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Phoneme Weighting and Energy-Based Weighting for Speaker Recognition

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PHONEME WEIGHTING AND ENERGY-BASED WEIGHTING FOR SPEAKER RECOGNITION

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ABSTRACT

This dissertation focuses on determining specific vowel phonemes which work best for speaker identification and speaker verification, and also developing new algorithms to improve speaker identification accuracy. Results from the first part of our research indicate that the vowels /i/, /E/ and /u/ were the ones having the highest recognition scores for both the Gaussian mixture model (GMM) and vector quantization (VQ) methods (at most one classification error). For VQ, /i/, /I/, /e/, /E/ and /@/ had no classification errors. Persons speaking /E/, /o/ and /u/ have been verified well by both GMM and VQ methods in our experiments. For VQ, the verification results are consistent with the identification results since the same five phonemes performed the best and had less than one verification error.

After determining several ideal vowel phonemes, we developed new algorithms for improved speaker identification accuracy. Phoneme weighting methods (which performed classification based on the ideal phonemes we found from the previous experiments) and other weighting methods based on energy were used. The energy weighting methods performed better than the phoneme weighting methods in our experiments. The first energy weighting method ignores the speech frames which have relatively small magnitude. Instead of ignoring the frames which have relatively small magnitude, the second method emphasizes speech frames which have relatively large magnitude. The third method and the adjusted third method are a combination of the previous two methods. The error reduction rate was 7.9% after applying the first method relative to a

baseline system (which used Mel frequency cepstral coefficients (MFCCs) as feature and VQ as classifier). After applying the second method and the adjusted third method, the error reduction rate was 28.9% relative to a baseline system.

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CHAPTER ONE

INTRODUCTION

Speaker recognition [1] is the process of automatically recognizing who is speaking by using speaker specific information included in the utterance. The technique can be used to verify the identity claimed by people accessing systems and many other applications. Therefore, it enables access control of various services by voice.

1.1 Speaker Recognition

Speaker recognition can be divided into two categories [2], closed-set and open-set problems. The closed-set problem (speaker identification) is to identify a speaker from a group of K known speakers. Certainly, the task would be more difficult if K is large. The speaker that scores best on the test utterance is declared to be identified. Alternatively, one may want to decide whether the speaker of a test utterance belongs to the group of K known speakers or to some other unknown speaker. This is called the open-set problem (speaker verification) since the speaker to be identified may not be one of the K known speakers. The speaker is accepted as being known if a speaker's score is well enough on the basis of a test utterance. Therefore, the open-set task makes only an accept or reject decision.

Speaker verification is not necessarily easier than speaker identification since it requires that a score be developed to provide a measure of belief that the target speaker is known. The decision is made by setting up a threshold; any speech which has the score larger than the threshold would be accepted as the speaker; otherwise, the speaker would be rejected. The process of developing the threshold is referred to as score normalization. While the normalization process is not required for speaker identification (closed-set), we will see that score normalization plays an important role in robust speaker verification (open-set) procedures.

1.2 Previous Work of Speaker Recognition

Research in automatic speaker recognition has now spanned five decades [3]. The first attempts for automatic speaker recognition were made in the 1960s. Pruzansky at Bell Labs [4] was the first to start the research by using filter banks and correlating two digital spectrograms for a similarity measure. Both text-independent methods and text-dependent methods were developed in the 1960s and 1970s. In addition, text-dependent methods have higher level of performance than text-independent methods. Also, Texas Instruments built the first fully automated large scale speaker verification system providing high operational security. Moreover, Bell Labs built an experimental system worked over dialed-up telephone lines. Furui [5] proposed using the combination of cepstral coefficients [36] and their first and second polynomial coefficients as frame-based features to increase robustness against distortions by the telephone system. The cepstrum-based features later became standard for not only speaker recognition, but also speech recognition.

The Hidden Markov Model-based text-dependent method was presented in the 1980s. HMMs have the same advantages for speaker recognition as they do for speech recognition. Robust models can be obtained with only small amounts of information accompanying training utterances. Furthermore, a vector quantization (VQ)/HMM-based text-independent method was also proposed. Nonparametric and parametric probability models were investigated for text-independent speaker recognition and vector quantization [6] [7] was investigated as a nonparametric model. In addition, Rose and Reynolds [8] presented using a single-state HMM, which is now called Gaussian mixture model (GMM), as a robust parametric model.

Research on increasing robustness became the goal in the 1990s. The text-prompted speaker recognition method was presented by Matsui, in which key sentences are completely changed every time the system is used [9]. The method not only recognizes speakers more accurately, but can also reject an utterance whose text differs from the prompted text, even if it is uttered by a registered speaker. Moreover, how to normalize intra-speaker variation of likelihood values (similarity) is also a difficult problem in speaker verification. Speakers cannot repeat an utterance precisely the same way from trial to trial. Therefore, likelihood ratio and a posteriori probability-based techniques were investigated [10][11][12].

A new normalization technique (score normalization) was proposed in the 2000s, in which the scores are normalized by subtracting the mean and then dividing by standard deviation, both terms having been estimated from the imposter score distribution [13]. In addition, some high-level features such as word idiolect, pronunciation, phone usage, and prosody have been successfully used in text-independent speaker verification.

1.3 Applications and Challenges of Speaker Recognition

The application of a speaker recognition system exists any time speakers are unknown and their identities are important. The technique, which enables access control of various services by voice can be used to verify the identity claimed by people accessing systems [1]. Applicable services include voice dialing, telephone shopping, telephone banking, information and reservation service, database access service, voice mail, security control for confidential information, forensic purposes and also remote access of computers.

The most important technical challenge for speaker recognition is dealing with the effects of the communication channel through which speech is received [2]. This would be a telephone channel in many applications. The difficulties do not arise from the existence of a channel by itself**,** but rather that in many situations the channel may vary from utterance to utterance. The changing channel effectively creates variability in a speaker's acoustics that exceeds their normal variability. The variability moves speakers about in feature space, and distorts their patterns, which decreases the accuracy of recognition.

1.4 Overview of Dissertation

Chapter 2 introduces some background of a speaker recognition system. After background discussion, the main work of this dissertation is presented in Chapters 3, 4, 5, 6 and 7, which includes a detailed statement of problem, method of research and results. Finally, the conclusions are given in Chapter 8.

CHAPTER TWO

SPEAKER RECOGNITION

The objective of automatic speaker recognition [14] is using a machine to recognize a person from a spoken phrase. This kind of system can work in two ways: to identify a particular person or to verify a person's claimed identity. Background of automatic speaker recognition systems and design tradeoffs will be discussed in the following sections.

2.1 Biometric Recognition

Biometric recognition refers to the automatic recognition of individuals based on their physiological or behavioral characteristics [15]. Examples of such applications include secure access to buildings, cell phones, computer systems and ATMs.

The human physiological or behavioral characteristics could be used as a biometric characteristic as long as it satisfies the following conditions. First, each person should have the characteristic (universality). Second, any two persons should be sufficiently different in terms of the characteristic (distinctiveness). Third, the characteristic should be sufficiently invariant over a period of time (permanence). Finally, the characteristic could be measured quantitatively (collectability).

In addition, there are several other issues that should be considered in a practical biometric system. The first issue is performance, which refers to the achievable recognition accuracy and speed. The second one is acceptability, which shows the extent to which people will accept the use of the biometric identifier in their daily lives. The third issue is circumvention, which reflects how easy the system could be fooled by using fraudulent methods.

A biometric system is a pattern recognition system that extracts features from the acquired data and compares the features with the template set in the database. The system may operate in either identification mode or verification mode, depending on the application context. For the identification mode, the system recognizes an individual by searching the templates of all users in the database for a match. Therefore, the system conducts a one-to-many comparison to check the user's identity without the subject having to claim an identity. On the other hand, the verification system validates a user's identity by comparing the biometric data with their own biometric template stored in the database. Therefore, the verification system is typically used for positive recognition, which is used to prevent multiple people from using the same identity [16].

An identification system makes only one kind of error, which is the classification error; while a verification system makes two types of error, which are known as the false match error and the false nonmatch error. The false match error occurs when the system mistakes biometric measurements from two different persons to be from the same person. On the other hand, the false nonmatch error happens when the system mistakes two biometric measurements from the same person to be from two different persons.

A number of biometric characteristics, such as DNA, ear, face, fingerprint, gait, hand and finger geometry, iris, keystroke, odor, palmprint, retinal scan, signature, and voice exists and used in many applications. Each biometric has its advantages and drawbacks, and the choice depends on the application. Therefore, there is no optimal biometric. Since voice has been a major biometric for lots of security systems, speaker recognition has become an important research topic.

2.2 Speaker Recognition

Voice is a combination of physiological and behavioral biometrics [15]. The features of a person's voice are based on the shape and size of the appendages such as vocal tract, mouth, nasal cavity, and lips that are used in the production of sound. These physiological characteristics of human speech are invariant for every people.

Also, a speaker recognition system falls into two categories, which are the text-independent system and the text-dependent system. A text-dependent speaker recognition system is based on the utterance of a fixed phrase. On the other hand, a text-independent speaker recognition system recognizes the speaker independent of what he or she speaks. A text-independent system is more difficult to design than a text-dependent system but it is more flexible and has more protection against fraud.

Moreover, speaker recognition [14] includes identification and verification. There is no a priori identity claim in automatic speaker identification (ASI), and the system decides who the person is. Furthermore, automatic speaker verification (ASV) is the use of a machine to verify a person's claimed identity from his or her voice. However, many factors could cause recognition errors; for example, misspoken or misread prompted phrases, extreme emotional states, time varying microphone placement, poor or inconsistent room acoustics, channel mismatch, sickness, and aging. Several papers [17] -

[23] have presented general overviews of speaker recognition.

2.3 Speech Processing for Speaker Recognition

The general approach to speaker recognition consists of four steps: digital speech data acquisition, feature extraction, pattern matching, and making a decision. Figure 2.1 shows the block diagram of this procedure.

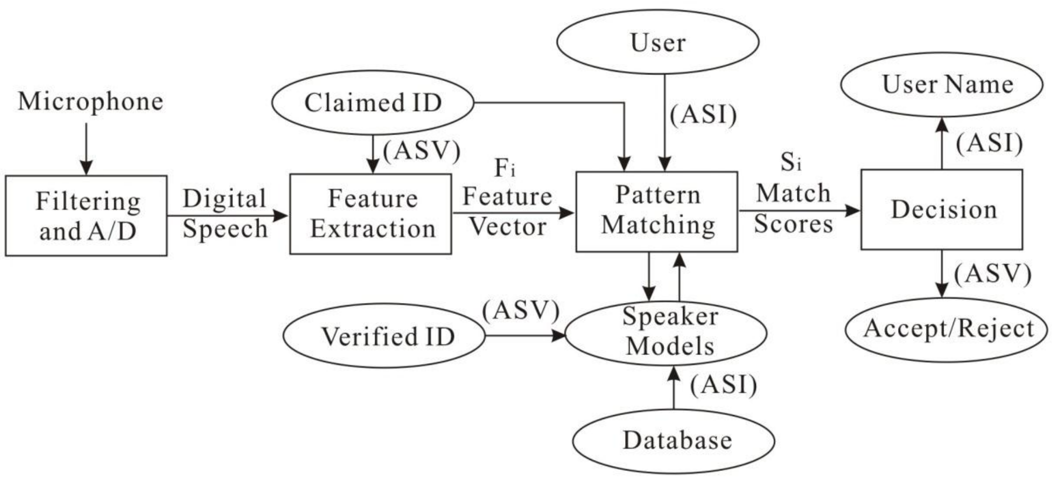

Figure 2.1 Speaker Recognition System

The feature extraction step maps each frame of speech to a multidimensional feature space. In addition, a speech frame usually spans 10-30 msec of the speech signal. This sequence of feature vectors F_i is then compared with those of the speaker models by pattern matching. This results in a match score S_i for each sequence of vectors. The match score measures the similarity of the computed input feature vectors to feature vector patterns for the target speaker. Ultimately, a decision is made according to the match score.

Features that display high speaker discrimination power, high interspeaker variability, and low intraspeaker variability are desired for speaker recognition [14]. Several forms of pattern matching and corresponding models are commonly used. Pattern-matching methods include dynamic time warping (DTW), hidden Markov model (HMM), artificial neural networks (ANNs), and vector quantization (VQ). Template models are used in DTW, statistical models are used in HMM, and codebook models are used in VQ.

Finally, speech processing extracts desired information from the speech signal. To process a signal by a digital computer, the signal must be represented in digital form.

2.3.1 Obtaining the Speech Signal

In the beginning, the acoustic sound wave is transformed into a digital signal suitable for speech processing. A microphone can be used to convert the acoustic wave into an analog signal. Also, this analog signal is conditioned with antialiasing filtering. The antialiasing filter limits the bandwidth of the signal to approximately half the sampling rate before sampling. The conditioned analog signal is then sampled to form a digital signal by an analog-to-digital (A/D) converter. The A/D converters for speech applications typically sample with 12-16 bits of resolution at 8000-20000 samples per second.

2.3.2 Speech Production

There are two main sources of speaker-specific characteristics of speech, which are physical and learned. For instance, vocal tract shape is an important physical distinguishing factor of speech. The vocal tract is generally considered as the speech production organs above the vocal folds [24]. As the acoustic wave passes through the vocal tract, its spectrum is varied by the resonances of the vocal tract. Vocal tract resonances are called formants. Therefore, the vocal tract shape can be estimated from the spectral shape of the voice signal.

Speaker recognition systems usually use features derived only from the vocal tract. The human vocal mechanism is driven by an excitation source, which also includes speaker-dependent information. The excitation is generated by airflow from the lungs, carried by the trachea through the vocal folds. In addition, the excitation could be characterized as whispering, phonation, frication, vibration, compression, or a combination of these. Other aspects of speech production that is useful for discriminating between speakers are learned characteristics, including speaking rate, prosodic effects, and localism.

2.3.3 Feature Selection

Speaker-dependent voice characteristics were categorized as “high-level” and “low-level” [25]. High-level attributes include clarity, magnitude, roughness and animation [26] [27]. Low-level attributes include vocal tract spectrum, instantaneous pitch and glottal flow excitation. We are interested in low-level attributes that contain speaker identifiability for the machine in this chapter.

We want our features to reflect the unique characteristics of a speaker in selecting acoustic spectral features. The short-time Fourier transform (STFT) is one basis for such features [25]. The STFT can be written as

$$\begin{aligned} X(n,\omega) &= \sum_{m=-\infty}^{\infty} x[m]w[n-m]e^{-j\omega m} \\ &= |X(n,\omega)|e^{j\angle X(n,\omega)}. \end{aligned} \tag{2.1}$$

Only the magnitude component $|X(n,\omega)|$ has been used in speaker recognition since features corresponding to the phase component are difficult to measure and are susceptible to channel distortion. This section will introduce two different spectral-based features for speaker recognition, which are the mel-cepstrum and the sub-cepstrum. They provide not only a useful speech features for speech recognition but also provide an illustrative comparison of time-frequency tradeoffs in feature selection.

The mel-cepstrum is introduced by Davies and Mermelstein [28] and has proven to be one of the most successful feature representations in speech-related recognition tasks [13] [31] [32]. Moreover, the mel-cepstrum could be computed as follows [14]:

1. window the signal;
2. take the fast Fourier transform (FFT);
3. take the magnitude
4. take the log;
5. warp the frequencies according to the mel scale
6. take the inverse FFT.

The mel warping is based on the nonlinear human perception of the frequency of sounds [29]. The cepstrum can be considered as the spectrum of the log spectrum. Also, the time derivatives of the mel cepstra, which are the delta cepstra, are used as additional features to model trajectory information. The cepstrum's density has the benefit of being modeled well by a linear combination of Gaussian densities as used in the Gaussian mixture model [30]. Finally, the most important reason for using the mel-warped cepstrum is that it has been demonstrated to work well in speaker recognition systems [2] and also in speech recognition systems [29]. Figure 2.2 shows the block diagram of obtaining the mel-cepstrum. The steps of this algorithm are summarized below.

- Pre-emphasis: The pre-emphasized signal is obtained by applying the filter $x_P(t) = x(t) – a\,x(t-1)$, where $x(t)$ is the speech signal and $x_P(t)$ is the pre-emphasized signal. "a" is a number typically between 0.95 and 0.98. This will allow us to compensate the effect from lips and work with only the vocal tract system from the speech signal.

- Frame Blocking and Windowing: In this step the speech signal is framed by windows. In addition, each frame will overlap for several samples (usually half of the window length) and every frame is multiplied by a Hamming window. In fact, other types of windows can be used but the Hamming window is known to be the best option to compensate for distortions at the end points when the speech is framed [13].

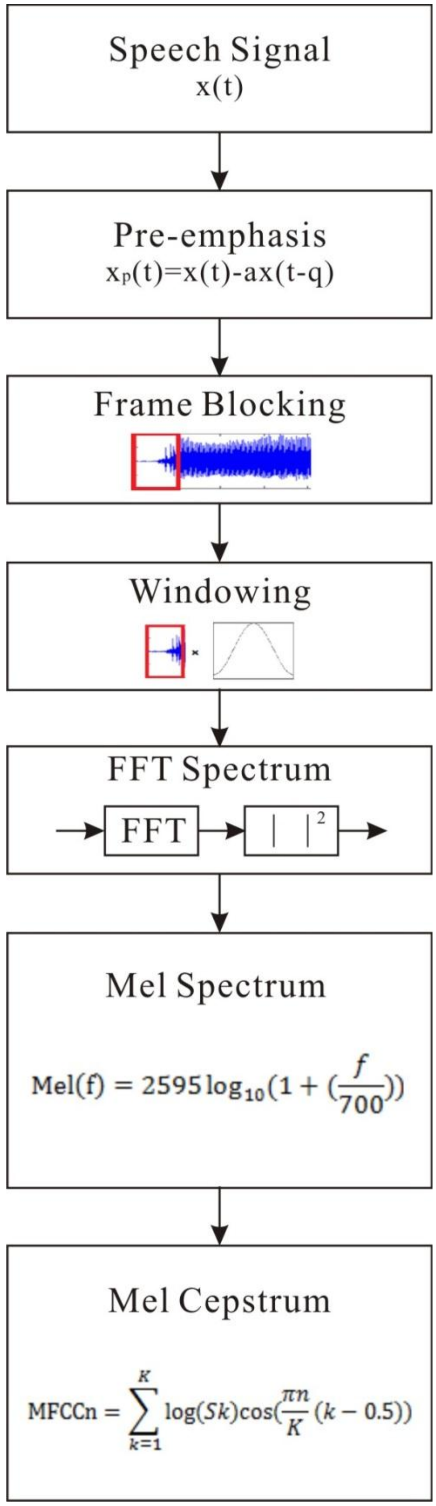

Figure 2.2 Block Diagram of Computing the Mel-Cepstrum

- DFT: The Discrete Fourier transform is applied by using the Fast Fourier transform (FFT). A 256 or 1024 FFT is commonly used for speech signals. After that, the magnitude is taken. Finally, we square the magnitude of the signal after the FFT.

- Mel Spectrum: The frequencies are warped by using $\mathrm{Mel(f)} = 2595\log_{10}(1 + (\frac{f}{700}))$, and the Mel filter bank is created [25]. The power signal obtained from the FFT spectrum is multiplied by the filter bank. The Mel spectrum S_k is created, for k=1,…,K, where K is the total number of filters.

- Mel Cepstrum: There are two steps for this part. First of all, take the log of the Mel spectrum, then the discrete cosine transform (DCT) is applied to convert them to the time domain by using

  $\mathrm{MFCCn} = \sum_{k=1}^{K} \log(Sk)\cos(\frac{\pi n}{K}(k - 0.5))$. n=1,…,N,

  where N is the total number of MFCC coefficients per frame.

Another method (sub-cepstrum) [25] for spectral features, which addresses the limited temporal resolution of the mel-scale filter energies and better exploits the auditory principles, convolves the mel-scale filter impulse response directly with the waveform x[n] [33], rather than applying the mel-scale frequency response as a weighting to the STFT magnitude, as shown below:

$$\mathrm{X(n,}\omega_l) = \mathrm{x[n]} * v_l[n] \tag{2.2}$$

where $v_l[n]$ is the impulse response corresponding to the frequency response of the *l*th mel-scale filter centered at frequency ω_l. We refer to $v_l[n]$ as a subband filter when invoking the convolution in equation (2.2). The energy of the output of the lth subband filter can be calculated as

$$E_{sub}(n,l) = \sum_{m=-N/2}^{N/2} p[n-m]|X(m,\omega_l)|^2 \quad . \tag{2.3}$$

The real cepstrum of the energies $E_{sub}(n,l)$ for l = 0, 1,…, R-1, where R is the number of filters, is referred to as the subband cepstrum and is written as

$$C_{sub} = \frac{1}{R}\sum_{l=0}^{R-1} \log\{E_{sub}(n,l)\}\cos(\frac{2\pi}{R}lm) \quad . \tag{2.4}$$

The energy of the subband filters, $E_{sub}(n,l)$, can capture more temporal characteristics of the signal than the mel-scale filter energies (particularly for high frequencies), since the short-duration, high-frequency subband filters are applied directly to the signal x[n]. Although the smoothing filter p[n] causes a loss of temporal resolution, the duration can be chosen together with the duration of $v_l[n]$.

In addition to MFCC and sub-cepstrum, a paper by Ravindran, Schlemmer and Anderson [74] indicates that other spectral features such as auditory model (AM), noise-robust auditory features (NRAF), and rate-scale-frequency (RSF) could also be alternate features to perform speaker recognition.

2.4 Speaker Recognition Algorithms

After extracting the features from the speech signal, as described in the previous section, several approaches to speaker recognition will now be introduced.

2.4.1 Minimum Distance Classifier

In speaker recognition, we obtain a set of features from each frame of the training and testing data. The feature set on each frame is a feature vector. One of the easiest approaches to speaker recognition is to compute the average of feature vectors over multiple frames for speakers from the training and testing data and find the average distance between the testing and training vectors [34] [48]. In speaker identification, we pick the target speaker as the one with the smallest average distance from the test speaker. In speaker verification, we set a distance threshold, and any speaker with an average distance less than the threshold is declared to be verified.

The average of the mel-cepstral features for the testing and training data is calculated as below:

$$\bar{C}_{mel}^{ts}[n] = \frac{1}{M}\sum_{m=1}^{M} C_{mel}^{ts}[mL, n] \tag{2.5}$$

$$\bar{C}_{mel}^{tr}[n] = \frac{1}{M}\sum_{m=1}^{M} C_{mel}^{tr}[mL, n] \tag{2.6}$$

where ts and tr represents the testing and training data. In addition, M is the number of frames, which differs in testing and training, and L is the frame length. Therefore, the mean-squared difference between the average testing and training feature vectors is calculate as

$$D = \frac{1}{R}\sum_{n=1}^{R} (\bar{C}_{mel}^{ts}[n] - \bar{C}_{mel}^{tr}[n])^2 \tag{2.7}$$

where R is the number of mel-cepstral coefficients, which is also the length of the feature vector. This is called the minimum distance classifier.

2.4.2 Vector Quantization

There exists a problem with the minimum distance classifier, in that it does not distinguish between acoustic speech classes. The method uses an average of feature vectors for each speaker computed over all sound classes. It is reasonable that the system could do better if it averages feature vectors over distinct sound classes. This would reduce the phonetic differences in the feature vectors and focus on speaker differences.

The task of the speaker verification using vector quantization (VQ) consists of two phases - training and recognition [35] - [37]. During the training phase a set of centroids are formed from the training data of each speaker. For speaker identification, the unknown speaker is selected as the reference speaker with the minimum average distance. For speaker verification, the unknown speaker is accepted as the reference speaker if the average distance is smaller than the threshold.

Several centroids will first be found for each speaker in the training data by using the Linde, Buzo, and Gray (LBG) algorithm. In 1980, Linde, Buzo, and Gray proposed a VQ algorithm based on a training sequence to generate the codebook [38]. The LBG-VQ algorithm requires an initial codebook C_1, which is calculated as the average of the feature vector of the entire training sequence. The code vector will then split into two and then split into four. The process is repeated until the desired number of code vectors is obtained. The algorithm is summarized as the steps shown below [39].

1. Calculate the initial codebook by equation (2.8).

$$C_1 = \frac{1}{F}\sum_{f=1}^{F} X_f \tag{2.8}$$

where F is the total number of frames and X_f is the feature vector of the *f*th frame. Also, set m equal to 1.

2. Split the m code vector(s) into 2m code vectors using equation (2.9) according to the current codebook C_m, where m is the number of current code vectors. ε is larger than 0.

$$\begin{cases} C_m^+ = (1+\varepsilon)C_m \\ C_m^- = (1-\varepsilon)C_m \end{cases} \tag{2.9}$$

3. Classify all the training vectors according to the new codebook C by the shortest Euclidean distance. After that, calculate the quantization distortion D^n and the relative distortion RD^n using

$$D^n = \sum_{f=1}^{F} (X_f, C) \tag{2.10}$$

$$RD^n = \left|\frac{D^n - D^{n-1}}{D^n}\right| \quad . \tag{2.11}$$

If RD^n is less than ε, stop iterating and go to step 5. C is the codebook for 2m code vectors. Otherwise, go to the next step.

4. Update the new code vectors using

$$C_j = \frac{1}{N} \sum_{X_i \in C_j} X_i \tag{2.12}$$

and go back to the previous step. N is the number of feature vectors quantized to C_j.

5. Repeat step 2 to step 4 until the desired number of code vectors is obtained.

After calculating the centroids for each training class, the system will assign the MFCC vector of each frame from different testing speakers to a class by first finding the minimum Euclidean distance from the test vector to the centroids of each speaker from the training stage. Then we compute the average of these minimum distances over all frames of the testing utterance. The last step is making the recognition decision.

2.4.3 Gaussian Mixture Model

The VQ method is making “hard” decisions since a single class is selected for each feature vector in testing. Another type of classifier is to make “soft” decisions by introducing probabilistic models using multi-dimensional probability density function (pdf) for feature vectors. The Gaussian mixture model (GMM) [12] [26] [30] [40] [41] is commonly used in a maximum likelihood approach to recognition. The Gaussian pdf is state-dependent in that there is assigned a different Gaussian pdf for each acoustic sound class.

A Gaussian mixture density is a weighted sum of M component densities as shown below:

$$p(\vec{x}_k|\lambda) = \sum_{m=1}^{M} p_m \frac{exp\left\{-\frac{1}{2}(\vec{x}_k - \vec{\mu}_m)'\Sigma_m^{-1}(\vec{x}_k - \vec{\mu}_m)\right\}}{(2\pi)^{D/2}(|\Sigma_m|)^{1/2}} \tag{2.13}$$

where $\vec{x}_k$ is a D-dimensional feature vector from the training speaker. $X = \{\vec{x}_1, \ldots, \vec{x}_T\}$ is a sequence of feature vectors which has T frames. p_m are the mixture weights and the sum of the mixture weights is always 1. In addition, $\vec{\mu}_m$ and Σ_m are the mean vectors and the covariance matrices. Therefore, the Gaussian mixture density is parameterized by the mixture weights, the mean vectors, and the covariance matrices. The model λ in equation (2.14) is considered as the template of each speaker in the database:

$$\lambda = \{p_i, \mu_i, \Sigma_i\} \tag{2.14}$$

The most common method to obtain each speaker model is to use maximum likelihood estimation to determine the mixture weights, the means, and the covariance matrices. The parameters can then be obtained iteratively by using the expectation-maximization (EM) algorithm over the feature vectors of the training data.

The maximum likelihood estimation finds a set of parameters which maximizes the likelihood of the Gaussian mixture models by using the training data for a particular speaker. It tries to maximize the model probability

$$P(X|\lambda) = \prod_{k=1}^{T} p(\vec{x}_k|\lambda) \tag{2.15}$$

where $X = \{\vec{x}_1, \ldots, \vec{x}_T\}$ is a sequence of feature vectors of the training speaker. The calculation is made by assuming that frames are independent. It is not possible to calculate the GMM parameters directly because of its non-linearity. However, these parameters can still be trained by using the EM algorithm iteratively.

The training will start with an initial guess for those parameters for the EM algorithm to start re-estimating. For each iteration, equations (2.16) to (2.18) are used to train the mixture weights, the means, and the variances, which guarantee a monotonic increase in the model's likelihood.

- mixture weights:

$$\bar{\mathrm{p}}_i = \frac{1}{T}\sum_{k=1}^{T} \mathrm{p}(i|\vec{x}_k\lambda) \tag{2.16}$$

- means:

$$\vec{\bar{\mu}}_i = \frac{\sum_{k=1}^{T} p(i|\vec{x}_k\lambda)\vec{x}_k}{\sum_{k=1}^{T} p(i|\vec{x}_k\lambda)} \tag{2.17}$$

- variances:

$$\bar{\sigma}_i{}^2 = \frac{\sum_{k=1}^{T} p(i|\vec{x}_k\lambda){x_k}^2}{\sum_{k=1}^{T} p(i|\vec{x}_k\lambda)} - \bar{\mu}_i{}^2 \tag{2.18}$$

Finally, the posteriori probability for acoustic class i can be calculated as

$$\mathrm{p}(i|\vec{x}_k\lambda) = \frac{p_i \frac{exp\left\{-\frac{1}{2}(\vec{x}_k - \vec{\mu}_m)'\Sigma_m^{-1}(\vec{x}_k - \vec{\mu}_m)\right\}}{(2\pi)^{D/2}(|\Sigma_m|)^{1/2}}}{\sum_{i=1}^{M} p_i \frac{exp\left\{-\frac{1}{2}(\vec{x}_k - \vec{\mu}_m)'\Sigma_m^{-1}(\vec{x}_k - \vec{\mu}_m)\right\}}{(2\pi)^{D/2}(|\Sigma_m|)^{1/2}}} \quad . \tag{2.19}$$

After training each GMM, each speaker would have their individual mixture model. The objective is to find the speaker model which has relatively high a posteriori probability for a given observation sequence. However, if we multiply the probabilities of each frame, the number would be close to zero. Therefore, we take the log of the probabilities and add them together as a log likelihood function, as shown below:

$$\text{log likelihood } = \sum_{k=1}^{T} log[\mathrm{p}(\vec{x}_k|\lambda)] \quad . \qquad (2.20)$$

The classification decision is made by determining the speaker for which the log likelihood function has the largest value (for speaker identification). The verification decision is made by setting up a threshold; any speaker who has the log likelihood function larger than the threshold would be accepted as the speaker; otherwise, the speaker would be rejected (for speaker verification).

2.5 Non-Spectral Features for Speaker Recognition

The previous two sections focus on spectral-based vocal tract feature, which is the mel-cepstrum, for speaker recognition. Another non-spectral feature will be introduced in this section.

The non-spectral feature that is most commonly used is the glottal flow derivative [25]. The method extracts and characterizes the glottal flow derivative during voicing by pitch-synchronous inverse filtering and temporal parameterization of the flow under the assumption that the time interval of glottal closure is known. The “coarse structure” of the flow derivative was represented by seven parameters, describing the shape and timing of the components of the piecewise-functional Liljencrants-Fant (LF) model [42]. Figure 2.3 [43] shows the seven parameters of the LF model and the parameters are then described.

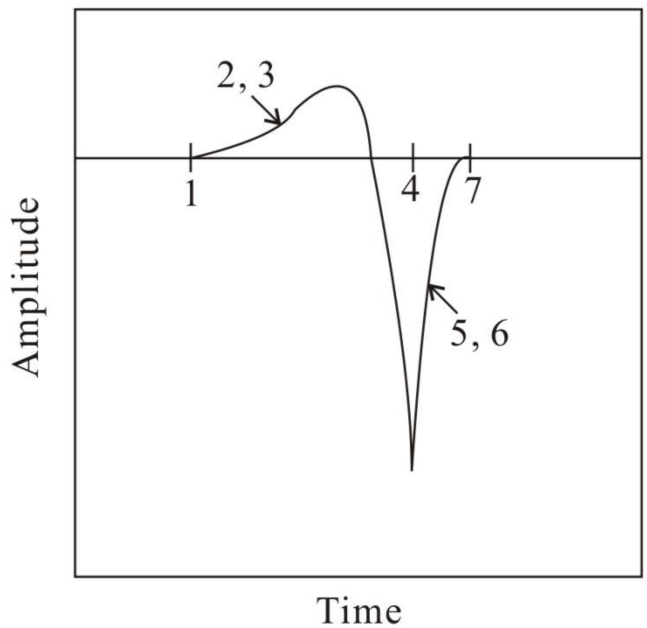

Figure 2.3 LF Model for the Glottal Flow Derivative Waveform

1. T_0: The time of glottal opening.
2. α: Factor that determines the ratio of E_e to the peak height of the positive portion of the glottal flow derivative.
3. ω_0: Frequency that determines flow derivative curvature to the left of the glottal pulse; also determines how much time elapses between the zero crossing and T_e.
4. T_e: The time of the maximum negative value of the glottal pulse.
5. E_e: The value of the flow derivative at time T_e.
6. β: An exponential time constant which determines how quickly the flow derivative returns to zero after time T_e.
7. T_c: The time of glottal closure.

These parameters are obtained by a nonlinear estimation method. The “coarse structure” was then subtracted from the glottal flow derivative estimate to give its “fine structure” component. This component has characteristics not captured by the general flow shape referred as “ripple”, which is associated with first-format modulation and is due to the time-varying and nonlinear coupling of the source and vocal tract cavity [44].

Liljencrants and Fant also defined five time intervals with a glottal cycle for the “fine structure” features [25]. The first three intervals correspond to the timing of the open, closed, and return glottal phase based on the LF model of the “coarse structure”. The last two intervals come from open and closed phase glottal timings. The latter is motivated by the observation that when the vocal folds are not fully shut during the closed phase, ripple can begin prior to the end of this closed phase estimation. Time domain energy measures are calculated over these five time intervals for each glottal cycle and normalized by the total energy in the estimated glottal flow derivative waveform. The “coarse structure” and “fine structure” features can then be used in speaker recognition. Figure 2.4 shows the approach to glottal flow derivative estimation and modeling, and its use in speaker recognition [43].

Other papers [45] [46] also discuss the topic of the glottal flow model. However, the speaker recognition performance is not as good as the spectral feature ones.

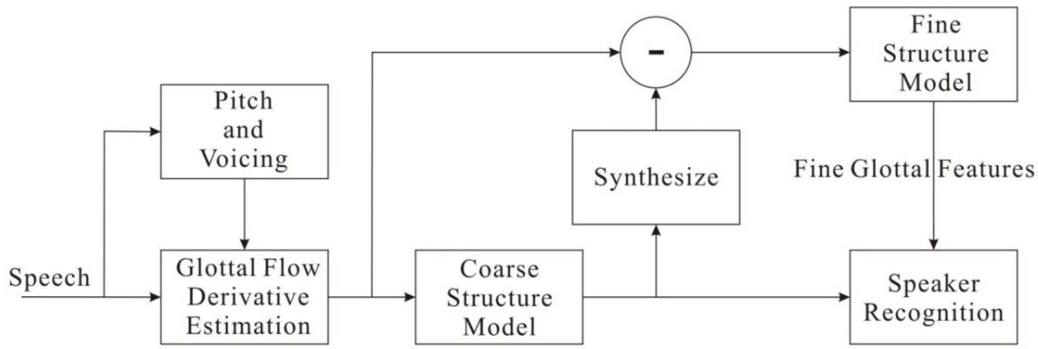

Figure 2.4 Approach to Glottal Flow Derivative Estimation and Modeling

2.6 Recent Researches for Speaker Recognition

As mentioned in the first chapter, researchers are trying different methods to improve the performance of speaker recognition. For instance, trying new algorithms or using new features. In this section, I will focus on phoneme weighting and phoneme specific methods.

2.6.1 Phoneme weighting and Phoneme Specific Methods

Previous papers indicate that vowel phonemes and phoneme-specific [47] models work well for speaker identification [48] [49]. The work by Hansen, Slyh and Anderson [50] used a phoneme-specific GMM system to perform speaker identification. Their results indicate that fusing the top 40 performing scores [51] of the individual phoneme system resulted in an error rate of 1.7%, which was a 2.6% reduction relative to their baseline system.

Another paper by Lee, Choi and Kang [52] proposes an efficient method to improve speaker recognition [53] performance by dynamically controlling the ratio of phoneme class information. First, they classified phonemes into five categories (stops, fricatives, nasals, semivowels and vowels), where the optimal ratio of each class in both training and testing processes was adjusted using a non-linear optimization technique. Then they experimentally re-evaluated the speaker discriminative power of each phoneme class using mutual information [54] [55] and found the optimal phoneme class ratio. Their results indicated that vowels have more speaker discriminative information. However, recognition performance improved when the ratio of consonants used was increased and the ratio of vowels was decreased. This is because semivowels and vowels have more redundant information than other classes even though they contribute greatly to the performance of the speaker recognition system.

The Lee, Choi and Kang paper indicates that redundancy of a class usually increases when the class ratio increases. In addition, including redundant data can degrade speaker recognition performance. For example, they found that speaker identification performance is better when the ratio of vowels is 80% compared to 90%, even though it is known that vowels have more speaker discriminative information than consonants. Thus, they concluded that it is important to consider the redundancy of the data while maximizing mutual information by controlling the phoneme class ratio. Finally, their paper also indicates that nasals are also important to improve the speaker recognition performance.

Moreover, a paper by Eatock and Mason [56] provides an assessment of the relative speaker discriminating properties of phonemes by showing the equal error rates (EERs) of speaker verification corresponding to 35 phonemes. Their research indicated that vowels and nasals are found to provide the best speaker verification performance. Another paper by Auckenthaler, Parris and Carey [57] describes the use of phonetic weighting to improve a GMM based speaker verification system. Their weighting score is based on the Eatock and Mason paper.

The Auckenthaler, Parris and Carey paper indicates that applying linear weighting to phonemes showed that less than half of the phonemes contributed significantly to the overall system performance. In addition, the best scoring GMM frames were strongly correlated with particular phonemes such as vowels and nasals. However, using phoneme weighting provided a significant improvement in performance for male speakers but not for female speakers.

2.6.2 Other Issues

Other than phoneme weighting and phoneme specific methods, researchers also tried different methods to improve the performance of speaker recognition recently. Some papers [58] - [61] modify the speaker recognition algorithm based on VQ and using Mel frequency cepstral coefficients (MFCC) as features. Other papers [62] - [64] tried to improve the feature extraction method or use multiple features for recognition. Furthermore, some papers [65] - [67] modify the speaker recognition algorithm based on GMM and a paper [68] even combined classifiers. Additional papers [69] - [73] also describe recent speaker recognition systems.

2.7 Summary

Feature extraction and recognition algorithms are the main issues of speaker recognition. Having completed the background review, this dissertation will now focus on finding several ways that could improve speaker recognition performance. The following chapter will be the statement of problem and method of research.

CHAPTER THREE

METHODS OF RESEARCH

This chapter presents the methods of research, which includes determination of which specific vowel phonemes work best for speaker recognition, and also the development of new algorithms for improved speaker identification accuracy. Then, Chapters 4 and 5 present the results of methods proposed in Chapter 3. Chapter 6 then investigates an energy characteristic as another parameter for speaker identification. Chapter 7 then combines information from Chapter 4, 5 and 6 to propose and evaluate a modified algorithm.

3.1 Determining Specific Vowel Phonemes which Work Best for Speaker Recognition

Nine phonemes (/i/, /I/, /e/, /E/, /@/, /a/, /o/, /U/ and /u/) were recorded for fifteen speakers for training and testing in this experiment. (Phoneme /c/ was not used since its formants are close to those of /a/.) Speech segments s1 - s15 are the training data and speech segments t1 - t15 are the testing data (sk and tk were recorded by the same person, speaker k) for each phoneme. In addition, speech segments s1 - s8, t1 - t8 are from male speakers and s9 - s15, t9 - t15 are from female speakers.

All the recorded phonemes in the training set and the test set have 2 seconds duration. Twenty mel-frequency cepstral coefficients [28] (MFCC) were used for classification. Also, the sampling frequency for each file is 44,100Hz and the window size for each speech frame is 256 samples. The windows are stepped by 100 samples;

therefore, the frames will overlap by 156 samples with adjacent frames. An additional experiment was performed using window length of 512 and 1024, and the results were similar.

3.1.1 Recognition by Using GMM

A speaker model based on Gaussian mixture models (GMM) [30] [40] was introduced and evaluated for text independent speaker identification by Reynolds [41]. In addition, the use of Gaussian mixture models for modeling speaker identity is motivated by the hypothesis that the Gaussian components represent some general speaker-dependent spectral shapes and by the proven capability of Gaussian mixtures to model arbitrary densities.

After training each GMM of order 16 in our experiment, each phoneme spoken by each speaker would have its individual mixture model. For speaker identification, the objective is to find the speaker model for that phoneme which has the maximum a posteriori probability for a given observation sequence. The classification decision is made by determining the phoneme for which the log likelihood function has the largest value. For speaker verification, the objective is to find the speaker model for that phoneme which has relatively high a posteriori probability for a given observation sequence. The verification decision is made by setting up a threshold; any spoken phoneme which has the log likelihood function larger than the threshold would be accepted as the speaker; otherwise, the speaker would be rejected.

3.1.2 Recognition by Using VQ

The principle of the speaker identification using vector quantization consists of two phases - training and identification [25] [35] [36]. During the training phase a set of centroids are formed from the training data of each speaker, for each vowel phoneme. During the identification phase, the unknown speaker will be selected as the reference speaker with the minimum average distance (distance from the testing speaker to the training speaker).

For our experiment 16 centroids for VQ were found for each phoneme utterance in our training set. We assign the MFCC vector of each frame from different testing speakers to a class by first finding the minimum Euclidean distance from the test vector to the centroids of each speaker from the training stage. Then we compute the average of these minimum distances over all frames of the testing utterance. For speaker identification, the speaker with the smallest average minimum distance is declared to be identified. For speaker verification, he or she is declared to be verified if the speaker has an average minimum distance less than the threshold.

3.1.3 Method of Research

In this experiment, both GMM and VQ classifiers were used to perform the recognition. After testing all the data by both methods, we switched the training data and the testing data and performed the recognition again. (Speech segments t1 - t15 were now used as training data and s1 - s15 as testing data.)

For speaker verification, a threshold was set for each phoneme to have the same number of false acceptance (FA) errors and false rejection (FR) errors. Since there are 15 training segments and 15 testing segments, there were 225 inputs for verification. The equal error rate (EER) was calculated as the ratio of the FA number to the number of inputs or the ratio of the FR number to the number of inputs, when these two ratios are equal.

3.2 Developing New Algorithms for Improved Speaker Identification Accuracy

Forty nine male speakers from the DARPA resource management continuous speech database were used for training and testing in this experiment. Speech segments s1 – s49 were the training data and speech segments t1 – t49 were the testing data (sk and tk were recorded by the same person, speaker k). Speech segments s1 – s49 were recorded by each speaker speaking the same sentence “she had your dark suit in greasy wash water all year”. Speech segments t1 – t49 were recorded by each speaker speaking the same sentence “don't ask me to carry an oily rag like that”. Both sentences are rich with vowel sounds, which are useful for speaker identification.

Twenty mel-frequency cepstral coefficients (MFCC) were used for classification. Also, the sampling frequency used for each file was 16,000Hz, the Hamming window was used, and the window size for each speech frame was 256 samples. Windows were stepped by 100 samples; therefore, frames overlapped by 156 samples with adjacent frames. An additional experiment was performed using window length of 128; however, the results were better for the window length of 256.

3.2.1 New Algorithms Based on Energy

In this experiment, three different methods were used to perform the classification. All three methods require evaluating the average magnitude of the speech segments as the first step. For the first method, we ignored the frames which have relatively small magnitude and determined what threshold works the best. This permits us to ignore noise and some low energy sound, which may not be useful for speaker identification.

Instead of ignoring the frames which have relatively small magnitude, the second method tries to emphasize frames which have relatively large magnitude. We also attempt to determine what threshold works the best for this method.

Finally, we combined the previous two methods together as a third method. This method not only ignores the frames which have relatively small magnitude but also emphasizes the frames which have relatively large magnitude.

Groups of 12, 18, 24, 30, 36, 42 and 49 speakers were used for training and testing. After each classification for different sizes of speakers, we switched the training data and the testing data and performed the classification again. (Speech segments t1 – t49 were now used as training data and s1 – s49 as testing data.) Moreover, we compared the accuracy provided by using the three new methods with the baseline system which used no weighting and no thresholding. All systems used MFCCs as features and VQ for the classifier.

3.2.2 New Algorithms Based on Selected Vowel Phonemes

Since we already determined specific vowel phonemes which work best for speaker identification, we performed identification by giving these phonemes larger weight or using only these frames of these phonemes to do the classification. The same groups of 12, 18, 24, 30, 36, 42 and 49 speakers were used for training and testing. After each classification for different sizes of speakers, we switched the training data and the testing data and performed the classification again.

CHAPTER FOUR

SPEAKER IDENTIFICATION RESULTS

This chapter focuses on determining specific vowel phonemes which work best for speaker identification. Utterances of nine different vowel phonemes were recorded for fifteen different speakers. Mel-frequency cepstral coefficients (MFCC) components were used for training and testing. Both Gaussian mixture models (GMM) and vector quantization (VQ) methods were used for classification. In addition to identification results, this paper also presents the winning ratio and the losing ratio to indicate which phonemes have the best speaker separation properties. Initial parameters of the MFCC vector were selected before the experiments as described below.

4.1 Initial Parameters of the MFCC Vector

Before the experiments, we would like to find out several initial parameters of the MFCC vector which works better for speaker recognition, such as the ideal dimension of the vector and the weighting method. The DARPA database was used for testing. There are 49 male speakers in the database and the following two sentences were recorded by all the speakers: “She had your dark suit in greasy wash water all year”, and “Don't ask me to carry an oily rag like that”, which includes lots of vowel phonemes. The first sentence would be the training set and the second sentence would be the testing set. After checking the identification accuracy, we switched the training and testing sentence and performed the classification again. The method we used for classification is VQ.

4.1.1 The Ideal Dimension

12, 16, 20 and 24 MFCCs were used and groups of 12, 18, 24, 30, 36 speakers were used for testing. Table 4.1 shows the classification accuracy.

Speakers	12 MFCCs	16 MFCCs	20 MFCCs	24 MFCCs
12	20/24	23/24	23/24	23/24
18	30/36	32/36	33/36	32/36
24	41/48	43/48	45/48	44/48
30	50/60	54/60	56/60	55/60
36	55/72	60/72	65/72	61/72

Table 4.1 Classification Accuracies by Using Different Dimensions of MFCC

For example, the “20/24” in row “12” and under column “12 MFCCs” means that 20 of the test files have been classified correctly when the speaker size is 12 and 12 MFCCs were used. We can see that the results were similar when the speaker size is small. When the speaker size increased to 30 or 36, the 20 MFCCs cases have higher accuracy than others. Therefore, we will use 20 MFCCs for the rest of our research.

4.1.2 The Weighting Method

Figure 4.1 shows the two weighting methods commonly used for the MFCC vector. The first one is the equal weight method, which gives all the components equal weight. The second one is the weighted method, which gives the middle ones larger weight.

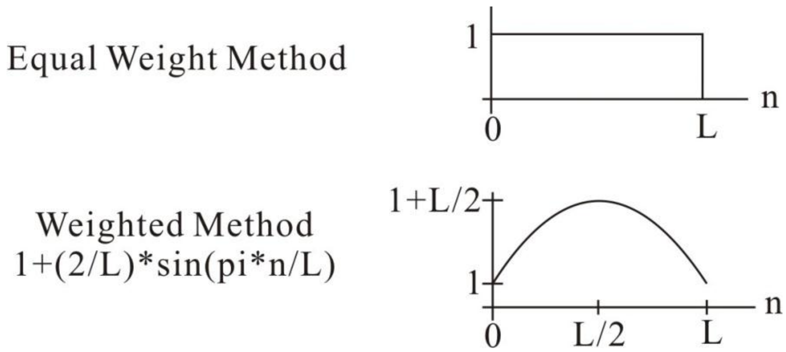

Figure 4.1 The Equal Weight Method and Weighted Method for MFCC

Previous research showed that the weighted method improved the performance for speech recognition [36] and we would like to check whether it also works well for speaker identification. We used the same method to do the testing and found out that both methods also have similar results when the speaker size is small (Table 4.2). The equal weight method works much better when the speaker size increased to 36, 42 and 49. Therefore, the weighted method works better for speech recognition but not for speaker identification.

Speakers	Equal Weight	1+(2/L)*sin(pi*n/L)
12	23/24	23/24
18	33/36	33/36
24	45/48	44/48
30	56/60	54/60
36	65/72	61/72
42	76/84	68/84
49	86/98	76/98

Table 4.2 Classification Accuracies by Using Different Weighting Methods

4.2 Results

Table 4.3 shows the classification error for each phoneme by using both GMM and VQ methods. For each phoneme (each row in the table), the numbers in the cell represent the speakers who have been misclassified. For example, the "14" in row "1 /i/" and under column "GMM 2" means that speaker 14 has been misclassified. Blank cells indicate that all speakers have been recognized correctly. For GMM1 and VQ1, s1 to s15 were used as training data and t1 to t15 as testing data. For GMM2 and VQ2, we switched the training data and the testing data and performed the classification again.

	GMM 1	GMM 2	VQ 1	VQ 2
1 /i/		14		
2 /I/	14	1		
3 /e/		4, 5, 8		
4 /E/				
5 /@/	10, 15	4, 10, 14		
6 /a/	10, 15	1, 7, 9, 12, 15	10	7
7 /o/	9	12		12
8 /U/	10, 11	10	11	10, 11
9 /u/		4		4

Table 4.3 Classification Errors for Nine Different Phonemes Using GMM and VQ Classifiers

From Table 4.3, we can see that persons speaking /i/, /E/ and /u/ have been classified well by both GMM and VQ classifiers (at most one classification error) in this experiment. For VQ, /i/, /I/, /e/, /E/ and /@/ had no classification errors. In addition, for

/I/ and /E/ which have similar formants, /E/ has the higher accuracy when using the GMM classifier. Furthermore, for /U/ and /u/ which also have similar formants, /u/ has the higher accuracy when using either the GMM or VQ classifier.

4.3 Winning Ratio and Losing Ratio

In addition to the classification results shown above, the winning ratio and losing ratio were also determined. For the cases of correct classification, the winning ratio is defined as the ratio of the winning score to the second place score. Therefore, this ratio will always be larger than 1. The cases with larger ratios are cases of strong winners. For cases of misclassification, the losing ratio is defined as the log likelihood function ratio of the selected speaker to the correct speaker (for GMM) or the distance ratio of the selected speaker to the correct speaker (for VQ). For these cases, the ratio will be less than 1. The cases where this ratio is close to 1 are cases where the classification was almost correct. Table 4.4 shows the average winning ratio for each phoneme.

We also evaluated three factors for the cases which had classification error. Table 4.5 and Table 4.6 provide the following information for each case where classification was incorrect.

1. The testing speaker who was incorrectly selected
2. The rank of the correct speaker
3. The probability/distance ratio of the chosen speaker and the correct speaker (losing ratio)

	GMM	VQ
1 /i/	3.523	1.873
2 /I/	3.857	1.813
3 /e/	2.948	1.658
4 /E/	3.513	1.789
5 /@/	2.710	1.644
6 /a/	2.724	1.548
7 /o/	2.936	1.727
8 /U/	3.510	1.687
9 /u/	2.599	1.537

Table 4.4 The Average Winning Ratio for Nine Different Phonemes by Using GMM and VQ Classifiers

For example, the first cell of Table 4.5 indicates that by using method GMM 2, for the /i/ phoneme, the classifier thinks that speaker 14 is speaker 2, the rank of the correct speaker (speaker 14) is 2 and the losing ratio is 0.459. The cells with higher ranks and higher losing ratios mean that the selected one is closer to the correct one.

GMM 2 /i/: ● 14 => 2 ● Rank=2 ● 0.459	GMM 1 /I/ ● 14 => 11 ● Rank=10 ● 0.397	GMM 2 /I/ ● 1 => 2 ● Rank=3 ● 0.399	GMM 2 /e/ ● 4 => 3 ● Rank=2 ● 0.891	GMM 2 /e/ ● 5 => 6 ● Rank=2 ● 0.731
GMM 2 /e/ ● 8 => 3 ● Rank=4 ● 0.467	GMM 1 /@/ ● 10 => 8 ● Rank=10 ● 0.358	GMM 1 /@/ ● 15 => 2 ● Rank=2 ● 0.787	GMM 2 /@/ ● 4 => 5 ● Rank=4 ● 0.737	GMM 2 /@/ ● 10 => 2 ● Rank=4 ● 0.755
GMM 2 /@/ ● 14 => 6 ● Rank=3 ● 0.724	GMM 1 /a/ ● 10 => 14 ● Rank=7 ● 0.787	GMM 1 /a/ ● 15 => 2 ● Rank=3 ● 0.846	GMM 2 /a/ ● 1 => 8 ● Rank=2 ● 0.721	GMM 2 /a/ ● 7 => 8 ● Rank=6 ● 0.414
GMM 2 /a/ ● 9 => 10 ● Rank=2 ● 0.954	GMM 2 /a/ ● 12 => 8 ● Rank=2 ● 0.869	GMM 2 /a/ ● 15 => 8 ● Rank=2 ● 0.844	GMM 1 /o/ ● 9 => 6 ● Rank=2 ● 0.757	GMM 2 /o/ ● 12 => 6 ● Rank=4 ● 0.624
GMM 1 /U/ ● 10 => 6 ● Rank=3 ● 0.626	GMM 1 /U/ ● 11 => 5 ● Rank=2 ● 0.916	GMM 2 /U/ ● 10 => 1 ● Rank=3 ● 0.947	GMM 2 /u/ ● 4 => 7 ● Rank=2 ● 0.687	

Table 4.5 Information for the Cases with Classification Error (GMM)

VQ 1 /a/ ● 10 => 12 ● Rank=2 ● 0.978	VQ 2 /a/ ● 7 => 3 ● Rank=2 ● 0.947	VQ 2 /o/ ● 12 => 9 ● Rank=2 ● 0.992	VQ 1 /U/ ● 11 => 3 ● Rank=3 ● 0.903	VQ 2 /U/ ● 10 => 6 ● Rank=2 ● 0.946
VQ 2 /U/ ● 11 => 6 ● Rank=2 ● 0.919	VQ 2 /u/ ● 4 => 7 ● Rank=2 ● 0.978			

Table 4.6 Information for the Cases with Classification Error (VQ)

Table 4.7 shows the average losing ratio for each phoneme, which is calculated from Table 4.5 and Table 4.6. The blank cells represent cases where classification was completely correct. For the VQ method, the average losing ratios are close to 1 in all cases, which means that the selected ones are very close to the correct ones even though they have been misclassified. For the GMM method, /i/ and /I/ have high winning ratios and low losing ratios. However, there are very few classification errors in these two cases. For other phonemes, when the winning ratio is high (low), the losing ratio is also high (low).

	GMM	VQ
1 /i/	0.459	
2 /I/	0.398	
3 /e/	0.696	
4 /E/		
5 /@/	0.672	
6 /a/	0.776	0.963
7 /o/	0.691	0.992
8 /U/	0.830	0.923
9 /u/	0.687	0.978

Table 4.7 The Average Losing Ratio for Nine Different Phonemes by Using GMM and VQ Classifiers

Combining the results from Table 4.5 and Table 4.6 with the results from Table 4.4, we found that in both cases (GMM and VQ), /i/, /I/ and /E/ have the highest winning ratio. /U/ also has a high winning ratio, but the classification accuracy is not as good as for the three phonemes mentioned above. The overall speaker identification accuracy is 91.1% for GMM classifier and 97.4% for VQ classifier in our experiment.

CHAPTER FIVE

SPEAKER VERIFICATION RESULTS

This chapter focuses on determining specific vowel phonemes which work best for speaker verification. Utterances of nine different vowel phonemes were recorded for fifteen different speakers. Mel-frequency cepstral coefficients (MFCC) components were used for training and testing. Both Gaussian mixture models (GMM) and vector quantization (VQ) methods were used for verification. In addition, this chapter also compares the verification results with the results of our speaker identification system which is based on the same features.

5.1 Results

Table 5.1 shows the verification errors for each phoneme by using the GMM method. For each phoneme and method (GMM1 and GMM2), the numbers in the cell represent the speakers who have verification error. For example, the “3 => 8” in row “1 /i/ GMM1” and under column “FA” means that speaker 3 has been accepted as speaker 8. In addition, the “2” in row “1 /i/ GMM1” and under column “FR” means that speaker 2 has been rejected as speaker 2. Blank cells indicate that all speakers have been verified correctly. For GMM1, s1 to s15 were used as training data and t1 to t15 as testing data. For GMM2, we switched the training data and the testing data and performed the verification again. The threshold is the value that results in an equal error rate.

	FA	FR	Threshold (*10^4)
1 /i/ GMM1	3 => 8, 9 => 6	2, 15	-2.88
1 /i/ GMM2	5=> 2, 14 => 2	8, 14	-2.77
2 /I/ GMM1	1 => 2	14	-2.73
2 /I/ GMM2	1 => 2, 6 => 2, 10 => 11	1, 8, 14	-2.73
3 /e/ GMM1	6 => 5	12	-2.63
3 /e/ GMM2	4 => 3, 6 => 2, 8 => 3, 13 => 2	1, 5, 8, 15	-3.49
4 /E/ GMM1			-2.32
4 /E/ GMM2	4 => 3, 3 => 2, 10 => 8	12, 14, 15	-3.15
5 /@/ GMM1	1 => 8, 7 => 2, 15 => 2	10, 13, 14	-2.82
5 /@/ GMM2	1 => 8, 7 => 2, 8 => 2, 10 => 2, 10 => 3	4, 9, 10, 12, 14	-4.17
6 /a/ GMM1	2 => 5, 3 => 7, 6 => 2	9, 10, 15	-2.82
6 /a/ GMM2	1 => 8, 3 => 8, 5 => 2, 5 => 8, 7 => 8	1, 7, 9, 12, 15	-2.31
7 /o/ GMM1	9 => 6, 14 => 6	9, 12	-2.54
7 /o/ GMM2	9 => 6	12	-2.91
8 /U/ GMM1	5 => 7, 13 => 5	10, 11	-2.47
8 /U/ GMM2	3 => 7, 7 => 5	10, 14	-2.51
9 /u/ GMM1	4 => 1, 4 => 7, 12 => 1	9, 13, 14	-1.99
9 /u/ GMM2	1 => 7, 3 => 7, 4 => 7	5, 8, 13	-2.07

Table 5.1 Verification Errors for Nine Different Phonemes Using GMM Method

Table 5.2 shows the verification error for each phoneme by using the VQ method. As in Table 1, for each phoneme and method (each row in the table), the numbers in the cell represent the speakers who have verification error. Also, s1 to s15 were used as training data and t1 to t15 as testing data for VQ1. For VQ2, we switched the training data and the testing data and performed the verification again.

	FA	FR	Threshold
1 /i/ VQ1	14 => 2	2	4.21
1 /i/ VQ2			3.88
2 /I/ VQ1			3.92
2 /I/ VQ2			4.22
3 /e/ VQ1			3.79
3 /e/ VQ2	10 => 13	5	3.75
4 /E/ VQ1			3.62
4 /E/ VQ2			4.05
5 /@/ VQ1	9 => 14	5	4.00
5 /@/ VQ2			4.44
6 /a/ VQ1	3 => 7	10	3.74
6 /a/ VQ 2	7 => 3	10	3.72
7 /o/ VQ 1	11 => 9	12	3.50
7 /o/ VQ 2	9 => 11	12	4.04
8 /U/ VQ 1	11 => 3, 11 => 13, 13 => 5	10, 11, 12	3.52
8 /U/ VQ 2	13 => 5, 13 => 11	10, 11	3.69
9 /u/ VQ 1	13 => 15, 15 => 13	5, 14	3.39
9 /u/ VQ 2	4 => 7	5	3.39

Table 5.2 Verification Errors for Nine Different Phonemes Using VQ Method

Table 5.3 and Table 5.4 show the overall equal error rate for each phoneme by combining both GMM1 and GMM2 or both VQ1 and VQ2 methods. The threshold is a range of values that provide the EER. Moreover, the “Error(s)” column lists the number of false acceptance or false rejection when they have equal number of errors. Finally, the EER is calculated as the number of errors divided by the total number of inputs, which is 450 (225*2) in this case.

	Threshold (*10^4)	Error(s)	EER
1 /i/	-2.88~-3.00	4	0.89%
2 /I/	-2.73~-2.88	4	0.89%
3 /e/	-2.71~-2.75	6	1.33%
4 /E/	-3.13~-3.14	3	0.67%
5 /@/	-3.40~-3.51	8	1.77%
6 /a/	-2.59~-2.78	9	2%
7 /o/	-2.77~-2.79	3	0.67%
8 /U/	-2.51	6	1.33%
9 /u/	-2.07	3	0.67%
total		46	1.14%

Table 5.3 The Overall EER for Each Phoneme by Using GMM Method

	Threshold	Error(s)	EER
1 /i/	4.21~4.49	1	0.22%
2 /I/	4.22~4.24	0	0
3 /e/	3.79~4.03	1	0.22%
4 /E/	4.05~4.26	0	0
5 /@/	4.44	1	0.22%
6 /a/	3.74~3.91	2	0.44%
7 /o/	4.02~4.03	2	0.44%
8 /U/	3.55~3.59	4	0.89%
9 /u/	3.39~3.42	3	0.67%
total		14	0.35%

Table 5.4 The Overall EER for Each Phoneme by Using VQ Method

From Table 5.3 and Table 5.4, we can see that persons speaking /E/, /o/ and /u/ have been verified well by both GMM and VQ methods (at most three verification errors) in this experiment. For VQ, /i/, /I/, /e/, /E/ and /@/ had less than one verification error. In addition, for /U/ and /u/ which have similar formants, /u/ has the higher verification accuracy when using either the GMM or VQ classifier.

The overall speaker verification equal error rate was 1.14% for the GMM method and 0.35% for the VQ method in our experiments. In addition, VQ worked better than GMM in our experiments (which used short segments of training and testing data).

5.2 Comparing the Results with Speaker Identification

We have previously performed experiments which focused on determining which specific vowel phonemes work best for speaker identification. Instead of setting a threshold, the identification decision is made by determining the phoneme for which the log likelihood function has the largest value (for GMM) or which the average minimum distance is smallest (for VQ). The same training and testing data were used in both the verification and identification system.

From the previous experiment, we found that persons speaking /i/, /E/ and /u/ were classified well by both GMM and VQ classifiers (at most one classification error). For VQ, /i/, /I/, /e/, /E/ and /@/ had no classification errors. Combining these results with the results from Table 5.3 and Table 5.4, we found that in both cases (GMM and VQ), /E/ and /u/ were verified well and classified well. The results of the current verification experiments are consistent with the results of the previous identification experiments for the VQ method, since /i/, /I/, /e/, /E/ and /@/ performed the best and had less than one verification error. Furthermore, VQ also worked better than GMM in the speaker identification system.

CHAPTER SIX

EFFECTIVENESS OF ENERGY PARAMETER FOR SPEAKER IDENTIFICATION

This chapter focuses on evaluating the effectiveness of an energy parameter for speaker identification. Forty nine male speakers from the DARPA resource management continuous speech database were used for training and testing. Mel-frequency cepstral coefficients (MFCC) components were used for training and testing. Vector quantization (VQ) was used for classification. In addition to presenting identification results, this chapter shows the error reduction rate relative to a baseline system.

6.1 The Baseline System

Table 6.1 shows the classification accuracies for different sizes of speaker sets using a baseline system, which uses MFCC as feature and VQ as classifier. Since we switched the training and testing data after every classification, the total number of test cases is two times the number of speakers. From this table, we can see that the speaker identification accuracy was around 96% when the speaker size was small. The accuracy decreased to about 90% when the speaker size increased. Table 6.2 shows which test speakers have been misclassified for different sizes of speaker sets. For example, “5” in the table means “speaker number 5”. Column “Error (a)” shows the classification errors when we used the first sentence as training and the second sentence as testing. Column “Error (b)” shows the classification errors when we used the second sentence as training and the first sentence as testing.

Speakers	Correct/Total	Accuracy
12	23/24	0.958
18	33/36	0.917
24	45/48	0.938
30	56/60	0.933
36	65/72	0.903
42	76/84	0.905
49	86/98	0.878

Table 6.1 Classification Accuracies for the Baseline System (MFCCs Used as Features; VQ Used as Classifier)

Speakers	Error (a)	Error (b)
12	5	
18	5, 13	13
24	5, 13	13
30	5, 13	13, 30
36	5, 13, 32	10, 13, 16, 30
42	5, 13, 32, 41	10, 13, 16, 30
49	5, 13, 32, 41, 49	10, 13, 16, 30, 46, 48, 49

Table 6.2 Classification Errors for the Baseline System

6.2 New Algorithms

The improved results obtained by using the new algorithm are presented in Tables 6.3 – 6.6. Table 6.3 shows the accuracy by using the first method, as described in Chapter 3. The first method requires calculating the average magnitude of the entire speech segment for each speaker as the first step. After breaking the speech segments into frames, this method ignores the frames for which the average magnitude is smaller than "x" times the overall average magnitude, where $x < 1$. In this table, "12-a" in the "Speakers" column indicates that s1-s12 are the training data and segments t1-t12 are the testing data. After checking the classification accuracy, we switched the training set with the testing set and performed the identification again as "12-b".

	Before Modification		Best Threshold	After Modification	
Speakers	Correct/Total	Accuracy	x	Correct/Total	New_ Accuracy
12-a	11/12	0.917	0.020	12/12	1.000
12-b	12/12	1.000	0.020	12/12	1.000
18-a	16/18	0.889	0.020	16/18	0.889
18-b	17/18	0.944	0.020	17/18	0.944
24-a	22/24	0.917	0.008	22/24	0.917
24-b	23/24	0.958	0.008	23/24	0.958
30-a	28/30	0.933	0.008	29/30	0.967
30-b	28/30	0.933	0.008	28/30	0.933
36-a	33/36	0.917	0.008	33/36	0.917
36-b	32/36	0.889	0.008	33/36	0.917
42-a	38/42	0.905	0.004	38/42	0.905
42-b	38/42	0.905	0.004	38/42	0.905
49-a	44/49	0.898	0.004	44/49	0.898
49-b	42/49	0.857	0.004	42/49	0.857

Table 6.3 Classification Results by Using the First Method

Three cases shown in Table 6.3 were improved by using the first method; boxes are used to identify these cases in the rightmost column. This table indicates that it is better to use larger x when the speaker size is small, and use smaller x when speaker size is large. In addition, this method was more effective for smaller speaker sizes, and the total errors for all tests included in Table 6.3 were reduced from 38 to 35. The percentage of frames which were used for classification for different x was approximately 99% when x = 0.008, approximately 98% when x = 0.01, approximately 90% when x = 0.02, approximately 80% when x = 0.05, and approximately 40% when x = 1.

Although the first method ignores some noise and low energy sounds, sometimes it may also remove useful information. Therefore, instead of ignoring the frames which have small average magnitude, our second method assigns a weight larger than 1 to frames which have average magnitude larger than "y" times the overall average magnitude. (Normally, y > 1, but this is not always the case.) The results of method two are shown in Table 6.4.

Relative to the baseline system, nine cases were improved and the total errors were reduced by eleven by using the second method. From Table 6.4, we can see that it is better to use smaller y and larger weight when the speaker size is small, and use larger y and smaller weight when the speaker size is large. This method improved identification performance for all sizes of speaker sets. However, it may not be possible to find a best value of y when the number of speakers is large. For example, the "Best y Value" is different for the cases "42-a" and "42-b", and also different for "49-a" and "49-b". This method also works better for a smaller number of speakers. The percentage of frames that were weighted was approximately 40% when y = 1, approximately 15% when y = 2, approximately 10% when y = 2.5, approximately 5% when y = 3, and approximately 3% when y = 3.5.

	Before modification				After modification	
Speakers	Correct/Total	Accuracy	y	Weight	Correct/Total	New_ Accuracy
12-a	11/12	0.917	1 or 2	3	12/12	$\boxed{1.000}$
12-b	12/12	1.000	1 or 2	3	12/12	1.000
18-a	16/18	0.889	2.5	2 or 3	17/18	$\boxed{0.944}$
18-b	17/18	0.944	2.5	2	18/18	$\boxed{1.000}$
24-a	22/24	0.917	2.5	2	23/24	$\boxed{0.958}$
24-b	23/24	0.958	2.5	2	24/24	$\boxed{1.000}$
30-a	28/30	0.933	2.65	2	28/30	0.933
30-b	28/30	0.933	2.65	2	29/30	$\boxed{0.967}$
36-a	33/36	0.917	2.65	2	33/36	0.917
36-b	32/36	0.889	2.65	2	34/36	$\boxed{0.944}$
42-a	38/42	0.905	2.65	2	38/42	0.905
42-b	38/42	0.905	3.2	2	39/42	$\boxed{0.929}$
49-a	44/49	0.898	8	2	44/49	0.898
49-b	42/49	0.857	3.2	2	44/49	$\boxed{0.898}$

Table 6.4 Classification Results by Using the Second Method

The third method evaluated is a combination of the first two methods. We used the x found from Table 6.3 and the y and weight from Table 6.4 to ignore frames with small average magnitude and emphasize frames with large magnitude. Table 6.5 shows the results obtained using this method. These results show that combining x from method one with y from method two didn't improve the accuracy. (Seven cases improved and the total errors reduced from 38 to 30, compared to the baseline system. However, this performance was not as good as obtained using method two.)

	Before Modification					After Modification	
Speakers	Correct/Total	Accuracy	x	y	Weight	Correct/Total	New_ Accuracy
12-a	11/12	0.917	0.020	2	3	11/12	0.917
12-b	12/12	1.000	0.020	2	3	12/12	1.000
18-a	16/18	0.889	0.020	2.5	2 or 3	17/18	$\boxed{0.944}$
18-b	17/18	0.944	0.020	2.5	2	17/18	0.944
24-a	22/24	0.917	0.008	2.5	2	23/24	$\boxed{0.958}$
24-b	23/24	0.958	0.008	2.5	2	24/24	$\boxed{1.000}$
30-a	28/30	0.933	0.008	2.65	2	28/30	0933
30-b	28/30	0.933	0.008	2.65	2	29/30	$\boxed{0.967}$
36-a	33/36	0.917	0.008	2.65	2	33/36	0.917
36-b	32/36	0.889	0.008	2.65	2	33/36	$\boxed{0.917}$
42-a	38/42	0.905	0.004	2.65	2	38/42	0.905
42-b	38/42	0.905	0.004	3.2	2	39/42	$\boxed{0.929}$
49-a	44/49	0.898	0.004	8	2	44/49	0.898
49-b	42/49	0.857	0.004	3.2	2	44/49	$\boxed{0.898}$

Table 6.5 Classification Results by Using the Third Method

Since method two worked better than method one, we decided to combine y from method two with a smaller x than the value used in method one to ignore the noise and some low energy sound. (We used 0.5 times the old x from Table 6.3 as the new threshold.) The resulting method is called "adjusted method three". Table 6.6 shows the results obtained using the smaller x threshold.

	Before modification					After modification	
Speakers	Correct/Total	Accuracy	x	y	Weight	Correct/Total	New_ Accuracy
12-a	11/12	0.917	0.010	2	3	12/12	1.000
12-b	12/12	1.000	0.010	2	3	12/12	1.000
18-a	16/18	0.889	0.010	2.5	2 or 3	17/18	0.944
18-b	17/18	0.944	0.010	2.5	2	18/18	1.000
24-a	22/24	0.917	0.004	2.5	2	23/24	0.958
24-b	23/24	0.958	0.004	2.5	2	24/24	1.000
30-a	28/30	0.933	0.004	2.65	2	28/30	0933
30-b	28/30	0.933	0.004	2.65	2	29/30	0.967
36-a	33/36	0.917	0.004	2.65	2	33/36	0.917
36-b	32/36	0.889	0.004	2.65	2	34/36	0.944
42-a	38/42	0.905	0.002	2.65	2	38/42	0.905
42-b	38/42	0.905	0.002	3.2	2	39/42	0.929
49-a	44/49	0.898	0.002	8	2	44/49	0.898
49-b	42/49	0.857	0.002	3.2	2	44/49	0.898

Table 6.6 Classification Results by Using the Adjusted Third Method

By using the new x threshold in the adjusted method three, the accuracy was the same as when using method two. Therefore, method two and adjusted method three had the best results. Although the two methods had the same results in this experiment, this doesn’t mean that setting a threshold x is not useful. The speech samples used in this experiment consisted of clean speech; using a threshold x to ignore low level noise would be important if the speech was not clean.

The experimental results show the effectiveness of several x and y values for several different sizes of speakers. This doesn't imply that we can use the same x and y for every database. For a given application, the best values of x and y would have to be experimentally determined.

All new methods were applied to both training and testing. Previous research showed that weighting the testing set is more effective in a phoneme weighting system. Therefore, we would also try to apply our three new methods to only the testing set but not the training set. Table 6.7 – 6.9 show the classification accuracy. Boxes are used to identify the cases which accuracy increases in the rightmost column. Underlines are used to identify the cases which accuracy decreases.

All methods have similar accuracies relative to the baseline system. Therefore, it is better to apply these methods to both training and testing when we are ignoring or weighting the frames based on their energy.

	Before Modification		Best Threshold	After Modification	
Speakers	Correct/Total	Accuracy	x	Correct/Total	New_ Accuracy
12-a	11/12	0.917	0.020	11/12	0.917
12-b	12/12	1.000	0.020	12/12	1.000
18-a	16/18	0.889	0.020	16/18	0.889
18-b	17/18	0.944	0.020	17/18	0.944
24-a	22/24	0.917	0.008	22/24	0.917
24-b	23/24	0.958	0.008	23/24	0.958
30-a	28/30	0.933	0.008	28/30	0.933
30-b	28/30	0.933	0.008	28/30	0.933
36-a	33/36	0.917	0.008	33/36	0.917
36-b	32/36	0.889	0.008	33/36	0.889
42-a	38/42	0.905	0.004	38/42	0.905
42-b	38/42	0.905	0.004	38/42	0.905
49-a	44/49	0.898	0.004	44/49	0.898
49-b	42/49	0.857	0.004	42/49	0.857

Table 6.7 Classification Results by Using the First Method (Only for Testing)

	Before modification				After modification	
Speakers	Correct/Total	Accuracy	y	Weight	Correct/Total	New_ Accuracy
12-a	11/12	0.917	1 or 2	3	11/12	0.917
12-b	12/12	1.000	1 or 2	3	12/12	1.000
18-a	16/18	0.889	2.5	2 or 3	16/18	0.889
18-b	17/18	0.944	2.5	2	17/18	0.944
24-a	22/24	0.917	2.5	2	22/24	0.917
24-b	23/24	0.958	2.5	2	23/24	0.958
30-a	28/30	0.933	2.65	2	28/30	0.933
30-b	28/30	0.933	2.65	2	28/30	0.933
36-a	33/36	0.917	2.65	2	33/36	0.917
36-b	32/36	0.889	2.65	2	33/36	$\boxed{0.917}$
42-a	38/42	0.905	2.65	2	38/42	0.905
42-b	38/42	0.905	3.2	2	37/42	<u>0.881</u>
49-a	44/49	0.898	8	2	44/49	0.898
49-b	42/49	0.857	3.2	2	42/49	0.857

Table 6.8 Classification Results by Using the Second Method (Only for Testing)

	Before modification					After modification	
Speakers	Correct/Total	Accuracy	x	y	Weight	Correct/Total	New_ Accuracy
12-a	11/12	0.917	0.010	2	3	11/12	0.917
12-b	12/12	1.000	0.010	2	3	12/12	1.000
18-a	16/18	0.889	0.010	2.5	2 or 3	16/18	0.889
18-b	17/18	0.944	0.010	2.5	2	17/18	0.944
24-a	22/24	0.917	0.004	2.5	2	22/24	0.917
24-b	23/24	0.958	0.004	2.5	2	23/24	0.958
30-a	28/30	0.933	0.004	2.65	2	28/30	0933
30-b	28/30	0.933	0.004	2.65	2	28/30	0.933
36-a	33/36	0.917	0.004	2.65	2	33/36	0.917
36-b	32/36	0.889	0.004	2.65	2	33/36	0.917
42-a	38/42	0.905	0.002	2.65	2	38/42	0.905
42-b	38/42	0.905	0.002	3.2	2	37/42	0.881
49-a	44/49	0.898	0.002	8	2	44/49	0.898
49-b	42/49	0.857	0.002	3.2	2	42/49	0.857

Table 6.9 Classification Results by Using the Adjusted Third Method (Only for Testing)

CHAPTER SEVEN

SPEAKER IDENTIFICATION RESULTS BASED ON PHONEME WEIGHTING

This chapter presents results based on the algorithms described in Chapter 3, along with energy considerations presented in Chapter 6. The same forty nine male speakers from the DARPA resource management continuous speech database were used for training and testing. Mel-frequency cepstral coefficients (MFCC) components were used for training and testing. Vector quantization (VQ) was used for classification. Since we already determined specific vowel phonemes which work best for speaker identification, we performed identification by giving these frames larger weight or use only these frames to do the classification.

7.1 Phoneme Weighting

Previous experiments determined /i/, /I/, /e/, /E/ and /@/ work better for speaker identification. Therefore, we give these selected vowel frames larger weight and see how the classification results change. The selected vowel frames are detected manually. The final goal is to do this automatically.

Table 7.1 – 7.3 shows the classification errors for different sizes of speaker sets by emphasizing selected vowel frames for both training and testing, for only training, and for only testing. These tables show which test speakers have been misclassified for different sizes of speaker sets. For example, “5, 12” in Table 7.1 means “speaker number 5 and speaker 12”. Column “Error (a)” shows the classification errors when we used the first

sentence as training and the second sentence as testing. Column “Error (b)” shows the classification errors when we used the second sentence as training and the first sentence as testing. From Table 7.1 – 7.3, all methods have fine results when the speaker size is small, but the accuracy decreases significantly when the speaker size increases. The results were not better than the baseline system.

Speakers	Error (a)	Error (b)
12	5, 12	
18	5, 10, 12, 13, 15	13
24	5, 10, 12, 13, 15	11, 13
30	5, 10, 12, 13, 15, 27, 30	11, 13, 30
36	5, 10, 12, 13, 15, 27, 30, 32	11, 13, 16, 30
42	5, 10, 12, 13, 15, 27, 30, 32, 41	11, 13, 16, 30, 39, 41
49	5, 10, 12, 13, 15, 27, 30, 32, 41, 45, 48, 49	11, 13, 16, 20, 30, 39, 41, 49

Table 7.1 Classification Errors When Emphasizing Selected Vowel Frames (Weight = 2) for Both Training and Testing

Speakers	Error (a)	Error (b)
12	5	
18	5, 13, 15	13
24	5, 13, 15	13, 21
30	5, 13, 15, 27, 29, 30	13, 21, 30
36	5, 13, 15, 27, 29, 30, 32	13, 21, 30
42	5, 13, 15, 27, 29, 30, 32	11, 13, 21, 30, 41
49	5, 13, 15, 27, 29, 30, 32, 41, 45, 48, 49	11, 13, 21, 30, 41, 49

Table 7.2 Classification Errors When Emphasizing Selected Vowel Frames (Weight = 2) for Only Training

Speakers	Error (a)	Error (b)
12	5, 12	
18	5, 12, 13, 15	13
24	5, 8, 12, 13, 15	13
30	5, 8, 12, 13, 15	10, 13, 16, 30
36	5, 8, 12, 13, 15, 32	10, 13, 16, 30
42	5, 8, 12, 13, 15, 32, 40, 41	10, 13, 16, 30, 36
49	5, 8, 12, 13, 15, 32, 40, 41, 43, 48, 49	10, 13, 16, 30, 36, 46, 48, 49

Table 7.3 Classification Errors When Emphasizing Selected Vowel Frames (Weight = 2) for Only Testing

Instead of emphasizing selected vowel frames, we also tried to emphasize all vowel frames and see how this affects performance. Table 7.4 – 7.6 shows the classification accuracies for different sizes of speaker sets by emphasizing all vowel frames for both training and testing, for only training, and for only testing.

Speakers	Error (a)	Error (b)
12		12
18	10, 13	12, 13
24	10, 13, 20	12, 13, 21
30	10, 13, 20, 27	12, 13, 21, 30
36	10, 13, 20, 27, 32	12, 13, 21, 29, 30
42	10, 13, 20, 27, 32, 41	12, 13, 21, 22, 29, 30, 39, 41
49	10, 13, 20, 27, 30, 32, 41, 44, 48	12, 13, 21, 22, 29, 30, 39, 41, 49

Table 7.4 Classification Errors When Emphasizing All Vowel Frames (Weight = 2) for Both Training and Testing

Speakers	Error (a)	Error (b)
12		
18	10, 13, 15, 18	13
24	10, 13, 15, 18	13, 21
30	10, 13, 15, 18, 27, 30	13, 21, 30
36	10, 13, 15, 18, 27, 30, 32	13, 16, 21, 29, 30
42	10, 13, 15, 18, 27, 30, 32, 41	13, 16, 21, 29, 30, 41
49	10, 13, 15, 18, 27, 30, 32, 41, 44, 48, 49	13, 16, 21, 29, 30, 41, 49

Table 7.5 Classification Errors When Emphasizing All Vowel Frames (Weight = 2) for Only Training

Speakers	Error (a)	Error (b)
12	5	
18	5, 13	13
24	5, 13	13
30	5, 13	13, 30
36	5, 13, 32	10, 13, 16, 30
42	5, 13, 32, 41	10, 13, 16, 30, 36, 39
49	5, 13, 32, 41, 43, 48, 49	10, 13, 16, 30, 36, 39, 46, 48, 49

Table 7.6 Classification Errors When Emphasizing All Vowel Frames (Weight = 2) for Only Testing

The results in Table 7.4 – 7.6 are also not better than the baseline system. Emphasizing the frames for only testing works better than emphasizing the frames for both training and testing. The accuracy of all methods depends highly on the utterance. For example, column "Error (a)" has less error than column "Error (b)" when we emphasize all vowel frames. However, column "Error (b)" has less error than column "Error (a)" when we emphasize all selected vowel frames. Also, the accuracy varies a lot when we switch the training and the testing sentence. Therefore, these methods could not be a good algorithm to improve speaker identification in all cases. We also tried to emphasize the frames by weight = 3, the results are shown in Table 7.7 and Table 7.8.

Speakers	Error (a)	Error (b)
12	5, 12	
18	5, 10, 12, 13	13
24	5, 8, 10, 12, 13	13
30	5, 8, 10, 12, 13	13, 16, 27, 30
36	5, 8, 10, 12, 13, 32, 34	13, 16, 27, 30, 33
42	5, 8, 10, 12, 13, 32, 34, 40, 41	13, 16, 27, 30, 33, 36, 41, 42
49	5, 8, 10, 12, 13, 32, 34, 40, 41, 43, 48, 49	13, 16, 27, 30, 33, 36, 41, 42, 46, 48, 49

Table 7.7 Classification Errors When Emphasizing All Vowel Frames (Weight = 3) for Only Testing

Speakers	Error (a)	Error (b)
12	5	
18	5, 13	13
24	5, 13	13
30	5, 13	10, 13, 16, 20, 30, 39
36	5, 13, 32	10, 12, 13, 16, 20, 30, 36
42	5, 13, 32, 41	10, 12, 13, 16, 20, 30, 36, 39
49	5, 13, 32, 41, 43, 48, 49	10, 12, 13, 16, 20, 30, 36, 39, 46, 48, 49

Table 7.8 Classification Errors When Emphasizing All Vowel Frames (Weight = 3) for Only Testing

The results in Table 7.7 and Table 7.8 were not better. Some of the phonemes in the sentences haven't been pronounced clearly by the speakers and have short duration and low energy. Emphasizing these frames might harm the model. Therefore, the next step would be trying to eliminate the low energy phoneme frames and see how will the results change.

Since we already found out several threshold "x" work well for the same group of speakers in Chapter 6, we will use two kinds of thresholds from Table 6.5 (the third method) and Table 6.6 (the adjusted third method) to eliminate the low energy phoneme frames. Table 7.9 and Table 7.10 show the results of emphasizing selected vowel phonemes, Table 7.11 and Table 7.12 show the results of emphasizing all vowel phonemes. Boxes are used to identify the cases which accuracy increases in the rightmost column. Underlines are used to identify the cases which accuracy decreases.

Speakers	Correct/Total	Accuracy	x	Correct/Total	New_ Accuracy
12	11/12	0.917	0.020	11/12	0.917
12	12/12	1.000	0.020	12/12	1.000
18	16/18	0.889	0.020	14/18	<u>0.778</u>
18	17/18	0.944	0.020	17/18	0.944
24	22/24	0.917	0.008	19/24	<u>0.792</u>
24	23/24	0.958	0.008	22/24	<u>0.917</u>
30	28/30	0.933	0.008	24/30	<u>0.800</u>
30	28/30	0.933	0.008	27/30	<u>0.900</u>
36	33/36	0.917	0.008	29/36	<u>0.806</u>
36	32/36	0.889	0.008	32/36	0.889
42	38/42	0.905	0.004	33/42	<u>0.786</u>
42	38/42	0.905	0.004	36/42	<u>0.857</u>
49	44/49	0.898	0.004	37/49	<u>0.755</u>
49	42/49	0.857	0.004	41/49	<u>0.837</u>

Table 7.9 Classification Accuracies When Emphasizing Selected Vowel Phonemes (Weight = 2) for Both Training and Testing Adding Larger Threshold x

Speakers	Correct/Total	Accuracy	x	Correct/Total	New_ Accuracy
12	11/12	0.917	0.010	10/12	0.833
12	12/12	1.000	0.010	12/12	1.000
18	16/18	0.889	0.010	12/18	0.667
18	17/18	0.944	0.010	17/18	0.944
24	22/24	0.917	0.004	19/24	0.792
24	23/24	0.958	0.004	22/24	0.917
30	28/30	0.933	0.004	23/30	0.767
30	28/30	0.933	0.004	27/30	0.900
36	33/36	0.917	0.004	28/36	0.778
36	32/36	0.889	0.004	32/36	0.889
42	38/42	0.905	0.002	33/42	0.786
42	38/42	0.905	0.002	36/42	0.857
49	44/49	0.898	0.002	37/49	0.755
49	42/49	0.857	0.002	41/49	0.837

Table 7.10 Classification Accuracies When Emphasizing Selected Vowel Phonemes (Weight = 2) for Both Training and Testing Adding Smaller Threshold x

Speakers	Correct/Total	Accuracy	x	Correct/Total	New_ Accuracy
12	11/12	0.917	0.020	12/12	0.917
12	12/12	1.000	0.020	12/12	1.000
18	16/18	0.889	0.020	16/18	0.889
18	17/18	0.944	0.020	17/18	0.944
24	22/24	0.917	0.008	21/24	<u>0.875</u>
24	23/24	0.958	0.008	22/24	<u>0.917</u>
30	28/30	0.933	0.008	27/30	<u>0.900</u>
30	28/30	0.933	0.008	27/30	<u>0.900</u>
36	33/36	0.917	0.008	32/36	<u>0.889</u>
36	32/36	0.889	0.008	32/36	0.889
42	38/42	0.905	0.004	36/42	<u>0.857</u>
42	38/42	0.905	0.004	34/42	<u>0.810</u>
49	44/49	0.898	0.004	40/49	<u>0.816</u>
49	42/49	0.857	0.004	40/49	<u>0.816</u>

Table 7.11 Classification Accuracies When Emphasizing All Vowel Phonemes (Weight = 2) for Both Training and Testing Adding Larger Threshold x

Speakers	Correct/Total	Accuracy	x	Correct/Total	New_ Accuracy
12	11/12	0.917	0.010	12/12	1.000
12	12/12	1.000	0.010	11/12	0.917
18	16/18	0.889	0.010	15/18	0.833
18	17/18	0.944	0.010	16/18	0.889
24	22/24	0.917	0.004	22/24	0.917
24	23/24	0.958	0.004	22/24	0.917
30	28/30	0.933	0.004	26/30	0.867
30	28/30	0.933	0.004	26/30	0.867
36	33/36	0.917	0.004	31/36	0.861
36	32/36	0.889	0.004	31/36	0.861
42	38/42	0.905	0.002	36/42	0.857
42	38/42	0.905	0.002	34/42	0.810
49	44/49	0.898	0.002	40/49	0.816
49	42/49	0.857	0.002	40/49	0.816

Table 7.12 Classification Accuracies When Emphasizing All Vowel Phonemes (Weight = 2) for Both Training and Testing Adding Smaller Threshold x

Most of the accuracies decreased relative to the baseline system. Therefore, emphasizing the frames based on their energy should be a better method to improve speaker identification performance. Table 7.13 – 7.16 show the results of applying this method to only testing but not training. The results were better than Table 7.9 – 7.12.

Speakers	Correct/Total	Accuracy	x	Correct/Total	New_ Accuracy
12	11/12	0.917	0.020	11/12	0.917
12	12/12	1.000	0.020	12/12	1.000
18	16/18	0.889	0.020	14/18	0.778
18	17/18	0.944	0.020	17/18	0.944
24	22/24	0.917	0.008	19/24	0.792
24	23/24	0.958	0.008	23/24	0.958
30	28/30	0.933	0.008	24/30	0.800
30	28/30	0.933	0.008	29/30	0.967
36	33/36	0.917	0.008	29/36	0.806
36	32/36	0.889	0.008	32/36	0.889
42	38/42	0.905	0.004	34/42	0.810
42	38/42	0.905	0.004	36/42	0.857
49	44/49	0.898	0.004	38/49	0.776
49	42/49	0.857	0.004	40/49	0.816

Table 7.13 Classification Accuracies When Emphasizing Selected Vowel Phonemes (Weight = 2) for Only Testing Adding Larger Threshold x

Speakers	Correct/Total	Accuracy	x	Correct/Total	New_Accuracy
12	11/12	0.917	0.010	10/12	0.833
12	12/12	1.000	0.010	12/12	1.000
18	16/18	0.889	0.010	14/18	0.778
18	17/18	0.944	0.010	17/18	0.944
24	22/24	0.917	0.004	19/24	0.792
24	23/24	0.958	0.004	23/24	0.958
30	28/30	0.933	0.004	25/30	0.833
30	28/30	0.933	0.004	28/30	0.933
36	33/36	0.917	0.004	30/36	0.833
36	32/36	0.889	0.004	31/36	0.861
42	38/42	0.905	0.002	34/42	0.810
42	38/42	0.905	0.002	37/42	0.881
49	44/49	0.898	0.002	38/49	0.776
49	42/49	0.857	0.002	40/49	0.816

Table 7.14 Classification Accuracies When Emphasizing Selected Vowel Phonemes (Weight = 2) for Only Testing Adding Smaller Threshold x

Speakers	Correct/Total	Accuracy	x	Correct/Total	New_ Accuracy
12	11/12	0.917	0.020	12/12	$\boxed{1.000}$
12	12/12	1.000	0.020	12/12	1.000
18	16/18	0.889	0.020	16/18	0.889
18	17/18	0.944	0.020	17/18	0.944
24	22/24	0.917	0.008	22/24	0.917
24	23/24	0.958	0.008	23/24	0.958
30	28/30	0.933	0.008	27/30	<u>0.900</u>
30	28/30	0.933	0.008	29/30	$\boxed{0.967}$
36	33/36	0.917	0.008	32/36	<u>0.889</u>
36	32/36	0.889	0.008	32/36	0.889
42	38/42	0.905	0.004	38/42	0.905
42	38/42	0.905	0.004	36/42	<u>0.857</u>
49	44/49	0.898	0.004	43/49	<u>0.878</u>
49	42/49	0.857	0.004	40/49	<u>0.816</u>

Table 7.15 Classification Accuracies When Emphasizing All Vowel Phonemes (Weight = 2) for Only Testing Adding Larger Threshold x

Speakers	Correct/Total	Accuracy	x	Correct/Total	New_ Accuracy
12	11/12	0.917	0.010	11/12	0.917
12	12/12	1.000	0.010	12/12	1.000
18	16/18	0.889	0.010	16/18	0.889
18	17/18	0.944	0.010	17/18	0.944
24	22/24	0.917	0.004	22/24	0.917
24	23/24	0.958	0.004	23/24	0.958
30	28/30	0.933	0.004	28/30	0.933
30	28/30	0.933	0.004	28/30	0.933
36	33/36	0.917	0.004	33/36	0.917
36	32/36	0.889	0.004	32/36	0.889
42	38/42	0.905	0.002	38/42	0.905
42	38/42	0.905	0.002	36/42	<u>0.857</u>
49	44/49	0.898	0.002	43/49	<u>0.878</u>
49	42/49	0.857	0.002	40/49	<u>0.816</u>

Table 7.16 Classification Accuracies When Emphasizing All Vowel Phonemes (Weight = 2) for Only Testing Adding Smaller Threshold x

<u>7.2 Use Only Selected Vowels or All Vowels for Identification</u>

An additional experiment was done by using only selected vowels or all vowels to perform identification. Results of classification errors are shown in Table 7.17 – 7.20. However, the errors increase a lot and the performance was not good. These short duration vowel phonemes do not provide enough speaker information. Some of them haven’t been pronounced clearly might also harm the model.

Speakers	Error (a)	Error (b)
12	1, 3, 4, 7, 10, 11, 12	3, 12
18	1, 3, 4, 7, 10, 11, 12, 13, 16, 17	3, 12, 13, 16, 17
24	1, 3, 4, 7, 10, 11, 12, 13, 14, 16, 17, 20, 22, 23, 24	3, 12, 13, 16, 17, 20, 22, 24
30	1, 3, 4, 7, 10, 11, 12, 13, 14, 16, 17, 20, 22, 23, 24, 25, 27, 28, 29, 30	3, 12, 13, 16, 17, 20, 22, 24, 25, 26, 27, 28, 29, 30
36	1, 3, 4, 7, 10, 11, 12, 13, 14, 16, 17, 20, 22, 23, 24, 25, 27, 28, 29, 30, 31, 32, 33	3, 12, 13, 15, 16, 17, 20, 22, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 36
42	1, 3, 4, 7, 10, 11, 12, 13, 14, 16, 17, 20, 22, 23, 24, 25, 27, 28, 29, 30, 31, 32, 33, 37, 39, 40, 41, 42	3, 12, 13, 15, 16, 17, 20, 22, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 36, 37, 41, 42
49	1, 3, 4, 7, 10, 11, 12, 13, 14, 16, 17, 20, 22, 23, 24, 25, 27, 28, 29, 30, 31, 32, 33, 37, 39, 40, 41, 42, 43-49	3, 12, 13, 15, 16, 17, 20, 22, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 36, 37, 41, 42, 43, 44, 45, 47, 48

Table 7.17 Classification Errors When Using Only Selected Vowel Frames for Training and Testing

Speakers	Error (a)	Error (b)
12	5, 12	3, 4, 5, 6, 8, 9, 12
18	5, 10, 12, 13	3, 4, 5, 6, 8, 9, 12, 13, 16, 17
24	5, 8, 10, 12, 13, 21	3, 4, 5, 6, 8, 9, 11, 12, 13, 14, 16, 17, 20, 21, 22
30	5, 8, 10, 12, 13, 21, 27, 30	3, 4, 5, 6, 8, 9, 11, 12, 13, 14, 16, 17, 20, 21, 22, 25, 27, 28, 29, 30
36	5, 8, 10, 12, 13, 21, 27, 28, 30, 32, 33, 34	3, 4, 5, 6, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 20, 21, 22, 25, 27, 28, 29, 30, 32, 33, 36
42	5, 8, 10, 12, 13, 16, 21, 27, 28, 30, 32, 33, 34, 39, 40, 41	3, 4, 5, 6, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 20, 21, 22, 25, 27, 28, 29, 30, 32, 33, 36, 37, 39, 40, 41, 42
49	5, 8, 10, 12, 13, 16, 21, 27, 28, 30, 32, 33, 34, 39, 40, 41, 43, 44, 45, 48	3, 4, 5, 6, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 20, 21, 22, 25, 27, 28, 29, 30, 32, 33, 36, 37, 39, 40, 41, 42, 43, 44, 46, 48, 49

Table 7.18 Classification Errors When Using Only Selected Vowel Frames for Only Testing

Speakers	Error (a)	Error (b)
12	4, 10, 12	8,
18	4, 10, 12, 13, 16	8, 13
24	4, 10, 12, 13, 14, 16, 20, 22, 24	8, 13, 20, 24
30	4, 10, 12, 13, 14, 16, 20, 22, 24, 26, 27	4, 8, 13, 20, 24, 27
36	4, 10, 12, 13, 14, 16, 20, 22, 24, 26, 27, 31, 32, 33	4, 8, 13, 20, 24, 27, 32, 36
42	4, 10, 12, 13, 14, 16, 20, 22, 24, 26, 27, 31, 32, 33, 37, 39, 41, 42	4, 8, 13, 20, 24, 27, 32, 36, 37, 41
49	4, 10, 12, 13, 14, 16, 20, 22, 24, 26, 27, 31, 32, 33, 37, 39, 41, 42, 43-49	4, 8, 13, 20, 24, 27, 32, 36, 37, 41, 46

Table 7.19 Classification Errors When Using Only All Vowel Frames for Training and Testing

Speakers	Error (a)	Error (b)
12	5	3, 8, 12
18	5, 10, 13	3, 8, 12, 13
24	5, 10, 13	3, 5, 6, 8, 12, 13, 14, 16, 20, 24
30	5, 8, 10, 13, 30	3, 4, 5, 6, 8, 12, 13, 14, 16, 20, 24, 25, 27, 29, 30
36	5, 8, 10, 13, 30, 32, 33, 34, 36	3, 4, 5, 6, 8, 12, 13, 14, 16, 20, 24, 25, 27, 29, 30, 32, 33, 36
42	5, 8, 10, 13, 30, 32, 33, 34, 36, 39, 41	3, 4, 5, 6, 8, 12, 13, 14, 16, 20, 22, 24, 25, 27, 29, 30, 32, 33, 36, 39, 41
49	5, 8, 10, 13, 30, 32, 33, 34, 36, 39, 41, 43, 45, 48	3, 4, 5, 6, 8, 12, 13, 14, 16, 20, 22, 24, 25, 27, 29, 30, 32, 33, 36, 39, 41, 46, 48, 49

Table 7.20 Classification Errors When Using Only All Vowel Frames for Only Testing

CHAPTER EIGHT

SUMMARY AND CONCLUSIONS

In this dissertation we identified several vowels which worked best for speaker identification and speaker verification. We also presented several methods for improving speaker identification accuracy, based on this investigation. Details of the findings of this dissertation are summarized below.

8.1 Summary

Results from Chapter 4 indicate that persons speaking /i/, /E/ and /u/ were identified well by both GMM and VQ methods (at most one classification error). For VQ, /i/, /I/, /e/, /E/ and /@/ had no classification errors. Phonemes /i/ and /I/ had the highest winning ratios in our experiments, which is consistent with the work of Eatock and Mason [47] since the EERs of the two phonemes were low in their speaker verification system, which indicates these phonemes have more speaker discriminative information. The overall speaker identification accuracy was 91.1% for the GMM classifier and 97.4% for the VQ classifier in our experiments. The 97.4% overall accuracy is similar to what Hansen, Slyh and Anderson [50] obtained (equal error rate 1.7%) by using a phoneme-specific speaker identification system. However, instead of using 8 conversations to do the training, we used only 2 seconds of each vowel sound. In addition, the speaker recognition error rate obtained by by Lee, Choi and Kang [6], who dynamically controlled the ratio of phoneme class information utilized, was around 3.7%.

Results from Chapter 5 show that persons speaking /E/, /o/ and /u/ have been verified well by both GMM and VQ methods in our experiments. For VQ, /i/, /I/, /e/, /E/ and /@/ had less than one verification error. In addition, VQ worked better than GMM in these experiments (which used short segments of training and testing data). The work of Eatock and Mason [47] indicates that phonemes /i/, /I/ and /a/ have low equal error rates (around 20%) for speaker verification by using the VQ method. These three phonemes also performed well in our experiments by using VQ and with much lower EERs (less than 0.5%). The overall speaker verification EER was 1.14% for GMM method and 0.35% for VQ method.

We also presented several methods for improving speaker identification accuracy. We use threshold x to ignore low energy frames and threshold y to emphasize high energy frames. It is better to use larger x when the speaker size is small, and use smaller x when speaker size is large. Moreover, it is better to use smaller y and larger weight when the speaker size is small, and use larger y and smaller weight when the speaker size is large. Weighting the high energy frames had the most effect. The accuracy when using the first method was 91.7%, and was 93.6% for our second method and also for our adjusted third method. For comparison, the baseline system had an accuracy of 91%. The corresponding error reduction rates were 7.9% for method one, 28.9% for method two and adjusted method three. The GMM classification accuracy by Reynolds [30] is 87.3% when 30 seconds training speech and 5 seconds testing speech is used; 90.5% when 30 seconds training speech and 10 seconds testing speech is used. The typical accuracy for short training and testing utterances is around 90%. Our system, which used only approximately 3 seconds training speech and 3 seconds testing speech did show some improvement.

The other methods based on phoneme weighting (which performed classification based on the ideal phonemes we found from the previous experiments) don't work better than the baseline system. The accuracy of all methods depends highly on the utterance which is spoken. Also, the accuracy varies significantly when we switch the training and the testing sentence. Therefore, these methods could not be a good algorithm to improve speaker identification in all cases. Some of the phonemes in the sentences from the DARPA database haven't been pronounced clearly by the speakers and have short duration and low energy. Therefore, emphasizing the frames based on their energy was a more effective approach for improving speaker identification performance.

8.2 Future Work

Vowels have more speaker information and have been shown to work well for speaker recognition. The ideal vowel phonemes we found should be important for development of future systems for speaker identification and speaker verification. Combining a robust speech recognizer with the speaker recognition system may also improve recognition accuracy. The speech recognizer could detect the words which are rich of these ideal vowels in the sentence by keyword spotting and give these words larger weight. However, the speech recognizer has to perform high accuracy to improve the system.

Another interesting research would be trying to find out which digits (zero to nine) have more speaker information, which might be useful for the security system (maybe would be the ones which include the ideal vowel phonemes we found). When the speaker is saying a combination of numbers, weighting the ideal digits may increase speaker identification accuracy or decrease the equal error rate of the speaker verification system. Combining speech recognition with speaker recognition would be the next interesting topic.

APPENDICES

Appendix A

Log Likelihood Data by Using GMM

Appendix A shows the log likelihood of each testing data belongs to each training data for the experiments in Chapter 4 and Chapter 5. The one which ends with a star (*) is the speaker who has the maximum a posteriori probability for a given observation sequence.

The following pages correspond to a single phoneme and a method. For example, the heading /i/ (GMM1) means that all speakers are saying phoneme /i/ and method GMM1 is used. Each cell begins with one of t1~t15 or s1~s15, which represent the testing data. p_1~p_15 are the log likelihoods. p_1 is the log likelihood that the test speaker belongs to training speaker number one, p_2 is the log likelihood that the test speaker belongs to training speaker number two, and so on.

/i/ (GMM1)

t1 p_1=-1.361114e+004 * p_2=-1.825770e+005 p_3=-3.432000e+005 p_4=-8.347727e+004 p_5=-1.779651e+005 p_6=-4.449699e+004 p_7=-5.852753e+004 p_8=-1.252658e+005 p_9=-3.356701e+005 p_10=-2.249385e+005 p_11=-3.140306e+005 p_12=-3.423139e+005 p_13=-3.308749e+005 p_14=-3.273438e+005 p_15=-3.280694e+005	t2 p_1=-1.695223e+005 p_2=-3.429501e+004 * p_3=-3.261755e+005 p_4=-5.581235e+004 p_5=-1.215504e+005 p_6=-7.807418e+004 p_7=-1.145311e+005 p_8=-6.387093e+004 p_9=-3.431926e+005 p_10=-1.560049e+005 p_11=-2.938817e+005 p_12=-3.379034e+005 p_13=-2.708993e+005 p_14=-1.891963e+005 p_15=-2.898091e+005	t3 p_1=-2.766039e+005 p_2=-1.142015e+005 p_3=-1.852782e+004 * p_4=-5.069981e+004 p_5=-2.432150e+005 p_6=-8.403773e+004 p_7=-1.472732e+005 p_8=-2.862974e+004 p_9=-3.432000e+005 p_10=-1.889174e+005 p_11=-1.397572e+005 p_12=-3.432000e+005 p_13=-2.610086e+005 p_14=-2.898862e+005 p_15=-3.407718e+005
t4 p_1=-2.156824e+005 p_2=-1.225130e+005 p_3=-3.328460e+005 p_4=-1.158887e+004 * p_5=-1.459920e+005 p_6=-5.973009e+004 p_7=-8.069641e+004 p_8=-5.322127e+004 p_9=-3.432000e+005 p_10=-1.910675e+005 p_11=-1.736658e+005 p_12=-3.432000e+005 p_13=-2.406321e+005 p_14=-2.756708e+005 p_15=-3.431980e+005	t5 p_1=-1.057965e+005 p_2=-6.555679e+004 p_3=-3.401474e+005 p_4=-5.807374e+004 p_5=-1.422842e+004 * p_6=-3.873779e+004 p_7=-8.664317e+004 p_8=-5.518959e+004 p_9=-3.414833e+005 p_10=-8.148911e+004 p_11=-2.184937e+005 p_12=-3.324960e+005 p_13=-3.073748e+005 p_14=-2.039676e+005 p_15=-1.828089e+005	t6 p_1=-1.368285e+005 p_2=-1.566150e+005 p_3=-3.432000e+005 p_4=-7.099624e+004 p_5=-8.847819e+004 p_6=-1.046243e+004 * p_7=-1.044509e+005 p_8=-9.533211e+004 p_9=-3.054219e+005 p_10=-1.628583e+005 p_11=-2.513866e+005 p_12=-3.344977e+005 p_13=-2.723085e+005 p_14=-3.078347e+005 p_15=-2.742293e+005

/i/ (GMM1)

t7 p_1=-1.390480e+005 p_2=-2.173389e+005 p_3=-3.432000e+005 p_4=-4.976939e+004 p_5=-2.009913e+005 p_6=-1.055873e+005 p_7=-1.943601e+004 * p_8=-1.019702e+005 p_9=-3.432000e+005 p_10=-2.264324e+005 p_11=-1.359867e+005 p_12=-3.432000e+005 p_13=-2.671608e+005 p_14=-3.368365e+005 p_15=-3.432000e+005	t8 p_1=-2.958967e+005 p_2=-5.384436e+004 p_3=-2.069295e+005 p_4=-4.739693e+004 p_5=-1.028558e+005 p_6=-8.072105e+004 p_7=-8.410149e+004 p_8=-9.058461e+003 * p_9=-3.432000e+005 p_10=-1.632909e+005 p_11=-1.782260e+005 p_12=-3.431325e+005 p_13=-2.694831e+005 p_14=-2.463487e+005 p_15=-3.303518e+005	t9 p_1=-6.246437e+004 p_2=-1.453417e+005 p_3=-3.146000e+005 p_4=-5.276735e+004 p_5=-1.831074e+005 p_6=-2.878119e+004 p_7=-8.019355e+004 p_8=-8.172859e+004 p_9=-3.934496e+003 * p_10=-6.011569e+004 p_11=-2.286575e+005 p_12=-2.614921e+005 p_13=-9.043221e+004 p_14=-1.956582e+005 p_15=-1.479082e+005
t10 p_1=-8.712109e+004 p_2=-5.362866e+004 p_3=-2.908562e+005 p_4=-5.938697e+004 p_5=-1.843548e+005 p_6=-5.502236e+004 p_7=-7.178989e+004 p_8=-4.472346e+004 p_9=-2.501423e+005 p_10=-1.513560e+004 * p_11=-1.004002e+005 p_12=-1.606589e+005 p_13=-1.174670e+005 p_14=-6.628964e+004 p_15=-1.178350e+005	t11 p_1=-1.037964e+005 p_2=-1.451474e+005 p_3=-2.112772e+005 p_4=-7.951098e+004 p_5=-3.255584e+005 p_6=-7.067089e+004 p_7=-5.118731e+004 p_8=-5.551822e+004 p_9=-2.914604e+005 p_10=-1.141226e+005 p_11=-2.133918e+004 * p_12=-3.416966e+005 p_13=-1.112391e+005 p_14=-2.340630e+005 p_15=-3.039086e+005	t12 p_1=-1.659667e+005 p_2=-6.581732e+004 p_3=-3.432000e+005 p_4=-7.084024e+004 p_5=-2.278031e+005 p_6=-6.781379e+004 p_7=-1.204539e+005 p_8=-7.421924e+004 p_9=-2.856642e+005 p_10=-2.185020e+005 p_11=-2.690834e+005 p_12=-1.298156e+004 * p_13=-1.993895e+005 p_14=-1.256905e+005 p_15=-6.998560e+004

/i/ (GMM1)

t13	t14	t15
p_1=-1.057718e+005	p_1=-1.164459e+005	p_1=-1.269090e+005
p_2=-5.672539e+004	p_2=-3.549155e+004	p_2=-8.174879e+004
p_3=-3.063255e+005	p_3=-3.208111e+005	p_3=-3.428338e+005
p_4=-3.208740e+004	p_4=-5.008704e+004	p_4=-9.150919e+004
p_5=-1.740091e+005	p_5=-1.494474e+005	p_5=-3.335255e+005
p_6=-4.762603e+004	p_6=-7.316596e+004	p_6=-5.353696e+004
p_7=-6.278171e+004	p_7=-8.881739e+004	p_7=-9.404274e+004
p_8=-5.058505e+004	p_8=-4.238544e+004	p_8=-8.660494e+004
p_9=-2.384835e+005	p_9=-3.353067e+005	p_9=-2.020231e+005
p_10=-5.742259e+004	p_10=-7.971545e+004	p_10=-1.433320e+005
p_11=-1.487394e+005	p_11=-1.968907e+005	p_11=-1.458651e+005
p_12=-2.964218e+005	p_12=-2.286736e+005	p_12=-2.608077e+005
p_13=-1.671511e+004 *	p_13=-1.636477e+005	p_13=-1.338754e+005
p_14=-6.271668e+004	p_14=-1.881139e+004 *	p_14=-1.186201e+005
p_15=-1.912075e+005	p_15=-1.092561e+005	p_15=-3.772843e+004 *

/i/ (GMM2)

s1 p_1=-1.452129e+004 * p_2=-5.122032e+004 p_3=-3.650566e+005 p_4=-1.538640e+005 p_5=-1.209623e+005 p_6=-7.443964e+004 p_7=-5.812401e+004 p_8=-3.525323e+005 p_9=-2.852550e+005 p_10=-2.684319e+005 p_11=-2.590091e+005 p_12=-3.657242e+005 p_13=-3.567192e+005 p_14=-2.752754e+005 p_15=-2.794634e+005	s2 p_1=-1.692483e+005 p_2=-1.334773e+004 * p_3=-2.922213e+005 p_4=-1.459284e+005 p_5=-2.122965e+005 p_6=-1.058646e+005 p_7=-1.538465e+005 p_8=-1.095134e+005 p_9=-3.427063e+005 p_10=-8.010204e+004 p_11=-2.138303e+005 p_12=-3.431806e+005 p_13=-2.639516e+005 p_14=-1.300215e+005 p_15=-3.055719e+005	s3 p_1=-2.633411e+005 p_2=-5.904971e+004 p_3=-1.439526e+004 * p_4=-8.811757e+004 p_5=-2.074056e+005 p_6=-7.549261e+004 p_7=-2.077322e+005 p_8=-1.344310e+005 p_9=-3.432000e+005 p_10=-2.371293e+005 p_11=-1.588952e+005 p_12=-3.432000e+005 p_13=-3.340106e+005 p_14=-3.321852e+005 p_15=-3.407995e+005
s4 p_1=-1.612641e+005 p_2=-3.005092e+004 p_3=-1.884012e+005 p_4=-1.624291e+004 * p_5=-1.103361e+005 p_6=-5.085710e+004 p_7=-9.751307e+004 p_8=-1.950950e+005 p_9=-3.411512e+005 p_10=-2.173174e+005 p_11=-1.398339e+005 p_12=-3.432000e+005 p_13=-3.020066e+005 p_14=-2.501345e+005 p_15=-2.959294e+005	s5 p_1=-7.690090e+004 p_2=-2.764532e+004 p_3=-3.372255e+005 p_4=-9.457807e+004 p_5=-1.912718e+004 * p_6=-3.563016e+004 p_7=-9.697297e+004 p_8=-1.063360e+005 p_9=-3.297994e+005 p_10=-2.104784e+005 p_11=-2.419405e+005 p_12=-3.159440e+005 p_13=-3.096439e+005 p_14=-1.970683e+005 p_15=-3.020476e+005	s6 p_1=-1.098593e+005 p_2=-5.340002e+004 p_3=-3.431766e+005 p_4=-8.302327e+004 p_5=-6.316376e+004 p_6=-1.028984e+004 * p_7=-8.378720e+004 p_8=-3.163871e+005 p_9=-2.599187e+005 p_10=-2.297862e+005 p_11=-1.879482e+005 p_12=-3.202281e+005 p_13=-3.097741e+005 p_14=-2.216978e+005 p_15=-2.268716e+005

/i/ (GMM2)

s7 p_1=-1.198459e+005 p_2=-3.809128e+004 p_3=-3.192418e+005 p_4=-5.878144e+004 p_5=-1.422201e+005 p_6=-6.132758e+004 p_7=-2.007979e+004 * p_8=-3.248007e+005 p_9=-3.428787e+005 p_10=-1.898583e+005 p_11=-8.873532e+004 p_12=-3.432000e+005 p_13=-3.322944e+005 p_14=-3.084735e+005 p_15=-3.419509e+005	s8 p_1=-2.404970e+005 p_2=-5.168300e+004 p_3=-1.324423e+005 p_4=-7.805390e+004 p_5=-1.529318e+005 p_6=-7.205564e+004 p_7=-1.761355e+005 p_8=-3.324752e+004 * p_9=-3.720447e+005 p_10=-2.333761e+005 p_11=-2.072747e+005 p_12=-3.702594e+005 p_13=-3.465196e+005 p_14=-3.180278e+005 p_15=-3.671117e+005	s9 p_1=-8.436607e+004 p_2=-6.026776e+004 p_3=-3.111206e+005 p_4=-1.365008e+005 p_5=-1.461561e+005 p_6=-3.889098e+004 p_7=-8.739237e+004 p_8=-2.534415e+005 p_9=-3.133129e+003 * p_10=-1.031294e+005 p_11=-1.174519e+005 p_12=-3.432000e+005 p_13=-1.477681e+005 p_14=-2.718024e+005 p_15=-1.921795e+005
s10 p_1=-6.941560e+004 p_2=-3.463589e+004 p_3=-2.187140e+005 p_4=-9.182816e+004 p_5=-1.230320e+005 p_6=-4.979155e+004 p_7=-1.120643e+005 p_8=-1.772081e+005 p_9=-1.187430e+005 p_10=-2.354339e+004 * p_11=-6.012391e+004 p_12=-3.107495e+005 p_13=-1.513657e+005 p_14=-1.230664e+005 p_15=-1.196151e+005	s11 p_1=-1.305313e+005 p_2=-6.546404e+004 p_3=-1.851306e+005 p_4=-1.732552e+005 p_5=-3.028337e+005 p_6=-9.822357e+004 p_7=-1.118807e+005 p_8=-3.285581e+005 p_9=-2.702002e+005 p_10=-1.827560e+005 p_11=-1.252159e+004 * p_12=-3.427980e+005 p_13=-2.508263e+005 p_14=-3.422871e+005 p_15=-2.727076e+005	s12 p_1=-2.154506e+005 p_2=-4.200639e+004 p_3=-3.347751e+005 p_4=-1.461933e+005 p_5=-2.912953e+005 p_6=-9.111861e+004 p_7=-1.178416e+005 p_8=-1.971344e+005 p_9=-2.583383e+005 p_10=-1.432139e+005 p_11=-1.578563e+005 p_12=-1.587513e+004 * p_13=-1.509141e+005 p_14=-1.765470e+005 p_15=-6.722372e+004

/i/ (GMM2)

s13	s14	s15
p_1=-1.086196e+005	p_1=-8.506200e+004	p_1=-1.703816e+005
p_2=-3.122101e+004	p_2=-2.278705e+004 *	p_2=-4.765646e+004
p_3=-2.093727e+005	p_3=-1.582344e+005	p_3=-3.120884e+005
p_4=-8.869104e+004	p_4=-1.147933e+005	p_4=-1.606627e+005
p_5=-2.014551e+005	p_5=-1.482115e+005	p_5=-2.433050e+005
p_6=-5.806156e+004	p_6=-1.064338e+005	p_6=-6.227300e+004
p_7=-8.228255e+004	p_7=-1.460653e+005	p_7=-1.593902e+005
p_8=-1.966160e+005	p_8=-8.158583e+004	p_8=-1.749834e+005
p_9=-1.428233e+005	p_9=-2.247276e+005	p_9=-1.695267e+005
p_10=-6.923512e+004	p_10=-6.659856e+004	p_10=-1.400363e+005
p_11=-5.049304e+004	p_11=-9.219493e+004	p_11=-1.218846e+005
p_12=-3.426703e+005	p_12=-3.106912e+005	p_12=-2.002614e+005
p_13=-1.703440e+004 *	p_13=-1.108320e+005	p_13=-1.642438e+005
p_14=-1.958759e+005	p_14=-4.966804e+004	p_14=-1.911190e+005
p_15=-1.085837e+005	p_15=-1.464654e+005	p_15=-2.743692e+004 *

/I/ (GMM1)

t1 p_1=-2.404875e+004 * p_2=-2.634179e+004 p_3=-1.570034e+005 p_4=-1.108092e+005 p_5=-6.420648e+004 p_6=-3.434446e+004 p_7=-1.100554e+005 p_8=-4.198609e+004 p_9=-2.814006e+005 p_10=-2.154211e+005 p_11=-8.364623e+004 p_12=-1.456359e+005 p_13=-2.902002e+005 p_14=-2.908601e+005 p_15=-2.194079e+005	t2 p_1=-9.719652e+004 p_2=-1.448928e+004 * p_3=-2.713316e+005 p_4=-2.004176e+005 p_5=-8.932700e+004 p_6=-4.562318e+004 p_7=-1.556454e+005 p_8=-4.883786e+004 p_9=-3.376703e+005 p_10=-2.823034e+005 p_11=-1.073479e+005 p_12=-1.903840e+005 p_13=-3.370655e+005 p_14=-3.313343e+005 p_15=-3.256758e+005	t3 p_1=-3.289759e+005 p_2=-2.319515e+005 p_3=-1.150447e+004 * p_4=-1.113743e+005 p_5=-1.270081e+005 p_6=-2.134546e+005 p_7=-3.403916e+005 p_8=-1.614699e+005 p_9=-3.414463e+005 p_10=-2.929529e+005 p_11=-1.390621e+005 p_12=-3.227353e+005 p_13=-2.296089e+005 p_14=-2.318757e+005 p_15=-2.833906e+005
t4 p_1=-2.704829e+005 p_2=-1.099910e+005 p_3=-3.358860e+004 p_4=-8.559259e+003 * p_5=-6.508045e+004 p_6=-1.058794e+005 p_7=-3.115435e+005 p_8=-6.070698e+004 p_9=-3.427226e+005 p_10=-1.998040e+005 p_11=-7.957968e+004 p_12=-3.119651e+005 p_13=-1.130600e+005 p_14=-2.110455e+005 p_15=-2.824057e+005	t5 p_1=-1.731407e+005 p_2=-7.072090e+004 p_3=-7.187687e+004 p_4=-6.401326e+004 p_5=-8.716072e+003 * p_6=-7.088706e+004 p_7=-2.896171e+005 p_8=-5.075652e+004 p_9=-2.411558e+005 p_10=-1.731841e+005 p_11=-7.902738e+004 p_12=-1.877186e+005 p_13=-1.815437e+005 p_14=-2.203850e+005 p_15=-2.215454e+005	t6 p_1=-5.761276e+004 p_2=-3.177479e+004 p_3=-1.595521e+005 p_4=-1.035505e+005 p_5=-4.150544e+004 p_6=-1.030353e+004 * p_7=-1.250105e+005 p_8=-3.468074e+004 p_9=-2.194768e+005 p_10=-1.590992e+005 p_11=-8.047416e+004 p_12=-1.064182e+005 p_13=-2.394645e+005 p_14=-2.587868e+005 p_15=-2.651465e+005

/I/ (GMM1)

t7 p_1=-1.067393e+005 p_2=-3.467811e+004 p_3=-1.953327e+005 p_4=-1.627612e+005 p_5=-1.031228e+005 p_6=-6.224814e+004 p_7=-1.371188e+004 * p_8=-5.236077e+004 p_9=-3.430730e+005 p_10=-2.282449e+005 p_11=-1.326317e+005 p_12=-2.620414e+005 p_13=-2.914186e+005 p_14=-3.425829e+005 p_15=-3.423449e+005	t8 p_1=-8.886687e+004 p_2=-3.883506e+004 p_3=-1.213408e+005 p_4=-1.180646e+005 p_5=-5.039968e+004 p_6=-3.938508e+004 p_7=-7.538095e+004 p_8=-1.221157e+004 * p_9=-3.322265e+005 p_10=-2.450116e+005 p_11=-1.108394e+005 p_12=-1.978959e+005 p_13=-2.606822e+005 p_14=-3.404136e+005 p_15=-3.302096e+005	t9 p_1=-1.504635e+005 p_2=-7.501470e+004 p_3=-1.744497e+005 p_4=-1.479496e+005 p_5=-8.524027e+004 p_6=-3.143343e+004 p_7=-3.144930e+005 p_8=-9.230611e+004 p_9=-4.876937e+003 * p_10=-1.829333e+005 p_11=-9.126716e+004 p_12=-8.821832e+004 p_13=-1.915225e+005 p_14=-1.445268e+005 p_15=-3.145630e+005
t10 p_1=-1.108745e+005 p_2=-3.702146e+004 p_3=-7.569415e+004 p_4=-8.650469e+004 p_5=-5.281646e+004 p_6=-2.941399e+004 p_7=-2.392645e+005 p_8=-4.617965e+004 p_9=-1.014451e+005 p_10=-8.584235e+003 * p_11=-3.927400e+004 p_12=-9.801631e+004 p_13=-6.247545e+004 p_14=-1.500908e+005 p_15=-2.909586e+005	t11 p_1=-2.310259e+005 p_2=-8.810384e+004 p_3=-5.816812e+004 p_4=-8.499484e+004 p_5=-5.740365e+004 p_6=-9.262234e+004 p_7=-3.117852e+005 p_8=-6.258411e+004 p_9=-2.267581e+005 p_10=-8.700642e+004 p_11=-1.658193e+004 * p_12=-1.011157e+005 p_13=-9.591860e+004 p_14=-1.733666e+005 p_15=-3.203309e+005	t12 p_1=-2.420822e+005 p_2=-8.460890e+004 p_3=-2.019373e+005 p_4=-1.913339e+005 p_5=-6.909767e+004 p_6=-6.421676e+004 p_7=-3.541419e+005 p_8=-9.267323e+004 p_9=-1.627816e+005 p_10=-1.594340e+005 p_11=-7.200028e+004 p_12=-2.728686e+004 * p_13=-2.312793e+005 p_14=-3.034642e+005 p_15=-3.689069e+005

/I/ (GMM1)

t13	t14	t15
p_1=-1.923068e+005	p_1=-2.434373e+005	p_1=-3.431517e+005
p_2=-6.446208e+004	p_2=-1.140968e+005	p_2=-2.407722e+005
p_3=-9.300641e+004	p_3=-1.201388e+005	p_3=-1.375357e+005
p_4=-6.078106e+004	p_4=-1.026613e+005	p_4=-1.745894e+005
p_5=-3.612211e+004	p_5=-6.701118e+004	p_5=-1.081964e+005
p_6=-5.283277e+004	p_6=-1.108635e+005	p_6=-2.369307e+005
p_7=-3.219898e+005	p_7=-3.548211e+005	p_7=-3.432000e+005
p_8=-6.222635e+004	p_8=-7.648175e+004	p_8=-2.255200e+005
p_9=-2.051043e+005	p_9=-1.758299e+005	p_9=-3.431871e+005
p_10=-1.558958e+005	p_10=-1.250150e+005	p_10=-3.404587e+005
p_11=-7.177261e+004	p_11=-6.376965e+004 *	p_11=-2.107554e+005
p_12=-1.377067e+005	p_12=-1.813077e+005	p_12=-3.358136e+005
p_13=-1.017826e+004 *	p_13=-7.550277e+004	p_13=-2.336434e+005
p_14=-2.233058e+005	p_14=-1.604668e+005	p_14=-1.940960e+005
p_15=-2.952744e+005	p_15=-3.176589e+005	p_15=-1.590786e+004 *

/I/ (GMM2)

s1	s2	s3
p_1=-4.437368e+004	p_1=-1.231154e+005	p_1=-3.347861e+005
p_2=-1.768459e+004 *	p_2=-9.663309e+003 *	p_2=-1.538802e+005
p_3=-2.448583e+005	p_3=-2.021205e+005	p_3=-1.407020e+004 *
p_4=-3.310072e+005	p_4=-2.955805e+005	p_4=-1.336250e+005
p_5=-1.079506e+005	p_5=-6.753815e+004	p_5=-1.113743e+005
p_6=-3.631341e+004	p_6=-3.150443e+004	p_6=-1.732821e+005
p_7=-8.876019e+004	p_7=-8.185199e+004	p_7=-2.465378e+005
p_8=-6.795965e+004	p_8=-1.008319e+005	p_8=-2.998668e+005
p_9=-3.407477e+005	p_9=-3.396157e+005	p_9=-3.399700e+005
p_10=-2.805779e+005	p_10=-2.376671e+005	p_10=-3.065137e+005
p_11=-1.593269e+005	p_11=-1.275410e+005	p_11=-9.094713e+004
p_12=-1.237219e+005	p_12=-1.242515e+005	p_12=-2.534958e+005
p_13=-3.378074e+005	p_13=-2.308214e+005	p_13=-3.256919e+005
p_14=-3.402071e+005	p_14=-3.098952e+005	p_14=-1.545961e+005
p_15=-3.424828e+005	p_15=-3.389886e+005	p_15=-3.419752e+005
s4	s5	s6
p_1=-2.709028e+005	p_1=-1.734152e+005	p_1=-8.540002e+004
p_2=-6.437558e+004	p_2=-5.686466e+004	p_2=-2.669853e+004
p_3=-5.241427e+004	p_3=-9.166001e+004	p_3=-1.710879e+005
p_4=-1.117328e+004 *	p_4=-1.083211e+005	p_4=-2.207748e+005
p_5=-4.108417e+004	p_5=-8.729418e+003 *	p_5=-5.018101e+004
p_6=-8.332291e+004	p_6=-5.506558e+004	p_6=-9.921840e+003 *
p_7=-1.494515e+005	p_7=-2.091972e+005	p_7=-9.967010e+004
p_8=-2.609011e+005	p_8=-1.673498e+005	p_8=-6.701876e+004
p_9=-3.431797e+005	p_9=-2.571961e+005	p_9=-2.715897e+005
p_10=-2.438146e+005	p_10=-1.756240e+005	p_10=-1.602233e+005
p_11=-6.265897e+004	p_11=-7.084692e+004	p_11=-1.048052e+005
p_12=-2.309547e+005	p_12=-9.925706e+004	p_12=-6.133000e+004
p_13=-1.852528e+005	p_13=-1.925747e+005	p_13=-2.601738e+005
p_14=-1.071421e+005	p_14=-1.175710e+005	p_14=-2.951417e+005
p_15=-2.904508e+005	p_15=-2.624829e+005	p_15=-3.244878e+005

/I/ (GMM2)

s7 p_1=-1.335196e+005 p_2=-2.881920e+004 p_3=-2.355924e+005 p_4=-3.016596e+005 p_5=-8.798381e+004 p_6=-5.026176e+004 p_7=-7.877344e+003 * p_8=-6.801705e+004 p_9=-3.432000e+005 p_10=-3.184568e+005 p_11=-1.220825e+005 p_12=-1.967990e+005 p_13=-3.122026e+005 p_14=-2.904377e+005 p_15=-3.398361e+005	s8 p_1=-1.073149e+005 p_2=-3.986559e+004 p_3=-1.619108e+005 p_4=-2.409254e+005 p_5=-6.674119e+004 p_6=-5.482414e+004 p_7=-9.371110e+004 p_8=-3.414620e+004 * p_9=-3.414995e+005 p_10=-3.070452e+005 p_11=-8.194293e+004 p_12=-1.460452e+005 p_13=-2.419069e+005 p_14=-2.578692e+005 p_15=-3.117371e+005	s9 p_1=-2.354889e+005 p_2=-4.935216e+004 p_3=-1.699530e+005 p_4=-1.984433e+005 p_5=-6.468558e+004 p_6=-3.338185e+004 p_7=-3.256902e+005 p_8=-2.063968e+005 p_9=-6.395422e+003 * p_10=-1.374917e+005 p_11=-9.248571e+004 p_12=-7.026403e+004 p_13=-3.039851e+005 p_14=-1.331561e+005 p_15=-3.432000e+005
s10 p_1=-1.489012e+005 p_2=-3.340392e+004 p_3=-7.442446e+004 p_4=-1.124392e+005 p_5=-4.622159e+004 p_6=-2.884050e+004 p_7=-9.979712e+004 p_8=-1.113698e+005 p_9=-1.390378e+005 p_10=-8.691114e+003 * p_11=-2.465342e+004 p_12=-4.983844e+004 p_13=-1.021331e+005 p_14=-6.468804e+004 p_15=-3.092197e+005	s11 p_1=-2.572891e+005 p_2=-5.911745e+004 p_3=-1.054711e+005 p_4=-1.598716e+005 p_5=-7.755828e+004 p_6=-6.157662e+004 p_7=-1.387898e+005 p_8=-1.581816e+005 p_9=-1.881297e+005 p_10=-1.419115e+005 p_11=-1.699187e+004 * p_12=-5.932192e+004 p_13=-3.130615e+005 p_14=-1.038897e+005 p_15=-3.432000e+005	s12 p_1=-2.611014e+005 p_2=-4.824973e+004 p_3=-2.229511e+005 p_4=-2.495405e+005 p_5=-7.363184e+004 p_6=-4.677438e+004 p_7=-3.032332e+005 p_8=-1.077462e+005 p_9=-1.201592e+005 p_10=-8.888467e+004 p_11=-7.349390e+004 p_12=-1.081973e+004 * p_13=-2.760695e+005 p_14=-1.863980e+005 p_15=-3.432000e+005

/I/ (GMM2)

s13	s14	s15
p_1=-2.450712e+005	p_1=-3.057636e+005	p_1=-3.432000e+005
p_2=-5.515608e+004	p_2=-6.427949e+004	p_2=-1.946235e+005
p_3=-1.014082e+005	p_3=-7.470567e+004	p_3=-1.040825e+005
p_4=-9.450925e+004	p_4=-1.394620e+005	p_4=-1.490963e+005
p_5=-3.774986e+004	p_5=-8.123708e+004	p_5=-8.838050e+004
p_6=-7.080324e+004	p_6=-7.430302e+004	p_6=-2.249861e+005
p_7=-2.409947e+005	p_7=-2.516421e+005	p_7=-3.421147e+005
p_8=-1.836953e+005	p_8=-2.363211e+005	p_8=-3.431838e+005
p_9=-2.809712e+005	p_9=-1.707405e+005	p_9=-3.388145e+005
p_10=-1.285001e+005	p_10=-1.855513e+005	p_10=-3.064459e+005
p_11=-5.385058e+004	p_11=-6.750991e+004	p_11=-1.355378e+005
p_12=-1.186629e+005	p_12=-1.250742e+005	p_12=-3.166930e+005
p_13=-2.302865e+004 *	p_13=-2.862906e+005	p_13=-3.114982e+005
p_14=-3.647138e+004	p_14=-4.995289e+004 *	p_14=-2.341359e+005
p_15=-3.015656e+005	p_15=-3.332261e+005	p_15=-2.503902e+004 *

/e/ (GMM1)

t1 p_1=-8.807799e+003 * p_2=-3.427043e+004 p_3=-5.861328e+004 p_4=-8.489256e+004 p_5=-2.927063e+004 p_6=-6.748759e+004 p_7=-1.115635e+005 p_8=-3.643420e+004 p_9=-3.432000e+005 p_10=-2.398873e+005 p_11=-7.501214e+004 p_12=-3.400893e+005 p_13=-2.708073e+005 p_14=-1.215415e+005 p_15=-2.083514e+005	t2 p_1=-9.188148e+004 p_2=-1.026558e+004 * p_3=-7.958874e+004 p_4=-1.290734e+005 p_5=-4.237321e+004 p_6=-4.649208e+004 p_7=-1.794501e+005 p_8=-4.795841e+004 p_9=-3.421605e+005 p_10=-2.386568e+005 p_11=-7.807398e+004 p_12=-3.337433e+005 p_13=-2.687112e+005 p_14=-1.561963e+005 p_15=-1.920704e+005	t3 p_1=-6.085107e+004 p_2=-4.690126e+004 p_3=-9.669064e+003 * p_4=-4.793825e+004 p_5=-2.649427e+004 p_6=-6.242140e+004 p_7=-7.335330e+004 p_8=-2.629098e+004 p_9=-3.431888e+005 p_10=-2.405890e+005 p_11=-5.282843e+004 p_12=-2.579289e+005 p_13=-2.558564e+005 p_14=-1.035385e+005 p_15=-2.328877e+005
t4 p_1=-1.123828e+005 p_2=-3.580352e+004 p_3=-2.750477e+004 p_4=-1.836038e+004 * p_5=-3.109957e+004 p_6=-5.674724e+004 p_7=-9.802725e+004 p_8=-5.033533e+004 p_9=-3.431550e+005 p_10=-2.327138e+005 p_11=-5.990920e+004 p_12=-3.132254e+005 p_13=-2.599464e+005 p_14=-1.482608e+005 p_15=-2.651602e+005	t5 p_1=-9.140738e+004 p_2=-5.039898e+004 p_3=-3.901899e+004 p_4=-6.606166e+004 p_5=-1.695138e+004 * p_6=-7.861856e+004 p_7=-1.415207e+005 p_8=-4.683977e+004 p_9=-3.366508e+005 p_10=-1.605002e+005 p_11=-5.854592e+004 p_12=-2.035418e+005 p_13=-2.559776e+005 p_14=-1.009575e+005 p_15=-2.241689e+005	t6 p_1=-8.795413e+004 p_2=-4.120740e+004 p_3=-3.374169e+004 p_4=-5.743099e+004 p_5=-2.351958e+004 p_6=-1.502715e+004 * p_7=-1.606507e+005 p_8=-3.782739e+004 p_9=-3.186299e+005 p_10=-1.585537e+005 p_11=-5.768610e+004 p_12=-2.655656e+005 p_13=-2.296673e+005 p_14=-1.047597e+005 p_15=-1.541279e+005

/e/ (GMM1)

t7 p_1=-1.841709e+005 p_2=-9.873328e+004 p_3=-7.037708e+004 p_4=-1.408435e+005 p_5=-6.550370e+004 p_6=-2.509384e+005 p_7=-9.077617e+003 * p_8=-8.437445e+004 p_9=-3.146000e+005 p_10=-2.942128e+005 p_11=-1.317892e+005 p_12=-3.018132e+005 p_13=-2.895912e+005 p_14=-2.263375e+005 p_15=-3.109828e+005	t8 p_1=-1.162142e+005 p_2=-2.966725e+004 p_3=-2.700189e+004 p_4=-1.959434e+005 p_5=-5.397983e+004 p_6=-3.205820e+004 p_7=-2.315131e+005 p_8=-1.368407e+004 * p_9=-3.432000e+005 p_10=-2.541317e+005 p_11=-8.558229e+004 p_12=-3.416836e+005 p_13=-3.334980e+005 p_14=-1.911245e+005 p_15=-2.117136e+005	t9 p_1=-1.482102e+005 p_2=-6.733811e+004 p_3=-1.225970e+005 p_4=-2.027660e+005 p_5=-6.890957e+004 p_6=-5.495125e+004 p_7=-2.472126e+005 p_8=-1.031650e+005 p_9=-2.372363e+004 * p_10=-7.519421e+004 p_11=-6.680905e+004 p_12=-2.522671e+005 p_13=-1.484374e+005 p_14=-1.402432e+005 p_15=-6.934437e+004
t10 p_1=-7.638228e+004 p_2=-4.110888e+004 p_3=-3.117186e+004 p_4=-1.349443e+005 p_5=-2.667230e+004 p_6=-4.484178e+004 p_7=-1.522722e+005 p_8=-4.186134e+004 p_9=-1.347691e+005 p_10=-2.042276e+004 * p_11=-3.290710e+004 p_12=-1.559790e+005 p_13=-8.197717e+004 p_14=-1.418722e+005 p_15=-9.617308e+004	t11 p_1=-1.168223e+005 p_2=-6.129489e+004 p_3=-7.944528e+004 p_4=-5.999491e+004 p_5=-7.419146e+004 p_6=-6.692706e+004 p_7=-1.116629e+005 p_8=-7.041626e+004 p_9=-3.397759e+005 p_10=-2.028731e+005 p_11=-8.803977e+003 * p_12=-2.935606e+005 p_13=-2.460799e+005 p_14=-6.526947e+004 p_15=-1.992237e+005	t12 p_1=-2.990755e+005 p_2=-8.507470e+004 p_3=-1.040713e+005 p_4=-2.208250e+005 p_5=-7.405308e+004 p_6=-5.247023e+004 p_7=-2.734312e+005 p_8=-8.348109e+004 p_9=-2.279215e+005 p_10=-9.237340e+004 p_11=-8.388570e+004 p_12=-3.752498e+004 * p_13=-1.043055e+005 p_14=-2.633266e+005 p_15=-2.771997e+005

/e/ (GMM1)

t13	t14	t15
p_1=-1.395239e+005	p_1=-7.698967e+004	p_1=-9.632060e+004
p_2=-3.814710e+004	p_2=-7.107650e+004	p_2=-5.034531e+004
p_3=-1.095806e+005	p_3=-8.973959e+004	p_3=-9.491830e+004
p_4=-1.128064e+005	p_4=-6.352008e+004	p_4=-2.012777e+005
p_5=-6.003053e+004	p_5=-6.611904e+004	p_5=-4.161446e+004
p_6=-4.583078e+004	p_6=-6.298126e+004	p_6=-5.323737e+004
p_7=-1.528170e+005	p_7=-1.417213e+005	p_7=-2.335166e+005
p_8=-6.668010e+004	p_8=-7.111852e+004	p_8=-7.028259e+004
p_9=-2.218171e+005	p_9=-3.548468e+005	p_9=-3.302026e+005
p_10=-7.082886e+004	p_10=-2.807920e+005	p_10=-6.093107e+004
p_11=-4.449301e+004	p_11=-4.496119e+004	p_11=-7.536633e+004
p_12=-1.138933e+005	p_12=-1.784606e+005	p_12=-3.148315e+005
p_13=-2.064660e+004 *	p_13=-1.242626e+005	p_13=-9.849784e+004
p_14=-1.060536e+005	p_14=-1.244103e+004 *	p_14=-1.619257e+005
p_15=-1.207717e+005	p_15=-1.911395e+005	p_15=-2.548544e+004 *

/e/ (GMM2)

s1 p_1=-3.921321e+004 * p_2=-4.641319e+004 p_3=-9.367040e+004 p_4=-1.182701e+005 p_5=-1.516534e+005 p_6=-7.846556e+004 p_7=-1.463159e+005 p_8=-1.621997e+005 p_9=-3.721250e+005 p_10=-2.578621e+005 p_11=-9.868855e+004 p_12=-2.847109e+005 p_13=-2.204586e+005 p_14=-1.077742e+005 p_15=-2.455302e+005	s2 p_1=-1.555912e+005 p_2=-1.139381e+004 * p_3=-1.022806e+005 p_4=-1.222524e+005 p_5=-1.184286e+005 p_6=-5.837544e+004 p_7=-2.179734e+005 p_8=-9.636917e+004 p_9=-3.431819e+005 p_10=-1.884552e+005 p_11=-1.070514e+005 p_12=-2.373114e+005 p_13=-2.096950e+005 p_14=-1.241098e+005 p_15=-2.495908e+005	s3 p_1=-1.871411e+005 p_2=-4.836839e+004 p_3=-1.301996e+004 * p_4=-9.292342e+004 p_5=-5.403966e+004 p_6=-3.826732e+004 p_7=-1.669023e+005 p_8=-1.443530e+005 p_9=-3.432000e+005 p_10=-1.635865e+005 p_11=-8.146934e+004 p_12=-1.778068e+005 p_13=-2.352593e+005 p_14=-1.106646e+005 p_15=-3.345681e+005
s4 p_1=-2.260194e+005 p_2=-4.556029e+004 p_3=-3.106664e+004 * p_4=-3.486410e+004 p_5=-1.045620e+005 p_6=-6.836890e+004 p_7=-9.001398e+004 p_8=-2.326940e+005 p_9=-3.432000e+005 p_10=-1.919687e+005 p_11=-7.763112e+004 p_12=-2.185196e+005 p_13=-2.342565e+005 p_14=-1.540373e+005 p_15=-3.270868e+005	s5 p_1=-1.977788e+005 p_2=-6.380223e+004 p_3=-7.451821e+004 p_4=-8.428252e+004 p_5=-5.411585e+004 p_6=-3.956861e+004 * p_7=-1.672201e+005 p_8=-2.169800e+005 p_9=-3.410427e+005 p_10=-1.741216e+005 p_11=-9.786128e+004 p_12=-1.961414e+005 p_13=-1.864675e+005 p_14=-1.401856e+005 p_15=-2.743576e+005	s6 p_1=-1.767967e+005 p_2=-2.580977e+004 p_3=-4.253915e+004 p_4=-9.367294e+004 p_5=-5.109037e+004 p_6=-1.552276e+004 * p_7=-2.871987e+005 p_8=-4.457778e+004 p_9=-3.393667e+005 p_10=-9.241785e+004 p_11=-7.897443e+004 p_12=-1.060204e+005 p_13=-1.401713e+005 p_14=-9.918183e+004 p_15=-2.165722e+005

/e/ (GMM2)

s7	s8	s9
p_1=-3.408065e+005	p_1=-1.734019e+005	p_1=-3.359529e+005
p_2=-1.362339e+005	p_2=-4.136091e+004	p_2=-6.156465e+004
p_3=-1.078416e+005	p_3=-3.351599e+004 *	p_3=-1.951597e+005
p_4=-2.915995e+005	p_4=-1.607713e+005	p_4=-2.548670e+005
p_5=-2.072337e+005	p_5=-7.674831e+004	p_5=-1.135010e+005
p_6=-2.359193e+005	p_6=-4.851944e+004	p_6=-6.973135e+004
p_7=-1.186048e+004 *	p_7=-2.206705e+005	p_7=-2.795669e+005
p_8=-3.430352e+005	p_8=-7.172165e+004	p_8=-2.546484e+005
p_9=-3.432000e+005	p_9=-3.721250e+005	p_9=-2.618605e+004 *
p_10=-3.382508e+005	p_10=-2.035349e+005	p_10=-9.526366e+004
p_11=-1.218776e+005	p_11=-1.101033e+005	p_11=-1.098532e+005
p_12=-3.195260e+005	p_12=-2.493533e+005	p_12=-9.533565e+004
p_13=-3.355816e+005	p_13=-2.824865e+005	p_13=-1.597014e+005
p_14=-2.976692e+005	p_14=-1.400848e+005	p_14=-2.136300e+005
p_15=-3.432000e+005	p_15=-3.475051e+005	p_15=-1.826631e+005
s10	s11	s12
p_1=-3.349158e+005	p_1=-2.938667e+005	p_1=-3.416046e+005
p_2=-4.650963e+004	p_2=-4.626962e+004	p_2=-5.948037e+004
p_3=-8.483435e+004	p_3=-1.068279e+005	p_3=-1.293834e+005
p_4=-1.646493e+005	p_4=-7.132832e+004	p_4=-9.536746e+004
p_5=-9.100511e+004	p_5=-8.489834e+004	p_5=-8.441847e+004
p_6=-3.603847e+004	p_6=-6.182446e+004	p_6=-4.527542e+004
p_7=-1.754378e+005	p_7=-1.361503e+005	p_7=-2.171337e+005
p_8=-2.506464e+005	p_8=-2.429648e+005	p_8=-2.234088e+005
p_9=-2.223794e+005	p_9=-3.428241e+005	p_9=-2.386102e+005
p_10=-2.420415e+004 *	p_10=-1.852647e+005	p_10=-1.387368e+005
p_11=-5.318725e+004	p_11=-9.361746e+003 *	p_11=-5.813146e+004
p_12=-7.606131e+004	p_12=-1.027897e+005	p_12=-1.821335e+004 *
p_13=-6.090800e+004	p_13=-2.260198e+005	p_13=-3.778096e+004
p_14=-1.961718e+005	p_14=-5.630263e+004	p_14=-1.152275e+005
p_15=-1.214785e+005	p_15=-3.048284e+005	p_15=-2.756260e+005

/e/ (GMM2)

s13	s14	s15
p_1=-2.696252e+005	p_1=-2.610913e+005	p_1=-1.739666e+005
p_2=-2.987255e+004	p_2=-6.334973e+004	p_2=-4.941683e+004
p_3=-1.219745e+005	p_3=-1.353955e+005	p_3=-1.706830e+005
p_4=-6.239871e+004	p_4=-1.092264e+005	p_4=-1.963485e+005
p_5=-6.342767e+004	p_5=-7.573538e+004	p_5=-1.016009e+005
p_6=-4.825811e+004	p_6=-5.757142e+004	p_6=-5.792693e+004
p_7=-1.262764e+005	p_7=-1.719639e+005	p_7=-2.945068e+005
p_8=-1.868051e+005	p_8=-2.514070e+005	p_8=-2.242030e+005
p_9=-2.351806e+005	p_9=-3.097538e+005	p_9=-1.902595e+005
p_10=-9.310206e+004	p_10=-2.427124e+005	p_10=-8.646828e+004
p_11=-3.727198e+004	p_11=-7.071918e+004	p_11=-9.779976e+004
p_12=-5.023071e+004	p_12=-1.829342e+005	p_12=-7.178031e+004
p_13=-1.627149e+004 *	p_13=-2.547545e+005	p_13=-7.788104e+004
p_14=-4.487295e+004	p_14=-1.448543e+004 *	p_14=-1.091544e+005
p_15=-1.422242e+005	p_15=-3.224331e+005	p_15=-3.601471e+004 *

/E/ (GMM1)

t1 p_1=-1.752051e+004 * p_2=-4.817155e+004 p_3=-6.569050e+004 p_4=-1.703177e+005 p_5=-1.100449e+005 p_6=-3.974636e+004 p_7=-2.517095e+005 p_8=-7.122993e+004 p_9=-2.305564e+005 p_10=-1.205171e+005 p_11=-1.222988e+005 p_12=-2.697373e+005 p_13=-1.760369e+005 p_14=-9.974467e+004 p_15=-2.481140e+005	t2 p_1=-1.681502e+005 p_2=-1.119114e+004 * p_3=-8.127389e+004 p_4=-1.367436e+005 p_5=-9.582043e+004 p_6=-4.965327e+004 p_7=-3.006895e+005 p_8=-1.186942e+005 p_9=-2.313747e+005 p_10=-1.320940e+005 p_11=-1.217392e+005 p_12=-3.377481e+005 p_13=-2.446387e+005 p_14=-8.671953e+004 p_15=-3.377185e+005	t3 p_1=-1.524443e+005 p_2=-4.989848e+004 p_3=-9.157864e+003 * p_4=-9.187581e+004 p_5=-6.821404e+004 p_6=-3.724441e+004 p_7=-1.702041e+005 p_8=-5.312452e+004 p_9=-1.504808e+005 p_10=-1.574469e+005 p_11=-8.555937e+004 p_12=-3.348384e+005 p_13=-2.266328e+005 p_14=-1.522494e+005 p_15=-3.075793e+005
t4 p_1=-1.522971e+005 p_2=-5.220713e+004 p_3=-3.764067e+004 p_4=-2.315673e+004 * p_5=-6.188671e+004 p_6=-3.376033e+004 p_7=-1.519958e+005 p_8=-3.625938e+004 p_9=-1.518459e+005 p_10=-1.025734e+005 p_11=-5.703945e+004 p_12=-2.778148e+005 p_13=-1.921390e+005 p_14=-1.049035e+005 p_15=-2.568620e+005	t5 p_1=-3.204398e+005 p_2=-1.273550e+005 p_3=-2.741540e+005 p_4=-2.595767e+005 p_5=-1.047744e+004 * p_6=-1.525236e+005 p_7=-1.501302e+005 p_8=-9.458014e+004 p_9=-2.505477e+005 p_10=-1.421279e+005 p_11=-1.208386e+005 p_12=-2.196061e+005 p_13=-1.582216e+005 p_14=-1.122796e+005 p_15=-1.907044e+005	t6 p_1=-1.578020e+005 p_2=-3.920116e+004 p_3=-4.978716e+004 p_4=-1.065321e+005 p_5=-7.019359e+004 p_6=-1.449381e+004 * p_7=-2.446503e+005 p_8=-6.614858e+004 p_9=-1.264471e+005 p_10=-8.433556e+004 p_11=-7.502008e+004 p_12=-2.864793e+005 p_13=-1.263857e+005 p_14=-7.316679e+004 p_15=-2.886643e+005

/E/ (GMM1)

t7 p_1=-3.373345e+005 p_2=-1.386988e+005 p_3=-2.927789e+005 p_4=-1.967811e+005 p_5=-4.113842e+004 p_6=-1.948489e+005 p_7=-2.238151e+004 * p_8=-4.662115e+004 p_9=-2.726445e+005 p_10=-1.213830e+005 p_11=-1.031921e+005 p_12=-1.863636e+005 p_13=-1.209293e+005 p_14=-1.301355e+005 p_15=-1.740048e+005	t8 p_1=-2.816319e+005 p_2=-1.142808e+005 p_3=-2.057479e+005 p_4=-2.057394e+005 p_5=-5.312723e+004 p_6=-1.111794e+005 p_7=-1.043398e+005 p_8=-1.746172e+004 * p_9=-3.077668e+005 p_10=-1.390265e+005 p_11=-8.015620e+004 p_12=-2.487028e+005 p_13=-1.619654e+005 p_14=-1.872046e+005 p_15=-1.844715e+005	t9 p_1=-1.520771e+005 p_2=-6.182758e+004 p_3=-6.133047e+004 p_4=-1.148931e+005 p_5=-6.420249e+004 p_6=-2.445515e+004 p_7=-2.313663e+005 p_8=-9.240086e+004 p_9=-4.726410e+003 * p_10=-1.097913e+005 p_11=-1.439784e+005 p_12=-3.130165e+005 p_13=-7.846578e+004 p_14=-4.861100e+004 p_15=-3.014378e+005
t10 p_1=-1.806245e+005 p_2=-5.293776e+004 p_3=-1.434018e+005 p_4=-1.029367e+005 p_5=-4.965548e+004 p_6=-5.619952e+004 p_7=-1.092235e+005 p_8=-3.628249e+004 p_9=-1.743859e+005 p_10=-1.011434e+004 * p_11=-4.092949e+004 p_12=-1.204889e+005 p_13=-5.583281e+004 p_14=-8.056831e+004 p_15=-9.922115e+004	t11 p_1=-1.826755e+005 p_2=-5.418594e+004 p_3=-8.459265e+004 p_4=-1.200063e+005 p_5=-5.805928e+004 p_6=-5.465191e+004 p_7=-1.205935e+005 p_8=-4.095601e+004 p_9=-1.667850e+005 p_10=-6.455498e+004 p_11=-7.810904e+003 * p_12=-2.486478e+005 p_13=-1.367058e+005 p_14=-9.388784e+004 p_15=-1.672813e+005	t12 p_1=-3.192078e+005 p_2=-9.874052e+004 p_3=-2.561587e+005 p_4=-1.946808e+005 p_5=-4.739132e+004 p_6=-1.205667e+005 p_7=-1.223882e+005 p_8=-6.060845e+004 p_9=-2.562524e+005 p_10=-5.633983e+004 p_11=-1.013705e+005 p_12=-1.276390e+004 * p_13=-5.489655e+004 p_14=-7.459199e+004 p_15=-1.235597e+005

/E/ (GMM1)

t13	t14	t15
p_1=-2.846931e+005	p_1=-1.109650e+005	p_1=-2.488394e+005
p_2=-6.654355e+004	p_2=-5.352314e+004	p_2=-9.788664e+004
p_3=-1.367089e+005	p_3=-9.647270e+004	p_3=-2.681667e+005
p_4=-1.139836e+005	p_4=-1.055994e+005	p_4=-2.103481e+005
p_5=-5.338696e+004	p_5=-7.375389e+004	p_5=-6.222141e+004
p_6=-7.453583e+004	p_6=-4.114796e+004	p_6=-8.388322e+004
p_7=-1.191790e+005	p_7=-2.114029e+005	p_7=-1.194676e+005
p_8=-4.890553e+004	p_8=-6.418758e+004	p_8=-4.430888e+004
p_9=-1.871844e+005	p_9=-9.238754e+004	p_9=-2.461863e+005
p_10=-5.010016e+004	p_10=-6.633773e+004	p_10=-6.323683e+004
p_11=-8.232994e+004	p_11=-9.425249e+004	p_11=-5.566433e+004
p_12=-1.060079e+005	p_12=-1.624769e+005	p_12=-1.234532e+005
p_13=-7.655130e+003 *	p_13=-8.087950e+004	p_13=-9.631455e+004
p_14=-5.250977e+004	p_14=-1.933440e+004 *	p_14=-8.523639e+004
p_15=-1.296696e+005	p_15=-2.113407e+005	p_15=-2.080858e+004 *

/E/ (GMM2)

s1 p_1=-2.771869e+004 * p_2=-5.088749e+004 p_3=-6.923565e+004 p_4=-7.749652e+004 p_5=-8.899404e+004 p_6=-3.330247e+004 p_7=-2.592443e+005 p_8=-7.541315e+004 p_9=-3.077765e+005 p_10=-9.777431e+004 p_11=-1.203892e+005 p_12=-2.034217e+005 p_13=-1.701789e+005 p_14=-6.981526e+004 p_15=-3.314959e+005	s2 p_1=-3.224324e+005 p_2=-1.358283e+004 * p_3=-7.280095e+004 p_4=-1.098422e+005 p_5=-9.483801e+004 p_6=-5.628600e+004 p_7=-3.264024e+005 p_8=-1.167625e+005 p_9=-3.294547e+005 p_10=-1.261440e+005 p_11=-1.600739e+005 p_12=-3.412855e+005 p_13=-2.841349e+005 p_14=-2.081754e+005 p_15=-3.426738e+005	s3 p_1=-2.572812e+005 p_2=-3.123977e+004 p_3=-7.938580e+003 * p_4=-4.410445e+004 p_5=-7.164514e+004 p_6=-4.075001e+004 p_7=-1.572467e+005 p_8=-5.345492e+004 p_9=-2.411547e+005 p_10=-1.469627e+005 p_11=-8.570831e+004 p_12=-3.400212e+005 p_13=-1.710811e+005 p_14=-2.172203e+005 p_15=-3.427927e+005
s4 p_1=-3.143278e+005 p_2=-4.458845e+004 p_3=-2.862213e+004 p_4=-1.164373e+004 * p_5=-7.039227e+004 p_6=-4.999269e+004 p_7=-1.558377e+005 p_8=-5.658298e+004 p_9=-2.468371e+005 p_10=-9.008213e+004 p_11=-6.817055e+004 p_12=-3.041889e+005 p_13=-1.873446e+005 p_14=-1.578507e+005 p_15=-3.256177e+005	s5 p_1=-3.424553e+005 p_2=-1.203639e+005 p_3=-1.536233e+005 p_4=-1.452887e+005 p_5=-1.079107e+004 * p_6=-1.338053e+005 p_7=-6.769599e+004 p_8=-5.347027e+004 p_9=-2.524223e+005 p_10=-1.118438e+005 p_11=-1.229947e+005 p_12=-1.868525e+005 p_13=-1.809653e+005 p_14=-1.717327e+005 p_15=-2.344604e+005	s6 p_1=-2.148556e+005 p_2=-4.752947e+004 p_3=-5.725639e+004 p_4=-7.004674e+004 p_5=-7.633107e+004 p_6=-1.760663e+004 * p_7=-2.562511e+005 p_8=-8.056442e+004 p_9=-1.638614e+005 p_10=-1.030388e+005 p_11=-1.064048e+005 p_12=-3.358929e+005 p_13=-1.719635e+005 p_14=-1.036634e+005 p_15=-3.552034e+005

/E/ (GMM2)

s7 p_1=-3.145598e+005 p_2=-1.264021e+005 p_3=-1.296947e+005 p_4=-1.723477e+005 p_5=-5.033172e+004 p_6=-2.356952e+005 p_7=-1.250927e+004 * p_8=-3.407264e+004 p_9=-3.127037e+005 p_10=-1.020826e+005 p_11=-1.420170e+005 p_12=-2.231416e+005 p_13=-1.754059e+005 p_14=-1.823362e+005 p_15=-2.370367e+005	s8 p_1=-3.185157e+005 p_2=-9.686241e+004 p_3=-6.844960e+004 p_4=-8.613481e+004 p_5=-6.759498e+004 p_6=-1.440771e+005 p_7=-9.181791e+004 p_8=-1.177416e+004 * p_9=-3.240126e+005 p_10=-1.365825e+005 p_11=-1.198770e+005 p_12=-2.326832e+005 p_13=-1.739081e+005 p_14=-2.158577e+005 p_15=-2.552369e+005	s9 p_1=-2.829014e+005 p_2=-5.199472e+004 p_3=-8.010617e+004 p_4=-9.352977e+004 p_5=-7.659148e+004 p_6=-3.530122e+004 p_7=-1.926471e+005 p_8=-9.737035e+004 p_9=-8.660988e+003 * p_10=-8.365282e+004 p_11=-1.953836e+005 p_12=-3.172230e+005 p_13=-1.601782e+005 p_14=-6.286472e+004 p_15=-2.970499e+005
s10 p_1=-3.341070e+005 p_2=-1.017122e+005 p_3=-8.060905e+004 p_4=-1.311262e+005 p_5=-5.259385e+004 p_6=-1.178659e+005 p_7=-1.122205e+005 p_8=-3.146947e+004 p_9=-2.364164e+005 p_10=-8.903024e+003 * p_11=-6.993273e+004 p_12=-1.196053e+005 p_13=-5.380032e+004 p_14=-5.162378e+004 p_15=-1.211630e+005	s11 p_1=-3.184384e+005 p_2=-8.322254e+004 p_3=-6.853894e+004 p_4=-8.105095e+004 p_5=-5.217869e+004 p_6=-9.247215e+004 p_7=-1.078221e+005 p_8=-3.907793e+004 p_9=-2.229701e+005 p_10=-6.250000e+004 p_11=-9.551289e+003 * p_12=-2.107816e+005 p_13=-1.637414e+005 p_14=-1.489879e+005 p_15=-1.868804e+005	s12 p_1=-3.721250e+005 p_2=-1.581009e+005 p_3=-1.476779e+005 p_4=-1.572806e+005 p_5=-6.583563e+004 p_6=-1.584259e+005 p_7=-7.563897e+004 p_8=-6.463594e+004 p_9=-3.297361e+005 p_10=-8.093904e+004 p_11=-1.382666e+005 p_12=-4.484644e+004 * p_13=-8.000081e+004 p_14=-1.691805e+005 p_15=-1.557856e+005

/E/ (GMM2)

s13	s14	s15
p_1=-3.375921e+005	p_1=-2.960892e+005	p_1=-3.721250e+005
p_2=-7.983170e+004	p_2=-7.035312e+004	p_2=-1.894343e+005
p_3=-7.571743e+004	p_3=-4.970557e+004	p_3=-1.814581e+005
p_4=-1.012621e+005	p_4=-7.942957e+004	p_4=-2.048509e+005
p_5=-5.714256e+004	p_5=-7.207844e+004	p_5=-6.326943e+004
p_6=-8.591588e+004	p_6=-4.031785e+004	p_6=-2.034228e+005
p_7=-1.314331e+005	p_7=-2.542131e+005	p_7=-1.002519e+005
p_8=-3.928961e+004	p_8=-7.509765e+004	p_8=-6.115535e+004
p_9=-2.103709e+005	p_9=-1.754564e+005	p_9=-3.620770e+005
p_10=-4.778922e+004	p_10=-8.013890e+004	p_10=-9.037957e+004
p_11=-1.569915e+005	p_11=-1.969791e+005	p_11=-1.016878e+005
p_12=-1.775751e+005	p_12=-2.671763e+005	p_12=-1.317135e+005
p_13=-9.585863e+003 *	p_13=-9.474408e+004	p_13=-1.934476e+005
p_14=-5.737053e+004	p_14=-3.977886e+004 *	p_14=-1.423004e+005
p_15=-1.976100e+005	p_15=-3.047091e+005	p_15=-3.326476e+004 *

/@/ (GMM1)

t1 p_1=-7.547942e+003 * p_2=-3.321692e+004 p_3=-1.016942e+005 p_4=-6.676680e+004 p_5=-7.577906e+004 p_6=-5.039609e+004 p_7=-1.864624e+005 p_8=-2.817801e+004 p_9=-1.626703e+005 p_10=-3.249411e+005 p_11=-9.350733e+004 p_12=-9.729897e+004 p_13=-1.824664e+005 p_14=-9.253557e+004 p_15=-2.435110e+005	t2 p_1=-1.550070e+005 p_2=-1.354283e+004 * p_3=-1.140722e+005 p_4=-9.353295e+004 p_5=-6.985661e+004 p_6=-2.214902e+005 p_7=-1.054404e+005 p_8=-4.736288e+004 p_9=-2.292793e+005 p_10=-2.360567e+005 p_11=-1.176689e+005 p_12=-1.254945e+005 p_13=-2.955152e+005 p_14=-1.582300e+005 p_15=-2.354302e+005	t3 p_1=-9.757983e+004 p_2=-2.732398e+004 p_3=-7.946582e+003 * p_4=-3.683643e+004 p_5=-8.257388e+004 p_6=-1.537222e+005 p_7=-7.803163e+004 p_8=-3.870221e+004 p_9=-2.339814e+005 p_10=-2.580111e+005 p_11=-1.711856e+005 p_12=-1.246067e+005 p_13=-3.392095e+005 p_14=-1.902942e+005 p_15=-3.351891e+005
t4 p_1=-2.014433e+005 p_2=-3.396338e+004 p_3=-9.241345e+004 p_4=-2.478126e+004 * p_5=-6.818273e+004 p_6=-2.108593e+005 p_7=-9.295094e+004 p_8=-8.524612e+004 p_9=-2.208569e+005 p_10=-2.840323e+005 p_11=-9.098340e+004 p_12=-8.533261e+004 p_13=-3.278653e+005 p_14=-1.660424e+005 p_15=-3.324764e+005	t5 p_1=-2.717118e+005 p_2=-3.903176e+004 p_3=-2.111938e+005 p_4=-9.398428e+004 p_5=-2.183926e+004 * p_6=-2.684546e+005 p_7=-1.453192e+005 p_8=-1.436333e+005 p_9=-1.539812e+005 p_10=-3.194138e+005 p_11=-1.628985e+005 p_12=-6.657893e+004 p_13=-3.534034e+005 p_14=-1.551256e+005 p_15=-3.075786e+005	t6 p_1=-3.281628e+005 p_2=-1.074622e+005 p_3=-1.696621e+005 p_4=-1.596505e+005 p_5=-6.671669e+004 p_6=-1.134980e+004 * p_7=-2.779114e+005 p_8=-7.831759e+004 p_9=-1.213020e+005 p_10=-3.721250e+005 p_11=-2.008500e+005 p_12=-8.721718e+004 p_13=-3.658222e+005 p_14=-8.723044e+004 p_15=-3.679347e+005

/@/ (GMM1)

t7	t8	t9
p_1=-1.706167e+005	p_1=-9.253064e+004	p_1=-2.069624e+005
p_2=-2.565498e+004	p_2=-2.990796e+004	p_2=-7.598092e+004
p_3=-4.691376e+004	p_3=-7.115490e+004	p_3=-1.354081e+005
p_4=-4.126137e+004	p_4=-5.953388e+004	p_4=-8.385823e+004
p_5=-5.742464e+004	p_5=-9.997184e+004	p_5=-3.751253e+004
p_6=-2.377504e+005	p_6=-1.157413e+005	p_6=-4.889771e+004
p_7=-1.719972e+004 *	p_7=-1.702937e+005	p_7=-1.837291e+005
p_8=-5.127775e+004	p_8=-1.772809e+004 *	p_8=-6.305479e+004
p_9=-2.277619e+005	p_9=-2.450595e+005	p_9=-1.390147e+004 *
p_10=-3.175271e+005	p_10=-3.000390e+005	p_10=-3.721250e+005
p_11=-9.316265e+004	p_11=-1.706446e+005	p_11=-2.622145e+005
p_12=-5.256990e+004	p_12=-1.352939e+005	p_12=-7.253444e+004
p_13=-2.818805e+005	p_13=-2.302349e+005	p_13=-2.122954e+005
p_14=-1.536531e+005	p_14=-1.735879e+005	p_14=-4.902956e+004
p_15=-2.629763e+005	p_15=-2.976907e+005	p_15=-3.707274e+005
t10	t11	t12
p_1=-1.013361e+005	p_1=-1.121082e+005	p_1=-2.643201e+005
p_2=-3.090614e+004 *	p_2=-3.021376e+004	p_2=-3.725823e+004
p_3=-5.061365e+004	p_3=-8.155175e+004	p_3=-1.284051e+005
p_4=-8.580083e+004	p_4=-4.336739e+004	p_4=-1.035865e+005
p_5=-4.843523e+004	p_5=-4.902440e+004	p_5=-4.111061e+004
p_6=-6.832851e+004	p_6=-1.211551e+005	p_6=-1.866344e+005
p_7=-8.722028e+004	p_7=-4.459242e+004	p_7=-9.277075e+004
p_8=-4.145336e+004	p_8=-4.892728e+004	p_8=-6.301163e+004
p_9=-1.370185e+005	p_9=-1.702358e+005	p_9=-2.203097e+005
p_10=-8.643649e+004	p_10=-2.380760e+005	p_10=-1.525062e+005
p_11=-6.941808e+004	p_11=-1.255897e+004 *	p_11=-8.367728e+004
p_12=-4.804055e+004	p_12=-4.174587e+004	p_12=-1.430690e+004 *
p_13=-3.215039e+005	p_13=-3.146000e+005	p_13=-3.413173e+005
p_14=-5.554406e+004	p_14=-1.165957e+005	p_14=-1.241642e+005
p_15=-2.156099e+005	p_15=-2.281992e+005	p_15=-2.199690e+005

/@/ (GMM1)

t13	t14	t15
p_1=-1.540993e+005	p_1=-9.116730e+004	p_1=-2.136608e+005
p_2=-4.987310e+004	p_2=-4.409706e+004	p_2=-2.151128e+004 *
p_3=-1.302487e+005	p_3=-1.036278e+005	p_3=-1.201328e+005
p_4=-6.260025e+004	p_4=-8.362081e+004	p_4=-8.070620e+004
p_5=-5.062740e+004	p_5=-4.746146e+004	p_5=-4.955469e+004
p_6=-1.907877e+005	p_6=-1.011239e+005	p_6=-1.655474e+005
p_7=-2.137917e+005	p_7=-1.471459e+005	p_7=-6.863563e+004
p_8=-4.943203e+004	p_8=-3.715078e+004	p_8=-4.092435e+004
p_9=-8.963606e+004	p_9=-1.105781e+005	p_9=-1.598765e+005
p_10=-3.689879e+005	p_10=-3.171850e+005	p_10=-1.274792e+005
p_11=-2.284373e+005	p_11=-1.011730e+005	p_11=-3.808469e+004
p_12=-6.196653e+004	p_12=-6.492713e+004	p_12=-5.391747e+004
p_13=-4.184127e+004 *	p_13=-2.317197e+005	p_13=-3.262593e+005
p_14=-9.524240e+004	p_14=-3.204968e+004 *	p_14=-8.590850e+004
p_15=-2.747670e+005	p_15=-2.547331e+005	p_15=-2.734290e+004

/@/ (GMM2)

s1 p_1=-1.004528e+004 * p_2=-4.496851e+004 p_3=-1.165165e+005 p_4=-1.637388e+005 p_5=-9.191471e+004 p_6=-8.428646e+004 p_7=-1.181690e+005 p_8=-3.939033e+004 p_9=-2.390335e+005 p_10=-1.735846e+005 p_11=-1.752812e+005 p_12=-2.744757e+005 p_13=-1.757464e+005 p_14=-1.184914e+005 p_15=-1.720225e+005	s2 p_1=-2.387624e+005 p_2=-1.743558e+004 * p_3=-9.507186e+004 p_4=-1.173578e+005 p_5=-5.572498e+004 p_6=-2.470168e+005 p_7=-8.754075e+004 p_8=-9.771493e+004 p_9=-3.650214e+005 p_10=-2.297389e+005 p_11=-1.627692e+005 p_12=-2.681656e+005 p_13=-2.911088e+005 p_14=-2.883820e+005 p_15=-1.756239e+005	s3 p_1=-1.935990e+005 p_2=-5.433525e+004 p_3=-8.423055e+003 * p_4=-5.346182e+004 p_5=-6.402741e+004 p_6=-2.057402e+005 p_7=-7.320887e+004 p_8=-5.868114e+004 p_9=-3.425488e+005 p_10=-1.859136e+005 p_11=-2.359142e+005 p_12=-2.915668e+005 p_13=-3.011109e+005 p_14=-2.158316e+005 p_15=-2.672522e+005
s4 p_1=-2.686748e+005 p_2=-4.963924e+004 p_3=-5.834140e+004 p_4=-5.998290e+004 p_5=-4.423233e+004 * p_6=-2.089141e+005 p_7=-6.022016e+004 p_8=-7.298215e+004 p_9=-3.667265e+005 p_10=-2.820136e+005 p_11=-1.581060e+005 p_12=-2.749134e+005 p_13=-2.496226e+005 p_14=-2.248537e+005 p_15=-2.628839e+005	s5 p_1=-2.351739e+005 p_2=-4.543093e+004 p_3=-1.402378e+005 p_4=-1.181984e+005 p_5=-2.043903e+004 * p_6=-1.747573e+005 p_7=-1.069712e+005 p_8=-8.159190e+004 p_9=-1.744443e+005 p_10=-2.767411e+005 p_11=-2.003390e+005 p_12=-1.682247e+005 p_13=-2.054219e+005 p_14=-2.070467e+005 p_15=-2.193076e+005	s6 p_1=-1.671531e+005 p_2=-1.278270e+005 p_3=-1.504531e+005 p_4=-2.993252e+005 p_5=-9.895550e+004 p_6=-1.257477e+004 * p_7=-2.381709e+005 p_8=-7.694595e+004 p_9=-1.898774e+005 p_10=-1.729605e+005 p_11=-2.305606e+005 p_12=-3.002157e+005 p_13=-2.838776e+005 p_14=-1.722737e+005 p_15=-2.543133e+005

/@/ (GMM2)

s7 p_1=-2.774538e+005 p_2=-3.511219e+004 p_3=-4.643406e+004 p_4=-6.848877e+004 p_5=-4.420876e+004 p_6=-2.592373e+005 p_7=-1.507245e+004 * p_8=-9.568331e+004 p_9=-3.427829e+005 p_10=-2.303063e+005 p_11=-1.496969e+005 p_12=-2.083949e+005 p_13=-2.995185e+005 p_14=-2.499260e+005 p_15=-1.739837e+005	s8 p_1=-1.232276e+005 p_2=-3.898293e+004 p_3=-8.219608e+004 p_4=-1.287332e+005 p_5=-9.168021e+004 p_6=-1.728876e+005 p_7=-1.224809e+005 p_8=-2.079947e+004 * p_9=-3.466650e+005 p_10=-2.309664e+005 p_11=-2.253870e+005 p_12=-2.963088e+005 p_13=-2.550040e+005 p_14=-2.229114e+005 p_15=-2.223595e+005	s9 p_1=-1.640095e+005 p_2=-7.788184e+004 p_3=-1.349073e+005 p_4=-2.092434e+005 p_5=-5.073416e+004 p_6=-1.133458e+005 p_7=-1.695574e+005 p_8=-6.397443e+004 p_9=-4.702349e+004 * p_10=-2.502897e+005 p_11=-2.449737e+005 p_12=-2.407587e+005 p_13=-1.729563e+005 p_14=-1.345338e+005 p_15=-2.903460e+005
s10 p_1=-2.161937e+005 p_2=-4.147711e+004 * p_3=-4.161174e+004 p_4=-8.262303e+004 p_5=-4.441310e+004 p_6=-1.932052e+005 p_7=-7.932556e+004 p_8=-6.939561e+004 p_9=-2.627630e+005 p_10=-5.496056e+004 p_11=-8.090648e+004 p_12=-1.324998e+005 p_13=-2.340495e+005 p_14=-1.002336e+005 p_15=-9.129768e+004	s11 p_1=-2.228906e+005 p_2=-5.272597e+004 p_3=-7.516855e+004 p_4=-1.143116e+005 p_5=-4.919172e+004 p_6=-1.650298e+005 p_7=-6.170623e+004 p_8=-1.438648e+005 p_9=-3.424281e+005 p_10=-1.384045e+005 p_11=-1.511742e+004 * p_12=-9.889587e+004 p_13=-2.959147e+005 p_14=-1.485985e+005 p_15=-9.621109e+004	s12 p_1=-3.226230e+005 p_2=-7.134186e+004 p_3=-1.426362e+005 p_4=-1.848508e+005 p_5=-6.118571e+004 p_6=-2.482214e+005 p_7=-8.503014e+004 p_8=-1.356903e+005 p_9=-3.204754e+005 p_10=-1.984137e+005 p_11=-1.073597e+005 p_12=-5.151959e+004 * p_13=-2.859175e+005 p_14=-2.050343e+005 p_15=-2.121439e+005

/@/ (GMM2)

s13	s14	s15
p_1=-1.463566e+005	p_1=-1.119477e+005	p_1=-1.119477e+005
p_2=-5.825785e+004	p_2=-8.097576e+004	p_2=-8.097576e+004
p_3=-1.332431e+005	p_3=-1.228584e+005	p_3=-1.228584e+005
p_4=-1.037909e+005	p_4=-2.476903e+005	p_4=-2.476903e+005
p_5=-6.245028e+004	p_5=-7.754443e+004	p_5=-7.754443e+004
p_6=-2.807794e+005	p_6=-4.633513e+004 *	p_6=-4.633513e+004 *
p_7=-1.109251e+005	p_7=-1.689775e+005	p_7=-1.689775e+005
p_8=-5.124640e+004	p_8=-5.077438e+004	p_8=-5.077438e+004
p_9=-2.067353e+005	p_9=-7.356367e+004	p_9=-7.356367e+004
p_10=-1.639777e+005	p_10=-1.295698e+005	p_10=-1.295698e+005
p_11=-2.559916e+005	p_11=-1.833432e+005	p_11=-1.833432e+005
p_12=-1.897195e+005	p_12=-2.257685e+005	p_12=-2.257685e+005
p_13=-4.146134e+004 *	p_13=-1.539498e+005	p_13=-1.539498e+005
p_14=-1.999398e+005	p_14=-6.396964e+004	p_14=-6.396964e+004
p_15=-2.355197e+005	p_15=-2.260445e+005	p_15=-2.260445e+005

/a/ (GMM1)

t1 p_1=-1.975505e+004 * p_2=-4.644597e+004 p_3=-1.152629e+005 p_4=-1.133769e+005 p_5=-3.203299e+004 p_6=-8.833311e+004 p_7=-1.169040e+005 p_8=-4.102406e+004 p_9=-3.402632e+005 p_10=-3.369378e+005 p_11=-2.432507e+005 p_12=-1.328681e+005 p_13=-2.945458e+005 p_14=-1.418777e+005 p_15=-2.093675e+005	t2 p_1=-8.847593e+004 p_2=-1.890941e+004 * p_3=-4.693442e+004 p_4=-1.052555e+005 p_5=-2.814402e+004 p_6=-3.976717e+004 p_7=-6.085404e+004 p_8=-3.447532e+004 p_9=-3.413986e+005 p_10=-2.847026e+005 p_11=-2.179864e+005 p_12=-8.612393e+004 p_13=-2.940034e+005 p_14=-1.230221e+005 p_15=-1.989495e+005	t3 p_1=-1.142248e+005 p_2=-2.853388e+004 p_3=-8.391713e+003 * p_4=-6.907703e+004 p_5=-2.840205e+004 p_6=-3.856280e+004 p_7=-2.761652e+004 p_8=-3.200372e+004 p_9=-3.158603e+005 p_10=-2.320096e+005 p_11=-1.939108e+005 p_12=-6.164533e+004 p_13=-2.681921e+005 p_14=-1.202300e+005 p_15=-2.290920e+005
t4 p_1=-2.124094e+005 p_2=-4.044000e+004 p_3=-5.876272e+004 p_4=-9.316690e+003 * p_5=-6.263166e+004 p_6=-6.171724e+004 p_7=-6.646043e+004 p_8=-6.965755e+004 p_9=-3.352324e+005 p_10=-3.197454e+005 p_11=-1.454568e+005 p_12=-1.062345e+005 p_13=-2.978732e+005 p_14=-1.428078e+005 p_15=-2.753444e+005	t5 p_1=-7.833822e+004 p_2=-3.118066e+004 p_3=-7.204496e+004 p_4=-1.180155e+005 p_5=-1.382497e+004 * p_6=-4.013088e+004 p_7=-5.229125e+004 p_8=-3.197077e+004 p_9=-3.431771e+005 p_10=-3.009059e+005 p_11=-2.700004e+005 p_12=-8.614938e+004 p_13=-3.292024e+005 p_14=-1.487727e+005 p_15=-2.090960e+005	t6 p_1=-1.487362e+005 p_2=-2.670328e+004 p_3=-5.734407e+004 p_4=-6.878532e+004 p_5=-3.785249e+004 p_6=-7.486101e+003 * p_7=-6.892141e+004 p_8=-3.572386e+004 p_9=-3.427787e+005 p_10=-2.019042e+005 p_11=-1.869272e+005 p_12=-8.510829e+004 p_13=-2.824726e+005 p_14=-1.291353e+005 p_15=-1.995188e+005

/a/ (GMM1)

t7 p_1=-1.147582e+005 p_2=-4.939444e+004 p_3=-6.872423e+004 p_4=-1.114062e+005 p_5=-3.413766e+004 p_6=-5.848950e+004 p_7=-2.789510e+004 * p_8=-3.492364e+004 p_9=-3.432000e+005 p_10=-2.642289e+005 p_11=-3.311786e+005 p_12=-1.301561e+005 p_13=-3.427861e+005 p_14=-2.191776e+005 p_15=-3.108973e+005	t8 p_1=-8.607339e+004 p_2=-3.411171e+004 p_3=-4.608720e+004 p_4=-1.312876e+005 p_5=-3.822643e+004 p_6=-5.474009e+004 p_7=-5.585167e+004 p_8=-1.290775e+004 * p_9=-3.406221e+005 p_10=-3.075908e+005 p_11=-2.288645e+005 p_12=-7.417769e+004 p_13=-3.010755e+005 p_14=-1.356498e+005 p_15=-2.168488e+005	t9 p_1=-3.168751e+005 p_2=-9.953249e+004 p_3=-1.335784e+005 p_4=-2.468868e+005 p_5=-9.020281e+004 p_6=-1.278881e+005 p_7=-1.455569e+005 p_8=-9.727110e+004 p_9=-5.410043e+004 * p_10=-1.338618e+005 p_11=-1.152221e+005 p_12=-9.775998e+004 p_13=-1.491641e+005 p_14=-5.688009e+004 p_15=-3.563014e+005
t10 p_1=-2.177150e+005 p_2=-5.868209e+004 p_3=-6.525873e+004 p_4=-1.239291e+005 p_5=-5.390296e+004 p_6=-7.874287e+004 p_7=-8.453018e+004 p_8=-5.804585e+004 p_9=-2.686175e+005 p_10=-6.687333e+004 p_11=-7.580225e+004 p_12=-5.697449e+004 p_13=-1.207605e+005 p_14=-5.262886e+004 * p_15=-2.114520e+005	t11 p_1=-1.696641e+005 p_2=-4.600853e+004 p_3=-5.529070e+004 p_4=-9.227269e+004 p_5=-5.326187e+004 p_6=-6.356920e+004 p_7=-7.939173e+004 p_8=-5.254719e+004 p_9=-3.073280e+005 p_10=-2.260995e+005 p_11=-1.079021e+004 * p_12=-5.070140e+004 p_13=-1.398107e+005 p_14=-5.856240e+004 p_15=-2.003573e+005	t12 p_1=-1.481373e+005 p_2=-3.613816e+004 p_3=-8.495451e+004 p_4=-1.690827e+005 p_5=-4.524538e+004 p_6=-7.343879e+004 p_7=-9.685828e+004 p_8=-3.328284e+004 p_9=-3.428243e+005 p_10=-3.233312e+005 p_11=-7.379122e+004 p_12=-8.135053e+003 * p_13=-1.017981e+005 p_14=-4.741847e+004 p_15=-1.029640e+005

/a/ (GMM1)

t13	t14	t15
p_1=-1.502595e+005	p_1=-1.878316e+005	p_1=-5.851202e+004
p_2=-6.403879e+004	p_2=-5.914964e+004	p_2=-2.982563e+004 *
p_3=-1.072818e+005	p_3=-8.567495e+004	p_3=-7.180558e+004
p_4=-2.161819e+005	p_4=-1.447292e+005	p_4=-1.022081e+005
p_5=-5.723052e+004	p_5=-5.127879e+004	p_5=-4.853856e+004
p_6=-1.143488e+005	p_6=-7.732552e+004	p_6=-4.689922e+004
p_7=-1.331390e+005	p_7=-1.166939e+005	p_7=-1.117704e+005
p_8=-4.703524e+004	p_8=-4.931956e+004	p_8=-3.255171e+004
p_9=-2.132608e+005	p_9=-3.374384e+005	p_9=-3.432000e+005
p_10=-2.138634e+005	p_10=-1.650127e+005	p_10=-3.270406e+005
p_11=-6.165468e+004	p_11=-7.455094e+004	p_11=-1.774524e+005
p_12=-3.755202e+004	p_12=-5.191486e+004	p_12=-7.470413e+004
p_13=-9.570480e+003 *	p_13=-6.602270e+004	p_13=-2.318157e+005
p_14=-3.913883e+004	p_14=-1.916156e+004 *	p_14=-7.224563e+004
p_15=-2.242476e+005	p_15=-1.673977e+005	p_15=-3.523862e+004

/a/ (GMM2)

<table>
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p_1=-3.202616e+004
p_2=-3.737220e+004
p_3=-9.534960e+004
p_4=-1.174676e+005
p_5=-3.476536e+004
p_6=-8.232544e+004
p_7=-1.102379e+005
p_8=-2.308048e+004 *
p_9=-3.131727e+005
p_10=-1.651321e+005
p_11=-1.870223e+005
p_12=-2.967654e+005
p_13=-3.023402e+005
p_14=-2.013186e+005
p_15=-1.863305e+005</td><td>s2
p_1=-1.009545e+005
p_2=-1.606781e+004 *
p_3=-5.859738e+004
p_4=-1.029099e+005
p_5=-3.647283e+004
p_6=-4.364585e+004
p_7=-1.374730e+005
p_8=-2.970327e+004
p_9=-2.618652e+005
p_10=-8.706225e+004
p_11=-1.763089e+005
p_12=-2.817942e+005
p_13=-2.784946e+005
p_14=-1.124446e+005
p_15=-1.347304e+005</td><td>s3
p_1=-1.393843e+005
p_2=-3.068379e+004
p_3=-1.177329e+004 *
p_4=-7.378979e+004
p_5=-4.872715e+004
p_6=-3.689524e+004
p_7=-8.282479e+004
p_8=-2.023770e+004
p_9=-3.103145e+005
p_10=-9.414047e+004
p_11=-1.486802e+005
p_12=-2.854421e+005
p_13=-2.983215e+005
p_14=-1.550235e+005
p_15=-2.344109e+005</td></tr>
<tr><td>s4
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p_2=-4.035724e+004
p_3=-8.967084e+004
p_4=-9.877428e+003 *
p_5=-8.699822e+004
p_6=-6.855219e+004
p_7=-1.888570e+005
p_8=-4.549866e+004
p_9=-3.558662e+005
p_10=-2.560955e+005
p_11=-1.184272e+005
p_12=-3.721250e+005
p_13=-3.101303e+005
p_14=-2.142909e+005
p_15=-2.578475e+005</td><td>s5
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p_2=-2.185987e+004
p_3=-6.225794e+004
p_4=-1.555112e+005
p_5=-1.437358e+004 *
p_6=-4.161632e+004
p_7=-5.591773e+004
p_8=-2.304880e+004
p_9=-3.321837e+005
p_10=-1.139679e+005
p_11=-2.772597e+005
p_12=-2.985070e+005
p_13=-3.206687e+005
p_14=-1.818056e+005
p_15=-1.993621e+005</td><td>s6
p_1=-1.914389e+005
p_2=-3.473766e+004
p_3=-6.920727e+004
p_4=-1.083565e+005
p_5=-4.592080e+004
p_6=-9.743039e+003 *
p_7=-1.227139e+005
p_8=-2.366897e+004
p_9=-3.289005e+005
p_10=-1.225452e+005
p_11=-1.929588e+005
p_12=-3.393606e+005
p_13=-2.933114e+005
p_14=-1.171001e+005
p_15=-1.469867e+005</td></tr>
</table>

/a/ (GMM2)

s7 p_1=-1.437822e+005 p_2=-3.165117e+004 p_3=-2.471141e+004 p_4=-6.049410e+004 p_5=-4.058833e+004 p_6=-3.978578e+004 p_7=-4.602903e+004 p_8=-1.906459e+004 * p_9=-2.882853e+005 p_10=-1.050580e+005 p_11=-1.690777e+005 p_12=-3.046442e+005 p_13=-3.012899e+005 p_14=-1.765134e+005 p_15=-2.397734e+005	s8 p_1=-1.163694e+005 p_2=-4.133744e+004 p_3=-9.699804e+004 p_4=-1.483063e+005 p_5=-6.236393e+004 p_6=-6.405460e+004 p_7=-1.303541e+005 p_8=-1.089427e+004 * p_9=-3.424731e+005 p_10=-1.364089e+005 p_11=-2.354967e+005 p_12=-2.398858e+005 p_13=-3.331986e+005 p_14=-1.667433e+005 p_15=-2.273009e+005	s9 p_1=-2.725966e+005 p_2=-1.168593e+005 p_3=-2.153258e+005 p_4=-2.104693e+005 p_5=-1.929110e+005 p_6=-1.129667e+005 p_7=-3.223425e+005 p_8=-7.606134e+004 p_9=-5.861611e+004 p_10=-5.594133e+004 * p_11=-1.098109e+005 p_12=-2.849238e+005 p_13=-1.488053e+005 p_14=-7.167150e+004 p_15=-3.432000e+005
s10 p_1=-2.194293e+005 p_2=-6.655559e+004 p_3=-1.082927e+005 p_4=-1.210354e+005 p_5=-8.935340e+004 p_6=-8.376427e+004 p_7=-2.213402e+005 p_8=-5.421871e+004 p_9=-1.253674e+005 p_10=-2.048620e+004 * p_11=-1.100155e+005 p_12=-2.592023e+005 p_13=-2.074409e+005 p_14=-7.363926e+004 p_15=-3.146000e+005	s11 p_1=-1.635210e+005 p_2=-8.018581e+004 p_3=-9.944130e+004 p_4=-1.229285e+005 p_5=-8.943193e+004 p_6=-7.822460e+004 p_7=-2.140089e+005 p_8=-5.048018e+004 p_9=-2.949053e+005 p_10=-7.352547e+004 p_11=-1.048868e+004 * p_12=-1.839773e+005 p_13=-1.406938e+005 p_14=-5.983574e+004 p_15=-3.368414e+005	s12 p_1=-1.038204e+005 p_2=-4.427165e+004 p_3=-9.858576e+004 p_4=-1.060384e+005 p_5=-7.552879e+004 p_6=-6.120366e+004 p_7=-1.936151e+005 p_8=-2.581101e+004 * p_9=-3.213382e+005 p_10=-5.178977e+004 p_11=-7.669687e+004 p_12=-2.969411e+004 p_13=-1.674937e+005 p_14=-6.146381e+004 p_15=-2.414929e+005

/a/ (GMM2)

s13	s14	s15
p_1=-1.412915e+005	p_1=-1.372185e+005	p_1=-5.548068e+004
p_2=-8.388181e+004	p_2=-5.304908e+004	p_2=-3.861039e+004
p_3=-1.817753e+005	p_3=-8.420334e+004	p_3=-1.127378e+005
p_4=-1.325269e+005	p_4=-8.077012e+004	p_4=-9.475703e+004
p_5=-1.178913e+005	p_5=-8.226818e+004	p_5=-8.217276e+004
p_6=-8.065517e+004	p_6=-5.495543e+004	p_6=-6.868932e+004
p_7=-2.648766e+005	p_7=-1.803337e+005	p_7=-1.466908e+005
p_8=-3.801389e+004	p_8=-3.048953e+004	p_8=-2.539177e+004 *
p_9=-2.086947e+005	p_9=-2.485691e+005	p_9=-3.146000e+005
p_10=-5.724338e+004	p_10=-4.215223e+004	p_10=-6.902927e+004
p_11=-5.619271e+004	p_11=-4.967199e+004	p_11=-2.150880e+005
p_12=-1.235572e+005	p_12=-1.266567e+005	p_12=-1.847091e+005
p_13=-1.248942e+004 *	p_13=-1.394245e+005	p_13=-2.668450e+005
p_14=-3.301668e+004	p_14=-1.550675e+004 *	p_14=-5.209612e+004
p_15=-3.305396e+005	p_15=-2.601350e+005	p_15=-3.008897e+004

/o/ (GMM1)

t1 p_1=-1.315191e+004 * p_2=-4.359502e+004 p_3=-9.977671e+004 p_4=-1.288953e+005 p_5=-9.940729e+004 p_6=-5.612496e+004 p_7=-1.502481e+005 p_8=-4.685478e+004 p_9=-1.141449e+005 p_10=-1.497951e+005 p_11=-1.618735e+005 p_12=-7.074052e+004 p_13=-3.300120e+005 p_14=-1.251224e+005 p_15=-2.418302e+005	t2 p_1=-4.371498e+004 p_2=-9.710095e+003 * p_3=-1.395441e+005 p_4=-1.740268e+005 p_5=-6.235729e+004 p_6=-7.114843e+004 p_7=-1.011882e+005 p_8=-7.981514e+004 p_9=-2.753106e+005 p_10=-2.570721e+005 p_11=-3.063099e+005 p_12=-1.133418e+005 p_13=-3.430364e+005 p_14=-2.671861e+005 p_15=-3.375231e+005	t3 p_1=-1.249184e+005 p_2=-5.280119e+004 p_3=-1.126009e+004 * p_4=-7.268236e+004 p_5=-5.939434e+004 p_6=-3.559680e+004 p_7=-5.963129e+004 p_8=-4.074600e+004 p_9=-1.503484e+005 p_10=-1.693176e+005 p_11=-1.431356e+005 p_12=-8.277419e+004 p_13=-3.140498e+005 p_14=-1.713931e+005 p_15=-2.658056e+005
t4 p_1=-1.250763e+005 p_2=-7.384508e+004 p_3=-1.367677e+005 p_4=-2.066846e+004 * p_5=-4.301151e+004 p_6=-2.766250e+004 p_7=-3.804282e+004 p_8=-5.148431e+004 p_9=-1.196246e+005 p_10=-1.643350e+005 p_11=-8.487639e+004 p_12=-7.674177e+004 p_13=-3.418969e+005 p_14=-1.029022e+005 p_15=-3.139262e+005	t5 p_1=-1.409572e+005 p_2=-8.236608e+004 p_3=-2.222805e+005 p_4=-1.972808e+005 p_5=-1.425077e+004 * p_6=-4.584120e+004 p_7=-1.753344e+005 p_8=-6.640255e+004 p_9=-1.400467e+005 p_10=-1.143929e+005 p_11=-1.440209e+005 p_12=-6.654571e+004 p_13=-3.430921e+005 p_14=-1.160119e+005 p_15=-3.112231e+005	t6 p_1=-1.146463e+005 p_2=-6.914907e+004 p_3=-1.338482e+005 p_4=-6.776494e+004 p_5=-3.675271e+004 p_6=-1.081706e+004 * p_7=-6.754853e+004 p_8=-6.064726e+004 p_9=-8.145585e+004 p_10=-1.704877e+005 p_11=-1.104488e+005 p_12=-5.952693e+004 p_13=-3.395123e+005 p_14=-6.345689e+004 p_15=-2.385362e+005

/o/ (GMM1)

t7 p_1=-1.988171e+005 p_2=-1.056946e+005 p_3=-1.845070e+005 p_4=-9.810972e+004 p_5=-1.072324e+005 p_6=-4.525263e+004 p_7=-2.518854e+004 * p_8=-4.899644e+004 p_9=-2.169113e+005 p_10=-1.507501e+005 p_11=-1.449163e+005 p_12=-1.557116e+005 p_13=-3.394884e+005 p_14=-2.301105e+005 p_15=-3.318374e+005	t8 p_1=-1.305430e+005 p_2=-9.176102e+004 p_3=-1.254860e+005 p_4=-1.211158e+005 p_5=-7.507010e+004 p_6=-3.531924e+004 p_7=-7.813027e+004 p_8=-1.254956e+004 * p_9=-1.385741e+005 p_10=-1.171591e+005 p_11=-1.056141e+005 p_12=-1.148375e+005 p_13=-3.393903e+005 p_14=-1.767970e+005 p_15=-2.360229e+005	t9 p_1=-1.168355e+005 p_2=-9.367015e+004 p_3=-2.358475e+005 p_4=-1.335563e+005 p_5=-4.014317e+004 p_6=-2.428632e+004 * p_7=-1.802312e+005 p_8=-6.052619e+004 p_9=-3.207209e+004 p_10=-4.901991e+004 p_11=-4.886080e+004 p_12=-5.081153e+004 p_13=-2.228685e+005 p_14=-5.475024e+004 p_15=-1.472931e+005
t10 p_1=-2.038742e+005 p_2=-1.793944e+005 p_3=-3.353702e+005 p_4=-2.715593e+005 p_5=-8.814566e+004 p_6=-4.459993e+004 p_7=-1.587174e+005 p_8=-1.024652e+005 p_9=-8.785128e+004 p_10=-1.751396e+004 * p_11=-6.915666e+004 p_12=-2.424749e+005 p_13=-1.929092e+005 p_14=-1.550247e+005 p_15=-2.779219e+005	t11 p_1=-1.193078e+005 p_2=-9.815595e+004 p_3=-2.441732e+005 p_4=-1.426842e+005 p_5=-5.059704e+004 p_6=-2.790112e+004 p_7=-1.215934e+005 p_8=-6.318782e+004 p_9=-2.926765e+004 p_10=-3.835638e+004 p_11=-1.159928e+004 * p_12=-9.924858e+004 p_13=-1.921053e+005 p_14=-7.248432e+004 p_15=-1.597546e+005	t12 p_1=-2.275830e+005 p_2=-1.348854e+005 p_3=-3.312266e+005 p_4=-3.234749e+005 p_5=-7.618059e+004 p_6=-8.702739e+004 p_7=-3.426258e+005 p_8=-8.873568e+004 p_9=-1.012237e+005 p_10=-9.447487e+004 p_11=-9.634569e+004 p_12=-3.929285e+004 * p_13=-1.897544e+005 p_14=-9.226312e+004 p_15=-1.456919e+005

/o/ (GMM1)

t13	t14	t15
p_1=-1.910431e+005	p_1=-1.369568e+005	p_1=-1.610591e+005
p_2=-1.613359e+005	p_2=-5.929560e+004	p_2=-1.026909e+005
p_3=-3.276403e+005	p_3=-2.223264e+005	p_3=-2.950035e+005
p_4=-2.916575e+005	p_4=-1.808554e+005	p_4=-1.725325e+005
p_5=-8.625160e+004	p_5=-5.088859e+004	p_5=-1.117569e+005
p_6=-7.083030e+004	p_6=-2.536823e+004	p_6=-4.209006e+004
p_7=-3.121599e+005	p_7=-1.582439e+005	p_7=-2.093676e+005
p_8=-9.140730e+004	p_8=-7.565694e+004	p_8=-8.693297e+004
p_9=-9.154928e+004	p_9=-1.170036e+005	p_9=-6.666774e+004
p_10=-3.726890e+004	p_10=-9.242631e+004	p_10=-6.728462e+004
p_11=-7.972931e+004	p_11=-1.034686e+005	p_11=-9.024373e+004
p_12=-1.704032e+005	p_12=-1.053180e+005	p_12=-1.343190e+005
p_13=-2.310522e+004 *	p_13=-2.430240e+005	p_13=-1.675244e+005
p_14=-1.291223e+005	p_14=-1.636967e+004 *	p_14=-6.077738e+004
p_15=-2.412979e+005	p_15=-1.275872e+005	p_15=-1.427349e+004 *

/o/ (GMM2)

s1	s2	s3
p_1=-2.323204e+004 *	p_1=-8.880941e+004	p_1=-9.707732e+004
p_2=-3.709002e+004	p_2=-1.217932e+004 *	p_2=-4.542425e+004
p_3=-9.805351e+004	p_3=-1.654605e+005	p_3=-6.980101e+003 *
p_4=-9.691150e+004	p_4=-1.181166e+005	p_4=-4.960528e+004
p_5=-1.095591e+005	p_5=-7.340396e+004	p_5=-8.130571e+004
p_6=-7.336747e+004	p_6=-8.830423e+004	p_6=-4.087538e+004
p_7=-1.205352e+005	p_7=-1.186386e+005	p_7=-6.927396e+004
p_8=-7.045056e+004	p_8=-9.027551e+004	p_8=-4.410396e+004
p_9=-1.575505e+005	p_9=-2.094213e+005	p_9=-2.112714e+005
p_10=-1.543157e+005	p_10=-1.919411e+005	p_10=-1.674597e+005
p_11=-2.187980e+005	p_11=-2.619485e+005	p_11=-1.619766e+005
p_12=-2.508066e+005	p_12=-2.424505e+005	p_12=-2.431262e+005
p_13=-3.209404e+005	p_13=-3.417030e+005	p_13=-2.965082e+005
p_14=-2.103212e+005	p_14=-3.001428e+005	p_14=-1.881317e+005
p_15=-2.382543e+005	p_15=-3.206677e+005	p_15=-2.316065e+005
s4	s5	s6
p_1=-1.396591e+005	p_1=-1.489756e+005	p_1=-9.600740e+004
p_2=-7.275774e+004	p_2=-1.119121e+005	p_2=-8.155903e+004
p_3=-1.172387e+005	p_3=-2.375837e+005	p_3=-1.675237e+005
p_4=-1.157137e+004 *	p_4=-1.284793e+005	p_4=-4.031259e+004
p_5=-6.236363e+004	p_5=-1.675947e+004 *	p_5=-6.166447e+004
p_6=-4.198052e+004	p_6=-4.774465e+004	p_6=-1.206161e+004 *
p_7=-3.973450e+004	p_7=-9.717461e+004	p_7=-5.347500e+004
p_8=-4.945558e+004	p_8=-7.190719e+004	p_8=-4.493292e+004
p_9=-1.596575e+005	p_9=-9.561527e+004	p_9=-9.338255e+004
p_10=-1.306617e+005	p_10=-9.301329e+004	p_10=-8.930104e+004
p_11=-1.369056e+005	p_11=-1.410488e+005	p_11=-1.013305e+005
p_12=-2.000750e+005	p_12=-1.577254e+005	p_12=-2.237265e+005
p_13=-2.134842e+005	p_13=-2.424657e+005	p_13=-1.938950e+005
p_14=-1.304195e+005	p_14=-1.663596e+005	p_14=-9.012850e+004
p_15=-2.315764e+005	p_15=-2.446826e+005	p_15=-1.621921e+005

/o/ (GMM2)

s7 p_1=-1.281593e+005 p_2=-7.211945e+004 p_3=-1.101570e+005 p_4=-3.650494e+004 p_5=-9.945965e+004 p_6=-6.302209e+004 p_7=-2.367597e+004 * p_8=-5.326389e+004 p_9=-2.655711e+005 p_10=-1.949384e+005 p_11=-1.817491e+005 p_12=-3.190239e+005 p_13=-3.059287e+005 p_14=-2.308470e+005 p_15=-2.872192e+005	s8 p_1=-1.328551e+005 p_2=-9.969092e+004 p_3=-1.696446e+005 p_4=-8.173381e+004 p_5=-1.895861e+005 p_6=-4.623851e+004 p_7=-6.372950e+004 p_8=-1.388993e+004 * p_9=-1.881006e+005 p_10=-1.547657e+005 p_11=-1.134255e+005 p_12=-2.867611e+005 p_13=-3.040364e+005 p_14=-1.718576e+005 p_15=-1.942586e+005	s9 p_1=-1.211004e+005 p_2=-1.049480e+005 p_3=-2.297755e+005 p_4=-8.916546e+004 p_5=-1.373745e+005 p_6=-2.903228e+004 p_7=-6.198677e+004 p_8=-4.422254e+004 p_9=-2.383690e+004 * p_10=-4.433333e+004 p_11=-3.876493e+004 p_12=-8.254170e+004 p_13=-1.462189e+005 p_14=-1.188185e+005 p_15=-7.017298e+004
s10 p_1=-1.876589e+005 p_2=-1.512686e+005 p_3=-2.903727e+005 p_4=-1.393888e+005 p_5=-1.811497e+005 p_6=-6.260283e+004 p_7=-7.085016e+004 p_8=-9.068200e+004 p_9=-8.535570e+004 p_10=-1.224919e+004 * p_11=-5.527457e+004 p_12=-2.041050e+005 p_13=-1.261110e+005 p_14=-1.770734e+005 p_15=-1.146693e+005	s11 p_1=-1.391443e+005 p_2=-1.159162e+005 p_3=-2.401623e+005 p_4=-1.083564e+005 p_5=-1.441120e+005 p_6=-4.315496e+004 p_7=-5.342931e+004 p_8=-4.870360e+004 p_9=-7.282099e+004 p_10=-3.689593e+004 p_11=-1.123122e+004 * p_12=-1.219164e+005 p_13=-9.165689e+004 p_14=-1.054667e+005 p_15=-7.733070e+004	s12 p_1=-1.912647e+005 p_2=-9.682129e+004 p_3=-3.029105e+005 p_4=-1.590950e+005 p_5=-6.822846e+004 p_6=-5.312100e+004 * p_7=-1.423900e+005 p_8=-9.516409e+004 p_9=-8.437159e+004 p_10=-1.638096e+005 p_11=-1.897409e+005 p_12=-8.506751e+004 p_13=-3.068435e+005 p_14=-1.242880e+005 p_15=-2.730782e+005

/o/ (GMM2)

s13	s14	s15
p_1=-2.555546e+005	p_1=-1.707449e+005	p_1=-2.661005e+005
p_2=-2.029494e+005	p_2=-9.028276e+004	p_2=-1.600289e+005
p_3=-3.420110e+005	p_3=-2.336273e+005	p_3=-3.080209e+005
p_4=-2.430359e+005	p_4=-1.154187e+005	p_4=-1.512690e+005
p_5=-2.587168e+005	p_5=-1.005796e+005	p_5=-2.636120e+005
p_6=-1.370351e+005	p_6=-5.395753e+004	p_6=-9.148579e+004
p_7=-1.460210e+005	p_7=-9.019770e+004	p_7=-1.043456e+005
p_8=-9.601173e+004	p_8=-7.268557e+004	p_8=-9.971011e+004
p_9=-1.619345e+005	p_9=-1.244245e+005	p_9=-8.208852e+004
p_10=-4.732091e+004	p_10=-6.688470e+004	p_10=-8.503251e+004
p_11=-9.702849e+004	p_11=-1.786444e+005	p_11=-1.426579e+005
p_12=-9.276964e+004	p_12=-2.131958e+005	p_12=-1.599817e+005
p_13=-2.254840e+004 *	p_13=-1.520464e+005	p_13=-1.690541e+005
p_14=-1.236720e+005	p_14=-2.362611e+004 *	p_14=-6.414505e+004
p_15=-1.357352e+005	p_15=-9.810200e+004	p_15=-1.477144e+004 *

/U/ (GMM1)

t1 p_1=-6.569896e+003 * p_2=-6.991567e+004 p_3=-6.459410e+004 p_4=-8.806912e+004 p_5=-3.951048e+004 p_6=-6.711051e+004 p_7=-5.653189e+004 p_8=-1.796972e+005 p_9=-1.429105e+005 p_10=-7.134642e+004 p_11=-9.403227e+004 p_12=-9.053675e+004 p_13=-8.745175e+004 p_14=-2.183864e+005 p_15=-1.431233e+005	t2 p_1=-5.638985e+004 p_2=-5.034835e+003 * p_3=-6.461107e+004 p_4=-1.167930e+005 p_5=-3.187959e+004 p_6=-5.336550e+004 p_7=-5.899434e+004 p_8=-1.690958e+005 p_9=-1.359220e+005 p_10=-7.861296e+004 p_11=-7.949939e+004 p_12=-1.242175e+005 p_13=-8.180368e+004 p_14=-1.878161e+005 p_15=-2.410669e+005	t3 p_1=-4.555604e+004 p_2=-1.147144e+005 p_3=-9.020430e+003 * p_4=-1.001031e+005 p_5=-5.862197e+004 p_6=-3.310717e+004 p_7=-3.956986e+004 p_8=-1.389085e+005 p_9=-9.445537e+004 p_10=-1.457688e+005 p_11=-7.105931e+004 p_12=-7.165897e+004 p_13=-1.046865e+005 p_14=-1.888279e+005 p_15=-2.149947e+005
t4 p_1=-7.222477e+004 p_2=-1.106755e+005 p_3=-5.135716e+004 p_4=-9.933330e+003 * p_5=-2.710221e+004 p_6=-4.344262e+004 p_7=-3.253842e+004 p_8=-8.806761e+004 p_9=-5.313139e+004 p_10=-9.954150e+004 p_11=-4.100252e+004 p_12=-7.581832e+004 p_13=-1.194238e+005 p_14=-1.906142e+005 p_15=-2.392180e+005	t5 p_1=-3.767293e+004 p_2=-3.894932e+004 p_3=-1.128880e+005 p_4=-1.367230e+005 p_5=-7.912730e+003 * p_6=-4.440053e+004 p_7=-2.465079e+004 p_8=-2.328008e+005 p_9=-1.453105e+005 p_10=-1.053084e+005 p_11=-1.057309e+005 p_12=-1.019770e+005 p_13=-1.427315e+005 p_14=-2.990804e+005 p_15=-2.195618e+005	t6 p_1=-8.661760e+004 p_2=-1.114942e+005 p_3=-9.044037e+004 p_4=-5.790373e+004 p_5=-3.072775e+004 p_6=-1.001984e+004 * p_7=-2.833941e+004 p_8=-1.367546e+005 p_9=-8.521917e+004 p_10=-6.231319e+004 p_11=-4.035302e+004 p_12=-9.463373e+004 p_13=-1.721060e+005 p_14=-2.821188e+005 p_15=-2.757284e+005

/U/ (GMM1)

t7	t8	t9
p_1=-7.700757e+004	p_1=-5.791521e+004	p_1=-7.262373e+004
p_2=-1.078351e+005	p_2=-1.048855e+005	p_2=-1.868445e+005
p_3=-1.145267e+005	p_3=-7.670956e+004	p_3=-8.165289e+004
p_4=-6.941449e+004	p_4=-8.356437e+004	p_4=-7.781668e+004
p_5=-1.806824e+004	p_5=-4.930758e+004	p_5=-6.202498e+004
p_6=-3.013673e+004	p_6=-4.451514e+004	p_6=-6.034052e+004
p_7=-8.403589e+003 *	p_7=-4.992388e+004	p_7=-8.144819e+004
p_8=-1.933845e+005	p_8=-6.753905e+003 *	p_8=-1.238290e+005
p_9=-1.233961e+005	p_9=-8.987971e+004	p_9=-1.472235e+004 *
p_10=-9.833377e+004	p_10=-1.690268e+005	p_10=-1.140191e+005
p_11=-8.109335e+004	p_11=-5.461180e+004	p_11=-6.550832e+004
p_12=-7.910493e+004	p_12=-1.714599e+005	p_12=-1.155035e+005
p_13=-1.871913e+005	p_13=-9.733942e+004	p_13=-1.288550e+005
p_14=-3.125046e+005	p_14=-8.735461e+004	p_14=-1.461020e+005
p_15=-2.573464e+005	p_15=-1.289664e+005	p_15=-8.618132e+004
t10	t11	t12
p_1=-5.152451e+004	p_1=-3.219076e+004	p_1=-8.734499e+004
p_2=-8.915346e+004	p_2=-6.912270e+004	p_2=-1.151753e+005
p_3=-7.523617e+004	p_3=-7.543928e+004	p_3=-8.974715e+004
p_4=-7.557282e+004	p_4=-8.840086e+004	p_4=-1.621181e+005
p_5=-7.291098e+004	p_5=-2.557926e+004 *	p_5=-4.076228e+004
p_6=-3.393565e+004 *	p_6=-5.931763e+004	p_6=-5.286151e+004
p_7=-8.516316e+004	p_7=-3.412764e+004	p_7=-7.426816e+004
p_8=-1.361049e+005	p_8=-1.294335e+005	p_8=-2.625612e+005
p_9=-9.339716e+004	p_9=-6.006402e+004	p_9=-7.420510e+004
p_10=-5.419050e+004	p_10=-5.971143e+004	p_10=-1.527414e+005
p_11=-9.081731e+004	p_11=-2.791462e+004	p_11=-5.441931e+004
p_12=-1.307925e+005	p_12=-8.316334e+004	p_12=-1.897892e+004 *
p_13=-8.228287e+004	p_13=-7.281659e+004	p_13=-1.303755e+005
p_14=-2.119728e+005	p_14=-2.303782e+005	p_14=-2.274133e+005
p_15=-1.133822e+005	p_15=-1.144834e+005	p_15=-2.319454e+005

/U/ (GMM1)

t13	t14	t15
p_1=-4.111980e+004	p_1=-6.793286e+004	p_1=-6.343652e+004
p_2=-5.239150e+004	p_2=-1.085463e+005	p_2=-1.338275e+005
p_3=-7.330969e+004	p_3=-7.052300e+004	p_3=-8.076327e+004
p_4=-7.262268e+004	p_4=-9.372604e+004	p_4=-1.141182e+005
p_5=-2.111812e+004	p_5=-4.953742e+004	p_5=-4.482588e+004
p_6=-5.652787e+004	p_6=-4.952827e+004	p_6=-5.178190e+004
p_7=-3.938253e+004	p_7=-1.269184e+005	p_7=-1.047446e+005
p_8=-1.026754e+005	p_8=-1.053876e+005	p_8=-1.336946e+005
p_9=-5.794083e+004	p_9=-1.028905e+005	p_9=-8.225604e+004
p_10=-7.735204e+004	p_10=-1.554713e+005	p_10=-8.586693e+004
p_11=-2.781098e+004	p_11=-5.771268e+004	p_11=-7.591142e+004
p_12=-6.830565e+004	p_12=-2.257495e+005	p_12=-1.444068e+005
p_13=-4.214772e+003 *	p_13=-8.651413e+004	p_13=-8.702277e+004
p_14=-1.502027e+005	p_14=-1.515066e+004 *	p_14=-1.256829e+005
p_15=-8.251203e+004	p_15=-1.379353e+005	p_15=-2.023063e+004 *

/U/ (GMM2)

s1	s2	s3
p_1=-7.064702e+003 *	p_1=-4.276289e+004	p_1=-3.017809e+004
p_2=-7.699536e+004	p_2=-5.002630e+003 *	p_2=-7.955882e+004
p_3=-1.017759e+005	p_3=-1.247870e+005	p_3=-1.159420e+004 *
p_4=-1.564347e+005	p_4=-1.270669e+005	p_4=-7.216073e+004
p_5=-4.426258e+004	p_5=-4.067188e+004	p_5=-3.859431e+004
p_6=-7.295322e+004	p_6=-5.414369e+004	p_6=-3.238891e+004
p_7=-4.895014e+004	p_7=-5.161851e+004	p_7=-2.480024e+004
p_8=-2.962920e+005	p_8=-2.372657e+005	p_8=-1.253784e+005
p_9=-1.107816e+005	p_9=-1.241886e+005	p_9=-8.244787e+004
p_10=-8.126287e+004	p_10=-8.083821e+004	p_10=-5.362510e+004
p_11=-5.994263e+004	p_11=-5.111906e+004	p_11=-2.514302e+004
p_12=-1.018520e+005	p_12=-7.756362e+004	p_12=-6.025526e+004
p_13=-1.317530e+005	p_13=-7.869673e+004	p_13=-1.120855e+005
p_14=-3.718608e+005	p_14=-2.737603e+005	p_14=-2.383905e+005
p_15=-1.547786e+005	p_15=-1.949275e+005	p_15=-1.308493e+005
s4	s5	s6
p_1=-7.162158e+004	p_1=-3.620830e+004	p_1=-6.426413e+004
p_2=-1.056575e+005	p_2=-4.846339e+004	p_2=-1.045470e+005
p_3=-1.255623e+005	p_3=-1.120219e+005	p_3=-8.923912e+004
p_4=-1.936931e+004 *	p_4=-1.601849e+005	p_4=-1.232269e+005
p_5=-4.908784e+004	p_5=-1.118546e+004 *	p_5=-4.220195e+004
p_6=-4.467597e+004	p_6=-2.522453e+004	p_6=-1.363728e+004 *
p_7=-3.859120e+004	p_7=-2.850780e+004	p_7=-3.203048e+004
p_8=-1.634297e+005	p_8=-2.643911e+005	p_8=-1.494070e+005
p_9=-8.554123e+004	p_9=-8.987091e+004	p_9=-9.018101e+004
p_10=-2.164666e+005	p_10=-1.139193e+005	p_10=-6.878640e+004
p_11=-7.039057e+004	p_11=-8.179395e+004	p_11=-5.143776e+004
p_12=-1.071576e+005	p_12=-9.708571e+004	p_12=-1.117972e+005
p_13=-1.300291e+005	p_13=-1.380620e+005	p_13=-1.727116e+005
p_14=-2.755009e+005	p_14=-3.400445e+005	p_14=-3.600946e+005
p_15=-1.637620e+005	p_15=-1.406698e+005	p_15=-1.528388e+005

/U/ (GMM2)

s7 p_1=-6.839866e+004 p_2=-6.733011e+004 p_3=-1.775434e+005 p_4=-1.643343e+005 p_5=-2.402200e+004 p_6=-3.603721e+004 p_7=-8.302524e+003 * p_8=-2.854855e+005 p_9=-1.109837e+005 p_10=-1.639846e+005 p_11=-1.236722e+005 p_12=-1.611482e+005 p_13=-2.083512e+005 p_14=-3.416304e+005 p_15=-2.488008e+005	s8 p_1=-4.843003e+004 p_2=-7.133739e+004 p_3=-1.220670e+005 p_4=-7.767887e+004 p_5=-5.807113e+004 p_6=-4.274017e+004 p_7=-5.094800e+004 p_8=-9.559029e+003 * p_9=-9.056751e+004 p_10=-1.171864e+005 p_11=-6.392679e+004 p_12=-1.281285e+005 p_13=-9.607281e+004 p_14=-1.436717e+005 p_15=-1.204918e+005	s9 p_1=-8.452722e+004 p_2=-1.618297e+005 p_3=-1.194873e+005 p_4=-9.924264e+004 p_5=-4.570980e+004 p_6=-5.946922e+004 p_7=-4.887525e+004 p_8=-1.182166e+005 p_9=-1.374813e+004 * p_10=-1.312474e+005 p_11=-5.030616e+004 p_12=-1.656398e+005 p_13=-1.769148e+005 p_14=-2.778755e+005 p_15=-9.966061e+004
s10 p_1=-4.167460e+004 * p_2=-9.312642e+004 p_3=-9.523070e+004 p_4=-9.930115e+004 p_5=-4.648649e+004 p_6=-4.242117e+004 p_7=-7.004515e+004 p_8=-1.956918e+005 p_9=-6.772937e+004 p_10=-4.400593e+004 p_11=-6.248701e+004 p_12=-8.322334e+004 p_13=-1.225946e+005 p_14=-3.146000e+005 p_15=-7.036738e+004	s11 p_1=-4.759383e+004 p_2=-6.256662e+004 p_3=-6.889292e+004 p_4=-6.570502e+004 p_5=-2.802683e+004 p_6=-2.836793e+004 p_7=-2.638819e+004 p_8=-7.347433e+004 p_9=-5.605029e+004 p_10=-8.392589e+004 p_11=-2.508451e+004 * p_12=-5.539144e+004 p_13=-1.099662e+005 p_14=-2.102828e+005 p_15=-1.146756e+005	s12 p_1=-6.748639e+004 p_2=-1.031193e+005 p_3=-1.500934e+005 p_4=-1.954466e+005 p_5=-4.582119e+004 p_6=-5.177543e+004 p_7=-6.461463e+004 p_8=-2.813166e+005 p_9=-1.266129e+005 p_10=-2.003779e+005 p_11=-7.120407e+004 p_12=-1.691776e+004 * p_13=-1.864039e+005 p_14=-3.385948e+005 p_15=-2.332633e+005

/U/ (GMM2)

s13	s14	s15
p_1=-2.749769e+004	p_1=-8.524808e+004	p_1=-6.402948e+004
p_2=-3.954870e+004	p_2=-1.540805e+005	p_2=-1.234197e+005
p_3=-7.000420e+004	p_3=-2.114420e+005	p_3=-1.554318e+005
p_4=-8.066643e+004	p_4=-1.023753e+005	p_4=-1.517269e+005
p_5=-1.858912e+004	p_5=-6.748532e+004	p_5=-6.872651e+004
p_6=-5.182904e+004	p_6=-5.995357e+004	p_6=-9.203214e+004
p_7=-3.365778e+004	p_7=-1.353197e+005	p_7=-7.086551e+004
p_8=-1.245154e+005	p_8=-2.035137e+005	p_8=-1.797431e+005
p_9=-5.080195e+004	p_9=-1.018966e+005	p_9=-6.629857e+004
p_10=-1.158316e+005	p_10=-1.305215e+005	p_10=-1.765495e+005
p_11=-1.717454e+004	p_11=-7.571383e+004	p_11=-5.877134e+004
p_12=-7.250599e+004	p_12=-1.159061e+005	p_12=-1.732736e+005
p_13=-6.620974e+003 *	p_13=-1.466536e+005	p_13=-1.154431e+005
p_14=-1.726381e+005	p_14=-3.207740e+004 *	p_14=-2.224147e+005
p_15=-7.136693e+004	p_15=-1.154915e+005	p_15=-2.399365e+004 *

/u/ (GMM1)

t1 p_1=-7.794721e+003 * p_2=-7.458124e+004 p_3=-1.155344e+005 p_4=-8.187584e+004 p_5=-4.600032e+004 p_6=-9.312401e+004 p_7=-2.284094e+004 p_8=-1.248118e+005 p_9=-2.370670e+005 p_10=-5.283411e+004 p_11=-8.038621e+004 p_12=-1.972197e+005 p_13=-3.681672e+005 p_14=-1.492815e+005 p_15=-3.520703e+005	t2 p_1=-2.787634e+004 p_2=-5.435574e+003 * p_3=-8.734116e+004 p_4=-1.093512e+005 p_5=-3.819426e+004 p_6=-7.679046e+004 p_7=-4.445370e+004 p_8=-1.329894e+005 p_9=-3.282320e+005 p_10=-5.570267e+004 p_11=-1.193816e+005 p_12=-3.059797e+005 p_13=-3.432000e+005 p_14=-1.596318e+005 p_15=-3.429435e+005	t3 p_1=-3.811671e+004 p_2=-1.398532e+005 p_3=-1.922412e+004 * p_4=-7.522158e+004 p_5=-3.489527e+004 p_6=-4.340385e+004 p_7=-2.574910e+004 p_8=-1.652859e+005 p_9=-2.332418e+005 p_10=-7.400589e+004 p_11=-5.785184e+004 p_12=-2.198958e+005 p_13=-3.432000e+005 p_14=-1.549020e+005 p_15=-3.379579e+005
t4 p_1=-1.944969e+004 p_2=-9.673550e+004 p_3=-9.081679e+004 p_4=-1.727937e+004 * p_5=-4.490824e+004 p_6=-3.890475e+004 p_7=-1.982882e+004 p_8=-9.965900e+004 p_9=-2.197918e+005 p_10=-5.484566e+004 p_11=-1.089458e+005 p_12=-1.644439e+005 p_13=-3.431714e+005 p_14=-1.534530e+005 p_15=-3.401746e+005	t5 p_1=-3.062356e+004 p_2=-6.216520e+004 p_3=-1.243367e+005 p_4=-1.337646e+005 p_5=-1.802765e+004 * p_6=-5.806987e+004 p_7=-3.668349e+004 p_8=-1.241909e+005 p_9=-2.438013e+005 p_10=-5.218519e+004 p_11=-3.426908e+004 p_12=-2.009601e+005 p_13=-3.265515e+005 p_14=-1.085233e+005 p_15=-2.713068e+005	t6 p_1=-5.241521e+004 p_2=-1.580133e+005 p_3=-2.100023e+005 p_4=-7.589579e+004 p_5=-4.442189e+004 p_6=-1.345812e+004 * p_7=-4.126126e+004 p_8=-1.928840e+005 p_9=-2.829950e+005 p_10=-4.695930e+004 p_11=-5.029190e+004 p_12=-2.036796e+005 p_13=-3.386515e+005 p_14=-1.354468e+005 p_15=-3.228973e+005

/u/ (GMM1)

t7 p_1=-2.493865e+004 p_2=-1.676755e+005 p_3=-1.253518e+005 p_4=-1.048197e+005 p_5=-5.965165e+004 p_6=-7.231934e+004 p_7=-8.384784e+003 * p_8=-2.111440e+005 p_9=-2.692181e+005 p_10=-6.311196e+004 p_11=-1.003218e+005 p_12=-3.089106e+005 p_13=-3.424870e+005 p_14=-1.335347e+005 p_15=-3.398578e+005	t8 p_1=-6.607955e+004 p_2=-1.135696e+005 p_3=-1.828687e+005 p_4=-9.185382e+004 p_5=-6.052938e+004 p_6=-5.518226e+004 p_7=-4.841522e+004 p_8=-1.711405e+004 * p_9=-2.847812e+005 p_10=-5.647655e+004 p_11=-6.411437e+004 p_12=-1.933219e+005 p_13=-3.328908e+005 p_14=-1.917685e+005 p_15=-2.938675e+005	t9 p_1=-5.093657e+004 p_2=-2.754759e+005 p_3=-3.036697e+005 p_4=-1.763069e+005 p_5=-6.752204e+004 p_6=-1.398160e+005 p_7=-4.698703e+004 p_8=-2.877080e+005 p_9=-2.655884e+004 * p_10=-5.127754e+004 p_11=-5.123691e+004 p_12=-1.428632e+005 p_13=-3.430147e+005 p_14=-2.383883e+005 p_15=-2.819863e+005
t10 p_1=-4.664614e+004 p_2=-2.496015e+005 p_3=-2.516612e+005 p_4=-1.025932e+005 p_5=-5.802051e+004 p_6=-4.571147e+004 p_7=-4.482250e+004 p_8=-2.525201e+005 p_9=-1.374304e+005 p_10=-1.009902e+004 * p_11=-6.494499e+004 p_12=-2.810480e+005 p_13=-3.361253e+005 p_14=-8.546900e+004 p_15=-2.681577e+005	t11 p_1=-2.303821e+004 p_2=-1.857123e+005 p_3=-1.475025e+005 p_4=-1.037632e+005 p_5=-2.674143e+004 p_6=-6.616483e+004 p_7=-2.482838e+004 p_8=-2.331617e+005 p_9=-1.743074e+005 p_10=-2.769852e+004 p_11=-7.973240e+003 * p_12=-2.543135e+005 p_13=-2.852503e+005 p_14=-9.777628e+004 p_15=-2.416424e+005	t12 p_1=-1.948354e+004 p_2=-1.453923e+005 p_3=-1.151157e+005 p_4=-1.222351e+005 p_5=-3.330387e+004 p_6=-1.071608e+005 p_7=-2.602105e+004 p_8=-1.430958e+005 p_9=-1.334680e+005 p_10=-3.756888e+004 p_11=-7.273628e+004 p_12=-1.920573e+004 * p_13=-3.381687e+005 p_14=-1.077329e+005 p_15=-2.748562e+005

/u/ (GMM1)

t13	t14	t15
p_1=-6.388170e+004	p_1=-7.316217e+004	p_1=-9.313574e+004
p_2=-1.101158e+005	p_2=-1.133007e+005	p_2=-1.730626e+005
p_3=-3.031497e+005	p_3=-2.860688e+005	p_3=-3.133980e+005
p_4=-1.727928e+005	p_4=-1.454258e+005	p_4=-2.439085e+005
p_5=-8.902648e+004	p_5=-7.148309e+004	p_5=-1.047233e+005
p_6=-6.324630e+004	p_6=-5.614547e+004	p_6=-6.866827e+004
p_7=-6.440816e+004	p_7=-5.770598e+004	p_7=-9.160372e+004
p_8=-7.888998e+004	p_8=-1.150383e+005	p_8=-1.007718e+005
p_9=-1.935994e+005	p_9=-2.042271e+005	p_9=-2.254682e+005
p_10=-7.084753e+004	p_10=-5.007787e+004	p_10=-1.052032e+005
p_11=-5.279845e+004	p_11=-6.268539e+004	p_11=-7.926482e+004
p_12=-2.412209e+005	p_12=-2.490568e+005	p_12=-2.559652e+005
p_13=-2.169456e+004 *	p_13=-2.255806e+005	p_13=-1.304914e+005
p_14=-8.296377e+004	p_14=-4.383915e+004 *	p_14=-1.891798e+005
p_15=-6.734068e+004	p_15=-1.578766e+005	p_15=-1.157599e+004 *

/u/ (GMM2)

s1 p_1=-9.711139e+003 * p_2=-2.002057e+005 p_3=-8.818434e+004 p_4=-1.268733e+005 p_5=-5.678658e+004 p_6=-1.178862e+005 p_7=-1.936889e+004 p_8=-2.086876e+005 p_9=-8.392879e+004 p_10=-8.208923e+004 p_11=-8.581999e+004 p_12=-2.150254e+005 p_13=-3.671018e+005 p_14=-6.673926e+004 p_15=-3.557538e+005	s2 p_1=-2.708831e+004 p_2=-9.599849e+003 * p_3=-5.628741e+004 p_4=-1.009728e+005 p_5=-4.299858e+004 p_6=-9.366213e+004 p_7=-3.165682e+004 p_8=-1.367940e+005 p_9=-1.316733e+005 p_10=-9.391320e+004 p_11=-9.894637e+004 p_12=-2.135676e+005 p_13=-3.341101e+005 p_14=-6.474013e+004 p_15=-3.422449e+005	s3 p_1=-2.426963e+004 p_2=-9.646231e+004 p_3=-5.976149e+003 * p_4=-8.943475e+004 p_5=-5.074437e+004 p_6=-4.697765e+004 p_7=-1.689407e+004 p_8=-1.160560e+005 p_9=-7.946075e+004 p_10=-6.948347e+004 p_11=-8.805150e+004 p_12=-7.937038e+004 p_13=-3.398276e+005 p_14=-8.883857e+004 p_15=-3.352779e+005
s4 p_1=-2.350777e+004 p_2=-1.659556e+005 p_3=-3.919898e+004 p_4=-2.069422e+004 p_5=-7.291213e+004 p_6=-4.195626e+004 p_7=-1.422019e+004 * p_8=-1.125958e+005 p_9=-8.167286e+004 p_10=-4.912037e+004 p_11=-1.776762e+005 p_12=-1.051132e+005 p_13=-3.431976e+005 p_14=-5.164611e+004 p_15=-3.416567e+005	s5 p_1=-3.388443e+004 p_2=-1.752017e+005 p_3=-5.822235e+004 p_4=-1.358388e+005 p_5=-2.956279e+004 * p_6=-4.716071e+004 p_7=-3.445475e+004 p_8=-1.849919e+005 p_9=-8.718144e+004 p_10=-7.418306e+004 p_11=-5.235982e+004 p_12=-1.278348e+005 p_13=-3.299156e+005 p_14=-5.546968e+004 p_15=-3.264123e+005	s6 p_1=-5.495419e+004 p_2=-1.422234e+005 p_3=-1.117896e+005 p_4=-1.049098e+005 p_5=-8.093275e+004 p_6=-1.369879e+004 * p_7=-3.138185e+004 p_8=-1.249880e+005 p_9=-1.048108e+005 p_10=-5.720863e+004 p_11=-7.495420e+004 p_12=-1.259952e+005 p_13=-3.426067e+005 p_14=-7.400897e+004 p_15=-3.281442e+005

/u/ (GMM2)

s7 p_1=-2.083716e+004 p_2=-1.961110e+005 p_3=-6.620601e+004 p_4=-1.121390e+005 p_5=-8.258146e+004 p_6=-9.208994e+004 p_7=-7.230140e+003 * p_8=-1.685618e+005 p_9=-9.044104e+004 p_10=-6.056793e+004 p_11=-1.413720e+005 p_12=-2.340108e+005 p_13=-3.431622e+005 p_14=-4.924440e+004 p_15=-3.251799e+005	s8 p_1=-8.821723e+004 p_2=-1.956824e+005 p_3=-1.741592e+005 p_4=-1.000368e+005 p_5=-6.250769e+004 p_6=-6.168628e+004 p_7=-6.451189e+004 p_8=-2.296626e+004 * p_9=-2.084654e+005 p_10=-1.452073e+005 p_11=-9.655834e+004 p_12=-1.438919e+005 p_13=-3.195007e+005 p_14=-7.271790e+004 p_15=-3.325902e+005	s9 p_1=-5.900522e+004 p_2=-3.298269e+005 p_3=-1.537607e+005 p_4=-2.140106e+005 p_5=-6.879150e+004 p_6=-1.368305e+005 p_7=-3.852524e+004 p_8=-3.014147e+005 p_9=-1.667170e+004 * p_10=-6.609566e+004 p_11=-7.246158e+004 p_12=-6.251689e+004 p_13=-3.432000e+005 p_14=-7.632116e+004 p_15=-3.080000e+005
s10 p_1=-7.290343e+004 p_2=-2.919163e+005 p_3=-1.411340e+005 p_4=-1.241901e+005 p_5=-6.854513e+004 p_6=-4.851309e+004 p_7=-3.759975e+004 p_8=-1.944446e+005 p_9=-7.331370e+004 p_10=-1.822506e+004 * p_11=-4.344632e+004 p_12=-2.078002e+005 p_13=-3.413651e+005 p_14=-3.708767e+004 p_15=-3.145380e+005	s11 p_1=-4.142416e+004 p_2=-2.950873e+005 p_3=-8.793704e+004 p_4=-1.489961e+005 p_5=-2.477925e+004 p_6=-1.081117e+005 p_7=-3.708131e+004 p_8=-2.868315e+005 p_9=-5.978645e+004 p_10=-5.361480e+004 p_11=-9.753828e+003 * p_12=-1.583884e+005 p_13=-3.430993e+005 p_14=-2.873056e+004 p_15=-3.345314e+005	s12 p_1=-2.079061e+004 p_2=-1.965331e+005 p_3=-8.258492e+004 p_4=-9.837873e+004 p_5=-3.529341e+004 p_6=-9.656044e+004 p_7=-3.263947e+004 p_8=-1.837902e+005 p_9=-5.167774e+004 p_10=-5.276823e+004 p_11=-7.652904e+004 p_12=-1.115454e+004 * p_13=-2.425494e+005 p_14=-3.687402e+004 p_15=-2.612260e+005

/u/ (GMM2)

s13	s14	s15
p_1=-1.032767e+005	p_1=-9.255705e+004	p_1=-1.399892e+005
p_2=-2.659892e+005	p_2=-1.946703e+005	p_2=-3.225065e+005
p_3=-2.368737e+005	p_3=-1.507085e+005	p_3=-2.901326e+005
p_4=-2.142705e+005	p_4=-2.041175e+005	p_4=-3.180653e+005
p_5=-6.499810e+004	p_5=-6.081155e+004	p_5=-6.986012e+004
p_6=-5.309369e+004	p_6=-3.826903e+004	p_6=-8.401506e+004
p_7=-7.357540e+004	p_7=-5.876310e+004	p_7=-1.101657e+005
p_8=-1.208164e+005	p_8=-1.552692e+005	p_8=-1.849517e+005
p_9=-1.112824e+005	p_9=-9.561365e+004	p_9=-8.992521e+004
p_10=-1.407598e+005	p_10=-7.898143e+004	p_10=-1.770818e+005
p_11=-9.321227e+004	p_11=-4.360278e+004	p_11=-1.144241e+005
p_12=-1.829861e+005	p_12=-1.606138e+005	p_12=-2.641935e+005
p_13=-3.713710e+004 *	p_13=-1.887524e+005	p_13=-1.957816e+005
p_14=-6.101676e+004	p_14=-1.158619e+004 *	p_14=-9.562309e+004
p_15=-1.400232e+005	p_15=-2.334328e+005	p_15=-1.591336e+004 *

Appendix B

Distance Data by Using VQ

Appendix B shows the average minimum distance of each testing data to each training data for the experiments in Chapter 4 and Chapter 5. The one which ends with a star (*) is the speaker who has the shortest average minimum distance for a given observation sequence.

The following pages correspond to a single phoneme and a method. For example, the heading /i/ (VQ1) means that all speakers are saying phoneme /i/ and method VQ1 is used. Each cell begins with one of t1~t15 or s1~s15, which represent the testing data. 1: ~ 15: are the average minimum distances. 1: is the average minimum distance of the test speaker to training speaker number one, 2: is the average minimum distance of the test speaker to training speaker number two, and so on.

/i/ (VQ1)

t1	t2	t3
1: 2.98754 *	1: 7.49529	1: 8.99673
2: 7.85394	2: 4.82257 *	2: 8.11192
3: 10.5546	3: 10.6697	3: 2.86344 *
4: 6.9512	4: 8.15704	4: 5.21644
5: 6.50298	5: 7.15994	5: 6.65284
6: 7.38189	6: 11.8679	6: 9.51098
7: 7.78966	7: 11.2348	7: 8.62431
8: 10.0762	8: 8.52048	8: 5.54835
9: 8.67408	9: 9.17412	9: 10.8339
10: 6.99592	10: 6.81185	10: 7.55106
11: 7.57564	11: 8.32326	11: 7.07887
12: 9.72048	12: 8.30666	12: 11.187
13: 7.18924	13: 7.0326	13: 8.01328
14: 9.80466	14: 5.64871	14: 10.1034
15: 10.7236	15: 8.02082	15: 11.568
t4	t5	t6
1: 6.95403	1: 6.09277	1: 7.70891
2: 9.09837	2: 6.60608	2: 13.5395
3: 6.20511	3: 6.58171	3: 10.067
4: 2.6792 *	4: 4.89954	4: 6.44977
5: 5.58306	5: 3.09772 *	5: 5.752
6: 6.8158	6: 7.48134	6: 2.78096 *
7: 5.98684	7: 9.22151	7: 6.58593
8: 8.91784	8: 7.21429	8: 13.1809
9: 9.19543	9: 7.83405	9: 8.2857
10: 7.6302	10: 5.29551	10: 9.83852
11: 7.95896	11: 7.2495	11: 9.47895
12: 12.4085	12: 9.32284	12: 15.4083
13: 7.22457	13: 6.87695	13: 8.31937
14: 11.8954	14: 8.7778	14: 15.5136
15: 12.1866	15: 9.16047	15: 13.6225

/i/ (VQ1)

t7	t8	t9
1: 6.60373	1: 10.4702	1: 6.40013
2: 11.8024	2: 6.25642	2: 9.93276
3: 9.68339	3: 5.14441	3: 11.5378
4: 5.3039	4: 7.55207	4: 7.94659
5: 6.93985	5: 8.0944	5: 7.61387
6: 6.55671	6: 14.0557	6: 6.10531
7: 3.63963 *	7: 11.9782	7: 9.63881
8: 12.5577	8: 2.75975 *	8: 12.9822
9: 9.3911	9: 12.2857	9: 1.88931 *
10: 9.4395	10: 7.74788	10: 6.51861
11: 8.57034	11: 8.17877	11: 8.38899
12: 14.1934	12: 9.44147	12: 9.82102
13: 7.52426	13: 9.40751	13: 5.85486
14: 14.6355	14: 7.08021	14: 11.1338
15: 14.0555	15: 9.16212	15: 7.92142
t10	t11	t12
1: 5.61846	1: 6.58364	1: 9.18777
2: 4.81428	2: 7.29603	2: 6.90121
3: 9.40488	3: 8.1442	3: 12.0626
4: 6.30922	4: 6.42198	4: 10.661
5: 5.95625	5: 7.14144	5: 9.57726
6: 9.94407	6: 7.68359	6: 13.6608
7: 10.058	7: 7.09958	7: 15.6743
8: 8.40927	8: 8.07065	8: 9.21313
9: 6.29599	9: 8.19631	9: 8.47418
10: 2.92253 *	10: 5.96686	10: 8.37663
11: 6.32322	11: 3.03132 *	11: 6.97825
12: 7.00724	12: 8.75502	12: 2.11876 *
13: 5.44862	13: 4.8297	13: 7.51587
14: 5.66738	14: 7.22313	14: 7.01558
15: 7.51341	15: 8.37291	15: 5.54213

/i/ (VQ1)

t13	t14	t15
1: 5.7394	1: 7.3608	1: 8.02781
2: 5.1019	2: 4.20732	2: 8.24219
3: 8.72716	3: 9.95593	3: 10.0875
4: 5.5453	4: 8.47633	4: 8.20262
5: 6.00911	5: 6.98678	5: 8.16076
6: 7.99933	6: 13.3675	6: 9.91443
7: 9.04428	7: 13.063	7: 12.5294
8: 8.66145	8: 7.0462	8: 9.65248
9: 5.29567	9: 8.46639	9: 6.99313
10: 4.73067	10: 5.55685	10: 7.64124
11: 5.80089	11: 6.85877	11: 5.44816
12: 6.79867	12: 6.38537	12: 5.73047
13: 2.5354 *	13: 6.67033	13: 6.45171
14: 5.88543	14: 2.72035 *	14: 7.92258
15: 7.05762	15: 5.91421	15: 3.74464 *

/i/ (VQ2)

s1	s2	s3
1: 3.03574 *	1: 8.14775	1: 9.77729
2: 6.3846	2: 3.6993 *	2: 9.33614
3: 9.36462	3: 9.24588	3: 2.78268 *
4: 7.04394	4: 9.22717	4: 5.96264
5: 6.38865	5: 7.30501	5: 6.49765
6: 7.18495	6: 14.7914	6: 10.8413
7: 6.83371	7: 12.5279	7: 8.91575
8: 10.7397	8: 6.50789	8: 5.6907
9: 6.70894	9: 10.357	9: 11.4471
10: 7.1559	10: 5.07797	10: 9.41343
11: 7.37943	11: 8.44565	11: 8.47325
12: 11.142	12: 7.45928	12: 12.384
13: 7.12214	13: 6.69732	13: 9.38019
14: 8.67523	14: 4.49327	14: 9.39481
15: 9.31345	15: 8.72251	15: 10.3255
s4	s5	s6
1: 6.73627	1: 6.38366	1: 7.15021
2: 6.48966	2: 6.15572	2: 9.11767
3: 5.29892	3: 6.69058	3: 9.10998
4: 2.89901 *	4: 5.87692	4: 6.62393
5: 5.22769	5: 3.21655 *	5: 6.06691
6: 7.11741	6: 7.23471	6: 2.92236 *
7: 5.26636	7: 7.84751	7: 6.59926
8: 8.17954	8: 8.624	8: 13.7435
9: 8.58528	9: 7.55383	9: 7.32756
10: 8.52964	10: 7.17731	10: 11.3589
11: 7.26867	11: 7.56538	11: 8.7207
12: 12.7257	12: 11.3618	12: 15.3417
13: 7.48406	13: 7.06503	13: 9.5159
14: 9.6115	14: 7.54065	14: 12.8948
15: 10.2138	15: 9.03025	15: 11.8098

/i/ (VQ2)

s7	s8	s9
1: 6.70161	1: 10.1205	1: 7.99629
2: 7.60165	2: 9.02706	2: 8.78312
3: 8.25911	3: 5.58448	3: 10.8401
4: 5.45337	4: 8.11603	4: 9.14375
5: 7.74309	5: 7.74714	5: 7.97666
6: 6.75671	6: 14.5523	6: 7.5864
7: 3.82017 *	7: 12.0544	7: 9.49321
8: 12.1623	8: 3.87909 *	8: 12.7444
9: 10.0741	9: 13.3561	9: 1.89359 *
10: 10.4759	10: 9.22077	10: 7.32659
11: 7.76806	11: 9.10355	11: 8.78862
12: 16.0073	12: 10.5665	12: 10.5179
13: 9.78577	13: 9.79065	13: 6.02854
14: 12.6846	14: 8.74864	14: 9.08892
15: 13.097	15: 10.6535	15: 8.34631
s10	s11	s12
1: 5.98905	1: 6.87179	1: 8.57984
2: 5.65483	2: 7.50564	2: 6.40299
3: 7.70275	3: 7.33368	3: 11.3254
4: 7.26272	4: 7.27263	4: 11.9027
5: 5.60865	5: 7.18649	5: 9.13629
6: 8.96199	6: 9.92434	6: 15.0889
7: 9.07937	7: 8.68829	7: 14.4364
8: 8.59843	8: 7.86287	8: 9.48626
9: 5.42152	9: 7.91954	9: 9.71213
10: 3.14973 *	10: 6.25208	10: 7.73216
11: 5.91541	11: 3.34048 *	11: 9.1903
12: 9.05892	12: 8.24375	12: 2.17194 *
13: 4.84715	13: 5.73878	13: 7.47564
14: 5.07456	14: 6.66619	14: 6.5195
15: 7.63619	15: 6.03607	15: 6.20288

/i/ (VQ2)

s13	s14	s15
1: 6.18314	1: 8.16433	1: 8.92621
2: 5.5288	2: 4.53184	2: 7.65949
3: 7.58877	3: 10.0674	3: 10.8569
4: 6.75582	4: 10.2141	4: 10.6875
5: 6.64588	5: 7.63713	5: 8.65378
6: 8.56266	6: 15.0656	6: 12.0392
7: 7.77657	7: 13.583	7: 13.1223
8: 8.36965	8: 7.46095	8: 10.3639
9: 5.00235	9: 9.79172	9: 7.05493
10: 5.4442	10: 5.24291	10: 7.54179
11: 4.75156	11: 8.28475	11: 7.82874
12: 7.57214	12: 7.14544	12: 5.54777
13: 2.55492 *	13: 6.43855	13: 7.15629
14: 5.59628	14: 3.06625 *	14: 7.02822
15: 6.62468	15: 8.63322	15: 3.55933 *

/I/ (VQ1)

t1	t2	t3
1: 3.91548 *	1: 4.63927	1: 10.8757
2: 4.52889	2: 3.29591 *	2: 9.78846
3: 8.99831	3: 9.65453	3: 3.37107 *
4: 6.75856	4: 7.59912	4: 6.33598
5: 6.13353	5: 6.86086	5: 8.23538
6: 6.11837	6: 6.02331	6: 8.08807
7: 6.20439	7: 7.33536	7: 8.98798
8: 5.14051	8: 6.06743	8: 8.48025
9: 10.2584	9: 7.6106	9: 13.3879
10: 5.76389	10: 5.37701	10: 9.96574
11: 8.08628	11: 6.52764	11: 10.9055
12: 8.90555	12: 7.27699	12: 12.0054
13: 7.47526	13: 5.96561	13: 9.56986
14: 7.847	14: 6.60508	14: 11.223
15: 7.83035	15: 10.2547	15: 10.602
t4	t5	t6
1: 8.20823	1: 7.92206	1: 6.45141
2: 6.54354	2: 7.06434	2: 5.3088
3: 4.48193	3: 8.16857	3: 8.2189
4: 2.65572 *	4: 6.18611	4: 5.93709
5: 5.50585	5: 2.80318 *	5: 4.30152
6: 5.20063	6: 5.65641	6: 3.2723 *
7: 5.75393	7: 7.78737	7: 6.16957
8: 6.15165	8: 6.48487	8: 6.41359
9: 10.628	9: 10.3835	9: 8.43115
10: 7.67811	10: 7.47322	10: 5.60039
11: 8.41985	11: 8.5168	11: 6.69271
12: 9.38114	12: 8.5533	12: 6.85883
13: 6.75782	13: 6.82108	13: 5.03246
14: 8.9657	14: 8.97645	14: 7.30332
15: 9.84071	15: 7.28459	15: 8.48496

/I/ (VQ1)

t7	t8	t9
1: 7.5705	1: 7.46327	1: 10.3913
2: 6.12143	2: 6.53514	2: 9.33571
3: 8.24673	3: 6.87313	3: 11.3833
4: 6.10149	4: 5.81378	4: 11.0606
5: 7.14906	5: 6.17444	5: 8.65886
6: 5.2606	6: 5.70229	6: 7.70998
7: 2.58522 *	7: 5.27157	7: 11.5766
8: 6.45822	8: 3.72257 *	8: 12.8747
9: 11.3817	9: 12.2569	9: 1.91659 *
10: 7.38849	10: 8.05202	10: 8.28952
11: 8.51174	11: 8.7377	11: 6.69859
12: 9.57776	12: 10.0038	12: 5.87534
13: 7.8571	13: 8.05067	13: 7.2828
14: 9.77029	14: 10.1831	14: 7.44919
15: 11.4627	15: 10.6492	15: 15.9074
t10	t11	t12
1: 5.36921	1: 6.56651	1: 9.70353
2: 5.14935	2: 6.05113	2: 8.95343
3: 9.21446	3: 7.21485	3: 10.6487
4: 8.73306	4: 7.53708	4: 9.85092
5: 7.40435	5: 5.76219	5: 6.00474
6: 6.30328	6: 5.56034	6: 6.28563
7: 8.09559	7: 7.67348	7: 9.12029
8: 7.50096	8: 7.38636	8: 10.4149
9: 6.35938	9: 7.33465	9: 7.01785
10: 2.38942 *	10: 4.94818	10: 7.80556
11: 5.22638	11: 3.44744 *	11: 5.91151
12: 6.56904	12: 5.23224	12: 3.19393 *
13: 5.70143	13: 5.21236	13: 7.09259
14: 4.84002	14: 5.99171	14: 8.87381
15: 10.7812	15: 11.7318	15: 14.2481

/I/ (VQ1)

t13	t14	t15
1: 7.12935	1: 6.35333	1: 9.46959
2: 5.70133	2: 5.94311	2: 8.36163
3: 8.38281	3: 11.5201	3: 10.3424
4: 7.40798	4: 10.0577	4: 8.56326
5: 5.79363	5: 8.52351	5: 5.73249
6: 4.81772	6: 8.56452	6: 8.91536
7: 8.40673	7: 10.1782	7: 10.1777
8: 8.07346	8: 8.30018	8: 6.78137
9: 5.89482	9: 7.04348	9: 13.3048
10: 5.02628	10: 5.32459	10: 9.5371
11: 6.05784	11: 7.44854	11: 11.6549
12: 5.86638	12: 7.93378	12: 11.5273
13: 2.08832 *	13: 6.87145	13: 10.015
14: 5.00052	14: 3.8654 *	14: 10.032
15: 9.4998	15: 9.5699	15: 2.61992 *

/I/ (VQ2)

s1	s2	s3
1: 3.74786 *	1: 4.80851	1: 9.71937
2: 4.24914	2: 3.21352 *	2: 10.1791
3: 9.81153	3: 10.0187	3: 3.54556 *
4: 8.35294	4: 7.90558	4: 5.54953
5: 7.3389	5: 6.67077	5: 8.33158
6: 5.96442	6: 5.53748	6: 9.46926
7: 7.70013	7: 6.71203	7: 8.34772
8: 6.72818	8: 6.95107	8: 7.28467
9: 10.075	9: 10.2634	9: 13.6878
10: 5.5041	10: 5.75655	10: 10.0899
11: 6.65525	11: 6.96261	11: 8.65492
12: 8.86366	12: 9.30419	12: 11.8633
13: 6.89175	13: 6.30049	13: 10.5897
14: 6.04521	14: 5.98654	14: 11.4193
15: 9.29976	15: 8.78042	15: 11.5921
s4	s5	s6
1: 6.63673	1: 7.12083	1: 6.05509
2: 6.35343	2: 7.22542	2: 5.13818
3: 5.44575	3: 8.23623	3: 7.2529
4: 2.66954 *	4: 6.64084	4: 6.01527
5: 5.25463	5: 2.78462 *	5: 4.46344
6: 6.01455	6: 5.27612	6: 3.40617 *
7: 5.41756	7: 7.52331	7: 5.58564
8: 5.61062	8: 6.98672	8: 5.83069
9: 10.9856	9: 10.4585	9: 8.59203
10: 8.09912	10: 8.12422	10: 6.05558
11: 6.72906	11: 6.84991	11: 5.63622
12: 9.15225	12: 7.83787	12: 6.32626
13: 7.61331	13: 7.39693	13: 6.21337
14: 8.9035	14: 8.29529	14: 7.48526
15: 8.99518	15: 7.89107	15: 9.81939

/I/ (VQ2)

	s7	s8	s9
1:	6.47677	6.22732	11.5293
2:	6.69461	7.15124	7.753
3:	8.98208	8.59222	11.4389
4:	6.55841	6.94331	10.9923
5:	7.39278	6.38809	8.6476
6:	5.66864	6.76221	8.60596
7:	2.47336 *	6.19336	10.7109
8:	5.7755	4.21017 *	11.1339
9:	11.9482	13.3388	2.04824 *
10:	7.86873	9.02968	8.2202
11:	7.66195	7.11687	7.96261
12:	9.4362	10.8496	6.23796
13:	8.91466	8.59743	7.38625
14:	9.8287	9.66076	7.95795
15:	10.7507	9.32378	15.5651

	s10	s11	s12
1:	5.1568	9.00114	9.33171
2:	5.00462	6.52018	7.37696
3:	8.84937	8.81327	10.6947
4:	8.19756	8.88463	10.1579
5:	6.43135	7.60068	7.25853
6:	5.47516	7.48672	6.78041
7:	7.30044	8.05421	9.43566
8:	7.34759	7.40193	9.01028
9:	7.46524	6.50126	6.22655
10:	2.28441 *	5.72557	7.11255
11:	4.88893	3.33951 *	5.83766
12:	6.51142	5.62932	2.8715 *
13:	4.95057	7.26943	7.07769
14:	4.51002	7.0549	7.78547
15:	9.79137	14.2169	12.86

/I/ (VQ2)

s13	s14	s15
1: 6.58967	1: 6.71656	1: 8.30073
2: 5.09306	2: 6.10812	2: 9.66032
3: 7.47305	3: 9.69138	3: 9.33842
4: 6.70168	4: 9.23908	4: 8.46631
5: 5.05474	5: 7.81884	5: 5.58128
6: 4.75596	6: 7.2283	6: 8.09871
7: 7.25276	7: 9.74418	7: 10.3231
8: 7.41547	8: 9.35367	8: 9.8138
9: 6.13527	9: 6.88663	9: 13.7871
10: 5.29681	10: 4.99229	10: 10.1453
11: 5.08513	11: 6.50576	11: 9.65272
12: 6.17036	12: 8.23461	12: 12.4347
13: 2.65382 *	13: 5.73012	13: 9.77714
14: 4.6848	14: 3.3241 *	14: 8.7088
15: 9.60584	15: 9.927	15: 2.67148 *

/e/ (VQ1)

t1	t2	t3
1: 2.68782 *	1: 5.87277	1: 6.32769
2: 5.88823	2: 3.23905 *	2: 7.56905
3: 6.31478	3: 7.8576	3: 2.83833 *
4: 8.94493	4: 8.96307	4: 5.16576
5: 5.03761	5: 7.53146	5: 4.61884
6: 6.10313	6: 6.37887	6: 4.92267
7: 9.07412	7: 10.3502	7: 5.47
8: 4.88053	8: 6.06954	8: 5.44095
9: 8.53273	9: 9.5868	9: 10.0889
10: 5.34105	10: 7.06062	10: 8.12972
11: 6.86882	11: 7.58651	11: 6.41442
12: 7.65485	12: 8.71919	12: 6.57411
13: 6.5874	13: 7.11555	13: 7.78808
14: 8.50711	14: 8.87883	14: 9.06153
15: 6.53392	15: 7.49265	15: 7.56778
t4	t5	t6
1: 8.0439	1: 5.70612	1: 7.2108
2: 7.83287	2: 7.11109	2: 7.17819
3: 4.48024	3: 5.23347	3: 4.38315
4: 2.58567 *	4: 6.42706	4: 5.32045
5: 5.68235	5: 3.75574 *	5: 4.33955
6: 6.14197	6: 5.22491	6: 3.78012 *
7: 5.34597	7: 7.1423	7: 6.84138
8: 8.16561	8: 5.94845	8: 6.3264
9: 11.3821	9: 8.45384	9: 9.17315
10: 10.0314	10: 6.25118	10: 7.90979
11: 6.76247	11: 6.37857	11: 6.25939
12: 7.98792	12: 5.80689	12: 5.92451
13: 8.42837	13: 6.42109	13: 6.92752
14: 9.57513	14: 7.45517	14: 8.18176
15: 8.94038	15: 6.51287	15: 6.62078

/e/ (VQ1)

t7 1: 8.35617 2: 9.46886 3: 5.85437 4: 5.00618 5: 6.74156 6: 7.97289 7: 2.85943 * 8: 8.94966 9: 11.9961 10: 10.9831 11: 7.87432 12: 7.81766 13: 8.68065 14: 9.1102 15: 9.66606	t8 1: 6.34193 2: 5.65845 3: 4.24271 4: 7.76664 5: 6.75099 6: 4.96329 7: 8.8177 8: 3.43679 * 9: 9.86403 10: 7.34892 11: 6.49831 12: 8.47639 13: 8.36299 14: 10.0605 15: 7.58975	t9 1: 7.2635 2: 8.38228 3: 9.38553 4: 10.5779 5: 6.78183 6: 6.76404 7: 11.1479 8: 8.45286 9: 2.24316 * 10: 4.50548 11: 7.66494 12: 6.55668 13: 4.69163 14: 5.50469 15: 4.03741
t10 1: 4.55019 2: 6.85809 3: 6.21886 4: 9.08146 5: 4.61126 6: 5.81634 7: 9.36632 8: 5.6706 9: 5.65073 10: 2.98579 * 11: 5.95504 12: 6.66681 13: 5.57679 14: 7.21728 15: 5.55137	t11 1: 8.0934 2: 7.6333 3: 6.2019 4: 6.1015 5: 6.82051 6: 6.04406 7: 6.5793 8: 7.67641 9: 9.65103 10: 8.46477 11: 2.67836 * 12: 5.50342 13: 6.52651 14: 6.46924 15: 7.90901	t12 1: 7.05683 2: 7.95551 3: 6.67858 4: 7.43877 5: 5.60443 6: 5.2457 7: 7.57235 8: 7.10167 9: 7.2049 10: 5.40489 11: 5.66129 12: 3.10962 * 13: 5.07418 14: 7.33889 15: 6.1013

/e/ (VQ1)

t13	t14	t15
1: 5.14584	1: 7.06672	1: 6.13427
2: 5.88548	2: 7.34912	2: 6.72627
3: 7.29405	3: 8.91143	3: 7.89268
4: 7.08443	4: 8.12906	4: 9.91206
5: 5.17421	5: 6.83688	5: 5.3986
6: 4.50902	6: 6.27447	6: 5.56646
7: 7.61786	7: 8.4528	7: 10.6742
8: 6.68986	8: 7.76033	8: 6.47525
9: 5.68851	9: 6.8411	9: 5.91754
10: 4.16324	10: 7.08386	10: 4.27542
11: 5.74514	11: 6.07492	11: 6.60838
12: 4.20496	12: 5.37949	12: 6.63536
13: 2.53222 *	13: 4.8246	13: 5.75309
14: 6.09286	14: 2.80396 *	14: 7.52401
15: 4.65235	15: 6.46606	15: 3.31903 *

/e/ (VQ2)

s1	s2	s3
1: 2.72973 *	1: 6.1774	1: 7.05983
2: 5.53414	2: 3.20413 *	2: 7.5703
3: 6.18255	3: 8.82734	3: 3.06976 *
4: 7.00633	4: 9.21313	4: 5.81958
5: 5.0572	5: 7.51254	5: 5.18865
6: 7.02362	6: 8.96143	6: 5.12824
7: 8.85267	7: 11.3958	7: 7.36727
8: 6.24489	8: 6.87797	8: 5.51798
9: 7.57207	9: 8.80658	9: 11.0895
10: 5.37112	10: 7.76531	10: 8.2559
11: 7.51983	11: 8.64813	11: 7.45173
12: 6.93569	12: 8.91511	12: 7.04454
13: 5.43781	13: 7.17218	13: 7.37983
14: 7.13268	14: 8.02226	14: 8.7229
15: 6.08909	15: 7.41856	15: 9.39673

s4	s5	s6
1: 9.31146	1: 6.51112	1: 5.70388
2: 7.80899	2: 7.63355	2: 5.17314
3: 4.32283	3: 5.527	3: 4.76541
4: 2.69454 *	4: 7.11644	4: 5.55848
5: 5.49499	5: 4.23854 *	5: 4.7487
6: 5.19045	6: 5.83752	6: 3.72944 *
7: 5.02595	7: 8.53383	7: 7.5793
8: 8.02614	8: 7.56735	8: 4.82588
9: 13.0479	9: 8.83288	9: 8.66845
10: 10.9123	10: 6.82022	10: 6.85561
11: 6.72254	11: 7.76068	11: 5.77031
12: 7.90957	12: 6.67287	12: 5.29291
13: 8.14909	13: 6.73811	13: 5.30765
14: 9.791	14: 7.58168	14: 6.91069
15: 11.7614	15: 7.37407	15: 6.72517

/e/ (VQ2)

s7	s8	s9
1: 11.449	1: 4.88842	1: 8.29366
2: 11.0647	2: 5.87438	2: 8.73056
3: 6.70142	3: 4.94263	3: 10.0441
4: 6.13528	4: 7.34704	4: 10.4317
5: 7.47221	5: 5.75717	5: 7.73615
6: 7.77419	6: 7.01373	6: 8.57686
7: 3.06806 *	7: 9.14775	7: 12.4781
8: 11.2356	8: 3.74173 *	8: 9.60447
9: 14.228	9: 9.51995	9: 2.40088 *
10: 13.1415	10: 6.60592	10: 5.81541
11: 7.20974	11: 7.61623	11: 9.45347
12: 8.69985	12: 7.46305	12: 7.26176
13: 9.33717	13: 7.21309	13: 4.91106
14: 9.56125	14: 7.99975	14: 6.78451
15: 13.7063	15: 7.30913	15: 5.91232
s10	s11	s12
1: 5.02298	1: 8.64455	1: 7.4172
2: 6.65276	2: 6.66774	2: 8.07359
3: 7.22749	3: 6.21625	3: 7.08839
4: 8.61979	4: 5.8798	4: 7.61106
5: 4.74574	5: 6.46554	5: 5.69245
6: 7.15549	6: 6.12092	6: 5.89808
7: 10.5959	7: 6.8369	7: 7.81968
8: 7.25469	8: 7.14933	8: 8.4574
9: 4.91387	9: 9.86043	9: 6.49492
10: 3.07974 *	10: 9.29399	10: 6.64062
11: 7.42954	11: 2.57792 *	11: 5.66829
12: 4.72453	12: 6.22839	12: 2.6895 *
13: 3.71889	13: 6.58525	13: 4.09069
14: 6.59436	14: 6.0749	14: 5.34759
15: 4.50741	15: 8.91649	15: 6.46783

/e/ (VQ2)

s13	s14	s15
1: 6.10432	1: 8.82168	1: 6.28839
2: 5.79383	2: 8.14688	2: 7.09618
3: 7.50203	3: 8.71383	3: 7.83977
4: 6.53212	4: 8.12678	4: 8.77508
5: 5.34179	5: 7.39424	5: 6.10363
6: 5.94503	6: 6.99972	6: 6.62677
7: 7.79781	7: 8.61918	7: 10.6063
8: 7.71947	8: 9.71889	8: 7.35866
9: 5.09824	9: 6.4246	9: 4.26148
10: 5.75439	10: 8.05874	10: 5.28154
11: 5.80845	11: 6.84405	11: 8.16686
12: 4.93327	12: 7.13493	12: 5.96704
13: 2.23529 *	13: 6.43815	13: 4.27871
14: 4.63666	14: 2.82544 *	14: 6.25942
15: 6.05937	15: 7.99053	15: 3.45866 *

/E/ (VQ1)

t1	t2	t3
1: 3.229 *	1: 6.28324	1: 8.76975
2: 6.81845	2: 3.61215 *	2: 7.32408
3: 9.2458	3: 8.68413	3: 2.89484 *
4: 9.5576	4: 8.13052	4: 5.0223
5: 7.44836	5: 8.00626	5: 7.32927
6: 8.58887	6: 7.62838	6: 5.76686
7: 9.29463	7: 9.32348	7: 6.01057
8: 7.06079	8: 8.25059	8: 6.67113
9: 9.52132	9: 8.38511	9: 8.34883
10: 8.14605	10: 8.23608	10: 9.36226
11: 6.77945	11: 7.72755	11: 6.75638
12: 6.54223	12: 9.46901	12: 9.37461
13: 8.24272	13: 8.52027	13: 7.59776
14: 6.75283	14: 7.88859	14: 11.2255
15: 5.34884	15: 8.4206	15: 11.2108
t4	t5	t6
1: 7.04433	1: 7.54762	1: 5.92446
2: 7.14801	2: 8.25861	2: 6.12783
3: 4.26171	3: 9.24584	3: 6.00368
4: 3.16953 *	4: 8.72691	4: 6.06329
5: 6.73103	5: 2.68418 *	5: 5.58015
6: 4.90679	6: 7.45455	6: 3.46869 *
7: 5.1934	7: 8.20386	7: 6.787
8: 5.53768	8: 7.14524	8: 5.76285
9: 7.5963	9: 8.6254	9: 6.14237
10: 7.96286	10: 7.05771	10: 5.32564
11: 6.12806	11: 6.33988	11: 5.68009
12: 7.2902	12: 6.46773	12: 6.72714
13: 6.60811	13: 7.36478	13: 4.90279
14: 9.01815	14: 8.2905	14: 6.67527
15: 8.84731	15: 7.37867	15: 8.06283

/E/ (VQ1)

t7	t8	t9
1: 7.49959	1: 6.27979	1: 8.46817
2: 8.61987	2: 8.65585	2: 8.28114
3: 5.66103	3: 7.18286	3: 8.36032
4: 5.57957	4: 7.94756	4: 7.12282
5: 7.05931	5: 7.1992	5: 7.18462
6: 6.50504	6: 7.86157	6: 5.42021
7: 2.90615 *	7: 5.78997	7: 8.5344
8: 4.54761	8: 3.16503 *	8: 8.64982
9: 8.29996	9: 9.9994	9: 1.92185 *
10: 8.30416	10: 7.83168	10: 6.60835
11: 7.06687	11: 6.23928	11: 8.22354
12: 6.23613	12: 7.58224	12: 7.48148
13: 7.3119	13: 8.40264	13: 4.82491
14: 9.63892	14: 9.52025	14: 6.50205
15: 8.10666	15: 6.82187	15: 9.66395

t10	t11	t12
1: 6.12073	1: 6.00573	1: 5.614
2: 6.41404	2: 6.88016	2: 7.47757
3: 8.08818	3: 6.54233	3: 9.23937
4: 7.65319	4: 6.98948	4: 7.9878
5: 5.36507	5: 5.58908	5: 5.59189
6: 5.58081	6: 6.16881	6: 5.76626
7: 7.70543	7: 6.40527	7: 8.19836
8: 5.61144	8: 5.28734	8: 6.85217
9: 6.71935	9: 8.72232	9: 6.76848
10: 2.68272 *	10: 5.01041	10: 4.79119
11: 4.96644	11: 2.20369 *	11: 6.31766
12: 7.37029	12: 7.31996	12: 3.08597 *
13: 4.92899	13: 6.72673	13: 4.31915
14: 6.86732	14: 8.09862	14: 5.75951
15: 6.88681	15: 7.09857	15: 6.03912

/E/ (VQ1)

t13	t14	t15
1: 6.01358	1: 5.12315	1: 4.56852
2: 6.97263	2: 7.30546	2: 7.87701
3: 7.09943	3: 10.3015	3: 10.1202
4: 5.71344	4: 9.45183	4: 9.21574
5: 6.09839	5: 6.66978	5: 5.61066
6: 4.44134	6: 6.88734	6: 8.26131
7: 6.70176	7: 10.592	7: 9.10914
8: 5.67595	8: 8.78547	8: 7.55297
9: 5.23903	9: 6.76893	9: 8.0637
10: 4.52116	10: 5.52895	10: 6.55724
11: 5.96389	11: 6.30733	11: 5.98004
12: 4.88427	12: 6.04254	12: 5.31207
13: 2.27982 *	13: 5.88977	13: 7.12405
14: 5.40253	14: 3.16812 *	14: 6.02909
15: 6.96056	15: 6.0681	15: 2.98592 *

/E/ (VQ2)

s1	s2	s3
1: 3.25508 *	1: 7.35422	1: 11.3081
2: 6.48502	2: 3.71593 *	2: 6.98604
3: 7.23097	3: 6.75938	3: 2.68467 *
4: 7.20613	4: 8.68213	4: 4.68678
5: 6.87732	5: 7.73261	5: 8.23478
6: 5.71877	6: 7.2099	6: 6.14792
7: 8.14658	7: 9.84469	7: 6.22527
8: 6.29554	8: 8.06512	8: 6.92469
9: 8.6204	9: 9.1851	9: 8.75129
10: 7.12995	10: 7.40229	10: 9.23972
11: 6.62777	11: 7.97855	11: 7.18893
12: 5.80478	12: 8.14832	12: 10.197
13: 6.32872	13: 7.98077	13: 7.27599
14: 5.13194	14: 7.96166	14: 13.3293
15: 4.88217	15: 7.67395	15: 11.6663
s4	s5	s6
1: 9.99782	1: 8.61868	1: 8.54881
2: 6.57625	2: 8.33574	2: 6.72054
3: 4.58993	3: 7.05628	3: 5.72778
4: 2.99918 *	4: 7.54715	4: 5.27845
5: 7.32321	5: 2.71438 *	5: 6.97231
6: 5.58602	6: 6.4818	6: 3.48831 *
7: 5.58386	7: 7.56328	7: 6.41868
8: 6.87773	8: 6.62163	8: 6.16385
9: 6.80586	9: 8.08132	9: 5.6516
10: 7.98124	10: 7.29677	10: 6.72605
11: 6.95893	11: 6.77603	11: 6.58815
12: 7.97214	12: 6.03525	12: 6.38797
13: 5.96956	13: 6.91969	13: 5.11246
14: 10.5292	14: 8.00564	14: 8.06567
15: 9.50405	15: 6.92834	15: 8.31471

/E/ (VQ2)

s7 1: 9.33369 2: 8.7717 3: 5.61168 4: 5.05031 5: 7.89164 6: 7.60453 7: 2.82809 * 8: 5.32946 9: 9.0729 10: 9.17401 11: 7.97254 12: 8.25194 13: 7.23467 14: 11.5224 15: 9.68668	s8 1: 7.25798 2: 9.21239 3: 6.15077 4: 5.67906 5: 7.74899 6: 7.01095 7: 4.90945 8: 3.00866 * 9: 10.1868 10: 8.18632 11: 7.0875 12: 8.03544 13: 7.68937 14: 9.85972 15: 8.05898	s9 1: 10.8875 2: 7.74325 3: 8.40903 4: 7.57061 5: 8.10255 6: 5.8455 7: 8.14745 8: 8.81846 9: 1.98858 * 10: 7.03493 11: 8.41964 12: 7.38321 13: 5.73241 14: 8.3184 15: 9.66599
s10 1: 7.50564 2: 7.80847 3: 6.19744 4: 7.46664 5: 6.1617 6: 4.97983 7: 7.69849 8: 5.68221 9: 6.41467 10: 2.7607 * 11: 5.62681 12: 4.66423 13: 4.43994 14: 5.26428 15: 5.7135	s11 1: 7.13241 2: 7.329 3: 5.71577 4: 5.6419 5: 5.65751 6: 5.83997 7: 6.37021 8: 4.93547 9: 8.72784 10: 5.19211 11: 2.41971 * 12: 6.09646 13: 6.27745 14: 7.18266 15: 6.39915	s12 1: 6.3794 2: 9.87261 3: 9.15443 4: 7.64234 5: 6.14864 6: 6.34297 7: 6.98909 8: 7.60584 9: 8.31034 10: 8.22532 11: 7.47486 12: 4.04802 * 13: 5.15257 14: 6.03384 15: 5.56629

/E/ (VQ2)

s13	s14	s15
1: 8.60441	1: 7.87348	1: 4.91919
2: 7.57896	2: 7.62979	2: 8.59875
3: 7.27559	3: 7.53656	3: 8.74583
4: 6.20095	4: 8.63125	4: 7.89195
5: 6.71432	5: 7.57585	5: 5.67559
6: 4.70369	6: 6.21738	6: 7.59841
7: 6.74643	7: 9.34736	7: 8.05778
8: 6.50272	8: 8.58836	8: 5.91476
9: 4.69994	9: 6.44778	9: 9.27293
10: 4.77692	10: 6.76633	10: 7.87433
11: 6.57784	11: 7.87157	11: 7.08676
12: 4.53654	12: 6.13276	12: 6.27117
13: 2.25048 *	13: 5.46834	13: 7.12941
14: 6.20879	14: 3.43603 *	14: 6.39551
15: 7.13901	15: 7.04457	15: 2.90135 *

/@/ (VQ1)

t1	t2	t3
1: 2.13286 *	1: 6.14434	1: 6.12005
2: 5.14178	2: 3.99656 *	2: 6.09956
3: 8.46113	3: 8.39251	3: 2.47904 *
4: 8.56194	4: 8.37743	4: 5.75282
5: 6.99106	5: 7.24437	5: 8.86373
6: 7.985	6: 9.64788	6: 6.1127
7: 10.3129	7: 9.98681	7: 4.93485
8: 5.05381	8: 6.15336	8: 5.19577
9: 9.11172	9: 10.0018	9: 10.2548
10: 6.25789	10: 7.12112	10: 9.10789
11: 6.92197	11: 7.07965	11: 6.52912
12: 7.31746	12: 9.461	12: 7.54268
13: 6.03946	13: 8.18434	13: 9.67871
14: 5.93065	14: 7.92384	14: 9.03989
15: 5.71486	15: 6.91272	15: 11.8556
t4	t5	t6
1: 6.53059	1: 7.53697	1: 7.99086
2: 5.81479	2: 6.38621	2: 9.06103
3: 5.77232	3: 8.48551	3: 6.98264
4: 3.89158 *	4: 7.0019	4: 7.47127
5: 8.01549	5: 4.52632 *	5: 6.49099
6: 8.0454	6: 8.33884	6: 3.30822 *
7: 5.89201	7: 8.47721	7: 7.72738
8: 6.58278	8: 7.92957	8: 7.5176
9: 9.78745	9: 7.50465	9: 6.16468
10: 8.95423	10: 9.30632	10: 12.0255
11: 5.49075	11: 6.90103	11: 8.60226
12: 6.91951	12: 7.02165	12: 7.92154
13: 8.75557	13: 8.44016	13: 10.2906
14: 9.12691	14: 7.64008	14: 5.90664
15: 10.1905	15: 9.1132	15: 14.0238

/@/ (VQ1)

t7	t8	t9
1: 6.69796	1: 5.29601	1: 7.68622
2: 6.84278	2: 6.18781	2: 8.73522
3: 4.44921	3: 5.12744	3: 9.05243
4: 6.0944	4: 7.43989	4: 8.39183
5: 8.13238	5: 8.32788	5: 5.22734
6: 6.26343	6: 6.83445	6: 5.72279
7: 2.76587 *	7: 6.67196	7: 9.63506
8: 5.8381	8: 3.71441 *	8: 8.20234
9: 9.94344	9: 10.1939	9: 2.47844 *
10: 10.7006	10: 7.43309	10: 8.62953
11: 6.03941	11: 6.80942	11: 8.75588
12: 5.23081	12: 7.98252	12: 7.93627
13: 10.048	13: 8.37045	13: 6.79545
14: 9.55587	14: 8.23417	14: 3.85928
15: 12.4297	15: 9.47938	15: 10.0742
t10	t11	t12
1: 4.95377	1: 5.86123	1: 6.39897
2: 6.00385	2: 5.82359	2: 7.72365
3: 5.51991	3: 5.84605	3: 9.23244
4: 7.04932	4: 5.4375	4: 9.67969
5: 6.69381	5: 6.8299	5: 7.01506
6: 5.63846	6: 6.79957	6: 8.12757
7: 7.87378	7: 5.46285	7: 9.30286
8: 4.8952	8: 5.86158	8: 7.48639
9: 8.09738	9: 8.84267	9: 9.46277
10: 3.81127 *	10: 8.01776	10: 6.65101
11: 5.2348	11: 2.89702 *	11: 6.78697
12: 5.83667	12: 5.15838	12: 3.47214 *
13: 6.5389	13: 8.45412	13: 6.71386
14: 4.96924	14: 7.42422	14: 7.05513
15: 5.86292	15: 9.06427	15: 6.78217

/@/ (VQ1)

t13	t14	t15
1: 6.03627	1: 5.40397	1: 5.42672
2: 6.81413	2: 5.70975	2: 4.88944
3: 9.73829	3: 9.09509	3: 8.92577
4: 7.82922	4: 9.34674	4: 7.83412
5: 5.60238	5: 5.6969	5: 6.31786
6: 7.16078	6: 7.2685	6: 8.5329
7: 10.9841	7: 10.9593	7: 9.42694
8: 7.69309	8: 6.49552	8: 5.86492
9: 5.72407	9: 7.41384	9: 8.18367
10: 6.34786	10: 5.64875	10: 5.62528
11: 7.39587	11: 7.47116	11: 5.76624
12: 7.70182	12: 7.74434	12: 6.67684
13: 3.69886 *	13: 6.40624	13: 6.26009
14: 4.98196	14: 3.86959 *	14: 6.93703
15: 7.02018	15: 6.23322	15: 2.94316 *

/@/ (VQ2)

s1	s2	s3
1: 2.13019 *	1: 6.17965	1: 7.62731
2: 5.89515	2: 4.01414 *	2: 6.87727
3: 9.34333	3: 8.15206	3: 2.64957 *
4: 9.26766	4: 7.22795	4: 5.97702
5: 7.6428	5: 6.44909	5: 8.23544
6: 11.3747	6: 10.8717	6: 7.77364
7: 11.1059	7: 8.96079	7: 5.03485
8: 5.95337	8: 6.46427	8: 5.17728
9: 8.09258	9: 9.01028	9: 9.68769
10: 5.94925	10: 7.45522	10: 7.65675
11: 8.53609	11: 6.97501	11: 6.84004
12: 6.05564	12: 8.05269	12: 9.27267
13: 6.05272	13: 7.64321	13: 10.2523
14: 5.36551	14: 6.35308	14: 7.24347
15: 5.59555	15: 5.88899	15: 8.72384
s4	s5	s6
1: 8.01602	1: 8.30694	1: 8.86007
2: 6.85257	2: 7.98231	2: 9.29783
3: 5.67436	3: 8.42343	3: 6.31363
4: 4.09814 *	4: 8.36281	4: 8.4574
5: 5.96379	5: 4.43915 *	5: 8.49026
6: 7.50444	6: 7.05032	6: 3.49494 *
7: 6.21358	7: 8.17251	7: 6.63464
8: 7.03392	8: 7.45047	8: 6.89549
9: 8.47721	9: 5.75726	9: 6.97738
10: 9.56484	10: 8.94226	10: 9.96184
11: 5.59794	11: 7.48155	11: 7.82226
12: 9.30781	12: 7.65875	12: 9.63899
13: 9.05952	13: 7.45739	13: 10.5684
14: 7.96537	14: 6.99838	14: 7.52145
15: 7.74172	15: 7.20916	15: 10.0337

/@/ (VQ2)

s7	s8	s9
1: 9.54019	1: 5.46827	1: 9.19415
2: 7.17316	2: 6.50277	2: 9.59248
3: 4.9461	3: 5.85325	3: 9.06031
4: 5.58858	4: 7.36915	4: 9.59449
5: 7.68296	5: 8.46293	5: 7.00529
6: 8.50142	6: 9.50269	6: 5.65513
7: 2.65254 *	7: 7.22716	7: 9.07109
8: 6.7095	8: 3.8062 *	8: 8.39606
9: 10.8001	9: 10.0942	9: 2.64388 *
10: 9.87969	10: 6.61442	10: 9.68713
11: 6.0798	11: 7.18726	11: 9.10596
12: 8.75192	12: 7.82649	12: 8.99439
13: 12.0469	13: 9.22336	13: 6.65308
14: 8.77091	14: 6.2054	14: 7.42716
15: 9.14783	15: 7.3069	15: 8.38432
s10	s11	s12
1: 5.53696	1: 6.16117	1: 8.45362
2: 6.05714	2: 6.27607	2: 9.34558
3: 7.52522	3: 5.98503	3: 8.69779
4: 7.69611	4: 5.34521	4: 8.30987
5: 6.21471	5: 6.35673	5: 6.68036
6: 10.5277	6: 8.83362	6: 9.46224
7: 9.34553	7: 5.91678	7: 7.09037
8: 5.82626	8: 5.99982	8: 8.58383
9: 7.3984	9: 8.90996	9: 9.26956
10: 3.79164 *	10: 6.13178	10: 8.08487
11: 6.7084	11: 3.00684 *	11: 6.60397
12: 6.06409	12: 5.95833	12: 4.85231 *
13: 6.04001	13: 7.88512	13: 9.28216
14: 4.50704	14: 5.59912	14: 7.67752
15: 5.49725	15: 5.25171	15: 7.62149

/@/ (VQ2)

s13	s14	s15
1: 5.71981	1: 6.2788	1: 5.59679
2: 7.79598	2: 7.45609	2: 5.77715
3: 9.39372	3: 9.82185	3: 10.7786
4: 7.96538	4: 9.88142	4: 8.83331
5: 6.66658	5: 7.01281	5: 6.57956
6: 10.1293	6: 8.10785	6: 13.106
7: 10.2074	7: 10.666	7: 11.6596
8: 7.52405	8: 7.95668	8: 7.79591
9: 6.46141	9: 4.45466	9: 8.78512
10: 6.68072	10: 6.07092	10: 6.37257
11: 7.95711	11: 8.59181	11: 8.22802
12: 6.34756	12: 7.05366	12: 6.05665
13: 3.79944 *	13: 5.41974	13: 6.99685
14: 6.30184	14: 3.92794 *	14: 5.96576
15: 6.3946	15: 7.41122	15: 2.52787 *

/a/ (VQ1)

t1	t2	t3
1: 3.66431 *	1: 5.65417	1: 6.58593
2: 4.63211	2: 3.73142 *	2: 5.42493
3: 7.79713	3: 5.72986	3: 2.5869 *
4: 12.5284	4: 9.18497	4: 6.51699
5: 5.2883	5: 4.12283	5: 4.61497
6: 8.80249	6: 7.22101	6: 5.57257
7: 8.83007	7: 6.48337	7: 3.69463
8: 6.11604	8: 5.51646	8: 5.85441
9: 8.47839	9: 9.06246	9: 8.47358
10: 9.68879	10: 8.27187	10: 6.78627
11: 7.46595	11: 6.94995	11: 5.87732
12: 5.41746	12: 5.67027	12: 5.49789
13: 6.58355	13: 7.76827	13: 9.11147
14: 6.9018	14: 6.62812	14: 7.22654
15: 5.88384	15: 6.18792	15: 9.21544
t4	t5	t6
1: 10.1457	1: 5.26373	1: 8.56471
2: 6.43702	2: 4.26445	2: 5.16862
3: 5.20118	3: 6.16752	3: 4.94053
4: 2.80772 *	4: 10.3822	4: 5.24203
5: 6.36027	5: 2.94338 *	5: 5.31941
6: 5.50813	6: 7.33778	6: 2.58299 *
7: 4.87484	7: 6.8764	7: 5.34871
8: 9.00022	8: 5.45435	8: 7.58497
9: 11.2144	9: 9.06514	9: 10.4202
10: 8.86991	10: 8.68981	10: 8.43401
11: 6.82384	11: 7.06426	11: 6.44316
12: 6.16792	12: 5.57659	12: 6.12611
13: 12.0907	13: 7.78787	13: 10.4239
14: 9.14906	14: 6.8998	14: 8.15214
15: 12.1083	15: 6.38166	15: 9.9595

/a/ (VQ1)

t7	t8	t9
1: 7.12561	1: 5.26297	1: 6.84489
2: 6.71302	2: 5.73979	2: 7.2405
3: 4.46204	3: 5.53088	3: 9.16042
4: 7.83695	4: 10.8865	4: 14.7733
5: 5.53792	5: 4.96622	5: 8.01898
6: 6.93162	6: 8.14998	6: 11.5746
7: 3.59667 *	7: 6.32635	7: 11.0803
8: 6.15766	8: 3.45607 *	8: 7.89009
9: 10.0826	9: 8.06557	9: 3.36982 *
10: 8.27859	10: 8.00805	10: 7.49216
11: 7.63269	11: 6.75355	11: 5.98519
12: 7.26679	12: 5.59266	12: 5.90173
13: 10.5967	13: 7.48945	13: 4.33133
14: 9.20165	14: 6.94638	14: 5.62105
15: 10.895	15: 7.32947	15: 7.86231
t10	t11	t12
1: 5.75301	1: 6.95762	1: 5.34548
2: 5.97383	2: 5.96421	2: 4.83288
3: 5.78821	3: 5.13063	3: 7.57292
4: 10.2081	4: 6.85529	4: 13.313
5: 6.36411	5: 5.59522	5: 5.49642
6: 8.07314	6: 5.47677	6: 9.76945
7: 7.33977	7: 5.47349	7: 9.63312
8: 5.83045	8: 6.10588	8: 5.42867
9: 5.17192	9: 6.86662	9: 6.23921
10: 4.34923	10: 7.0606	10: 8.20108
11: 4.94083	11: 2.67342 *	11: 5.61123
12: 4.25444 *	12: 4.68181	12: 2.40443 *
13: 4.49907	13: 6.73193	13: 4.0535
14: 5.26038	14: 5.11429	14: 4.95463
15: 6.25076	15: 8.11434	15: 4.81368

/a/ (VQ1)

t13	t14	t15
1: 6.47705	1: 6.32427	1: 5.78749
2: 6.38477	2: 6.19756	2: 5.00505
3: 9.43082	3: 7.60947	3: 7.83281
4: 15.6072	4: 11.1501	4: 12.6551
5: 7.23571	5: 6.30499	5: 5.73887
6: 12.2115	6: 7.81062	6: 8.9195
7: 11.9012	7: 8.69089	7: 9.45276
8: 6.76427	8: 6.27287	8: 5.84418
9: 5.19389	9: 6.36134	9: 8.70438
10: 8.63147	10: 8.02118	10: 8.98361
11: 6.87187	11: 4.84255	11: 7.40059
12: 4.85358	12: 5.17489	12: 5.2433
13: 2.73145 *	13: 4.51539	13: 5.89271
14: 5.95867	14: 3.48275 *	14: 6.18263
15: 6.14098	15: 5.23965	15: 2.63872 *

/a/ (VQ2)

s1	s2	s3
1: 3.67642 *	1: 4.81789	1: 7.72353
2: 5.19624	2: 3.68104 *	2: 5.75173
3: 6.66521	3: 6.3082	3: 2.73288 *
4: 10.7183	4: 9.02933	4: 5.95461
5: 4.98018	5: 4.26887	5: 5.58617
6: 9.15732	6: 8.16535	6: 5.55157
7: 6.78081	7: 7.08271	7: 4.77626
8: 4.55061	8: 5.3776	8: 4.3527
9: 7.05086	9: 7.41562	9: 9.43736
10: 6.13876	10: 6.16932	10: 6.67851
11: 6.28536	11: 6.58982	11: 5.52173
12: 5.57811	12: 5.72171	12: 8.6982
13: 6.16122	13: 6.67958	13: 9.34685
14: 6.84135	14: 6.59987	14: 8.05564
15: 5.95234	15: 5.71303	15: 9.04582
s4	s5	s6
1: 12.0408	1: 5.4699	1: 8.86761
2: 7.68549	2: 4.17589	2: 6.5465
3: 5.52554	3: 5.21694	3: 5.04671
4: 2.80111 *	4: 8.6266	4: 5.57628
5: 8.35093	5: 3.01662 *	5: 5.52988
6: 5.41421	6: 7.60109	6: 2.65748 *
7: 7.17678	7: 5.71536	7: 6.39715
8: 7.71158	8: 4.72833	8: 5.37714
9: 13.2754	9: 8.8491	9: 10.9423
10: 10.9207	10: 6.5187	10: 8.71541
11: 5.78614	11: 6.77529	11: 5.17843
12: 12.7929	12: 6.70706	12: 9.88329
13: 13.7847	13: 8.08517	13: 10.8895
14: 11.0493	14: 7.2666	14: 8.05311
15: 13.2285	15: 6.84796	15: 9.92094

/a/ (VQ2)

s7	s8	s9
1: 8.18896	1: 6.2699	1: 8.26803
2: 6.18971	2: 6.28425	2: 9.21462
3: 3.51988 *	3: 7.35626	3: 8.55327
4: 5.36992	4: 11.3482	4: 12.6209
5: 5.64985	5: 5.72023	5: 9.11111
6: 5.69247	6: 10.1518	6: 11.2815
7: 3.7161	7: 6.90356	7: 10.185
8: 4.64896	8: 3.29913 *	8: 8.01648
9: 10.3929	9: 8.54297	9: 3.5665 *
10: 7.46493	10: 6.72433	10: 5.13594
11: 6.05351	11: 7.49886	11: 5.85518
12: 9.58637	12: 6.46877	12: 6.75298
13: 10.3183	13: 7.32206	13: 5.23229
14: 9.14294	14: 7.82924	14: 6.39503
15: 10.3707	15: 7.18328	15: 9.06675
s10	s11	s12
1: 7.96585	1: 7.03227	1: 5.09244
2: 7.67714	2: 6.79131	2: 5.84257
3: 6.17355	3: 5.8678	3: 6.7421
4: 8.25727	4: 7.98781	4: 10.4025
5: 7.4727	5: 6.35034	5: 5.78449
6: 8.41734	6: 7.22837	6: 8.70425
7: 7.32556	7: 7.07616	7: 7.79056
8: 6.98125	8: 5.7242	8: 5.19412
9: 6.19262	9: 5.95304	9: 6.60356
10: 3.91177 *	10: 5.24122	10: 4.46679
11: 6.89371	11: 2.69648 *	11: 5.24975
12: 7.64507	12: 6.51148	12: 3.28458 *
13: 6.82314	13: 6.11531	13: 5.20498
14: 7.65868	14: 4.75134	14: 5.71333
15: 7.85236	15: 7.72705	15: 5.89237

/a/ (VQ2)

s13	s14	s15
1: 6.28683	1: 6.2157	1: 5.33981
2: 7.21624	2: 5.74197	2: 5.46613
3: 9.2935	3: 6.50799	3: 8.51721
4: 13.0377	4: 9.43651	4: 11.057
5: 7.51546	5: 5.65866	5: 5.77998
6: 11.4855	6: 8.22831	6: 9.38517
7: 10.1152	7: 7.08226	7: 8.25814
8: 6.66823	8: 5.36378	8: 5.60344
9: 4.43072	9: 5.3989	9: 7.82578
10: 4.47973	10: 4.82506	10: 5.6638
11: 5.66966	11: 4.60925	11: 7.08492
12: 4.11802	12: 5.52298	12: 4.63496
13: 2.56265 *	13: 5.43249	13: 6.0169
14: 4.08375	14: 3.07813 *	14: 5.29443
15: 6.19661	15: 6.21311	15: 2.62229 *

/o/ (VQ1)

t1	t2	t3
1: 2.50889 *	1: 5.47129	1: 7.92214
2: 5.42826	2: 2.90002 *	2: 5.63922
3: 6.05375	3: 4.93034	3: 2.07284 *
4: 10.4871	4: 8.46598	4: 7.70067
5: 8.30158	5: 6.22082	5: 6.25292
6: 6.21213	6: 6.48228	6: 5.56629
7: 6.9828	7: 6.76754	7: 5.471
8: 6.43852	8: 7.16225	8: 4.99869
9: 5.92959	9: 7.1246	9: 6.85008
10: 6.91818	10: 8.66128	10: 8.15367
11: 6.98579	11: 7.43953	11: 6.58944
12: 5.92736	12: 5.85094	12: 7.38032
13: 7.68263	13: 9.79315	13: 10.1631
14: 6.22605	14: 7.76349	14: 8.90948
15: 7.08004	15: 8.88259	15: 10.2513
t4	t5	t6
1: 12.8789	1: 9.98893	1: 12.3415
2: 8.41238	2: 6.67168	2: 7.85115
3: 7.22815	3: 6.01558	3: 6.38847
4: 2.63812 *	4: 5.30031	4: 4.41586
5: 5.10383	5: 2.92379 *	5: 4.01672
6: 4.98326	6: 4.27238	6: 3.24901 *
7: 5.78412	7: 6.08293	7: 6.59046
8: 9.0415	8: 8.21224	8: 8.17985
9: 8.00445	9: 6.19355	9: 6.08563
10: 10.846	10: 8.31896	10: 9.43462
11: 7.902	11: 6.04427	11: 6.16068
12: 5.7458	12: 5.25638	12: 5.24151
13: 14.3356	13: 11.3513	13: 13.0981
14: 7.7609	14: 6.26846	14: 6.82679
15: 13.1912	15: 10.1533	15: 11.4178

/o/ (VQ1)

t7	t8	t9
1: 8.73257	1: 8.52557	1: 8.6706
2: 7.44612	2: 7.28058	2: 7.3065
3: 6.15801	3: 5.03326	3: 6.45552
4: 6.1888	4: 8.89476	4: 6.85275
5: 6.87208	5: 6.99754	5: 4.94572
6: 6.35079	6: 6.22998	6: 4.44277
7: 3.35151 *	7: 5.67157	7: 7.16706
8: 6.91816	8: 3.23537 *	8: 6.88841
9: 7.35697	9: 6.294	9: 3.06149 *
10: 7.89786	10: 7.01904	10: 4.91513
11: 7.13544	11: 5.64435	11: 4.29557
12: 8.10827	12: 7.96473	12: 4.86555
13: 10.7107	13: 8.79059	13: 6.81698
14: 9.21367	14: 9.032	14: 5.31365
15: 10.8491	15: 9.62392	15: 6.46267
t10	t11	t12
1: 9.82828	1: 10.4892	1: 7.45536
2: 9.39652	2: 7.82782	2: 7.78278
3: 7.9045	3: 6.06763	3: 7.5444
4: 8.13366	4: 5.98886	4: 9.83162
5: 6.9338	5: 5.1654	5: 7.47178
6: 5.76474	6: 4.20053	6: 6.81925
7: 7.88966	7: 6.66883	7: 8.54825
8: 7.75948	8: 6.58567	8: 7.76037
9: 4.68703	9: 3.49429	9: 4.46795
10: 3.15833 *	10: 5.56926	10: 6.2265
11: 4.88349	11: 2.45805 *	11: 6.01541
12: 7.15602	12: 6.30631	12: 4.4561 *
13: 6.3789	13: 8.49423	13: 5.10801
14: 6.11006	14: 6.35503	14: 5.84761
15: 7.19908	15: 8.30129	15: 5.60019

/o/ (VQ1)

t13	t14	t15
1: 8.35078	1: 8.6775	1: 8.66553
2: 9.33662	2: 7.052	2: 8.78679
3: 8.59818	3: 6.79199	3: 8.19923
4: 10.8777	4: 7.40501	4: 10.2202
5: 8.34252	5: 5.84381	5: 8.00773
6: 7.66655	6: 4.72549	6: 6.3855
7: 7.94634	7: 7.93839	7: 8.70518
8: 7.38732	8: 7.90384	8: 7.87334
9: 4.84153	9: 4.98748	9: 4.55585
10: 4.72423	10: 5.87905	10: 5.50913
11: 5.1957	11: 5.42222	11: 5.42944
12: 6.61693	12: 5.04029	12: 5.53816
13: 2.15505 *	13: 7.61433	13: 5.01809
14: 5.96654	14: 3.18514 *	14: 4.83934
15: 5.13404	15: 5.72739	15: 2.14089 *

/o/ (VQ2)

s1 1: 2.58376 * 2: 6.05856 3: 6.91236 4: 10.5284 5: 9.52191 6: 11.7925 7: 8.91622 8: 7.13078 9: 7.41883 10: 9.06681 11: 10.5513 12: 7.00749 13: 8.20676 14: 7.99055 15: 8.45015	s2 1: 5.59413 2: 3.05496 * 3: 5.67332 4: 7.82814 5: 6.29433 6: 8.52262 7: 7.8073 8: 7.28034 9: 7.51773 10: 9.28723 11: 8.62715 12: 7.71168 13: 9.40206 14: 7.41611 15: 9.04123	s3 1: 6.3683 2: 5.30864 3: 2.00876 * 4: 6.10278 5: 7.12336 6: 6.24794 7: 6.54289 8: 4.93313 9: 7.31344 10: 8.70037 11: 6.82546 12: 8.76141 13: 9.88915 14: 8.01037 15: 9.6097
s4 1: 9.8783 2: 8.03706 3: 7.00536 4: 2.62665 * 5: 5.39022 6: 4.65933 7: 5.90608 8: 6.98674 9: 6.43877 10: 7.33429 11: 6.42528 12: 9.18757 13: 12.0035 14: 7.11084 15: 11.018	s5 1: 9.3048 2: 7.41323 3: 6.50138 4: 5.1143 5: 3.20054 * 6: 4.19 7: 7.11124 8: 6.1822 9: 5.36664 10: 6.85223 11: 5.5651 12: 8.64871 13: 10.982 14: 6.9234 15: 9.74936	s6 1: 8.14892 2: 7.28575 3: 5.38135 4: 4.96462 5: 4.49335 6: 3.19486 * 7: 6.22671 8: 5.30737 9: 4.75556 10: 6.12718 11: 4.63928 12: 8.02284 13: 9.95801 14: 5.99548 15: 8.43755

/o/ (VQ2)

s7	s8	s9
1: 7.1242	1: 6.73336	1: 6.98775
2: 6.59393	2: 7.53108	2: 7.79219
3: 5.12649	3: 5.35351	3: 6.23764
4: 4.46138	4: 8.57976	4: 7.3834
5: 6.99769	5: 9.19707	5: 6.86448
6: 6.60662	6: 9.33147	6: 6.16345
7: 3.32854 *	7: 6.65928	7: 7.00293
8: 5.53251	8: 3.32447 *	8: 5.81465
9: 7.08439	9: 7.32642	9: 2.9096 *
10: 8.55769	10: 8.13976	10: 4.85289
11: 6.77936	11: 7.14772	11: 4.03254
12: 9.70689	12: 8.0938	12: 4.81614
13: 10.5288	13: 7.96864	13: 5.80231
14: 8.64447	14: 8.4952	14: 5.53548
15: 10.5904	15: 8.39858	15: 5.11131
s10	s11	s12
1: 6.58621	1: 7.16804	1: 6.74695
2: 8.79808	2: 7.63896	2: 6.65638
3: 7.18284	3: 5.76147	3: 7.26027
4: 7.84437	4: 7.17199	4: 7.24178
5: 7.60008	5: 6.75858	5: 5.89215
6: 7.63464	6: 6.29982	6: 6.86238
7: 6.55031	7: 6.21141	7: 8.31782
8: 6.45075	8: 5.18379	8: 7.76875
9: 4.77284	9: 4.19097	9: 5.23411 *
10: 2.80158 *	10: 4.66409	10: 7.6088
11: 5.03675	11: 2.81982 *	11: 7.35344
12: 6.01838	12: 5.84356	12: 5.27494
13: 5.17347	13: 5.80953	13: 8.47072
14: 6.07197	14: 5.74628	14: 5.93453
15: 5.88055	15: 5.69471	15: 7.36474

/o/ (VQ2)

s13	s14	s15
1: 7.52818	1: 7.061	1: 7.25843
2: 9.46237	2: 7.90404	2: 8.84072
3: 8.79867	3: 7.84061	3: 8.52031
4: 10.9181	4: 8.50308	4: 10.3248
5: 10.0221	5: 6.51652	5: 9.0173
6: 11.7589	6: 7.80156	6: 10.0361
7: 8.63076	7: 8.25423	7: 8.46751
8: 7.31596	8: 8.31171	8: 8.21816
9: 5.09314	9: 5.49352	9: 5.49478
10: 5.7647	10: 6.14883	10: 6.02976
11: 8.35173	11: 7.36171	11: 8.12871
12: 4.85689	12: 6.20682	12: 5.51798
13: 2.25389 *	13: 6.71001	13: 5.20844
14: 6.22617	14: 3.29722 *	14: 4.85907
15: 5.08493	15: 5.6159	15: 2.15391 *

/U/ (VQ1)

t1 1: 2.48085 * 2: 5.38788 3: 4.67343 4: 5.32885 5: 4.85548 6: 6.28026 7: 6.60794 8: 6.2509 9: 5.71543 10: 5.34667 11: 5.82032 12: 9.41622 13: 4.59159 14: 6.49278 15: 5.03267	t2 1: 5.56722 2: 2.06377 * 3: 5.59295 4: 6.99071 5: 4.29357 6: 6.49765 7: 6.55768 8: 7.09087 9: 7.79488 10: 6.06164 11: 5.48893 12: 9.57216 13: 4.42196 14: 7.86607 15: 6.88034	t3 1: 6.75862 2: 6.62267 3: 2.30265 * 4: 6.09561 5: 4.99732 6: 5.20189 7: 5.94672 8: 6.39634 9: 7.79372 10: 6.90785 11: 5.71187 12: 8.31857 13: 5.67181 14: 7.24511 15: 7.95818
t4 1: 6.76359 2: 6.90159 3: 4.39548 4: 2.58456 * 5: 4.96538 6: 4.85181 7: 3.85699 8: 6.69161 9: 5.62441 10: 5.98321 11: 4.78546 12: 6.36648 13: 5.32026 14: 7.50571 15: 8.12489	t5 1: 5.38957 2: 3.90783 3: 4.43146 4: 6.02071 5: 2.66581 * 6: 5.30346 7: 4.93345 8: 6.10106 9: 6.40763 10: 5.77019 11: 5.06042 12: 9.08063 13: 4.0155 14: 6.94785 15: 6.3405	t6 1: 9.7462 2: 7.69174 3: 5.13522 4: 5.19369 5: 3.85799 6: 2.8394 * 7: 3.80193 8: 9.32774 9: 6.4921 10: 5.59262 11: 3.73108 12: 5.51192 13: 6.55168 14: 9.06031 15: 10.0728

/U/ (VQ1)

t7	t8	t9
1: 8.49613	1: 5.5824	1: 6.22269
2: 7.13127	2: 6.36124	2: 7.20979
3: 4.2902	3: 5.46997	3: 5.77844
4: 4.10717	4: 7.01505	4: 6.03982
5: 4.20341	5: 6.07164	5: 5.67442
6: 4.18027	6: 7.8959	6: 5.9306
7: 2.61801 *	7: 7.9318	7: 6.50637
8: 7.29662	8: 2.09826 *	8: 6.96473
9: 6.65507	9: 7.68259	9: 2.93717 *
10: 6.49398	10: 8.70374	10: 5.60194
11: 4.38087	11: 7.72942	11: 5.99397
12: 5.50609	12: 12.6976	12: 9.00656
13: 5.88492	13: 5.64902	13: 5.71065
14: 8.94261	14: 7.84021	14: 6.15423
15: 9.41771	15: 6.78516	15: 5.11543
t10	t11	t12
1: 4.9539	1: 5.35928	1: 9.77647
2: 5.55142	2: 5.27926	2: 6.85618
3: 4.89123	3: 3.20583 *	3: 7.27075
4: 6.42868	4: 5.3779	4: 8.50884
5: 5.26348	5: 3.87447	5: 5.00539
6: 5.83068	6: 4.12677	6: 5.92788
7: 6.57708	7: 5.38963	7: 6.49677
8: 5.9726	8: 5.85465	8: 11.6737
9: 5.90884	9: 5.19539	9: 7.43329
10: 4.40721 *	10: 4.94367	10: 7.48045
11: 6.21506	11: 3.54869	11: 5.21214
12: 10.7807	12: 7.46254	12: 3.54704 *
13: 5.11679	13: 3.50593	13: 6.62743
14: 6.52732	14: 5.78755	14: 10.1714
15: 4.90166	15: 5.68622	15: 11.1067

/U/ (VQ1)

t13	t14	t15
1: 5.40514	1: 6.5073	1: 4.98908
2: 4.28955	2: 6.48679	2: 5.69923
3: 4.45109	3: 5.23405	3: 5.17949
4: 5.38089	4: 7.24512	4: 6.79962
5: 3.43613	5: 5.81361	5: 4.8611
6: 4.58141	6: 7.05682	6: 6.54661
7: 5.50839	7: 7.95561	7: 7.19418
8: 6.4201	8: 6.20416	8: 6.02996
9: 5.25718	9: 6.80706	9: 5.05288
10: 5.09677	10: 7.03387	10: 4.63303
11: 3.95039	11: 6.69742	11: 6.18338
12: 6.56238	12: 11.7715	12: 10.6852
13: 1.99301 *	13: 5.28561	13: 4.22534
14: 6.19424	14: 3.51982 *	14: 4.91652
15: 5.54014	15: 5.67787	15: 2.57062 *

/U/ (VQ2)

s1	s2	s3
1: 2.34506 *	1: 5.45112	1: 5.47912
2: 5.10434	2: 2.06128 *	2: 5.39739
3: 5.31505	3: 6.27063	3: 2.39327 *
4: 5.97557	4: 7.06714	4: 4.9623
5: 4.68752	5: 4.08349	5: 4.40259
6: 7.31733	6: 7.56168	6: 5.15107
7: 5.95504	7: 6.12073	7: 4.57499
8: 5.47136	8: 6.73861	8: 5.11815
9: 6.0289	9: 7.78647	9: 6.94468
10: 4.93555	10: 5.90495	10: 5.3324
11: 4.7017	11: 5.75864	11: 3.69551
12: 7.18499	12: 6.96052	12: 6.62644
13: 4.53526	13: 4.68512	13: 4.69581
14: 6.57271	14: 7.40184	14: 6.23138
15: 5.18754	15: 6.30505	15: 6.43674
s4	s5	s6
1: 5.88781	1: 6.18649	1: 7.41083
2: 6.85765	2: 4.88324	2: 6.6283
3: 5.23392	3: 4.65281	3: 4.57756
4: 2.80776 *	4: 5.35657	4: 4.7952
5: 5.51059	5: 2.97312 *	5: 4.46646
6: 5.04306	6: 4.62946	6: 3.04752 *
7: 4.27799	7: 4.13329	7: 4.06817
8: 6.04001	8: 6.72902	8: 7.99583
9: 6.22687	9: 6.81465	9: 6.50015
10: 6.62495	10: 6.4261	10: 6.058
11: 5.4374	11: 4.7462	11: 4.70952
12: 7.71314	12: 5.73799	12: 5.41732
13: 5.56452	13: 4.40058	13: 5.49055
14: 7.75546	14: 7.61515	14: 8.47811
15: 7.2757	15: 6.65801	15: 7.45742

/U/ (VQ2)

<table>
<tr><td>s7
1: 7.95155
2: 6.98033
3: 5.02865
4: 4.03378
5: 4.30099
6: 3.86687
7: 2.68452 *
8: 7.99553
9: 7.76126
10: 7.48977
11: 6.0576
12: 6.34393
13: 6.13546
14: 10.0347
15: 9.06234</td><td>s8
1: 5.7552
2: 6.07172
3: 5.71372
4: 7.10106
5: 5.77054
6: 7.89836
7: 6.06898
8: 2.12713 *
9: 7.29962
10: 6.37669
11: 6.01831
12: 10.4514
13: 5.70337
14: 6.42461
15: 6.88245</td><td>s9
1: 5.90497
2: 7.4
3: 6.34345
4: 5.76338
5: 5.60444
6: 6.06173
7: 5.78775
8: 7.44109
9: 3.11668 *
10: 6.45515
11: 5.3815
12: 6.86255
13: 5.45033
14: 7.41367
15: 5.69794</td></tr>
<tr><td>s10
1: 5.74001
2: 6.07297
3: 5.73391
4: 5.34066
5: 5.06254
6: 4.78431 *
7: 5.47572
8: 8.50416
9: 5.59005
10: 5.05921
11: 5.05975
12: 5.09194
13: 5.24154
14: 7.84051
15: 5.41679</td><td>s11
1: 7.20132
2: 5.88103
3: 4.89936
4: 4.59025
5: 4.43828
6: 3.76278 *
7: 4.31736
8: 7.85579
9: 6.49167
10: 6.79136
11: 4.09424
12: 4.80041
13: 4.77435
14: 8.85288
15: 7.72705</td><td>s12
1: 10.1783
2: 7.76111
3: 7.5497
4: 7.75619
5: 5.55239
6: 4.82389
7: 6.19197
8: 12.4253
9: 10.136
10: 11.7276
11: 7.57441
12: 3.489 *
13: 7.51247
14: 13.3969
15: 12.2896</td></tr>
</table>

/U/ (VQ2)

s13	s14	s15
1: 4.38106	1: 7.146	1: 4.71051
2: 3.97351	2: 7.72155	2: 6.05283
3: 4.76432	3: 6.81219	3: 6.40804
4: 4.80442	4: 7.24848	4: 7.29193
5: 3.24617	5: 5.85011	5: 5.47363
6: 5.39392	6: 7.4916	6: 8.00434
7: 4.94585	7: 7.30286	7: 6.77043
8: 5.22881	8: 7.4713	8: 6.0382
9: 5.61739	9: 6.98798	9: 4.93136
10: 5.05421	10: 7.27975	10: 4.85903
11: 3.59215	11: 5.743	11: 5.32459
12: 6.03674	12: 8.26613	12: 7.76727
13: 2.00079 *	13: 6.39482	13: 4.94329
14: 5.33287	14: 3.68743 *	14: 5.63034
15: 4.17917	15: 5.98986	15: 2.66582 *

/u/ (VQ1)

t1	t2	t3
1: 2.61391 *	1: 4.73948	1: 4.76913
2: 4.09512	2: 1.85763 *	2: 6.74974
3: 4.7435	3: 7.2172	3: 2.3732 *
4: 6.32226	4: 10.0776	4: 4.99053
5: 4.02809	5: 4.45906	5: 4.25819
6: 7.75649	6: 11.267	6: 4.97598
7: 5.66256	7: 8.75077	7: 4.89283
8: 6.5508	8: 6.67068	8: 8.35247
9: 6.02503	9: 7.40821	9: 6.27954
10: 5.96792	10: 8.42241	10: 6.42116
11: 5.47125	11: 7.34375	11: 5.39065
12: 4.50829	12: 5.18909	12: 6.08645
13: 7.93013	13: 7.72169	13: 10.0495
14: 6.31871	14: 6.54459	14: 7.38089
15: 8.4254	15: 8.32115	15: 10.6757
t4	t5	t6
1: 3.67181	1: 4.58675	1: 5.94118
2: 5.95276	2: 4.57873	2: 8.16505
3: 3.96628	3: 5.50753	3: 4.86595
4: 3.11143 *	4: 7.91132	4: 5.31016
5: 4.62179	5: 3.50185 *	5: 4.26008
6: 5.19016	6: 7.98	6: 2.92044 *
7: 3.59123	7: 7.23157	7: 5.15242
8: 6.6709	8: 5.38723	8: 9.08799
9: 5.76279	9: 6.14164	9: 6.47995
10: 5.36897	10: 6.38981	10: 5.41553
11: 4.94645	11: 4.87404	11: 5.49412
12: 4.89166	12: 3.91037	12: 6.54452
13: 8.46003	13: 6.23917	13: 9.35324
14: 7.33893	14: 4.8913	14: 7.10124
15: 9.01431	15: 6.47374	15: 9.96528

/u/ (VQ1)

t7	t8	t9
1: 4.98648	1: 6.0948	1: 5.40768
2: 9.38257	2: 6.64475	2: 7.24651
3: 5.06149	3: 6.03562	3: 5.5409
4: 3.52377	4: 7.48384	4: 6.06987
5: 7.00366	5: 5.06575	5: 5.77568
6: 5.09669	6: 8.68047	6: 5.82733
7: 2.7401 *	7: 7.00492	7: 6.07799
8: 10.6309	8: 2.7957 *	8: 8.84613
9: 7.09515	9: 7.87055	9: 3.05795 *
10: 7.51128	10: 6.68196	10: 4.90444
11: 6.27901	11: 6.07334	11: 4.32828
12: 7.87184	12: 5.74527	12: 4.40117
13: 11.6169	13: 7.80853	13: 7.47519
14: 10.3322	14: 6.86333	14: 6.05907
15: 12.4117	15: 8.47408	15: 7.51142
t10	t11	t12
1: 5.37429	1: 4.60718	1: 4.21998
2: 7.28509	2: 7.70205	2: 5.443
3: 5.35654	3: 4.99575	3: 4.10082
4: 5.4251	4: 4.77898	4: 5.09867
5: 5.75938	5: 5.07805	5: 4.02981
6: 4.29694	6: 4.83935	6: 5.6656
7: 5.36801	7: 5.19184	7: 5.30721
8: 9.46049	8: 8.38598	8: 7.01204
9: 4.40351	9: 4.76894	9: 4.53133
10: 2.85662 *	10: 4.69427	10: 4.78677
11: 4.5748	11: 2.38763 *	11: 4.02446
12: 5.40712	12: 5.22549	12: 2.57704 *
13: 8.41211	13: 9.2036	13: 7.68225
14: 5.64667	14: 7.2049	14: 5.59171
15: 7.95648	15: 8.65322	15: 7.69667

/u/ (VQ1)

t13	t14	t15
1: 7.07621	1: 6.24466	1: 7.75604
2: 6.48597	2: 6.31528	2: 7.52871
3: 7.71169	3: 6.57899	3: 8.39833
4: 9.42957	4: 8.17785	4: 9.84301
5: 6.20807	5: 5.53648	5: 6.9842
6: 9.10597	6: 7.79582	6: 9.42842
7: 8.66359	7: 7.55043	7: 9.16267
8: 6.73877	8: 7.43035	8: 7.79078
9: 6.55325	9: 6.11499	9: 6.91993
10: 6.40396	10: 5.81297	10: 6.78497
11: 6.06401	11: 5.6232	11: 6.73182
12: 5.39328	12: 5.20874	12: 6.48719
13: 2.3829 *	13: 6.21191	13: 3.38049
14: 4.26047	14: 3.86952 *	14: 5.18169
15: 3.25506	15: 6.25733	15: 2.47247 *

/u/ (VQ2)

s1 1: 2.70787 * 2: 5.2124 3: 4.44815 4: 4.27702 5: 4.76129 6: 5.61416 7: 4.46589 8: 6.75263 9: 5.71445 10: 5.86454 11: 5.12082 12: 4.46412 13: 8.07197 14: 5.44099 15: 8.05791	s2 1: 3.677 2: 2.06351 * 3: 7.65948 4: 7.4217 5: 4.34074 6: 8.50354 7: 7.78711 8: 6.80128 9: 8.19751 10: 8.85192 11: 8.13954 12: 5.56865 13: 6.37989 14: 5.62687 15: 7.23779	s3 1: 4.86304 2: 6.48169 3: 2.17408 * 4: 4.5177 5: 5.19697 6: 4.83308 7: 4.71379 8: 7.3382 9: 5.79178 10: 5.38605 11: 5.29066 12: 4.28028 13: 9.62312 14: 5.47671 15: 9.61229
s4 1: 5.85218 2: 8.755 3: 4.53536 4: 3.14669 5: 7.09142 6: 4.90246 7: 3.07844 * 8: 8.99017 9: 6.16066 10: 4.91825 11: 5.30085 12: 5.14118 13: 11.2091 14: 5.18605 15: 10.5514	s5 1: 4.80869 2: 6.26118 3: 4.52982 4: 5.45379 5: 4.04 * 6: 5.12553 7: 6.57244 8: 5.63003 9: 5.94789 10: 6.22828 11: 5.59879 12: 4.48539 13: 7.34011 14: 4.88615 15: 7.59026	s6 1: 6.98504 2: 8.89517 3: 4.62993 4: 5.51125 5: 5.73772 6: 2.94402 * 7: 5.24822 8: 8.94688 9: 5.9388 10: 4.52286 11: 5.83532 12: 5.4029 13: 9.72563 14: 4.82246 15: 9.21832

/u/ (VQ2)

s7 1: 5.98949 2: 8.54885 3: 4.54518 4: 3.8653 5: 6.94356 6: 5.02029 7: 2.59739 * 8: 8.67956 9: 6.2797 10: 5.08294 11: 5.63022 12: 5.51804 13: 11.1086 14: 5.29348 15: 10.6914	s8 1: 6.51965 2: 7.08123 3: 7.85846 4: 7.2747 5: 5.71912 6: 7.82365 7: 9.0397 8: 3.3883 * 9: 8.23 10: 9.47789 11: 8.56553 12: 7.02196 13: 7.04201 14: 6.65998 15: 8.10019	s9 1: 6.0045 2: 8.58765 3: 5.38801 4: 5.99698 5: 6.11331 6: 5.04018 7: 5.95924 8: 9.24508 9: 2.96048 * 10: 4.32104 11: 4.75221 12: 4.69696 13: 7.43346 14: 5.15422 15: 7.5193
s10 1: 5.229 2: 7.71077 3: 5.28696 4: 5.36275 5: 5.83126 6: 4.48552 7: 5.72132 8: 8.28538 9: 4.62719 10: 2.92105 * 11: 4.28139 12: 4.99858 13: 6.88744 14: 4.48391 15: 6.85396	s11 1: 5.29694 2: 8.35025 3: 4.65782 4: 5.05735 5: 4.31694 6: 4.88142 7: 5.61614 8: 7.0377 9: 4.11341 10: 4.49338 11: 2.32582 * 12: 4.07556 13: 7.85501 14: 3.85768 15: 7.74707	s12 1: 4.01222 2: 5.52335 3: 5.36732 4: 4.9349 5: 3.70364 6: 5.92973 7: 6.4285 8: 5.84689 9: 4.42377 10: 5.33767 11: 5.1928 12: 2.60885 * 13: 5.46986 14: 4.01277 15: 6.2872

/u/ (VQ2)

s13	s14	s15
1: 7.11099	1: 5.99552	1: 7.57619
2: 8.09178	2: 6.66864	2: 8.81007
3: 8.42602	3: 6.55526	3: 9.11628
4: 7.71733	4: 7.31198	4: 8.84566
5: 6.51873	5: 4.95752	5: 6.48161
6: 6.71048	6: 6.13439	6: 8.06477
7: 8.93188	7: 8.19186	7: 9.97092
8: 7.75373	8: 6.94678	8: 8.36759
9: 5.86441	9: 5.58605	9: 6.00365
10: 7.50737	10: 5.88478	10: 7.674
11: 7.82591	11: 6.87515	11: 8.12681
12: 6.61975	12: 5.39322	12: 7.2058
13: 2.49438 *	13: 4.25808	13: 3.52544
14: 5.36175	14: 2.78914 *	14: 5.49253
15: 3.4273	15: 4.97492	15: 2.4457 *

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