/ had 40%, 60% and 70% correct identification in group A, B and C, respectively. Nasals in the context of vowel /i/ had 30%, 60% and 90% correct identification in group A, B, and C, respectively in males; in females it was 30%, 60% and 80%. Nasals in the context of vowel /u/ had 20%, 50% and 60% correct identification in group A, B, and C, respectively in males; in females it was 30%, 60% and 70%. Of the vowel contexts, context of /i/ in group C was the best with 90% correct identification. Contexts of vowels /a/ /i/ and /u/ in group A had the poorest benchmarking.

Glenn & Kleiner (1968) derived a benchmark of 43% for 300 vectors, 62 % for 150 vectors and 82 % for 60 vectors using power spectra of nasal phonation /n/. However, in the present study palatal nasal /ñ/ had the best correct percent identification in the context of vowel /i/. The results of the present study are also not in consonance with those of Ying-Yong Qi & Robert (1992) who used perceptual linear predictive method (PLP) for the initial nasal consonants /m/ and /n/ and derived 83 % of benchmark. Jakhar (2009) and Srividya (2010) used cepstra of vowels and reported a benchmarking of more than 80%. In the present study, even with two subjects the benchmarking was 70-90%.

The results suggest that the benchmarking will be best in the context of vowel /i/ for the palatal nasal / ñ/. Hence, it is recommended that the palatal nasal /ñ/ be used for speaker identification.

The results of the present study have contributed to the field of forensic speaker identification. In general it could be concluded that nasals /ñ/ and / ŋ / in the context of vowels /a/ and /i/ could be used for speaker identification as their benchmarking is \geq 70% when two speakers are compared. The present study is restricted to three vowels, and the language Telugu, field recording, words, and reading. The results can't be generalized to other vowels, other languages, telephone recording and disguise conditions. Future studies in these areas are warranted.

References

- Behrman, A. (2007). *Speech and voice science*, Plural publishing Inc, San Diego, CA
- Borden, G. F., & Harris, K.S. (1980). *Speech Science Primer: physiology, acoustics and perception of speech*, Williams & Wilkins, Baltimore, USA.
- Boersma, P. & Weenink, D. (2009). PRAAT 5.1.14 software. Retrieved from <http://www.goofull.com/au/program/14235/speedytunes.html>.
- Deller, J. R., Hansen. J. H.L. & Proakis. J.G (2000). *Discrete-Time Processing of Speech signals*, IEEE Press, Piscataway, NJ.
- Glenn, J. W., & Kleiner, N. (1968). Speaker identification based on nasal phonation, *J Acoust. Soc. Amer* vol, 43 (2), 368-372.
- Glass, J. R. (1984). *Nasal consonants and nasalized vowels: An acoustic study and recognition experiment*”, Master’s thesis, Massachusetts Institute of Technology.
- Pickett, J. M. (1999). *The Acoustics of Speech Communication: Fundamentals, Speech Perception Theory, and Technology*. Boston: Allyn & Bacon
- Jakhar, S. S. (2009). *Benchmarks for speaker identification using Cepstral coefficient in Hindi*. Unpublished project of Post graduate Diploma in Forensic Speech Science and Technology submitted to university of Mysore, Mysore.
- Kent R. D. (1997). *The speech sciences*, singular publications, London
- Kent R. D. & Read (2002) .*The acoustics analysis of speech*, 2nd edition, singular publications, London
- Lakshmi, P. (2009). *Benchmark for speaker identification using vector $F_2 \approx F_1$ vector*. Unpublished project of Post graduate Diploma in Forensic Speech Science and Technology submitted to university of Mysore, Mysore.
- Lakshmi, P & Savithri, S. R (2009). *Benchmark for speaker identification using vector $F_2 \approx F_1$ vector*, FRSM-09 Proceedings.
- Orlikoff, R. F., & Baken, R. J. (1993). *Clinical Speech and voice measurement; laboratory exercises*, Singular publishing group, INC. San Diego, CA.
- Potter, R., Kopp, G., & Green, H. (1947). *Visible Speech*. New York: Dover.

- Ramakrishna, B.S., Nair, K.K., Chiplunkar, V.N., Atal, B.S., Ramachandran, V., & Subramanian, R. (1962). *Some aspects of the relative efficiencies of Indian languages*. Bangalore.
- Rossing, T. D., Moore, F. R., & Wheeler, P. A. (2002). *The science of sound* 3rd edn. San Francisco: Addison Wesley.
- Srividya, C. (2010). Benchmarks for speaker identification using Cepstral coefficient in Kannada. Unpublished project of Post graduate Diploma in Forensic Speech Science and Technology submitted to university of Mysore, Mysore.
- Venkateswara, S. J. (1972 & 2000). Telugu phonetic reader, Central institute of Indian languages, Mysore.
- Ying-Yong Qi & Robert, A. F. (1989). Acoustic features of nasal consonants in VC contexts J. Acoust. Soc. Amer . vol 85 (S1), S56-S56.
- Ying-Yong Qi & Robert, A. F. (1992). Analysis of nasal consonants using perceptual linear prediction. J. Acoust. Soc. Am. 91 (3), 1718-1726.
- [www./http//.telugulanguage.com](http://www.telugulanguage.com)

Appendix I – List of words (test material)

S.no	Nasal (target sound)	Position of the nasal sound		
		I	M	F
1	/ma/	/manamu/	/tamaki/	/kusuma/
2		/mad.ugu/	/tamaru/	/godhuma/
3		/mad.ici/	/samatha/	/kanuma/
4	/mi/	/mirapa/	/samithi/	/tad.imi/
5		/minaha/	/bhi:mili/	/pud.ami/
6		/mid.tha/	/namili/	/dasami/
7	/mu/	/muriki/	/camuru/	/tharumu/
8		/mud.atha/	/d.amuru/	/kalamu/
9		/muthaka/	/pa:mulu/	/dzanamu/
10	/na/	/nalusu/	/panasa/	/madana/
11		/nalaka/	/manasu/	/ve:dana/
12		/navala/	/vanamu/	/pudi:na/
13	/ni/	/niluva/	/manishi/	/va:rini/
14		/niluvu/	/vanitha/	/ra:gini/
15		/nidulu/	/va:niki/	/pa:vani/
16	/nu/	/nuduru/	/vinut.a/	/padunu/
17		/nurugu/	/kanut.a/	/cadunu/
18		/nulaka/	/dzanumu/	/pad.unu/
		/a/	/i/	/u/
19	/ŋ/	/raŋam/	/biŋdi/	/guŋdzu/
20		/caŋka/	/giŋdza/	/puŋd.u/
21		/vaŋka/	/biŋdu/	/vuŋd.u/
22	/ɲ/	/saɲci/	/ciɲcu/	/cuɲcu/
23		/vaɲci/	/miɲcu/	/muɲcu/
24		/gaɲdzi/	/kiɲcu/	/tuɲcu/
25	/ɳ/	/ruɳamu/	/maɳi/	/miɳuku/
26		/guɳamu/	/phaɳi/	/kaɳupu/
27		/ba:ɳamu/	/bo:ɳi/	/beɳuku/
28	/ɳ/	/paɳdi/	/viɳtha/	/vuɳdi/
29		/baɳthi/	/piɳde/	/kuɳti/
30		/vaɳda/	/viɳdu/	/kuɳdu/

Appendix II – Tables of Euclidean distance of all nasals in males (correct/false identification was kept in bold numbers)

/m/ Speaker 1

Unknown speaker	Speakers	Euclidean distance (ED)		
		ma	mi	mu
USP1	SP1	0.150612	0.327259	0.171005
	SP2	0.132661	0.708882	0.513457
	SP3	0.139998	0.491714	0.899272
	SP4	0.171301	0.402117	0.922363
	SP5	0.206774	0.49976	0.440627
	SP6	0.115026	0.338387	0.573655
	SP7	0.392943	0.442717	0.247188
	SP8	0.152341	0.299933	0.369612
	SP9	0.243736	0.620285	0.33713
	SP10	0.509839	0.984351	0.160074

Speaker 2

Unknown speaker	Speakers	Euclidean distance (ED)		
		ma	mi	mu
USP2	SP1	0.612346	0.429089	0.883385
	SP2	0.616019	0.104226	0.616557
	SP3	0.543729	0.320988	0.336878
	SP4	0.829037	0.46026	0.234593
	SP5	0.672303	0.214435	0.572717
	SP6	0.702384	0.342518	0.546921
	SP7	0.988235	0.362203	0.805003
	SP8	0.816209	0.38165	0.672771
	SP9	0.878815	0.08467	0.680451
	SP10	1.053904	0.510228	0.959592

Speaker 3

Unknown speaker	Speakers	Euclidean distance (ED)		
		ma	mi	mu
USP3	SP1	0.456166	0.173325	0.390437
	SP2	0.286419	0.481799	0.408942
	SP3	0.30659	0.30049	0.554155
	SP4	0.58361	0.271832	0.519471
	SP5	0.543722	0.278386	0.184912
	SP6	0.359071	0.108174	0.392552
	SP7	0.803905	0.266793	0.308215
	SP8	0.56392	0.071559	0.320685
	SP9	0.656571	0.391865	0.273956
	SP10	0.913858	0.78977	0.458481

Speaker 4

Unknown speaker	Speakers	Euclidean distance (ED)		
		ma	mi	mu
USP4	SP1	0.332874	0.438663	0.732049
	SP2	0.101399	0.539455	0.357181
	SP3	0.211	0.260007	0.107253
	SP4	0.355349	0.116401	0.096938
	SP5	0.40774	0.472724	0.407069
	SP6	0.106309	0.300598	0.28426
	SP7	0.585348	0.518648	0.66597
	SP8	0.334389	0.302566	0.459229
	SP9	0.432298	0.537284	0.49285

	SP10	0.709811	0.706323	0.814405
--	------	----------	----------	----------

Speaker 5

Unknown speaker	Speakers	Euclidean distance (ED)		
		ma	mi	mu
USP5	SP1	0.916183	0.126333	0.827581
	SP2	0.95905	0.507322	0.469046
	SP3	0.876327	0.349873	0.130635
	SP4	1.141025	0.32924	0.02835
	SP5	0.958813	0.27458	0.501557
	SP6	1.04416	0.133474	0.396129
	SP7	1.267912	0.231876	0.757683
	SP8	1.13108	0.089306	0.565997
	SP9	1.18001	0.398767	0.594495
	SP10	1.309569	0.833623	0.909086

Speaker 6

Unknown speaker	Speakers	Euclidean distance (ED)		
		ma	mi	mu
USP6	SP1	0.227531	0.428255	0.518962
	SP2	0.124588	0.607403	0.118495
	SP3	0.186305	0.33545	0.307947
	SP4	0.191279	0.199858	0.342588
	SP5	0.280203	0.502388	0.220485
	SP6	0.057761	0.320585	0.053269
	SP7	0.421278	0.522356	0.465652
	SP8	0.17032	0.310069	0.222042
	SP9	0.268228	0.584113	0.270958
	SP10	0.546286	0.79418	0.601528

Speaker 7

Unknown speaker	Speakers	Euclidean distance (ED)		
		ma	mi	mu
USP7	SP1	0.120383	0.1465	0.692681
	SP2	0.118182	0.422989	0.229592
	SP3	0.043356	0.274216	0.210403
	SP4	0.259424	0.280647	0.293823
	SP5	0.205098	0.210722	0.406218
	SP6	0.165482	0.048105	0.176484
	SP7	0.462973	0.21701	0.645732
	SP8	0.24323	0.004033	0.385631
	SP9	0.323602	0.324558	0.446143
	SP10	0.567809	0.750867	0.774092

Speaker 8

Unknown speaker	Speakers	Euclidean distance (ED)		
		ma	mi	mu
USP8	SP1	0.500201	0.623884	0.513243
	SP2	0.271336	0.15285	0.070477
	SP3	0.354504	0.315105	0.335852
	SP4	0.549488	0.452767	0.382053
	SP5	0.582762	0.433928	0.238799
	SP6	0.300448	0.481568	0.00308
	SP7	0.779487	0.587622	0.467155
	SP8	0.528529	0.525765	0.206948

Speaker 9

	SP9	0.626437	0.331606	0.266842
	SP10	0.90356	0.25501	0.594785

Unknown speaker	Speakers	Euclidean distance (ED)		
		ma	mi	mu
USP9	SP1	0.207392	0.380224	0.461221
	SP2	0.237324	0.118114	0.375494
	SP3	0.252793	0.21269	0.465291
	SP4	0.064772	0.350533	0.426776
	SP5	0.218226	0.188888	0.190346
	SP6	0.184268	0.258369	0.343924
	SP7	0.294771	0.341669	0.380783
	SP8	0.043812	0.301147	0.325863
	SP9	0.141721	0.121667	0.298404
	SP10	0.42049	0.495611	0.534636

Speaker 10

Unknown speaker	Speakers	Euclidean distance (ED)		
		ma	mi	mu
USP10	SP1	0.237056	0.228063	0.380087
	SP2	0.378463	0.316583	0.237681
	SP3	0.354804	0.372483	0.449797
	SP4	0.103279	0.464091	0.444984
	SP5	0.183022	0.057416	0.056093
	SP6	0.341671	0.233376	0.224666
	SP7	0.15127	0.138291	0.310386
	SP8	0.12171	0.251544	0.177437
	SP9	0.054558	0.142233	0.1649
	SP10	0.264217	0.719079	0.461318

/n/ Speaker 1

Unknown speaker	Speakers	Euclidean distance (ED)		
		na	ni	nu
USP1	SP1	0.400162	0.289902	0.481809
	SP2	0.331697	0.32908	0.247461
	SP3	0.464957	0.171042	0.545632
	SP4	0.581746	0.294297	0.397812
	SP5	0.828267	0.29711	0.424572
	SP6	0.914614	0.090497	0.587862
	SP7	0.853609	0.673612	0.612142
	SP8	0.811293	0.387244	0.512011
	SP9	0.529881	0.460632	0.569495
	SP10	0.706061	0.617122	0.900195

Speaker 2

Unknown speaker	Speakers	Euclidean distance (ED)		
		na	ni	nu
USP2	SP1	0.4345	0.302873	0.378299
	SP2	0.312658	0.254269	0.866174
	SP3	0.249834	0.48694	0.305242
	SP4	0.063668	0.46248	0.352021
	SP5	0.211181	0.726071	0.476714
	SP6	0.583155	0.502829	0.25251
	SP7	0.335731	0.334576	0.297323
	SP8	0.400874	0.60909	0.349971
	SP9	0.148045	0.209228	0.296233

	SP10	0.515456	0.28822	0.524039
--	------	----------	---------	----------

Speaker 3

Unknown speaker	Speakers	Euclidean distance (ED)		
		na	ni	nu
USP3	SP1	0.218515	0.39167	0.370317
	SP2	0.116084	0.424599	0.319212
	SP3	0.212446	0.254719	0.437937
	SP4	0.339065	0.374899	0.275368
	SP5	0.573045	0.257473	0.341374
	SP6	0.696784	0.18496	0.476064
	SP7	0.601082	0.771322	0.497033
	SP8	0.57137	0.403533	0.40884
	SP9	0.274067	0.561866	0.461939
	SP10	0.509323	0.71579	0.810513

Speaker 4

Unknown speaker	Speakers	Euclidean distance (ED)		
		na	ni	nu
USP4	SP1	0.52543	0.265591	0.212602
	SP2	0.316001	0.229411	0.73169
	SP3	0.514747	0.242307	0.609013
	SP4	0.546793	0.35106	0.368732
	SP5	0.818055	0.266049	0.634602
	SP6	1.013034	0.167132	0.608922
	SP7	0.888699	0.6573	0.295474
	SP8	0.878872	0.275869	0.61262
	SP9	0.54219	0.42896	0.626545
	SP10	0.82551	0.59747	1.00031

Speaker 5

Unknown speaker	Speakers	Euclidean distance (ED)		
		na	ni	nu
USP5	SP1	0.498471	0.211093	0.460885
	SP2	0.56339	0.331518	0.230263
	SP3	0.633711	0.027235	0.398327
	SP4	0.799348	0.138502	0.317084
	SP5	1.015418	0.456649	0.257077
	SP6	0.985028	0.080749	0.446749
	SP7	1.000038	0.548569	0.574482
	SP8	0.92645	0.52135	0.359218
	SP9	0.720672	0.361173	0.421298
	SP10	0.763529	0.496789	0.731835

Speaker 6

Unknown speaker	Speakers	Euclidean distance (ED)		
		na	ni	nu
USP6	SP1	0.325206	0.106851	0.369756
	SP2	0.334415	0.185351	0.585073
	SP3	0.165049	0.125143	0.040894

	SP4	0.182091	0.195933	0.203865
	SP5	0.2207	0.430901	0.178801
	SP6	0.432459	0.115166	0.07073
	SP7	0.238345	0.498394	0.395859
	SP8	0.257592	0.43286	0.060172
	SP9	0.109045	0.278132	0.061566
	SP10	0.352504	0.440031	0.439403

Speaker 7

Unknown speaker	Speakers	Euclidean distance (ED)		
		na	ni	nu
USP7	SP1	0.492267	0.263508	0.199399
	SP2	0.38705	0.142065	0.78393
	SP3	0.310054	0.433222	0.608002
	SP4	0.136854	0.445277	0.376834
	SP5	0.149308	0.596757	0.652554
	SP6	0.573958	0.426551	0.601646
	SP7	0.302243	0.446677	0.252097
	SP8	0.389807	0.469558	0.616781
	SP9	0.210081	0.258813	0.623608
	SP10	0.535224	0.392194	0.990972

Speaker 8

Unknown speaker	Speakers	Euclidean distance (ED)		
		na	ni	nu
USP8	SP1	0.465662	0.28869	0.238196
	SP2	0.459557	0.320757	0.529895
	SP3	0.309934	0.178487	0.198439
	SP4	0.244325	0.301524	0.051001
	SP5	0.082752	0.287615	0.232338
	SP6	0.426426	0.096	0.216375
	SP7	0.149124	0.674956	0.307595
	SP8	0.243749	0.373659	0.194354
	SP9	0.23754	0.459827	0.21959
	SP10	0.421967	0.618013	0.597385

Speaker 9

Unknown speaker	Speakers	Euclidean distance (ED)		
		na	ni	nu
USP9	SP1	0.405882	0.244914	0.244113
	SP2	0.520201	0.073524	0.744257
	SP3	0.318947	0.371049	0.249561
	SP4	0.376615	0.420648	0.210484
	SP5	0.256512	0.458885	0.391711
	SP6	0.242797	0.339999	0.214116
	SP7	0.11074	0.542765	0.200534
	SP8	0.059365	0.33798	0.284016
	SP9	0.304322	0.323847	0.25246
	SP10	0.25268	0.483844	0.575894

Speaker 10

Unknown speaker	Speakers	Euclidean distance (ED)		
		na	ni	nu
USP10	SP1	0.267077	0.291122	0.586404
	SP2	0.229056	0.188159	0.649971
	SP3	0.083111	0.467549	0.177164
	SP4	0.145871	0.468872	0.418373
	SP5	0.308042	0.645884	0.236506
	SP6	0.510645	0.466846	0.194022
	SP7	0.34405	0.423326	0.599387
	SP8	0.348085	0.51551	0.176202
	SP9	0.021519	0.256261	0.162895
	SP10	0.389039	0.37201	0.241919

/ŋ/ Speaker 1

Unknown speaker	Speakers	Euclidean distance (ED)		
		aŋ	iŋ	uŋ
USP1	SP1	0.117298	0.470652	0.233843
	SP2	0.455589	0.184801	0.214913
	SP3	0.464447	0.307669	0.322852
	SP4	0.201248	0.44753	0.382504
	SP5	0.160508	0.294799	0.447639
	SP6	0.082865	0.392665	0.380593
	SP7	0.544412	0.874415	0.76094
	SP8	0.187517	0.429207	0.517289
	SP9	0.100309	0.211879	0.200736
	SP10	0.47982	0.440475	0.543836

Speaker 2

Unknown speaker	Speakers	Euclidean distance (ED)		
		aŋ	iŋ	uŋ
USP2	SP1	0.610253	0.326134	0.935231
	SP2	0.74315	0.694377	1.130327
	SP3	1.025116	0.730628	0.791903
	SP4	0.591481	0.623009	0.71833
	SP5	0.562828	0.624035	0.655029
	SP6	0.626958	1.049027	0.631192
	SP7	0.245703	0.588039	0.625131
	SP8	0.773023	0.704078	0.680294
	SP9	0.65159	0.83519	0.794533
	SP10	0.738054	0.780542	0.698357

Speaker 3

Unknown speaker	Speakers	Euclidean distance (ED)		
		aŋ	iŋ	uŋ
USP3	SP1	0.232252	0.369904	0.361757
	SP2	0.619014	0.723312	0.602751
	SP3	0.619111	0.73738	0.370327
	SP4	0.188599	0.607331	0.180056
	SP5	0.184626	0.638415	0.16
	SP6	0.261502	1.13019	0.055949

	SP7	0.204998	0.493167	0.600024
	SP8	0.37134	0.690612	0.249598
	SP9	0.344712	0.857847	0.221237
	SP10	0.378279	0.76648	0.287058

Speaker 4

Unknown speaker	Speakers	Euclidean distance (ED)		
		a _{ij}	i _{ij}	j _{ij}
USP4	SP1	0.414557	0.36629	0.403889
	SP2	0.508793	0.296046	0.044123
	SP3	0.869562	0.430938	0.334844
	SP4	0.425417	0.509865	0.550586
	SP5	0.3729	0.360412	0.612028
	SP6	0.421288	0.411925	0.529134
	SP7	0.265453	0.874641	0.765165
	SP8	0.592622	0.526448	0.68688
	SP9	0.41967	0.397382	0.355481
	SP10	0.657461	0.564984	0.71492

Speaker 5

Unknown speaker	Speakers	Euclidean distance (ED)		
		a _{ij}	i _{ij}	j _{ij}
USP5	SP1	0.073061	0.345371	0.163022
	SP2	0.44439	0.05651	0.420265
	SP3	0.513329	0.191798	0.337766
	SP4	0.162069	0.300311	0.174749
	SP5	0.096765	0.14403	0.235708
	SP6	0.041179	0.540145	0.176597
	SP7	0.466711	0.719563	0.711853
	SP8	0.225342	0.297092	0.311679
	SP9	0.090697	0.185522	0.039736
	SP10	0.465412	0.327246	0.341874

Speaker 6

Unknown speaker	Speakers	Euclidean distance (ED)		
		a _{ij}	i _{ij}	j _{ij}
USP6	SP1	0.402036	0.482004	0.463086
	SP2	0.272926	0.202625	0.193493
	SP3	0.863029	0.32531	0.182011
	SP4	0.45917	0.465315	0.540351
	SP5	0.382395	0.312338	0.587647
	SP6	0.386931	0.374783	0.479285
	SP7	0.480899	0.89152	0.596191
	SP8	0.574811	0.447036	0.675037
	SP9	0.314038	0.226406	0.338114
	SP10	0.752803	0.457808	0.708366

Speaker 7

Unknown speaker	Speakers	Euclidean distance (ED)		
		a _{ij}	i _{ij}	j _{ij}
USP7	SP1	0.479783	0.500044	0.598825
	SP2	0.606605	0.479769	0.622533
	SP3	0.916876	0.615917	0.260671

	SP4	0.474109	0.694622	0.482608
	SP5	0.434246	0.546886	0.471395
	SP6	0.492447	0.353721	0.353019
	SP7	0.214294	1.038548	0.289641
	SP8	0.650939	0.713128	0.559033
	SP9	0.507339	0.566529	0.404849
	SP10	0.667373	0.750807	0.595932

Speaker 8

Unknown speaker	Speakers	Euclidean distance (ED)		
		a _{ij}	i _{ij}	j _{ij}
USP8	SP1	0.19148	0.275572	0.290353
	SP2	0.352718	0.157593	0.2392
	SP3	0.650396	0.2812	0.216934
	SP4	0.259664	0.34731	0.373964
	SP5	0.180159	0.199248	0.428568
	SP6	0.174171	0.531329	0.335904
	SP7	0.432678	0.727022	0.654105
	SP8	0.362049	0.366383	0.510644
	SP9	0.12561	0.290213	0.170972
	SP10	0.565331	0.410457	0.542027

Speaker 9

Unknown speaker	Speakers	Euclidean distance (ED)		
		a _{ij}	i _{ij}	j _{ij}
USP9	SP1	0.319241	0.506109	0.553033
	SP2	0.744457	0.299863	0.567456
	SP3	0.616497	0.431003	0.208047
	SP4	0.246874	0.556946	0.452522
	SP5	0.278022	0.400536	0.448986
	SP6	0.354393	0.287767	0.325408
	SP7	0.188396	0.966771	0.324118
	SP8	0.413548	0.548499	0.539778
	SP9	0.455699	0.340335	0.357592
	SP10	0.308074	0.565873	0.577228

Speaker 10

Unknown speaker	Speakers	Euclidean distance (ED)		
		a _{ij}	i _{ij}	j _{ij}
USP10	SP1	0.420241	0.258863	0.157056
	SP2	0.855025	0.306107	0.472412
	SP3	0.051837	0.261781	0.383023
	SP4	0.402492	0.116099	0.121411
	SP5	0.455357	0.193847	0.18624
	SP6	0.427856	0.86005	0.151929
	SP7	0.766634	0.394821	0.736956
	SP8	0.239923	0.198995	0.257924
	SP9	0.513461	0.406131	0.090007
	SP10	0.371032	0.275208	0.287403

/ñ/ Speaker 1

Unknown speaker	Speakers	Euclidean distance (ED)		
		añ	iñ	uñ
USP1	SP1	0.450428	0.227532	0.100318
	SP2	0.754993	0.601938	0.33331
	SP3	0.91344	0.749362	0.71342
	SP4	0.39802	0.922174	0.359835
	SP5	0.532628	1.148611	0.711248
	SP6	0.249138	0.818781	0.938599
	SP7	0.352693	0.652696	1.046851
	SP8	0.03121	0.825031	0.586559
	SP9	0.094792	0.685362	0.875439
	SP10	0.463593	1.233374	0.774491

Speaker 2

Unknown speaker	Speakers	Euclidean distance (ED)		
		añ	iñ	uñ
USP2	SP1	0.458994	0.169878	0.555265
	SP2	0.814306	0.218825	0.323749
	SP3	0.976132	0.470435	0.417014
	SP4	0.534058	0.610212	0.376997
	SP5	0.669341	0.926831	0.54114
	SP6	0.347525	0.490874	0.410819
	SP7	0.215257	0.450699	0.433083
	SP8	0.158134	0.639378	0.104314
	SP9	0.216058	0.543561	0.373165
	SP10	0.601631	1.054039	0.179087

Speaker 3

Unknown speaker	Speakers	Euclidean distance (ED)		
		añ	iñ	uñ
USP3	SP1	0.519762	0.681614	0.257263
	SP2	0.80524	0.332337	0.16263
	SP3	0.961021	0.337656	0.477924
	SP4	0.353578	0.265275	0.134747
	SP5	0.489497	0.662211	0.470996
	SP6	0.289598	0.20305	0.864964
	SP7	0.39923	0.486109	0.870878
	SP8	0.092869	0.560129	0.416329
	SP9	0.030844	0.597207	0.662007
	SP10	0.428571	0.835762	0.60019

Speaker 4

Unknown speaker	Speakers	Euclidean distance (ED)		
		añ	iñ	uñ
USP4	SP1	0.186581	0.513394	0.312921
	SP2	0.294265	0.270526	0.167757
	SP3	0.454959	0.135061	0.504759
	SP4	0.573644	0.205574	0.260323
	SP5	0.648081	0.570182	0.581453
	SP6	0.234534	0.084728	0.564511
	SP7	0.644179	0.263466	0.676594

	SP8	0.431966	0.373396	0.241359
	SP9	0.511031	0.379751	0.567602
	SP10	0.560324	0.725965	0.413037

Speaker 5

Unknown speaker	Speakers	Euclidean distance (ED)		
		añ	iñ	uñ
USP5	SP1	0.624224	0.907366	0.799957
	SP2	0.783114	0.915073	0.5133
	SP3	0.918523	0.546744	0.110136
	SP4	0.093406	0.593781	0.451349
	SP5	0.229325	0.324554	0.134527
	SP6	0.319498	0.655887	0.879248
	SP7	0.656444	0.481759	0.577501
	SP8	0.296727	0.310315	0.426389
	SP9	0.229328	0.383942	0.278726
	SP10	0.174904	0.257848	0.436056

Speaker 6

Unknown speaker	Speakers	Euclidean distance (ED)		
		añ	iñ	uñ
USP6	SP1	0.294431	0.358889	0.408987
	SP2	0.303035	0.13158	0.147334
	SP3	0.449818	0.509499	0.298748
	SP4	0.503866	0.599736	0.061081
	SP5	0.562131	0.968123	0.312396
	SP6	0.226367	0.475935	0.791067
	SP7	0.708905	0.547422	0.718029
	SP8	0.443461	0.722434	0.291276
	SP9	0.504406	0.658683	0.487571
	SP10	0.476916	1.115629	0.456479

Speaker 7

Unknown speaker	Speakers	Euclidean distance (ED)		
		añ	iñ	uñ
USP7	SP1	0.511275	0.272191	0.581248
	SP2	0.848014	0.519361	0.437783
	SP3	1.008594	0.459272	0.610108
	SP4	0.48727	0.642151	0.515183
	SP5	0.623188	0.795277	0.732003
	SP6	0.356602	0.569247	0.27267
	SP7	0.269278	0.322498	0.508719
	SP8	0.14307	0.46977	0.292927
	SP9	0.164535	0.323912	0.542052
	SP10	0.561241	0.86746	0.326313

Speaker 8

Unknown speaker	Speakers	Euclidean distance (ED)		
		añ	iñ	uñ
USP8	SP1	0.253885	0.667952	0.411792

	SP2	0.577885	0.379152	0.234467
	SP3	0.739405	0.218518	0.485741
	SP4	0.483633	0.121064	0.315562
	SP5	0.602632	0.521702	0.583881
	SP6	0.149649	0.085821	0.473703
	SP7	0.384373	0.376555	0.584542
	SP8	0.173164	0.421976	0.181525
	SP9	0.273846	0.476952	0.504913
	SP10	0.518348	0.693223	0.329123

Speaker 9

Unknown speaker	Speakers	Euclidean distance (ED)		
		añ	iñ	uñ
USP9	SP1	0.553304	0.069224	0.701449
	SP2	0.785006	0.437432	0.423239
	SP3	0.933631	0.608065	0.29755
	SP4	0.238894	0.773738	0.435563
	SP5	0.374813	1.031969	0.441164
	SP6	0.274244	0.664998	0.502739
	SP7	0.512242	0.532378	0.305269
	SP8	0.164161	0.715917	0.171217
	SP9	0.08384	0.587668	0.178066
	SP10	0.315451	1.133194	0.060555

Speaker 10

Unknown speaker	Speakers	Euclidean distance (ED)		
		añ	iñ	uñ
USP10	SP1	0.516697	1.081743	0.389516
	SP2	0.673393	0.996002	0.147364
	SP3	0.812612	0.612635	0.325733
	SP4	0.168093	0.574396	0.053022
	SP5	0.286004	0.176539	0.329051
	SP6	0.210357	0.676397	0.813361
	SP7	0.617089	0.617645	0.749317
	SP8	0.247748	0.42902	0.318558
	SP9	0.221679	0.559949	0.51904
	SP10	0.205226	0.014493	0.486776

/ŋ/ Speaker 1

Unknown speaker	Speakers	Euclidean distance (ED)		
		ŋa	ŋi	ŋu
USP1	SP1	0.244173	0.600501	0.656244
	SP2	0.518504	0.975974	0.253572
	SP3	0.679389	0.576608	0.295083
	SP4	1.146944	0.261343	0.451681
	SP5	0.56511	0.334602	0.268928
	SP6	0.105345	0.074023	0.604973
	SP7	0.844348	0.547138	0.715731
	SP8	0.627957	0.479407	0.701352
	SP9	0.062257	0.543016	0.670106
	SP10	0.36832	0.123439	0.522148

Speaker 2

Unknown speaker	Speakers	Euclidean distance (ED)		
		ᵠa	ᵠi	ᵠu
USP2	SP1	0.656582	0.264855	0.111021
	SP2	0.613148	0.112833	0.4117
	SP3	0.959856	0.938647	0.945904
	SP4	0.984894	0.986241	0.257621
	SP5	0.657361	0.549607	0.514294
	SP6	0.344564	0.844198	0.660024
	SP7	1.166028	0.618014	0.377048
	SP8	1.025367	0.715214	0.432881
	SP9	0.437242	0.358137	0.201111
	SP10	0.689457	0.895956	0.486569

Speaker 3

Unknown speaker	Speakers	Euclidean distance (ED)		
		ᵠa	ᵠi	ᵠu
USP3	SP1	0.508559	0.64762	1.040896
	SP2	0.024695	0.848442	0.65377
	SP3	0.437532	0.248719	0.327877
	SP4	0.670916	0.964647	0.852531
	SP5	0.051634	0.696767	0.683631
	SP6	0.563827	0.634261	0.99935
	SP7	0.659327	0.996701	1.130483
	SP8	0.681865	1.007904	1.117982
	SP9	0.468696	0.749669	1.069409
	SP10	0.347684	0.823476	0.936276

Speaker 4

Unknown speaker	Speakers	Euclidean distance (ED)		
		ᵠa	ᵠi	ᵠu
USP4	SP1	0.313186	0.264868	0.674863
	SP2	0.546836	0.267574	0.324679
	SP3	0.739103	1.003622	0.431444
	SP4	1.147775	0.88762	0.507315
	SP5	0.59479	0.479748	0.422886
	SP6	0.037051	0.808522	0.775698
	SP7	0.909407	0.462754	0.804907
	SP8	0.69697	0.570031	0.807413
	SP9	0.112996	0.270728	0.71489
	SP10	0.429056	0.818908	0.660932

Speaker 5

Unknown speaker	Speakers	Euclidean distance (ED)		
		ᵠa	ᵠi	ᵠu
USP5	SP1	1.836228	0.560776	0.81712
	SP2	1.348723	0.864103	0.495163

	SP3	1.548232	0.189086	0.50705
	SP4	0.697724	0.699236	0.668124
	SP5	1.31285	0.498101	0.596672
	SP6	1.835567	0.36559	0.949114
	SP7	1.682373	0.804828	0.969381
	SP8	1.90254	0.793021	0.975863
	SP9	1.778888	0.614858	0.866668
	SP10	1.65546	0.558605	0.834696

Speaker 6

Unknown speaker	Speakers	Euclidean distance (ED)		
		ᵠa	ᵠi	ᵠu
USP6	SP1	0.416503	0.488442	0.365474
	SP2	0.075022	0.846572	0.177226
	SP3	0.409517	0.387412	0.652282
	SP4	0.761465	0.48391	0.240436
	SP5	0.11963	0.321323	0.335467
	SP6	0.488546	0.161406	0.637472
	SP7	0.629902	0.616562	0.538954
	SP8	0.612437	0.588461	0.560022
	SP9	0.383692	0.489304	0.417236
	SP10	0.263906	0.342727	0.477456

Speaker 7

Unknown speaker	Speakers	Euclidean distance (ED)		
		ᵠa	ᵠi	ᵠu
USP7	SP1	0.603704	0.206403	0.674089
	SP2	0.372747	0.524172	0.271677
	SP3	0.163822	0.82023	0.265399
	SP4	0.853393	0.582346	0.465026
	SP5	0.340623	0.181923	0.259231
	SP6	0.833392	0.519921	0.581521
	SP7	0.326489	0.244721	0.716453
	SP8	0.522293	0.316177	0.697688
	SP9	0.700192	0.060363	0.682121
	SP10	0.406424	0.511427	0.510915

Speaker 8

Unknown speaker	Speakers	Euclidean distance (ED)		
		ᵠa	ᵠi	ᵠu
USP8	SP1	0.383784	0.342682	0.577073
	SP2	0.657172	0.586544	0.195638
	SP3	0.358475	0.967306	0.364733
	SP4	1.317497	0.596435	0.362647
	SP5	0.666158	0.294394	0.127486
	SP6	0.732974	0.617912	0.45182
	SP7	0.335259	0.134349	0.589978
	SP8	0	0.243235	0.567188
	SP9	0.600526	0.200992	0.572725
	SP10	0.364233	0.561076	0.37684

Speaker 9

Unknown speaker	Speakers	Euclidean distance (ED)		
-----------------	----------	-------------------------	--	--

		ŋa	ŋi	ŋu
USP9	SP1	0.594175	0.105269	0.078396
	SP2	0.116809	0.282753	0.406047
	SP3	0.426585	0.834603	0.941508
	SP4	0.605273	0.816672	0.240531
	SP5	0.072044	0.3798	0.50011
	SP6	0.671892	0.682241	0.632143
	SP7	0.641753	0.474676	0.344451
	SP8	0.717318	0.562177	0.400606
	SP9	0.573713	0.192207	0.168486
	SP10	0.415301	0.726363	0.459696

Speaker 10

Unknown speaker	Speakers	Euclidean distance (ED)		
		ŋa	ŋi	ŋu
USP10	SP1	0.474947	0.15679	0.477912
	SP2	0.017667	0.509857	0.15268
	SP3	0.420495	0.589728	0.528588
	SP4	0.704544	0.655547	0.312299
	SP5	0.066433	0.234851	0.295936
	SP6	0.539036	0.447493	0.637186
	SP7	0.642522	0.490564	0.613379
	SP8	0.652878	0.529965	0.621752
	SP9	0.439722	0.22476	0.516857
	SP10	0.314916	0.538279	0.498083

/ŋ/ Speaker 1

Unknown speaker	Speakers	Euclidean distance (ED)		
		aŋ	iŋ	uŋ
USP1	SP1	0.319666	0.748401	0.225339
	SP2	1.11026	0.284737	0.263052
	SP3	0.909968	0.09792	0.60868
	SP4	0.733177	0.328786	0.998434
	SP5	0.713389	0.270347	0.299189
	SP6	1.129588	0.420924	0.615096
	SP7	0.934773	0.545422	0.760756
	SP8	1.037189	0.338649	0.196049
	SP9	0.888867	0.3719	0.436434
	SP10	0.949724	0.436931	0.510903

Speaker 2

Unknown speaker	Speakers	Euclidean distance (ED)		
		aŋ	iŋ	uŋ
USP2	SP1	0.592834	0.473796	0.547532
	SP2	0.779594	0.223534	0.450302
	SP3	0.179016	0.468359	0.034449
	SP4	0.583218	0.327017	0.364291
	SP5	0.240075	0.271177	0.498067
	SP6	0.320074	0.842284	0.541715
	SP7	0.180616	0.287889	0.354792
	SP8	0.351151	0.284905	0.54449
	SP9	0.512529	0.136476	0.489933
	SP10	0.709119	0.598446	0.598875

Speaker 3

Unknown speaker	Speakers	Euclidean distance (ED)		
		an	in	un
USP3	SP1	0.562355	0.75257	0.280766
	SP2	0.591461	0.426749	0.144106
	SP3	0.756867	0.178293	0.308937
	SP4	0.215702	0.364852	0.696446
	SP5	0.369721	0.448948	0.218595
	SP6	0.80055	0.22103	0.453548
	SP7	0.600931	0.584082	0.537413
	SP8	0.630107	0.529217	0.219007
	SP9	0.393078	0.507673	0.367089
	SP10	0.430775	0.63182	0.419419

Speaker 4

Unknown speaker	Speakers	Euclidean distance (ED)		
		an	in	un
USP4	SP1	0.202926	0.313743	0.465696
	SP2	0.898046	0.696764	0.546507
	SP3	0.520059	0.691155	0.264592
	SP4	0.547935	0.502892	0.528326
	SP5	0.366658	0.79898	0.616273
	SP6	0.744315	0.740872	0.7566
	SP7	0.558237	0.423034	0.13394
	SP8	0.684824	0.880473	0.620404
	SP9	0.629081	0.690245	0.316477
	SP10	0.760539	1.159001	0.779451

Speaker 5

Unknown speaker	Speakers	Euclidean distance (ED)		
		an	in	un
USP5	SP1	0.606415	0.645775	0.177711
	SP2	0.517417	0.473306	0.365795
	SP3	0.723769	0.273208	0.375584
	SP4	0.139952	0.332293	0.750558
	SP5	0.318927	0.529607	0.443761
	SP6	0.735374	0.221425	0.688875
	SP7	0.539521	0.517265	0.3995
	SP8	0.555099	0.619746	0.405256
	SP9	0.30999	0.537512	0.129853
	SP10	0.360205	0.781117	0.656735

Speaker 6

Unknown speaker	Speakers	Euclidean distance (ED)		
		an	in	un
USP6	SP1	1.065413	0.789342	0.222105
	SP2	0.816568	0.449154	0.198401
	SP3	0.485981	0.198969	0.324194
	SP4	0.839212	0.398505	0.717046
	SP5	0.60025	0.46404	0.275986
	SP6	0.159975	0.21434	0.522712
	SP7	0.361802	0.618988	0.500303
	SP8	0.346909	0.540907	0.25482
	SP9	0.667149	0.531894	0.298638
	SP10	0.842151	0.624094	0.485653

Speaker 7

Unknown speaker	Speakers	Euclidean distance (ED)		
		aṅ	iṅ	uṅ
USP7	SP1	0.439738	0.41391	0.564562
	SP2	1.11458	0.366006	0.669264
	SP3	0.272639	0.304906	0.360778
	SP4	0.845783	0.165804	0.538357
	SP5	0.524391	0.456335	0.738989
	SP6	0.635443	0.456235	0.868575
	SP7	0.542243	0.289292	0.011453
	SP8	0.713473	0.546842	0.742295
	SP9	0.835441	0.397481	0.386954
	SP10	1.018012	0.791089	0.898455

Speaker 8

Unknown speaker	Speakers	Euclidean distance (ED)		
		aṅ	iṅ	uṅ
USP8	SP1	0.636428	0.728779	0.160541
	SP2	0.623684	0.201586	0.455113
	SP3	0.333882	0.171965	0.49008
	SP4	0.440699	0.324172	0.853861
	SP5	0.122974	0.153329	0.531607
	SP6	0.321563	0.546232	0.797603
	SP7	0.119079	0.513873	0.441414
	SP8	0.243248	0.211966	0.474937
	SP9	0.35555	0.283628	0.054748
	SP10	0.55285	0.349929	0.753502

Speaker 9

Unknown speaker	Speakers	Euclidean distance (ED)		
		aṅ	iṅ	uṅ
USP9	SP1	0.59845	0.533088	0.667436
	SP2	0.771012	0.422145	0.752536
	SP3	0.186068	0.278469	0.404846
	SP4	0.57725	0.248992	0.496497
	SP5	0.234905	0.495977	0.819007
	SP6	0.313992	0.333568	0.920717
	SP7	0.171594	0.411429	0.097358
	SP8	0.341999	0.588306	0.830362
	SP9	0.504525	0.473081	0.490027
	SP10	0.7014	0.791815	0.96377

Speaker 10

Unknown speaker	Speakers	Euclidean distance (ED)		
		aṅ	iṅ	uṅ
USP10	SP1	0.398979	0.370087	0.564641
	SP2	1.174954	0.301443	0.674583
	SP3	0.358846	0.29978	0.369925
	SP4	0.888502	0.097793	0.547807
	SP5	0.581482	0.398591	0.744722
	SP6	0.720829	0.521831	0.876878
	SP7	0.620802	0.214336	0.008159

	SP8	0.791229	0.485964	0.746804
	SP9	0.894163	0.321599	0.38451
	SP10	1.070679	0.750439	0.905724

Appendix III – Tables of Euclidean distance of all nasals in females (correct/false identification was kept in bold numbers)

/m/ Speaker 1

Unknown speaker	Speakers	Euclidean distance (ED)		
		ma	mi	mu
USP1	SP1	0.29471	0.23352	0.54723
	SP2	0.480771	0.393893	0.679066
	SP3	0.462653	0.532064	0.624597
	SP4	0.45925	0.29292	0.394113
	SP5	0.437066	0.415084	0.214068
	SP6	0.19565	0.464728	0.282223
	SP7	0.856269	0.53586	0.22858
	SP8	0.235347	0.564162	0.179276
	SP9	0.843357	0.359157	0.788261
	SP10	0.957224	0.6841	0.577774

Speaker 2

Unknown speaker	Speakers	Euclidean distance (ED)		
		ma	mi	mu
USP2	SP1	0.34143	0.266927	0.388058
	SP2	0.34143	0.26693	0.38806
	SP3	0.461824	0.391078	0.487227
	SP4	0.368398	0.444976	0.580634
	SP5	0.205846	0.26457	0.329296
	SP6	0.217425	0.522304	0.200511
	SP7	0.899406	0.589773	0.366363
	SP8	0.347447	0.302717	0.328067
	SP9	0.917381	0.481088	0.733255
	SP10	0.726715	0.404434	0.334794

Speaker 3

Unknown speaker	Speakers	Euclidean distance (ED)		
		ma	mi	mu
USP3	SP1	0.38838	0.135968	0.343625
	SP2	0.161652	0.217338	0.193079
	SP3	0.39023	0.2657	0.3181
	SP4	0.111978	0.240591	0.359659
	SP5	0.27897	0.194106	0.421596
	SP6	0.457645	0.160586	0.518254
	SP7	0.443895	0.205809	0.396476
	SP8	0.622598	0.098348	0.46752
	SP9	0.456446	0.197712	0.247364
	SP10	0.542992	0.156182	0.162509

Speaker 4

Unknown speaker	Speakers	Euclidean distance (ED)		
		ma	mi	mu
USP4	SP1	0.41541	0.120538	0.177982
	SP2	0.149288	0.146379	0.211221
	SP3	0.042702	0.142351	0.233465
	SP4	0.10606	0.27371	0.37636
	SP5	0.278662	0.121445	0.255538
	SP6	0.484968	0.284467	0.295517
	SP7	0.428346	0.344271	0.256235
	SP8	0.652874	0.062288	0.291249
	SP9	0.446971	0.273567	0.475536
	SP10	0.500755	0.196772	0.113711

Speaker 5

Unknown speaker	Speakers	Euclidean distance (ED)		
		ma	mi	mu
USP5	SP1	0.455014	0.39655	0.31482
	SP2	0.424334	0.148719	0.61435
	SP3	0.281608	0.31381	0.475376
	SP4	0.374194	0.121742	0.122185
	SP5	0.49835	0.17001	0.29647
	SP6	0.507519	0.307334	0.475462
	SP7	0.496445	0.39188	0.252588
	SP8	0.623056	0.326196	0.319387
	SP9	0.468552	0.203018	0.54714
	SP10	0.81012	0.455078	0.519176

Speaker 6

Unknown speaker	Speakers	Euclidean distance (ED)		
		ma	mi	mu
USP6	SP1	0.144522	0.369344	0.242512
	SP2	0.292705	0.171952	0.576006
	SP3	0.280401	0.261851	0.459147
	SP4	0.269069	0.029517	0.149213
	SP5	0.272528	0.182075	0.214082
	SP6	0.20293	0.22057	0.39109
	SP7	0.701409	0.303488	0.173063
	SP8	0.349599	0.301297	0.234483
	SP9	0.698736	0.112216	0.569312
	SP10	0.768523	0.414663	0.476477

Speaker 7

Unknown speaker	Speakers	Euclidean distance (ED)		
		ma	mi	mu
USP7	SP1	0.759446	0.409285	0.197446
	SP2	0.420778	0.481276	0.195759
	SP3	0.414116	0.304361	0.168652
	SP4	0.422147	0.382971	0.337458
	SP5	0.540491	0.465831	0.278661
	SP6	0.827205	0.19856	0.351136
	SP7	0.36803	0.11417	0.26704
	SP8	1.000995	0.399347	0.320431
	SP9	0.431252	0.300346	0.407477
	SP10	0.232325	0.369608	0.09434

Speaker 8

Unknown speaker	Speakers	Euclidean distance (ED)		
		ma	mi	mu
USP8	SP1	0.26167	0.336946	0.312818
	SP2	0.241106	0.591231	0.11248
	SP3	0.384089	0.394649	0.248909
	SP4	0.278376	0.630711	0.497095
	SP5	0.1058	0.565293	0.387355
	SP6	0.299253	0.481698	0.387918
	SP7	0.805783	0.447046	0.392044
	SP8	0.45386	0.3989	0.41874
	SP9	0.830069	0.57099	0.491628

	SP10	0.603246	0.260691	0.089222
--	------	----------	-----------------	-----------------

Speaker 9

Unknown speaker	Speakers	Euclidean distance (ED)		
		ma	mi	mu
USP9	SP1	0.609576	0.204763	0.257722
	SP2	0.357014	0.199556	0.379403
	SP3	0.225866	0.071823	0.216648
	SP4	0.318759	0.175335	0.143241
	SP5	0.491055	0.1819	0.309445
	SP6	0.677956	0.10627	0.466235
	SP7	0.21824	0.174128	0.266417
	SP8	0.836771	0.154391	0.35575
	SP9	0.574871	0.396788	0.606707
	SP10	0.534919	0.227187	0.299592

Speaker 10

Unknown speaker	Speakers	Euclidean distance (ED)		
		ma	mi	mu
USP10	SP1	0.780471	0.275381	0.265721
	SP2	0.442419	0.075637	0.188935
	SP3	0.485965	0.266013	0.296247
	SP4	0.460203	0.251391	0.486414
	SP5	0.536469	0.083159	0.333216
	SP6	0.844308	0.35788	0.313567
	SP7	0.513617	0.435765	0.345701
	SP8	1.017928	0.215565	0.359303
	SP9	0.576633	0.29638	0.543452
	SP10	1.095636	0.65148	0.809271

/n/ Speaker 1

Unknown speaker	Speakers	Euclidean distance (ED)		
		na	ni	nu
USP1	SP1	0.233516	0.547225	0.264957
	SP2	0.319267	0.097448	0.532671
	SP3	0.17644	0.074017	0.576219
	SP4	0.059758	0.083354	0.113681
	SP5	0.10382	0.179198	0.341848
	SP6	0.042305	0.213415	0.704818
	SP7	0.049101	0.235627	0.317414
	SP8	0.465212	0.576729	0.286416
	SP9	0.093787	0.272347	0.333059
	SP10	0.582986	0.392025	0.489608

Speaker 2

Unknown speaker	Speakers	Euclidean distance (ED)		
		na	ni	nu
USP2	SP1	0.11039	0.876525	0.232975
	SP2	0.185757	1.013873	0.516061
	SP3	0.570382	0.745362	0.221734
	SP4	0.758961	0.342392	0.657087
	SP5	0.320968	0.907347	0.4081
	SP6	0.36188	0.644398	0.185891

	SP7	0.358282	0.983034	0.424529
	SP8	0.345147	0.800529	0.459987
	SP9	0.32166	0.857138	1.028027
	SP10	0.455329	1.142924	0.222067

Speaker 3

Unknown speaker	Speakers	Euclidean distance (ED)		
		na	ni	nu
USP3	SP1	0.408813	0.551654	0.337054
	SP2	0.487695	0.148394	0.04691
	SP3	0.12111	0.30543	0.0544
	SP4	0.234251	0.061843	0.497479
	SP5	0.271302	0.216064	0.237042
	SP6	0.214932	0.150729	0.128872
	SP7	0.220331	0.290805	0.260161
	SP8	0.58448	0.547497	0.29389
	SP9	0.253678	0.285638	0.865304
	SP10	0.688778	0.447003	0.186739

Speaker 4

Unknown speaker	Speakers	Euclidean distance (ED)		
		na	ni	nu
USP4	SP1	0.267473	0.578279	0.087246
	SP2	0.423217	0.180065	0.216106
	SP3	0.292894	0.032288	0.2556
	SP4	0.19436	0.05221	0.24188
	SP5	0.16917	0.248288	0.02072
	SP6	0.190481	0.1521	0.384193
	SP7	0.185597	0.29592	0.020421
	SP8	0.637156	0.563176	0.039519
	SP9	0.275957	0.271157	0.610918
	SP10	0.761162	0.478953	0.237011

Speaker 5

Unknown speaker	Speakers	Euclidean distance (ED)		
		na	ni	nu
USP5	SP1	0.420473	0.577542	0.1992
	SP2	0.495579	0.162877	0.283464
	SP3	0.015241	0.2621	0.330364
	SP4	0.245885	0.25395	0.260988
	SP5	0.28398	0.2086	0.15849
	SP6	0.226732	0.390324	0.451168
	SP7	0.232326	0.178634	0.141471
	SP8	0.585632	0.680259	0.147737
	SP9	0.2616	0.32563	0.616461
	SP10	0.688222	0.290389	0.204044

Speaker 6

Unknown speaker	Speakers	Euclidean distance (ED)		
		na	ni	nu

USP6	SP1	0.190942	0.489993	0.136321
	SP2	0.354514	0.03147	0.170348
	SP3	0.346892	0.157057	0.202886
	SP4	0.179624	0.177265	0.301244
	SP5	0.137648	0.105839	0.061969
	SP6	0.18514	0.26307	0.32868
	SP7	0.178369	0.252837	0.085313
	SP8	0.588277	0.559382	0.107459
	SP9	0.254825	0.339665	0.664227
	SP10	0.713698	0.298256	0.234645

Speaker 7

Unknown speaker	Speakers	Euclidean distance (ED)		
		na	ni	nu
USP7	SP1	0.146588	0.806286	0.260975
	SP2	0.306505	0.413185	0.279233
	SP3	0.330665	0.272193	0.325214
	SP4	0.136796	0.234793	0.326237
	SP5	0.091225	0.487524	0.201645
	SP6	0.14589	0.325662	0.436463
	SP7	0.13879	0.38356	0.19047
	SP8	0.536641	0.745873	0.204846
	SP9	0.207199	0.237178	0.675464
	SP10	0.662025	0.710159	0.168026

Speaker 8

Unknown speaker	Speakers	Euclidean distance (ED)		
		na	ni	nu
USP8	SP1	0.328741	0.464982	0.256241
	SP2	0.383616	0.249146	0.536095
	SP3	0.112926	0.395143	0.564056
	SP4	0.161547	0.412348	0.210692
	SP5	0.207591	0.217491	0.360422
	SP6	0.146022	0.477236	0.681894
	SP7	0.153013	0.37157	0.350001
	SP8	0.472508	0.634672	0.318163
	SP9	0.152059	0.522684	0.365811
	SP10	0.579308	0.101734	0.576312

Speaker 9

Unknown speaker	Speakers	Euclidean distance (ED)		
		na	ni	nu
USP9	SP1	0.223311	0.610132	0.218996
	SP2	0.315306	0.211426	0.423288
	SP3	0.185628	0.065604	0.469333
	SP4	0.048734	0.054616	0.164143
	SP5	0.090822	0.281595	0.252573
	SP6	0.02997	0.167744	0.594927
	SP7	0.036319	0.297061	0.227764
	SP8	0.469252	0.587163	0.207643
	SP9	0.095627	0.252182	0.476064
	SP10	0.588092	0.510519	0.357151

Speaker 10

Unknown speaker	Speakers	Euclidean distance (ED)		
		na	ni	nu
USP10	SP1	0.504321	0.003729	0.516988
	SP2	0.339368	0.467936	0.258198
	SP3	0.767872	0.553882	0.25888
	SP4	0.5951	0.611706	0.64652
	SP5	0.598702	0.387507	0.410159
	SP6	0.610337	0.490939	0.248732
	SP7	0.610493	0.742299	0.423197
	SP8	0.210215	0.254538	0.457666
	SP9	0.531389	0.822065	1.014182
	SP10	0.206929	0.39	0.203021

/ŋ/ Speaker 1

Unknown speaker	Speakers	Euclidean distance (ED)		
		aŋ	iŋ	uŋ
USP1	SP1	0.23127	0.183028	0.379732
	SP2	0.881042	0.861861	0.175714
	SP3	0.752677	0.358806	0.301491
	SP4	0.274807	0.573834	0.293556
	SP5	0.255949	0.631957	0.185575
	SP6	0.609375	0.174555	0.239138
	SP7	0.249427	0.631957	0.244929
	SP8	0.662277	0.648913	0.796294
	SP9	0.796162	0.535026	0.199658
	SP10	0.43414	0.137214	0.72514

Speaker 2

Unknown speaker	Speakers	Euclidean distance (ED)		
		aŋ	iŋ	uŋ
USP2	SP1	0.24816	0.852191	0.810328
	SP2	0.673517	0.602353	0.346525
	SP3	0.483836	0.679347	0.789833
	SP4	0.494208	0.501533	0.73779
	SP5	0.31673	1.167403	0.436264
	SP6	0.567229	0.848677	0.662941
	SP7	0.324142	1.167403	0.523502
	SP8	0.183577	0.283856	0.50897
	SP9	0.627149	0.589961	0.363866
	SP10	0.374185	0.811786	0.954431

Speaker 3

Unknown speaker	Speakers	Euclidean distance (ED)		
		aŋ	iŋ	uŋ
USP3	SP1	0.59474	0.47826	0.17286
	SP2	0.19495	0.58556	0.4769
	SP3	0.26285	0.23764	0.33794
	SP4	0.561347	0.312026	0.128291
	SP5	0.496849	0.494134	0.459599
	SP6	0.301767	0.425028	0.179107
	SP7	0.503253	0.494134	0.469613
	SP8	0.495335	0.504822	0.989388
	SP9	0.182416	0.225019	0.441312

	SP10	0.331555	0.412496	0.627875
--	------	----------	----------	----------

Speaker 4

Unknown speaker	Speakers	Euclidean distance (ED)		
		aη	iη	uη
USP4	SP1	0.70951	0.13066	0.35428
	SP2	0.17498	0.89636	0.20995
	SP3	0.12245	0.3521	0.33281
	SP4	0.68239	0.60685	0.27661
	SP5	0.618195	0.553404	0.270286
	SP6	0.400037	0.096382	0.204117
	SP7	0.624751	0.553404	0.349024
	SP8	0.553314	0.709311	0.693854
	SP9	0.220987	0.553107	0.10932
	SP10	0.453756	0.067014	0.633473

Speaker 5

Unknown speaker	Speakers	Euclidean distance (ED)		
		aη	iη	uη
USP5	SP1	0.33033	0.36551	0.36675
	SP2	0.53685	0.95643	0.22503
	SP3	0.44635	0.38248	0.26002
	SP4	0.11558	0.69373	0.28065
	SP5	0.16741	0.22716	0.2008
	SP6	0.24948	0.305766	0.242011
	SP7	0.165645	0.227156	0.231191
	SP8	0.598528	0.878742	0.86436
	SP9	0.446787	0.59938	0.267955
	SP10	0.123171	0.33134	0.74836

Speaker 6

Unknown speaker	Speakers	Euclidean distance (ED)		
		aη	iη	uη
USP6	SP1	0.56731	0.57695	0.26636
	SP2	0.27029	0.91667	0.28404
	SP3	0.26837	0.41953	0.24777
	SP4	0.39131	0.69578	0.1866
	SP5	0.41779	0.08333	0.3203
	SP6	0.04333	0.51465	0.11635
	SP7	0.420286	0.083333	0.381366
	SP8	0.660184	0.916621	0.754906
	SP9	0.176042	0.589064	0.195033
	SP10	0.233985	0.535187	0.588613

Speaker 7

Unknown speaker	Speakers	Euclidean distance (ED)		
		aη	iη	uη
USP7	SP1	0.51516	0.30711	0.19784
	SP2	0.37388	1.04529	0.38079
	SP3	0.35184	0.46196	0.10114

	SP4	0.29799	0.77322	0.11632
	SP5	0.35609	0.30435	0.37497
	SP6	0.06026	0.25793	0.11713
	SP7	0.35682	0.30435	0.40015
	SP8	0.67777	0.9407	0.90181
	SP9	0.27963	0.6852	0.34144
	SP10	0.19459	0.29177	0.62121

Speaker 8

Unknown speaker	Speakers	Euclidean distance (ED)		
		aη	iη	uη
USP8	SP1	0.42591	0.87276	0.79466
	SP2	0.54699	0.4231	0.34007
	SP3	0.35257	0.40272	0.66546
	SP4	0.59161	0.36079	0.70909
	SP5	0.43525	0.63343	0.25509
	SP6	0.53819	0.81477	0.66811
	SP7	0.44363	0.63343	0.19843
	SP8	0.1428	0.59163	1.02615
	SP9	0.52502	0.29102	0.53444
	SP10	0.40062	0.80792	1.15669

Speaker 9

Unknown speaker	Speakers	Euclidean distance (ED)		
		aη	iη	uη
USP9	SP1	0.33988	0.5856	0.48115
	SP2	0.60221	0.61483	0.14312
	SP3	0.51969	0.17657	0.37479
	SP4	0.04896	0.39359	0.39463
	SP5	0.18591	0.38825	0.08482
	SP6	0.30266	0.52429	0.34856
	SP7	0.18097	0.38825	0.13017
	SP8	0.6537	0.62382	0.85398
	SP9	0.51041	0.28565	0.27117
	SP10	0.19697	0.52323	0.84027

Speaker 10

Unknown speaker	Speakers	Euclidean distance (ED)		
		aη	iη	uη
USP10	SP1	0.29983	0.44665	0.66961
	SP2	0.48539	0.79116	0.2597
	SP3	0.36651	0.24111	0.66012
	SP4	0.20467	0.54081	0.59953
	SP5	0.15106	0.25678	0.36636
	SP6	0.2439	0.38234	0.52392
	SP7	0.15464	0.25678	0.46437
	SP8	0.50248	0.74572	0.48811
	SP9	0.40249	0.44017	0.22424
	SP10	0.03835	0.39262	0.81833

/ñ/ Speaker 1

Unknown speaker	Speakers	Euclidean distance (ED)		
-----------------	----------	-------------------------	--	--

		añ	iñ	uñ
USP1	SP1	0.12593	0.70871	0.22938
	SP2	0.68684	0.5132	0.4548
	SP3	0.87133	0.30388	0.31121
	SP4	0.62031	0.55091	0.3491
	SP5	0.50867	0.71597	0.0925
	SP6	0.29633	0.46945	0.10484
	SP7	0.80276	0.86887	0.17628
	SP8	0.63494	0.23374	0.61681
	SP9	0.56132	0.98214	0.73935
	SP10	0.31786	0.12788	0.31526

Speaker 2

Unknown speaker	Speakers	Euclidean distance (ED)		
		añ	iñ	uñ
USP2	SP1	0.47369	0.5185	0.72568
	SP2	0.24993	0.2351	0.56749
	SP3	0.4211	0.09536	0.31374
	SP4	0.13678	0.47427	0.39588
	SP5	0.50204	0.50847	0.52392
	SP6	0.22541	0.31793	0.7192
	SP7	0.59326	0.64849	0.59306
	SP8	0.23737	0.29284	1.03504
	SP9	0.26858	0.94323	1.19743
	SP10	0.27877	0.23664	0.35459

Speaker 3

Unknown speaker	Speakers	Euclidean distance (ED)		
		añ	iñ	uñ
USP3	SP1	0.8821	0.61381	0.47143
	SP2	0.45365	0.32756	0.35652
	SP3	0.44912	0.40021	0.35019
	SP4	0.35999	0.55965	0.26874
	SP5	0.89705	0.60376	0.21872
	SP6	0.57516	0.40865	0.41468
	SP7	0.87883	0.74293	0.28312
	SP8	0.50817	0.33786	0.75433
	SP9	0.61234	1.02942	0.9095
	SP10	0.69962	0.18726	0.07855

Speaker 4

Unknown speaker	Speakers	Euclidean distance (ED)		
		añ	iñ	uñ
USP4	SP1	0.18619	0.38635	0.37316
	SP2	0.51218	0.68928	0.62261
	SP3	0.84416	0.97938	0.27321
	SP4	0.50851	0.45346	0.01672
	SP5	0.20489	0.41338	0.31005
	SP6	0.37095	0.57326	0.45402
	SP7	0.5087	0.36026	0.45882
	SP8	0.44503	0.77048	0.95199
	SP9	0.33647	0.23764	1.0901
	SP10	0.14477	1.02389	0.34901

Speaker 5

Unknown speaker	Speakers	Euclidean distance (ED)		
		añ	iñ	uñ
USP5	SP1	0.66889	0.15856	0.38533
	SP2	0.08568	0.41036	0.73114
	SP3	0.5231	0.73574	0.70597
	SP4	0.22594	0.38753	0.70857
	SP5	0.46941	0.14428	0.48884
	SP6	0.53513	0.39226	0.29294
	SP7	0.35716	0.00912	0.47534
	SP8	0.10193	0.64638	0.57909
	SP9	0.19341	0.55239	0.61184
	SP10	0.42777	0.83595	0.69631

Speaker 6

Unknown speaker	Speakers	Euclidean distance (ED)		
		añ	iñ	uñ
USP6	SP1	0.52023	0.10584	0.22316
	SP2	0.22179	0.41102	0.53968
	SP3	0.66433	0.7157	0.45433
	SP4	0.31118	0.27027	0.47158
	SP5	0.27408	0.13212	0.23613
	SP6	0.48089	0.32607	0.03975
	SP7	0.25567	0.14944	0.25711
	SP8	0.15737	0.56351	0.57463
	SP9	0.07062	0.43333	0.67113
	SP10	0.29063	0.786	0.45109

Speaker 7

Unknown speaker	Speakers	Euclidean distance (ED)		
		añ	iñ	uñ
USP7	SP1	0.78842	0.33049	0.50772
	SP2	0.5823	0.58664	0.36481
	SP3	1.03333	0.91354	0.04097
	SP4	0.70424	0.54076	0.28038
	SP5	0.40155	0.32289	0.25962
	SP6	0.86479	0.56897	0.45565
	SP7	0.15629	0.17213	0.31924
	SP8	0.53997	0.82031	0.78206
	SP9	0.47667	0.56615	0.93932
	SP10	0.62598	1.01604	0.09369

Speaker 8

Unknown speaker	Speakers	Euclidean distance (ED)		
		añ	iñ	uñ
USP8	SP1	1.05315	0.52398	0.89085
	SP2	1.15795	0.65438	0.63464
	SP3	0.88205	0.78098	0.88986
	SP4	1.01773	0.31463	1.06251
	SP5	1.34776	0.56167	0.767
	SP6	0.81792	0.46137	0.68083

	SP7	1.52268	0.65836	0.62247
	SP8	1.16624	0.45348	0.14034
	SP9	1.19661	0.39232	0.03478
	SP10	1.07527	0.72431	0.82736

Speaker 9

Unknown speaker	Speakers	Euclidean distance (ED)		
		añ	iñ	uñ
USP9	SP1	0.3525	0.33825	0.04042
	SP2	0.2901	0.57514	0.68866
	SP3	0.64467	0.9027	0.45747
	SP4	0.29337	0.5586	0.32429
	SP5	0.26197	0.32514	0.28852
	SP6	0.31166	0.57326	0.24478
	SP7	0.41699	0.17217	0.41705
	SP8	0.22497	0.82734	0.82592
	SP9	0.13272	0.61081	0.92629
	SP10	0.11243	1.01272	0.49599

Speaker 10

Unknown speaker	Speakers	Euclidean distance (ED)		
		añ	iñ	uñ
USP10	SP1	0.30031	0.44929	0.6182
	SP2	0.33513	0.28032	0.06908
	SP3	0.65884	0.26845	0.2928
	SP4	0.31912	0.3178	0.54766
	SP5	0.27362	0.45582	0.33563
	SP6	0.27067	0.21014	0.45588
	SP7	0.46525	0.60872	0.22868
	SP8	0.27333	0.0914	0.5155
	SP9	0.18828	0.78035	0.68155
	SP10	0.05918	0.25821	0.21464

/ŋ/ Speaker 1

Unknown speaker	Speakers	Euclidean distance (ED)		
		ŋa	ŋi	ŋu
USP1	SP1	0.244	0.26831	0.32528
	SP2	0.17387	0.24838	0.34301
	SP3	0.22124	0.49918	0.10172
	SP4	0.14541	0.28468	0.49153
	SP5	0.228	0.22226	0.18056
	SP6	0.01444	0.40695	0.1804
	SP7	0.15171	0.37638	0.55659
	SP8	0.28894	0.38068	0.40235
	SP9	0.17058	0.61219	0.24634
	SP10	0.55476	0.16749	0.14532

Speaker 2

Unknown speaker	Speakers	Euclidean distance (ED)		
		ŋa	ŋi	ŋu
USP2	SP1	0.42786	0.16576	0.41005
	SP2	0.31608	0.26747	0.21552
	SP3	0.61253	0.70987	0.42794
	SP4	0.4359	0.03788	0.85649

	SP5	0.42764	0.35603	0.59737
	SP6	0.47884	0.6568	0.56731
	SP7	0.36795	0.46734	0.04262
	SP8	0.27323	0.37377	0.43043
	SP9	0.3804	0.80484	0.51061
	SP10	0.13887	0.27138	0.37691

Speaker 3

Unknown speaker	Speakers	Euclidean distance (ED)		
		ᵠa	ᵠi	ᵠu
USP3	SP1	0.46504	0.6136	0.31749
	SP2	0.31375	0.73399	0.24246
	SP3	0.22232	0.17541	0.20686
	SP4	0.3665	0.72701	0.57348
	SP5	0.44905	0.65134	0.25943
	SP6	0.23566	0.24258	0.17748
	SP7	0.24973	0.35422	0.46766
	SP8	0.48604	0.85469	0.3945
	SP9	0.38503	0.1295	0.28038
	SP10	0.63725	0.64209	0.05199

Speaker 4

Unknown speaker	Speakers	Euclidean distance (ED)		
		ᵠa	ᵠi	ᵠu
USP4	SP1	0.29609	0.35574	0.48017
	SP2	0.23116	0.49755	0.14912
	SP3	0.54434	0.26623	0.39158
	SP4	0.31207	0.461	0.89924
	SP5	0.29652	0.44404	0.61042
	SP6	0.37466	0.28676	0.49377
	SP7	0.29497	0.20155	0.17857
	SP8	0.14133	0.62752	0.51956
	SP9	0.25622	0.36683	0.55262
	SP10	0.26029	0.41127	0.34759

Speaker 5

Unknown speaker	Speakers	Euclidean distance (ED)		
		ᵠa	ᵠi	ᵠu
USP5	SP1	0.10526	0.50079	0.29767
	SP2	0.20004	0.36096	0.44299
	SP3	0.47396	0.43655	0.21733
	SP4	0.14422	0.51818	0.36427
	SP5	0.10647	0.24263	0.0609
	SP6	0.25254	0.24136	0.29424
	SP7	0.26098	0.49791	0.62377
	SP8	0.0495	0.45349	0.36601
	SP9	0.09703	0.56579	0.1784
	SP10	0.44241	0.27357	0.24672

Speaker 6

Unknown speaker	Speakers	Euclidean distance (ED)		
		ṅa	ṅi	ṅu
USP6	SP1	0.29386	0.62298	0.32142
	SP2	0.19501	0.48631	0.07826
	SP3	0.17149	0.41267	0.17035
	SP4	0.19527	0.65085	0.69126
	SP5	0.27786	0.35961	0.39083
	SP6	0.0643	0.17516	0.30693
	SP7	0.15561	0.56767	0.30411
	SP8	0.33212	0.56486	0.38418
	SP9	0.2185	0.53935	0.35429
	SP10	0.56965	0.40307	0.1234

Speaker 7

Unknown speaker	Speakers	Euclidean distance (ED)		
		ṅa	ṅi	ṅu
USP7	SP1	0.42778	0.38089	0.48193
	SP2	0.2493	0.74646	0.1589
	SP3	0.5172	0.50789	0.22665
	SP4	0.40865	0.53454	0.7997
	SP5	0.42317	0.75266	0.48598
	SP6	0.41929	0.65639	0.25142
	SP7	0.28576	0.18857	0.40908
	SP8	0.28433	0.87857	0.54932
	SP9	0.35738	0.51024	0.48856
	SP10	0.13193	0.6881	0.21393

Speaker 8

Unknown speaker	Speakers	Euclidean distance (ED)		
		ṅa	ṅi	ṅu
USP8	SP1	0.9706	1.60462	1.0072
	SP2	0.74457	1.2053	1.38693
	SP3	0.54074	1.69696	1.2775
	SP4	0.87737	1.49818	0.79137
	SP5	0.9554	1.17257	1.05093
	SP6	0.75562	1.45742	1.40383
	SP7	0.68258	1.7597	1.36408
	SP8	0.93443	1.09286	0.95411
	SP9	0.87653	1.82342	0.99752
	SP10	0.85532	1.24307	1.27143

Speaker 9

Unknown speaker	Speakers	Euclidean distance (ED)		
		ṅa	ṅi	ṅu
USP9	SP1	0	0.23549	0.39163
	SP2	0.25255	0.6295	0.54587
	SP3	0.46504	0.59246	0.31045
	SP4	0.09859	0.38056	0.32065
	SP5	0.016	0.66188	0.12547
	SP6	0.22956	0.68436	0.33878
	SP7	0.22956	0.68436	0.33878
	SP8	0.15476	0.75558	0.45296

	SP9	0.09779	0.62711	0.26125
	SP10	0.54543	0.58701	0.34716

Speaker 10

Unknown speaker	Speakers	Euclidean distance (ED)		
		ṅa	ṅi	ṅu
USP10	SP1	0.62	0.22696	0.18347
	SP2	0.49289	0.35731	0.37072
	SP3	0.76466	0.42602	0.19349
	SP4	0.62779	0.30538	0.39787
	SP5	0.62021	0.33561	0.10857
	SP6	0.66113	0.39096	0.33444
	SP7	0.53462	0.26178	0.51982
	SP8	0.46524	0.49127	0.25638
	SP9	0.57256	0.52735	0.09103
	SP10	0.13134	0.28126	0.19692

/ṅ/ Speaker 1

Unknown speaker	Speakers	Euclidean distance (ED)		
		aṅ	iṅ	uṅ
USP1	SP1	0.27488	0.09892	0.47142
	SP2	0.21284	0.53303	0.70575
	SP3	0.37293	0.5499	0.40073
	SP4	0.35731	0.63743	0.34918
	SP5	0.35983	0.31658	0.86121
	SP6	0.16436	0.64885	0.57331
	SP7	0.28395	0.20686	0.18079
	SP8	0.60059	0.26479	0.51972
	SP9	0.22918	0.33051	0.727
	SP10	0.71949	0.42022	0.54109

Speaker 2

Unknown speaker	Speakers	Euclidean distance (ED)		
		aṅ	iṅ	uṅ
USP2	SP1	0.52588	0.28226	0.32136
	SP2	0.41526	0.40116	0.18576
	SP3	0.5999	0.34693	0.49649
	SP4	0.58017	0.26045	0.98054
	SP5	0.60882	0.06971	0.16427
	SP6	0.40336	0.27202	0.22462
	SP7	0.39785	0.2011	0.70384
	SP8	0.821	0.51498	0.26503
	SP9	0.47902	0.56303	0.11634
	SP10	0.90384	0.04175	0.25103

Speaker 3

Unknown speaker	Speakers	Euclidean distance (ED)		
		aṅ	iṅ	uṅ
USP3	SP1	0.25144	0.48883	0.30966
	SP2	0.42104	0.09616	0.35596
	SP3	0.22232	0.17541	0.20686
	SP4	0.02436	0.36104	0.72015
	SP5	0.28722	0.33593	0.51604
	SP6	0.20913	0.36519	0.27569

	SP7	0.29354	0.35794	0.24925
	SP8	0.5774	0.50445	0.26301
	SP9	0.18	0.51409	0.4975
	SP10	0.76995	0.35317	0.34133

Speaker 4

Unknown speaker	Speakers	Euclidean distance (ED)		
		aṅ	iṅ	uṅ
USP4	SP1	0.48625	0.58494	0.69132
	SP2	0.30681	0.26748	0.94385
	SP3	0.65604	0.17463	0.63747
	SP4	0.64323	0.24694	0.24374
	SP5	0.54887	0.38482	1.09758
	SP6	0.44855	0.2461	0.80805
	SP7	0.55573	0.45734	0.39949
	SP8	0.67732	0.66424	0.75151
	SP9	0.48926	0.68066	0.94406
	SP10	0.71337	0.34812	0.76228

Speaker 5

Unknown speaker	Speakers	Euclidean distance (ED)		
		aṅ	iṅ	uṅ
USP5	SP1	0.08271	0.26194	0.25659
	SP2	0.12621	0.40421	0.44488
	SP3	0.29572	0.35426	0.56489
	SP4	0.29308	0.28098	0.75334
	SP5	0.15978	0.05397	0.49161
	SP6	0.1551	0.29255	0.35006
	SP7	0.38436	0.1842	0.66911
	SP8	0.40967	0.49964	0.31893
	SP9	0.11756	0.54887	0.21229
	SP10	0.55567	0.06102	0.23101

Speaker 6

Unknown speaker	Speakers	Euclidean distance (ED)		
		aṅ	iṅ	uṅ
USP6	SP1	0.0645	0.43378	0.18283
	SP2	0.23392	0.4206	0.15841
	SP3	0.27026	0.33938	0.36372
	SP4	0.27943	0.10922	0.84623
	SP5	0.02389	0.21484	0.25516
	SP6	0.23953	0.12082	0.08902
	SP7	0.46129	0.34179	0.55808
	SP8	0.32163	0.64263	0.11741
	SP9	0.15578	0.68364	0.13817
	SP10	0.5028	0.1137	0.11813

Speaker 7

Unknown speaker	Speakers	Euclidean distance (ED)		
		aṅ	iṅ	uṅ
USP7	SP1	0.13907	0.11262	0.14925
	SP2	0.3231	0.59932	0.18366
	SP3	0.11619	0.60123	0.34829
	SP4	0.12549	0.62683	0.81266
	SP5	0.17217	0.31651	0.28848
	SP6	0.17249	0.63843	0.08239
	SP7	0.34585	0.24334	0.53291
	SP8	0.46724	0.37169	0.09171
	SP9	0.09971	0.43741	0.14922
	SP10	0.65573	0.40395	0.08516

Speaker 8

Unknown speaker	Speakers	Euclidean distance (ED)		
		aṅ	iṅ	uṅ
USP8	SP1	0.53913	0.71535	0.54649
	SP2	0.55759	0.71042	0.66585
	SP3	0.73713	0.79906	0.3099
	SP4	0.75227	1.09939	0.60849
	SP5	0.46463	0.83925	0.82589
	SP6	0.7168	1.10806	0.5732
	SP7	0.94556	0.71475	0.12945
	SP8	0.16631	0.40144	0.54312
	SP9	0.64049	0.3452	0.78017
	SP10	0.1472	0.94508	0.60178

Speaker 9

Unknown speaker	Speakers	Euclidean distance (ED)		
		aṅ	iṅ	uṅ
USP9	SP1	0.56194	0.098	0.26163
	SP2	0.54797	0.48926	0.56274
	SP3	0.50815	0.47132	0.39427
	SP4	0.48401	0.46297	0.40182
	SP5	0.64817	0.15665	0.69668
	SP6	0.38617	0.47457	0.41444
	SP7	0.22034	0.13475	0.33911
	SP8	0.92235	0.40431	0.34983
	SP9	0.47398	0.46515	0.49973
	SP10	1.05367	0.24018	0.33002

Speaker 10

Unknown speaker	Speakers	Euclidean distance (ED)		
		aṅ	iṅ	uṅ
USP10	SP1	0.51024	0.37445	0.11161
	SP2	0.54463	0.14715	0.37993
	SP3	0.69893	0.11483	0.25161
	SP4	0.71487	0.34564	0.57989
	SP5	0.43236	0.22989	0.52143
	SP6	0.68921	0.35301	0.2331
	SP7	0.9161	0.24335	0.3232
	SP8	0.14143	0.42567	0.17055
	SP9	0.61036	0.44732	0.3665
	SP10	0.18521	0.27009	0.18