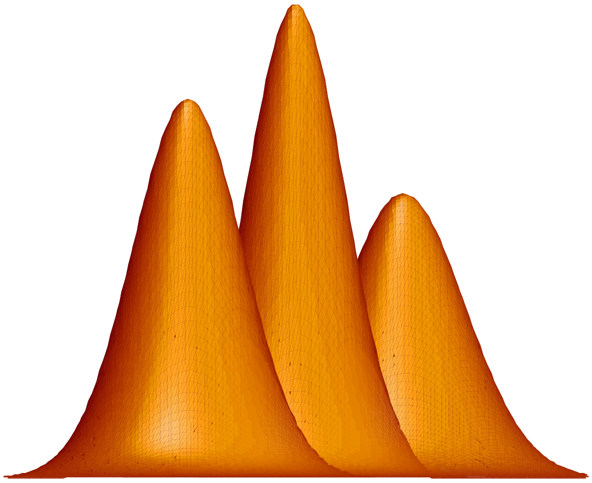
MSR Identity Toolbox

Version 1.0



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Technical Report
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MSR Identity Toolbox:

A MATLAB Toolbox for Speaker Recognition Research

Version 1.0

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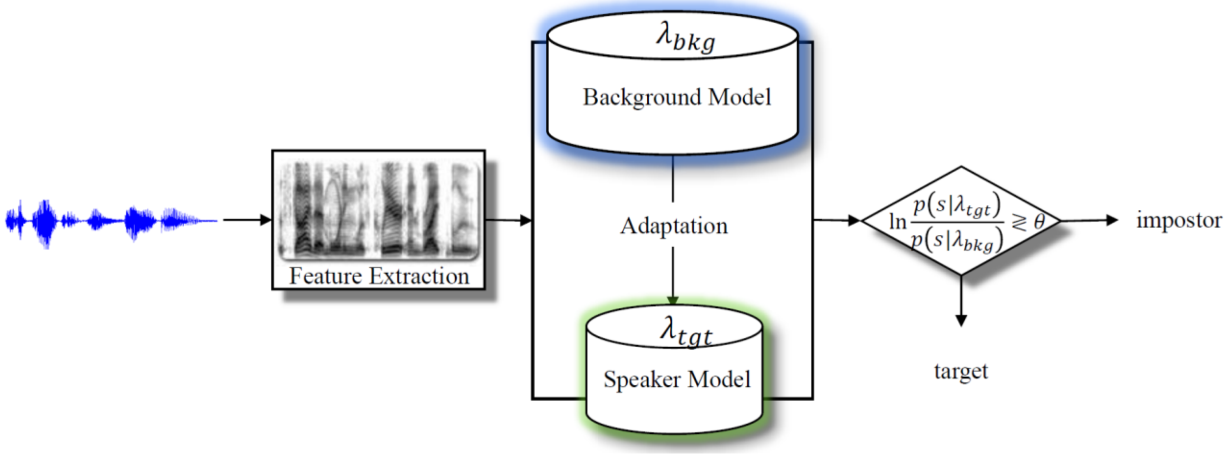
This report serves as a user manual for the tools available in the Microsoft Research (MSR) Identity Toolbox. This toolbox contains a collection of MATLAB tools and routines that can be used for research and development in speaker recognition. It provides researchers with a test bed for developing new front-end and back-end techniques, allowing replicable evaluation of new advancements. It will also help newcomers in the field by lowering the “barrier to entry”, enabling them to quickly build baseline systems for their experiments. Although the focus of this toolbox is on speaker recognition, it can also be used for other speech related applications such as language, dialect and accent identification.

In recent years, the design of robust and effective speaker recognition algorithms has attracted significant research effort from academic and commercial institutions. Speaker recognition has evolved substantially over the past 40 years; from discrete vector quantization (VQ) based systems to adapted Gaussian mixture model (GMM) solutions, and more recently to factor analysis based Eigenvoice (i-vector) frameworks. The Identity Toolbox provides tools that implement both the conventional GMM-UBM and state-of-the-art i-vector based speaker recognition strategies.



A speaker recognition system includes two primary components: a front-end and a back-end. The front-end transforms acoustic waveforms into more compact and less redundant representations called acoustic features. Cepstral features are most often used for speaker recognition. It is practical to only retain the high signal-to-noise ratio (SNR) regions of the waveform, therefore there is also a need for a speech activity detector (SAD) in the front-end. After dropping the low SNR frames, acoustic features are further post-processed to remove the linear channel effects. Cepstral mean and variance normalization (CMVN) is commonly used for the post-processing. The CMVN can be applied globally over the entire recording or locally over a sliding window. Feature warping, which is also applied over a sliding window, is another popular feature normalization technique that has been successfully applied for speaker recognition. This toolbox provides support for these normalization techniques, although no tool for feature extraction or SAD is provided. The Auditory Toolbox (Malcolm Slaney) and VOICEBOX (Mike Brooks) which are both written in MATLAB can be used for feature extraction and SAD purposes.

The main component of every speaker recognition system is the back-end where speakers are modelled (enrolled) and verification trials are scored. The enrollment phase includes estimating a model that represents (summarizes) the acoustic (and often phonetic) space of each speaker. This is usually accomplished with the help of a statistical background model from which the speaker-specific models are adapted. In the conventional GMM-UBM framework the universal background model (UBM) is a Gaussian mixture model (GMM) that is trained on a pool of data (known as the background or development data) from a large number of speakers. The speaker-specific models are then adapted from the UBM using the maximum *a posteriori* (MAP) estimation. During the evaluation phase, each test segment is scored either against all enrolled speaker models to determine who is speaking (speaker identification), or against the background model and a given speaker model to accept/reject an identity claim (speaker verification). On the other hand, in the i-vector framework the speaker models are estimated through a procedure called Eigenvoice adaptation. A total variability subspace is learned from the development set and is used to estimate a low (and fixed) dimensional latent factor called the identity vector (i-vector) from adapted mean supervectors (the term "i-vector" sometimes also refers to a vector of "intermediate" size, bigger than the underlying cepstral feature vector but much smaller than the GMM supervector). Unlike the GMM-UBM framework, which uses acoustic feature vectors to represent the test segments, in the i-vector paradigm both the model and test segments are represented as i-vectors. The dimensionality of the i-vectors are normally reduced through linear discriminant analysis (with Fisher criterion) to annihilate the non-speaker related directions (e.g., the channel subspace), thereby increasing the discrimination between speaker subspaces. Before modelling the dimensionality reduced i-vectors via a generative factor analysis approach called the probabilistic LDA (PLDA), they are mean and length normalized. In addition, a whitening transformation that is learned from i-vectors in the development set is applied. Finally, a fast and linear strategy, which computes the log-likelihood ratio (LLR) between same versus different speakers hypotheses, scores the verification trials. The Identity toolbox provides tools for speaker recognition using both the GMM-UBM and i-vector paradigms.

This report does not provide a detailed description of each speaker recognition tool available. The function descriptions include references to more detailed descriptions of corresponding components. We have attempted to maintain consistency with the naming convention in the code to follow the formulation and symbolization used in the literature. This will make it easier for the users to compare the theory with the implementation and help them better understand the concept behind each algorithm.

Usage

In order to better support interactive or batch usage, most of the tools in the Identity Toolbox accept either floating point or string arguments. String arguments, either for a file name or a numerical value, are useful when these tools are compiled and called from a shell command line. This makes it easy to use the tools on machines with limited memory (but enough disk space) as well as computer clusters (from a terminal). In addition, the interactive tools can optionally write the output products (models or matrices) to the disk if an output file name is specified.

This toolbox makes extensive use of parfor loops (as opposed to for loops) so that parallel processing can speed up the computations. However, if the Distributed Computing Toolbox is not installed, MATLAB automatically considers all parfor loops as for loops and there is no need to modify the tools. MATLAB by default sets the number of parallel workers to the number of physical CPU cores (not logical threads!) available on a computer. At the time of writing this report, MATLAB supports a maximum of 12 workers on a local machine.

The Identity toolbox has been tested on Windows 8 as well as Ubuntu Linux computers running MATLAB R2013a. The toolbox is portable and is expected to work on any machine that runs MATLAB.

Compilation

In case MATLAB is not installed or MATLAB license is not available (for instance on a computer cluster), we provide standalone executables that can be used in conjunction with the MATLAB Compiler Runtime (MCR). The MCR is a standalone set of shared libraries that enables the execution of compiled MATLAB applications or components on computers that do not have MATLAB installed. The MCR installer can be obtained free of charge from the web address:

http://www.mathworks.com/products/compiler/mcr/

The binaries supplied with this version of the toolkit need version 8.1 (R2013a) of the MCR.

The MCR installer is easy to use and provides users with an installation wizard. Assuming that the MCR is installed, a MATLAB code can be compiled from either the command window or a DOS/bash terminal as:

```
mcc -m -R -singleCompThread -R -nodisplay -R -nojvm foo.m -I libs/ -o foo -d bin/
```

for a standalone single-threaded executable. Single-threaded executables are useful when running the tools on clusters that only allow a single CPU process per scheduled job. To generate multithreaded executables (this is important when using parfor) the mcc can be used as following:

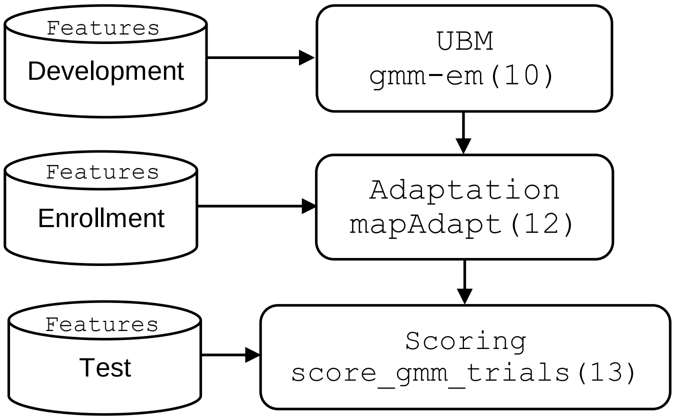
```
mcc -m -R -nodisplay foo.m -I libs/ -o foo -d bin/
```

For more details on the “mcc” command see the MATLAB documentation.

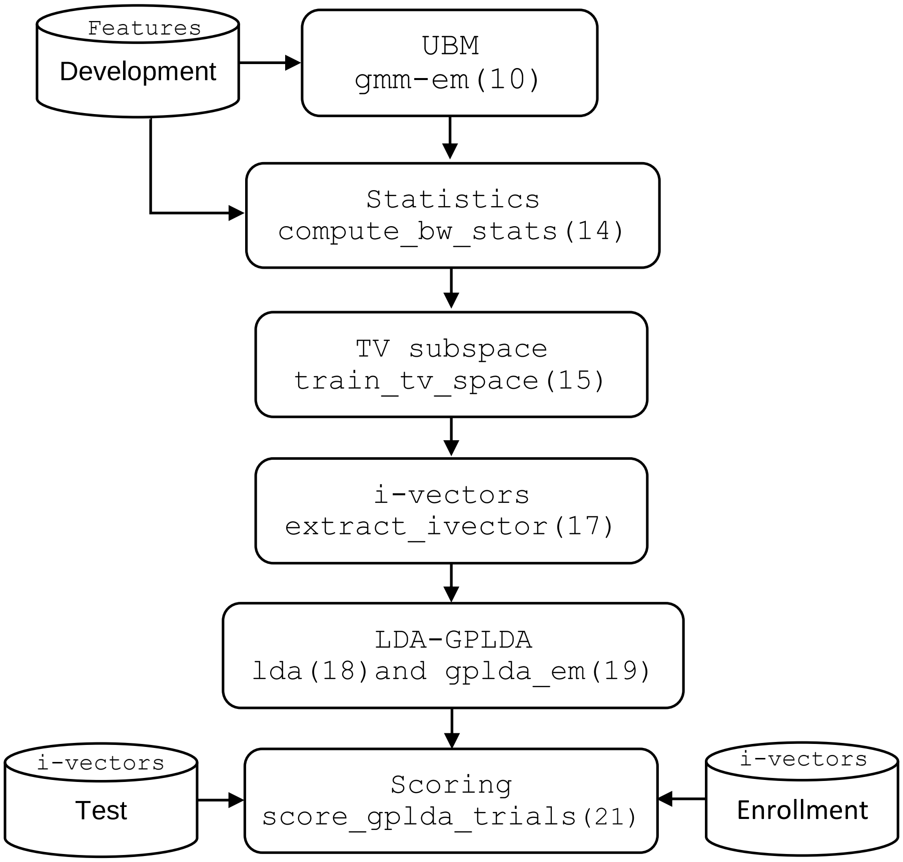
Flow Charts

The Identity toolbox provides researchers with tools that implement both the conventional GMM-UBM and state-of-the-art i-vector based systems. The block diagrams below show the overall signal flow and the routines (page numbers in parenthesis) used by each system.

GMM-UBM



i-vector-PLDA



Purpose

Global cepstral mean and variance normalization (CMVN)

Synopsis

Fea = cmvn(fea, varnorm)

Description

This function implements global cepstral mean and variance normalization (CMVN) on input feature matrix *fea* to remove the linear channel effects. The code assumes that there is one observation per column. The CMVN should be applied after dropping the low SNR frames.

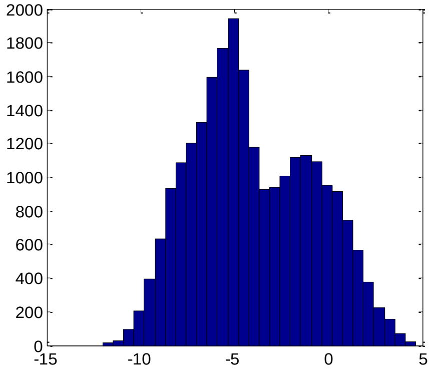
The logical switch *varnorm* (false | true) is used to instruct the code to perform variance normalization in addition to mean normalization.

Examples

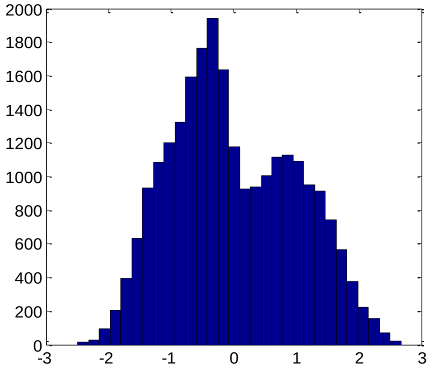
In an example we plot the distribution (histogram) of C_1 (first cepstral coefficient) in sample feature file, before and after global CMVN:

```
>> load('mfcc')
>> size(mfcc)

ans =

     39        24252
>> hist(mfcc(2,:), 30)
>> hist(cmvn(mfc(2,:), true), 30)
```

Before



After



As expected there is no change in overall shape of the distribution, and only the dynamic range of the feature stream is modified.

Purpose

Cepstral mean and variance normalization (CMVN) over a sliding window

Synopsis

Fea = wcmvn(fea, win, varnorm)

Description

This function implements cepstral mean and variance normalization (CMVN) on input feature matrix *fea* to remove the (locally) linear channel effects. The code assumes that there is one observation per column.

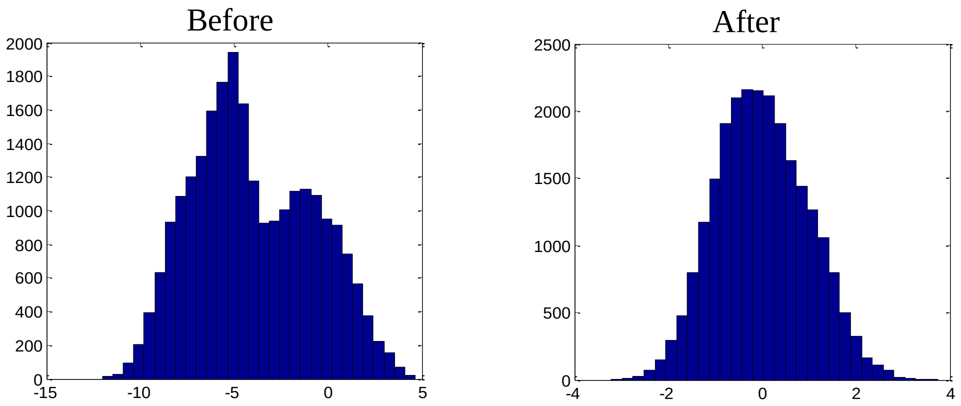
The normalization is performed over a sliding window that typically spans 301 frames (that is 3 seconds at a typical 100 Hz frame rate). The middle frame in the window is normalized based on the mean and variance computed over the specified time interval. The length of the sliding window can be specified through the scalar input *win* which must be an odd number. The CMVN should be applied after dropping the low SNR frames.

The logical scalar *varnorm* (false | true) is used to instruct the code to perform variance normalization in addition to mean normalization. The normalized feature streams are return in *Fea*.

Examples

In this example we plot the distribution (histogram) of C_1 (first cepstral coefficient) in a sample feature file, before and after windowed CMVN:

```
>> load('mfcc')
>> size(mfcc)

ans =

      39       24252
>> hist(mfcc(2,:), 30)
>> hist(wcmvn(mfc(2,:), 301, true), 30)
```



Unlike with the global CMVN, for this sample feature stream the overall shape of the feature stream distribution is approximately mapped to a standard normal distribution.

fea_warping

Purpose

Short-term Gaussianization over a sliding window (a.k.a feature warping)

Synopsis

Fea = fea_warping(fea, win)

Description

This routine warps the distribution of the cepstral feature streams in *fea* to the standard normal distribution (i.e., $\mathcal{N}(0,1)$) to mitigate the effects of (locally) linear channel mismatch. This is specifically useful because the distribution of cepstral feature streams is often modeled by Gaussians. The code assumes that there is one observation per column.

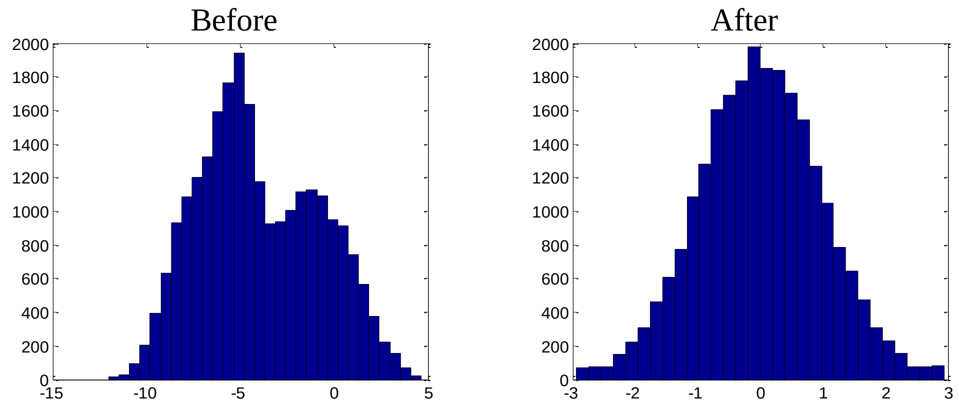
The normalization is performed over a sliding window that typically spans 301 frames (that is 3 seconds at a typical 100 Hz frame rate). The middle frame in the window is normalized based on its rank in a array of sorted feature values over the specified time interval. The length of the sliding window is specified through the scalar input *win* which must be an odd number.

Fea contains the normalized feature streams. Note that the feature warping should be applied after dropping the low SNR frames.

Examples

In this example we plot the distribution (histogram) of C_1 (first cepstral coefficient) in a sample feature file, before and after feature warping:

```
>> load('mfcc')
>> size(mfcc)

ans =

     39       24252
>> hist(mfcc(2,:), 30)
>> hist(fea_warping(mfc(2,:), 301), 30)
```



Notice that the overall distribution of the feature stream is warped to the standard normal distribution.

See Also

[1] J. Pelecanos and S. Sridharan, “Feature warping for robust speaker verification,” in *Proc. ISCA Odyssey*, Crete, Greece, Jun. 2001.

Purpose

Fit a Gaussian mixture model (GMM) to observations

Synopsis

gmm = gmm_em(dataList, nmix, final_niter, ds_factor, nworkers, gmmFilename)

Description

This function fits a GMM to acoustic feature vectors using binary splitting and expectation-maximization (EM). The input argument *dataList* can be either the name of an ASCII list containing feature file names (assuming one file per line), or a cell array containing features (assuming one feature matrix per cell). In case a list of files (the former option) is provided, the features must be saved in uncompressed HTK format. In case a cell array of features is provided, the function assumes one observation per column.

The scalar *nmix* specifies the number of desired components in the GMM, and must be a power of 2. A binary splitting procedure is used to boot up the GMM from a single component to *nmix* components. After each split the model is re-estimated several times using the EM algorithm. The number of EM iterations at each split is gradually increased from 1 to *final_niter* (scalar) for the nmix component GMM.

While booting up a GMM (from one to nmix components) on a large number of observations, it is practical to down-sample (sub-sample) the acoustic features. It is usually not necessary to re-estimate the model parameters at each split using all feature frames. This is due to the redundancy of speech frames and the fact that the analysis frames are overlapping. The scalar argument *ds_factor* specifies the down-sampling factor. The value assigned to the *ds_factor* is reset to one in the last two splits.

The scalar argument *nworkers* specifies the number of MATLAB parallel workers in the parfor loop. MATLAB by default sets the number of workers to the number of Cores (not virtual processors!) available on a computer. At the time of writing this report, MATLAB only supports a maximum of 12 workers on a local machine.

The optional argument *gmmFilename* (string) specifies the file name of GMM model to be saved. If this is specified, the GMM hyper-parameters (as structure fields, see below) are saved in a .mat file on disk.

The model hyper-parameters are returned in gmm which is a structure with three fields:

-	gmm.mu	component means
-	gmm.sigma	component covariance matrices
-	gmm.w	component weights

The code reports the accumulated likelihood of observations given the model in each EM iteration. It also reports the elapsed time for each iteration.

Purpose

Adapt a speaker specific GMM from a universal background model (UBM)

Synopsis

gmm = mapAdapt(dataList, ubm, tau, config, gmmFilename)

Description

This routine adapts a speaker specific GMM from a UBM using maximum *a posteriori* (MAP) estimation. The adaptation data is specified input via *dataList*, which should be either the name of an ASCII list containing feature file names (assuming one file per line), or a cell array containing features (assuming one feature matrix per cell). In case a list of files is provided, the features must be saved in uncompressed HTK format.

The input argument *ubm* can be either a file name (string) or a structure with UBM hyper-parameters (in form of gmm.mu, gmm.sigma, and gmm.w, see also gmm_em). The UBM file should be a .mat file with the same structure as above.

The code supports adaptation of all model hyper-parameters (i.e., means, covariance matrices, and weights). The input string parameter *config* is used to specify which parameters should be adapted. Any sensible combination of ‘m’, ‘v’, and ‘w’ is accepted (default is mean ‘m’). The MAP adaptation relevance factor is set via the scalar input *tau*.

The optional argument *gmmFilename* (string) specifies the file name of the adapted GMM model to be saved. If this is specified, the GMM hyper-parameters (as structure fields, see below) are saved in a .mat file on disk.

The model hyper-parameters are returned in *gmm*, which is a structure with three fields (i.e., gmm.mu, gmm.sigma, gmm.w).

See Also

[1] D.A. Reynolds, T.F. Quatieri, R.B. Dunn, “Speaker verification using adapted Gaussian mixture models”, *Digital Signal Processing*, vol. 10, pp. 19-41, Jan. 2000.

Purpose

Compute verification scores for GMM trials

Synopsis

scores = score_gmm_trials(models, tests, trials, ubmFilename)

Description

This function computes the verification scores for trials specified in the input argument trials. The scores are computed as the log-likelihood ratio between the given speaker models and the UBM given the test observations.

The input argument *models* is a cell array containing the speaker models. The speaker models are GMM structures with fields described before (see also gmm_em).

The input argument *tests* is also cell array that should either contain the feature matrices or the feature file names.

The input argument *trials* is a 2-dimensional array with 2 columns. The first column contains the numerical model IDs (1 ... N, assuming N models), while the second column contains the numerical test IDs (1 … M, assuming M test files). Each row of the two-column array specifies a model-test trial (e.g., [3 10] means model number 3 should be tested against test segment 10).

The input argument *ubmFilename* can be either a file name (string) or a structure with UBM hyper-parameters (in form of gmm.mu, gmm.sigma, and gmm.w, see also gmm_em). The UBM file should be a .mat file with the same structure as above.

The verification likelihood ratios are returned in *scores* (one score per trial).

See Also

[1] D.A. Reynolds, T.F. Quatieri, R.B. Dunn, “Speaker verification using adapted Gaussian mixture models,” *Digital Signal Processing*, vol. 10, pp. 19-41, Jan. 2000.

Purpose

Compute the sufficient statistics for observations given the UBM

Synopsis

[N, F] = compute_bw_stats(fea, ubm, statFilename)

Description

This function computes the zeroth (N) and first (F) order sufficient statistics (Baum-Welch statistics) for observations given a UBM:

$$N_g = \sum_t p(g|\mathbf{O}_t, \lambda_{ubm})$$

$$\boldsymbol{F}_g = \sum_t \mathbf{O}_t \cdot p(g|\mathbf{O}_t, \lambda_{ubm}) - \mathbf{m}_{\boldsymbol{g}} \cdot N_g$$

where $p(g|\mathbf{O}_t, \lambda_{ubm})$ denotes the posterior probability of the UBM mixture component g given the observations $\mathbf{O}_t$.

The input argument *fea* can be either a feature file name (string) or a feature matrix with one observation per column. In case a file name is provided, the features must be saved in uncompressed HTK format.

The input argument *ubm* can be either a file name (string) or a structure with UBM hyper-parameters (in form of gmm.mu, gmm.sigma, and gmm.w, see also gmm_em). The UBM file should be a .mat file with the same structure as above.

The optional argument *statFilename* (string) specifies the stat file name to be saved. If this is specified, the statistics are saved in a .mat file on disk. The zeroth order statistic, N, is a one-dimensional array with nmix elements (i.e., the number of Gaussian components from the UBM). The first order statistic, F, is also a one-dimensional array with nmix × ndim components (i.e., the supervector dimension). The first order statistic is centered.

See Also

[1] N. Dehak, P. Kenny, R. Dehak, P. Dumouchel, and P. Ouellet, “Front-end factor analysis for speaker verification,” *IEEE TASLP*, vol. 19, pp. 788-798, May 2011.

[2] P. Kenny, "A small footprint i-vector extractor," in *Proc. ISCA Odyssey, The Speaker and Language Recognition Workshop*, Singapore, Jun. 2012.

Purpose

Learn a total variability subspace from the observations

Synopsis

T = train_tv_space(dataList, ubm, tv_dim, niter, nworkers, tvFilename)

Description

This routine uses EM to learn a total variability subspace from the observations. Technically, assuming a factor analysis (FA) model of the form:

$$\mathbf{M} = \mathbf{m} + \mathbf{T} \cdot \mathbf{x}$$

for mean supervectors, $\mathbf{M}$, the code computes the maximum likelihood estimate (MLE) of the factor loading matrix $\mathbf{T}$ (a.k.a. the total variability subspace). Here, $\mathbf{M}$ is the adapted mean supervector, $\mathbf{m}$ is the UBM mean supervector, and $\mathbf{x} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ is a vector of total factors (a.k.a. the i-vector).

The observations are assumed to be in form of sufficient statistics computed with the background model (UBM). The input argument *dataList* is either the name (string) of an ASCII list containing statistics file names (one file per line), or a cell array of concatenated stats that is the zeroth order stats, N, appended with the first order stats, F, in a column vector.

The input argument *ubm* can be either a file name (string) or a structure with UBM hyper-parameters (in form of gmm.mu, gmm.sigma, and gmm.w, see also gmm_em). The UBM file should be a .mat file with the same structure as described above.

The scalar input *tv_dim* specifies the dimensionality of the total subspace. The *tv_dim* values typically range from 400 to 800. The total subspace is learned in an EM framework. The number of EM iterations can be set using the scalar *niter* argument. The accumulation of statistics in each EM iteration can be sped up using a parfor loop. The scalar argument *nworkers* specifies the number of MATLAB parallel workers in the parfor loop.

The optional argument *tvFilename* (string) specifies the output file name. If this is specified, the total subspace matrix is saved in a .mat file on disk.

See Also

[1] D. Matrouf, N. Scheffer, B. Fauve, J.-F. Bonastre, “A straightforward and efficient implementation of the factor analysis model for speaker verification,” in *Proc. INTERSPEECH*, Antwerp, Belgium, Aug. 2007, pp. 1242-1245.

[2] N. Dehak, P. Kenny, R. Dehak, P. Dumouchel, and P. Ouellet, “Front-end factor analysis for speaker verification,” *IEEE TASLP*, vol. 19, pp. 788-798, May 2011.

[3] P. Kenny, “A small footprint i-vector extractor,” in *Proc. ISCA Odyssey, The Speaker and Language Recognition Workshop*, Singapore, Jun. 2012.

[4] “Joint Factor Analysis Matlab Demo,” 2008. [Online]. Available: http://speech.fit.vutbr.cz/software/joint-factor-analysis-matlab-demo/.

Purpose

Compute the identity vector (i-vector) for observations

Synopsis

x = extract_ivector(stat, ubm, tv_matrix, ivFilename)

Description

This function computes the i-vector for observations as the mean (conditional expectation) of the posterior distribution of the latent variable **x**. The observations are assumed to be in form of sufficient statistics computed with the background model (UBM). The input argument *stat* is either the name (string) of .mat file containing the statistics or a one-dimensional array of concatenated stats, that is the zeroth order stats, N, appended with the first order stats, F, in a column vector.

The input argument *ubm* can be either a file name (string) or a structure with UBM hyper-parameters (specifying gmm.mu, gmm.sigma, and gmm.w, see also gmm_em). The UBM file should be a .mat file with this same structure.

The i-vector extractor *tv_matrix* can be specified either with a file name (string) or a matrix.

The code can optionally save the i-vectors into a .mat file. The input argument *ivFilename* specifies the output file name. The i-vector is returned in **x**, a column vector of size tv_dim (see also train_tv_space).

See Also

[1] D. Matrouf, N. Scheffer, B. Fauve, J.-F. Bonastre, “A straightforward and efficient implementation of the factor analysis model for speaker verification,” in *Proc. INTERSPEECH*, Antwerp, Belgium, Aug. 2007, pp. 1242-1245.

[2] P. Kenny, “A small footprint i-vector extractor,” *in Proc. ISCA Odyssey, The Speaker and Language Recognition Workshop*, Singapore, Jun. 2012.

[3] N. Dehak, P. Kenny, R. Dehak, P. Dumouchel, and P. Ouellet, “Front-end factor analysis for speaker verification,” *IEEE TASLP*, vol. 19, pp. 788-798, May 2011.

Purpose

Linear discriminant analysis (LDA) using Fisher criterion

Synopsis

[V, D] = lda(data, labels)

Description

This routine computes a linear transformation that maximizes the between class variation while minimizing the within class variances. It uses the Fisher criterion for this purpose.

Technically, the Fisher criterion to be maximized is in the form:

$$J(\boldsymbol{V}) = \frac{\boldsymbol{V}^{\boldsymbol{T}}\boldsymbol{\Sigma}_{\boldsymbol{b}}\boldsymbol{V}}{\boldsymbol{V}^{\boldsymbol{T}}\boldsymbol{\Sigma}_{\boldsymbol{w}}\boldsymbol{V}}$$

where $\boldsymbol{\Sigma}_{\boldsymbol{b}}$ and $\boldsymbol{\Sigma}_{\boldsymbol{w}}$ are between- and within-class covariance matrices, respectively. The above relationship is a Rayleigh quotient, therefore the solution, $\boldsymbol{V}$, is the generalized eigenvectors of

$$\boldsymbol{\Sigma}_{\boldsymbol{b}}\boldsymbol{V} = \boldsymbol{D}\boldsymbol{\Sigma}_{\boldsymbol{w}}\boldsymbol{V}.$$

The input argument *data* is a two-dimensional array that specifies the data matrix, assuming one observation per column. Class labels for observations in the data matrix can be specified via *labels* which is a one dimensional array (or cell array) with one numerical (or string) element per class.

The LDA transformation matrix (generalized eigenvectors stored in columns) is returned in V. Note that the maximum number of columns in V is the minimum of dimensionality of observations and the number of unique class minus 1. The generalized eigenvalues are returned in D.

See Also

[1] K. Fukunaga, *Introduction to Statistical Pattern Recognition*. 2nd ed. New York: Academic Press, 1990, ch. 10.

Purpose

Learn a Gaussian probabilistic LDA (PLDA) from observations

Synopsis

plda = gplda_em(data, spk_labs, nphi, niter)

Description

This function uses EM to learn a Gaussian PLDA model from observations. The observations are i-vectors computed from the development set. The input argument *data* contains the i-vectors (one observation per column). The development i-vectors are internally centered (mean is removed), length-normalized, and whitened before modeling.

Technically, assuming a factor analysis (FA) model of the i-vectors of the form:

$$\mathbf{x} = \mathbf{m} + \boldsymbol{\Phi} \cdot \mathbf{y} + \boldsymbol{\epsilon},$$

this routine computes the maximum likelihood estimate (MLE) of the factor loading matrix $\boldsymbol{\Phi}$ (a.k.a. the Eigenvoice subspace). Here, $\mathbf{x}$ is the i-vector, $\mathbf{m}$ is the mean of training i-vectors, and $\mathbf{y} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ is a vector of latent factors. The full covariance residual noise term $\boldsymbol{\epsilon}$ explains the variability not captured through the latent variables.

The input argument *spk_labs* determines the class (i.e., speaker) labels for observations in the data matrix. *spk_labs* is a one-dimensional array (or cell array) with one numerical (or string) element per class.

The dimensionality of the Eigenvoice subspace is specified using scalar argument *nphi*. The scalar input *niter* determines the number of EM iteration for learning the PLDA model.

The Gaussian PLDA model is returned in plda, which is a structure with fields:

-	plda.Phi	Eigenvoice matrix
-	plda.Sigma	covariance matrix of the residual noise (full)
-	plda.M	mean of the development i-vectors
-	plda.W	whitening transformation

See Also

[1] S.J.D. Prince and J.H. Elder, “Probabilistic linear discriminant analysis for inferences about identity,” in *Proc. IEEE ICCV*, Rio de Janeiro, Brazil, Oct. 2007.

[2] D. Garcia-Romero and C.Y. Espy-Wilson, “Analysis of i-vector length normalization in speaker recognition systems,” in *Proc. INTERSPEECH*, Florence, Italy, Aug. 2011, pp. 249-252.

[3] P. Kenny, “Bayesian speaker verification with heavy-tailed priors,” *in Proc. Odyssey, The Speaker and Language Recognition Workshop*, Brno, Czech Republic, Jun. 2010.

Purpose

Compute verification scores for i-vector trials using the PLDA model

Synopsis

scores = score_gplda_trials(plda, model_iv, test_iv)

Description

This function computes the verification scores for all possible model-test i-vector trials. The scores are computed as the "batch" log-likelihood ratio between the same (H_1) versus different (H_0) speaker models hypotheses:

$$llr = \ln \frac{p(\mathbf{x}_1, \mathbf{x}_2 | H_1)}{p(\mathbf{x}_1 | H_0) \cdot p(\mathbf{x}_2 | H_0)}$$

The i-vectors, **x,** are modeled with a Gaussian PLDA provided via *plda*. The input *plda* model is a structure with PLDA hyperparameters (i.e., plda.Phi, plda.Sigma, plda.M, and plda.W).

Before computing the verification scores, the enrollment and test i-vectors are internally mean- and length-normalized and whitened. The input arguments *model_iv* and *test_iv* are two-dimensional arrays (one observation per column) containing unprocessed enrollment and test i-vectors, respectively.

The likelihood ratio test has a linear and closed form solution. Therefore, it is practical to compute the verification scores at once for all possible combination of model-test i-vectors, and then select a subset of scores according to a trial list. The output argument scores is a matrix that contains the verification scores for all possible trials.

See Also

[1] D. Garcia-Romero and C.Y. Espy-Wilson, "Analysis of i-vector length normalization in speaker recognition systems," in *Proc. INTERSPEECH,* Florence, Italy, Aug. 2011, pp. 249-252.

[2] P. Kenny, "Bayesian speaker verification with heavy-tailed priors," *in Proc. Odyssey, The Speaker and Language Recognition Workshop*, Brno, Czech Republic, Jun. 2010.

Purpose

Compute the equal error rate (EER) performance measure

Synopsis

[eer, dcf08, dcf10] = compute_eer(scores, labels, showfig)

Description

This routine computes the EER given the verification scores for target and impostor trials. The EER is calculated as the operating point on the detection error tradeoff (DET) curve where the false-alarm and missed-detection rates are equal.

The input argument *scores* is a one-dimensional array containing the verification scores for all target and impostor trials. The trial labels are specified via the argument *labels* which can be a one-dimensional binary array (0's and 1's for impostor and target), or a cell array with "target" and "impostor" string labels.

The logical switch *showfig* (false | true) is used to instruct the code as to whether the DET curve should be plotted.

The EER is returned in *eer* (in percent). Additionally, the minimum detection cost functions (DCF) are computed and returned if the optional output arguments *dcf08* and *dcf10* are specified. The dcf08 (×100) is computed according to the NIST SRE 2008 cost parameters, while the dcf10 (×100) is calculated based on the NIST SRE 2010 parameters.

See Also

[1] "The NIST year 2008 speaker recognition evaluation plan," 2008. [Online]. Available: http://www.nist.gov/speech/tests/sre/2008/sre08_evalplan_release4.pdf

[2] "The NIST year 2010 speaker recognition evaluation plan," 2010. [Online]. Available: http://www.itl.nist.gov/iad/mig/tests/sre/2010/NIST_SRE10_evalplan.r6.pdf

Demos

Introduction

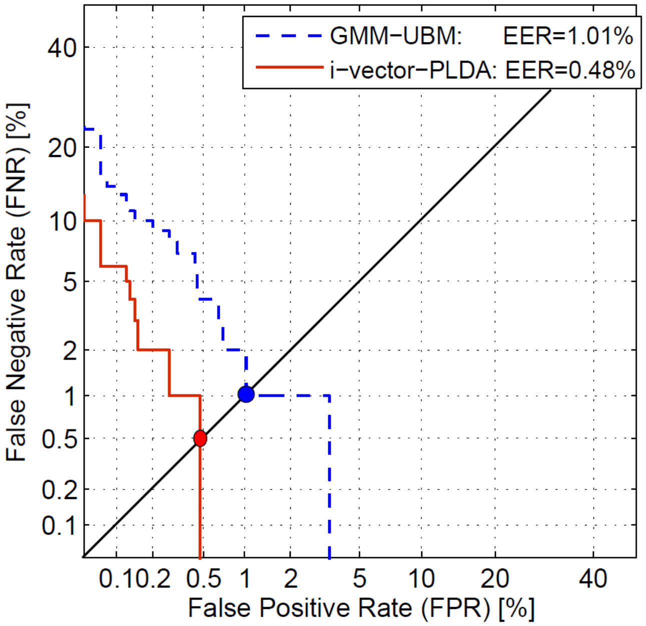
We demonstrate the use of this toolbox with two different kinds of demonstrations. The first example demonstrates that this toolbox can achieve state-of-the-art performance on a standard identity task, using the TIMIT corpus. The second demonstration uses artificial data to show the simplest usage cases for the toolbox.

TIMIT Task

In order to demonstrate how the tools in the Identity Toolbox work individually and when combined together, we provide two sample demos using the TIMIT corpus: 1) demo_gmm_ubm and 2) demo_ivector_plda. The first and the second demo show how to use the tools to run speaker recognition experiments in a GMM-UBM and i-vector frameworks, respectively.

A relatively small scale speaker verification task has been designed using speech material from the TIMIT corpus. There are a total of 630 (192 female and 438 male) speakers in TIMIT, from which 530 speakers have been selected for background model training and the remaining 100 (30 female and 70 male) speakers are used for tests. There are 10 short sentences per speaker in TIMIT. For background model training all sentences from all 530 speakers (i.e., 5300 speech recordings in total) are used. For speaker-specific model training 9 out of 10 sentences per speaker are selected and the remaining 1 sentence is kept for tests. Verification trials consist of all possible model-test combinations, resulting in a total of 10,000 trials (100 target versus 9900 impostor trials).

The figure below shows the detection error tradeoff (DET) curves for the two systems: GMM-UBM (solid) and i-vector-PLDA (dashed). Also shown in the figure are the system performances on the TIMIT task in terms of the EER. The EER operating points are circled as the intersection of a diagonal line with the DET curves.



- - GMM−UBM: EER=1.01%
— i−vector−PLDA: EER=0.48%
40
20
10
5
2
1
0.5
0.2
0.1
False Negative Rate (FNR) [%]
0.1
0.2
0.5
1
2
5
10
20
40
False Positive Rate (FPR) [%]

Demos

Artificial Task

A small-scale task generates artificial features for 20 speakers. Each speaker has 10 sessions (channels) and each session is 1000 frames long (which translates to 10 seconds assuming a frame rate of 100 Hz).

The following script (demo_create_data.m) generates the features used in the following demonstrations:

```
nSpeakers = 20;
nDims = 13;             % dimensionality of feature vectors
nMixtures = 32;         % How many mixtures used to generate data
nChannels = 10;         % Number of channels (sessions) per speaker
nFrames = 1000;         % Frames per speaker (10 seconds assuming 100 Hz)
nWorkers = 1;           % Number of parfor workers, if available
rng('default');         % To promote reproducibility.

% Pick random centers for all the mixtures.
mixtureVariance = .10;
channelVariance = .05;
mixtureCenters = randn(nDims, nMixtures, nSpeakers);
channelCenters = randn(nDims, nMixtures, nSpeakers, nChannels)*.1;
trainSpeakerData = cell(nSpeakers, nChannels);
testSpeakerData = cell(nSpeakers, nChannels);
speakerID = zeros(nSpeakers, nChannels);

% Create the random data. Both training and testing data have the same
% layout.
for s=1:nSpeakers
    trainSpeechData = zeros(nDims, nMixtures);
    testSpeechData = zeros(nDims, nMixtures);
    for c=1:nChannels
        for m=1:nMixtures
            % Create data from mixture m for speaker s
            frameIndices = m:nMixtures:nFrames;
            nMixFrames = length(frameIndices);
            trainSpeechData(:,frameIndices) = ...
                randn(nDims, nMixFrames)*sqrt(mixtureVariance) + ...
                repmat(mixtureCenters(:,m,s),1,nMixFrames) + ...
                repmat(channelCenters(:,m,s,c),1,nMixFrames);
            testSpeechData(:,frameIndices) = ...
                randn(nDims, nMixFrames)*sqrt(mixtureVariance) + ...
                repmat(mixtureCenters(:,m,s),1,nMixFrames) + ...
                repmat(channelCenters(:,m,s,c),1,nMixFrames);
        end
        trainSpeakerData{s, c} = trainSpeechData;
        testSpeakerData{s, c} = testSpeechData;
        speakerID(s,c) = s;                 % Keep track of who this is
    end
end
```

After generating the features are generated we can use them to train and test GMM-UBM and i-vector speaker recognition systems.

GMM-UBM Demo

There are four steps involved in training and testing a GMM-UBM speaker recognition system:

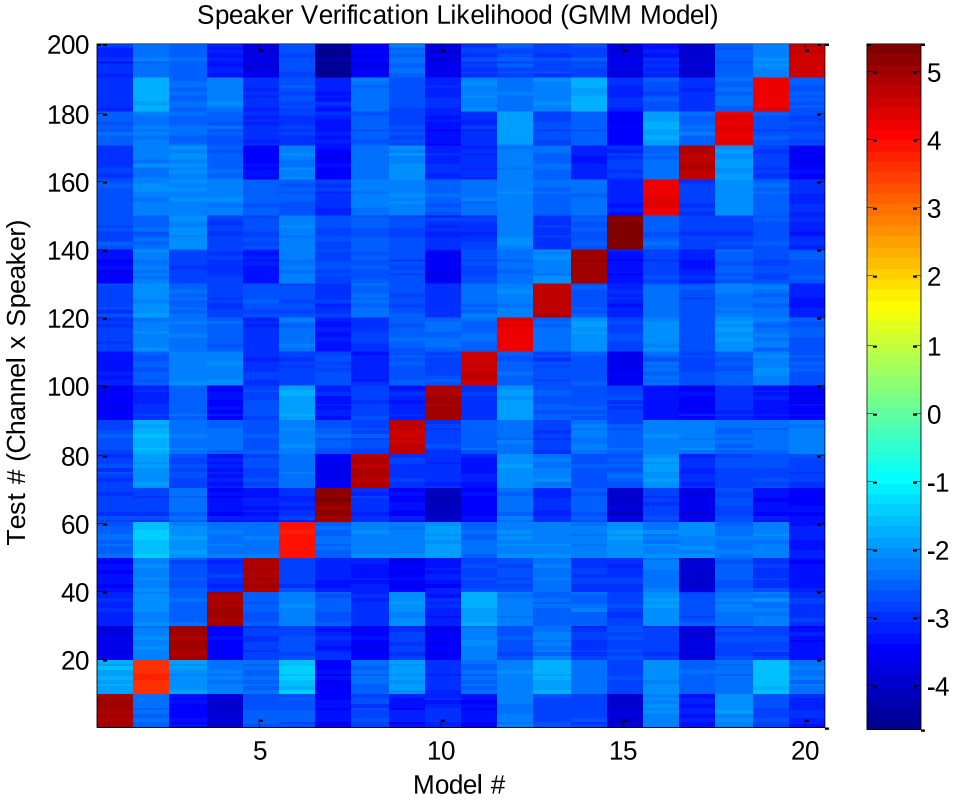
1. Training a UBM from the background data
2. MAP adapting speaker models from the UBM using enrollment data
3. Scoring verification trials
4. Computing the performance measures (e.g., confusion matrix and EER)

The following MATLAB script (demo_gmm_ubm_artificial.m) generates a UBM speaker-recognition model and tests it:

```
%%
rng('default')
% Step1: Create the universal background model from all the
% training speaker data
nmix = nMixtures;        % In this case, we know the # of mixtures needed
final_niter = 10;
ds_factor = 1;
ubm = gmm_em(trainSpeakerData(:), nmix, final_niter, ds_factor, ...
       nWorkers);

%%
% Step2: Now adapt the UBM to each speaker to create GMM speaker model.
map_tau = 10.0;
config = 'mwv';
gmm = cell(nSpeakers, 1);
for s=1:nSpeakers
    gmm{s} = mapAdapt(trainSpeakerData(s, :), ubm, map_tau, config);
end

%%
% Step3: Now calculate the score for each model versus each speaker's
% data.
% Generate a list that tests each model (first column) against all the
% testSpeakerData.
trials = zeros(nSpeakers*nChannels*nSpeakers, 2);
answers = zeros(nSpeakers*nChannels*nSpeakers, 1);
for ix = 1 : nSpeakers,
    b = (ix-1)*nSpeakers*nChannels + 1;
    e = b + nSpeakers*nChannels - 1;
    trials(b:e, :)  = [ix * ones(nSpeakers*nChannels, 1), ...
       (1:nSpeakers*nChannels)'];
    answers((ix-1)*nChannels+b : (ix-1)*nChannels+b+nChannels-1) = 1;
```

```
end

gmmScores = score_gmm_trials(gmm, reshape(testSpeakerData', ...
       nSpeakers*nChannels,1), trials, ubm);

%%
% Step4: Now compute the EER and plot the DET curve and confusion matrix
imagesc(reshape(gmmScores,nSpeakers*nChannels, nSpeakers))
title('Speaker Verification Likelihood (GMM Model)');
ylabel('Test # (Channel x Speaker)'); xlabel('Model #');
colorbar; drawnow; axis xy
figure
eer = compute_eer(gmmScores, answers, false);
```

This generates the confusion matrix (image) shown below. (The EER curve is blank because recognition is perfect at these noise levels.)



i-vector Demo

There are five steps involved in training and testing an i-vector speaker recognition system:

1. Training a UBM from the background data
2. Learning a total variability subspace from background statistics
3. Training a Gaussian PLDA model with development i-vectors
4. Scoring verification trials with model and test i-vectors
5. Computing the performance measures (e.g., EER and confusion matrix)

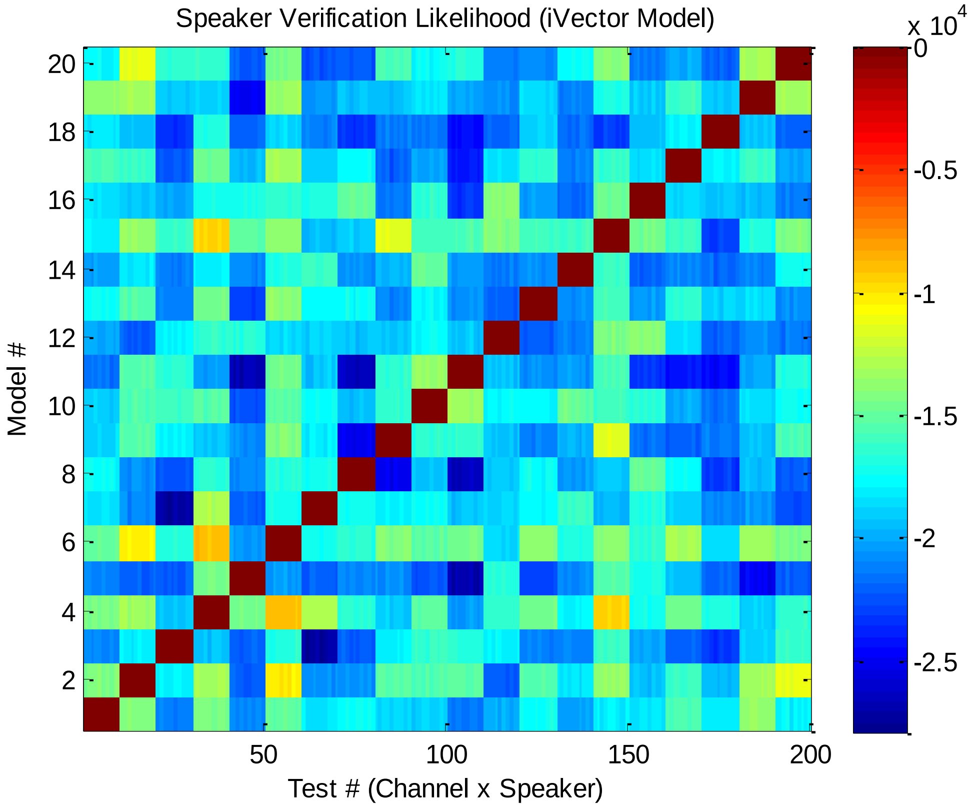
The following MATLAB script (demo_ivector_plda_artificial.m) demonstrates the use of the i-vector code and shows simple results:

```
%%
rng('default');
% Step1: Create the universal background model from all the
% training speaker data
nmix = nMixtures;% In this case, we know the # of mixtures needed
final_niter = 10;
ds_factor = 1;
ubm = gmm_em(trainSpeakerData(:), nmix, final_niter, ...
      ds_factor, nWorkers);


%%
% Step2.1: Calculate the statistics needed for the iVector model.
stats = cell(nSpeakers, nChannels);
for s=1:nSpeakers
    for c=1:nChannels
        [N,F] = compute_bw_stats(trainSpeakerData{s,c}, ubm);
        stats{s,c} = [N; F];
    end
end

% Step2.2: Learn the total variability subspace from all the
speaker data.
tvDim = 100;
niter = 5;
T = train_tv_space(stats(:), ubm, tvDim, niter, nWorkers);
%
% Now compute the ivectors for each speaker and channel.
% The result is size
%   tvDim x nSpeakers x nChannels
devIVs = zeros(tvDim, nSpeakers, nChannels);
for s=1:nSpeakers
    for c=1:nChannels
```

```
        devIVs(:, s, c) = extract_ivector(stats{s, c}, ubm, T);
    end
end

%%
% Step3.1: Now do LDA on the iVectors to find the dimensions that
% matter.
ldaDim = min(100, nSpeakers-1);
devIVbySpeaker = reshape(devIVs, tvDim, nSpeakers*nChannels);
[V,D] = lda(devIVbySpeaker, speakerID(:));
finalDevIVs = V(:, 1:ldaDim)' * devIVbySpeaker;

% Step3.2: Now train a Gaussian PLDA model with development
% i-vectors
nphi = ldaDim;                  % should be <= ldaDim
niter = 10;
pLDA = gplda_em(finalDevIVs, speakerID(:), nphi, niter);

%%
% Step4.1: OK now we have the channel and LDA models. Let's build
% actual speaker
% models. Normally we do that with new enrollment data, but now
% we'll just reuse the development set.
averageIVs = mean(devIVs, 3);   % Average IVs across channels.
modelIVs = V(:, 1:ldaDim)' * averageIVs;


% Step4.2: Now compute the ivectors for the test set
% and score the utterances against the models
testIVs = zeros(tvDim, nSpeakers, nChannels);
for s=1:nSpeakers
    for c=1:nChannels
        [N, F] = compute_bw_stats(testSpeakerData{s, c}, ubm);
        testIVs(:, s, c) = extract_ivector([N; F], ubm, T);
    end
end
testIVbySpeaker = reshape(permute(testIVs, [1 3 2]), ...
                            tvDim, nSpeakers*nChannels);
finalTestIVs = V(:, 1:ldaDim)' * testIVbySpeaker;

%%
% Step5: Now score the models with all the test data.
ivScores = score_gplda_trials(pLDA, modelIVs, finalTestIVs);
imagesc(ivScores)
title('Speaker Verification Likelihood (iVector Model)');
xlabel('Test # (Channel x Speaker)'); ylabel('Model #');
colorbar; axis xy; drawnow;

answers = zeros(nSpeakers*nChannels*nSpeakers, 1);
```

```
for ix = 1 : nSpeakers,
    b = (ix-1)*nSpeakers*nChannels + 1;
    answers((ix-1)*nChannels+b : (ix-1)*nChannels+b+nChannels-1)
= 1;
end

ivScores = reshape(ivScores', nSpeakers*nChannels* nSpeakers, 1);
figure;
eer = compute_eer(ivScores, answers, false);
```

This generates the confusion matrix (image) shown below:


Speaker Verification Likelihood (iVector Model)
x 10^4
Model #
Test # (Channel x Speaker)