

Recent Improvements on ILP-based Clustering for Broadcast News Speaker Diarization

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Abstract

First we propose a reformulation of the Integer Linear Programming (ILP) clustering method we introduced at Odyssey 2012, for broadcast news Speaker Diarization. We included an overall distance filtering which drastically reduce the complexity of the problems to be solved. Then, we present a clustering approach where the problem is globally considered as a connected graph. The search for Star-graph sub-components allows the system to solve almost the whole clustering problem: only 8 of the 28 shows that compose the January 2013 test corpus of the REPERE 2012 French evaluation campaign, on which the experiments were conducted, were processed with the ILP clustering. Compared to the original formulation of the ILP clustering problem, our contribution lead to a reduction of the number of variables in the ILP problem, from 1743 to 53 on average, and a reduction of the number of constraints, from 3449 to 53 on average. The graph content clustering method appears to be an interesting alternative to the current clustering methods, since its results are better than that of the state of the art approaches like GMM-based HAC (15.18% against 16.22% DER).

1. Introduction

The speaker diarization task plays an important role in many speech processing applications, such as automatic transcription, speaker identification, and multimedia indexing. Its purpose is to automatically annotate the temporal regions of an audio recording with speaker labels, in order to answer the well-known question “Who spoke when?”. This task has been defined by the NIST in the context of the *Rich Transcription* evaluation campaigns as the partitioning of an input audio stream into segments, and the clustering of those segments according to the speakers. Speaker diarization is carried out without any *a priori* knowledge about speakers: neither the number of speakers, their identities, nor samples of their voices are available.

Speaker diarization systems dedicated to broadcast news are usually based on several segmentation and clustering steps. The state of the art clustering methods used so far rest on the hierarchical agglomerative clustering (HAC) approach, which iteratively merges the two closest clusters until the similarity between the two candidate clusters is positive. Systems using this bottom up approach along with Gaussian Mixture Models (GMMs) to model the speakers, obtained good results in various broadcast news evaluation campaigns, such as REPERE [1], Albayzin [2], ESTER2 [3] and RT-04F [4]. However, the HAC/GMM approach suffers from two main drawbacks. The first is the computational time: a new GMM has to be computed each time a merge occurs, and the similarities between this new GMM and the others must be estimated. In order to save time, the new GMM can be estimated using the saved sta-

tistical accumulators from the merged clusters. But no such shortcut is available for the time-consuming similarity estimation step. The second drawback is the error propagation: HAC algorithm is not able to globally deal with the clustering problem. Although merges are decided according to the best similarity between the candidate clusters, this is done only locally. Therefore, an incorrect merge will be propagated until the end of the process, which may lead to some other incorrect merges, and may ultimately increase the diarization error rate (DER).

We recently proposed a global optimization framework in order to overcome these drawbacks [5]. In our approach, the clusters (speakers) are modeled by i-vectors, which have become the state of the art in the Speaker Verification field. We expressed the clustering problem as an Integer Linear Programming (ILP) problem, in which all of the clusters are processed simultaneously (as opposed to the HAC approach in which clusters are processed sequentially). The objective solving function of our ILP clustering aims to minimize both the number of clusters and the dispersion within each cluster, and this can be quickly solved using an ILP solver. This global optimization framework achieved better results than the HAC/GMM approach, on broadcast news data, in terms of DER and computation time [6]. The ILP clustering approach has also been investigated in [7] and [8], as part of the REPERE [1] evaluation campaign.

In this paper, we give a reformulation of the ILP clustering problem to reduce solving complexity, by removing unnecessary variables and constraints. Then, we introduce a graph-content speaker clustering approach. We first present the data on which experiments were performed, in section 2. In section 3, we give a presentation of the speaker diarization architecture. We focused on the HAC/GMM and ILP/i-vector clustering approaches, and we reproduced the experiments as presented in [5], with different data. In section 4, we introduce the changes made towards the ILP clustering formulation, in order to reduce the number of variables and constraints. We then present a speaker clustering approach where the problem is globally considered as a connected graph. The search for connected sub-components allows us to solve almost the whole clustering problem. Only a few independent sub-components have to be solved using a clustering algorithm like the ILP approach. Experiments and discussion on the methods and the results are given in section 5.

2. Data

The experiments presented in this paper are performed on the test corpus of the REPERE 2012 French evaluation campaign [9]. This campaign is in the field of multimedia people recognition in television documents. The challenge was to answer the questions “who is speaking?” and “who is seen?” at any time

during the videos. One of the sub-tasks was Speaker Diarization.

The January 2013 test corpus is composed of 28 TV shows recorded from the French TV channels BFM and LCP. The corpus is balanced between prepared speech, with 7 broadcast news TV programs, and spontaneous speech, with 21 political discussions or street interviews. Only 3 hours of the recordings are annotated.

3. Speaker diarization architecture

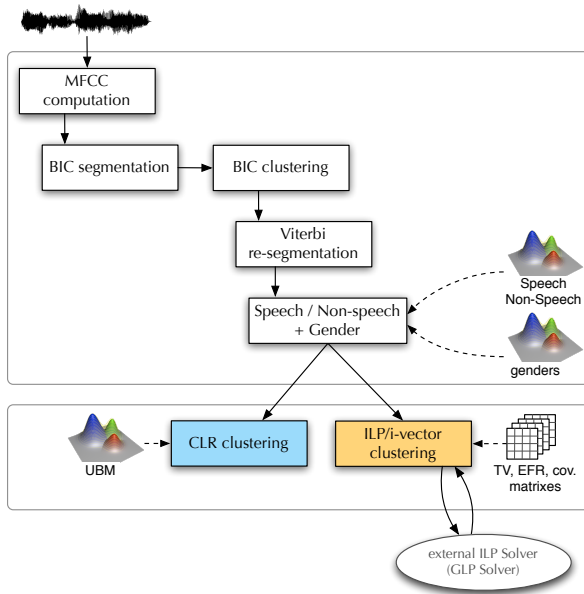


Figure 1: Diarization steps of the speaker diarization systems used to conduct experiments in this paper.

Experiments were carried out using the *LIUM_SpkDiarization* toolkit¹ [10]. This speaker diarization system, which was originally developed during the ESTER1 evaluation campaign [11], has achieved the best or second best results in the speaker diarization task on French broadcast news evaluation campaigns, such as ESTER2, ETAPE (2011) [12] and REPERE (January 2012, 2013 and 2014) [1].

As presented in Figure 1, the diarization system is based on an acoustic segmentation and a hierarchical agglomerative clustering using the Bayesian Information Criterion (BIC), both as a similarity measure between clusters (speakers), and as a stop criterion for the merging process. In this clustering, speakers are modeled with full-covariance matrix Gaussian distributions. Segment boundaries are adjusted through a Viterbi decoding using 8-component GMMs learned on the data of each speaker via the Expectation-Maximization (EM) algorithm. Another Viterbi decoding is carried out to remove non-speech areas. This decoding relies on 8 one-state HMMs represented by 64-component GMMs, trained by EM on ESTER1 training data [11]. Gender (male / female) and bandwidth (nar-

row / wide band) detection is performed using 4×128 diagonal component GMMs trained on 1 hour of speech from the ESTER1 training corpus (there is 1 GMM for each of the combinations gender-bandwidth). Segmentation, clustering, and decoding are performed using 12 MFCC parameters, supplemented with energy.

At this point, each cluster is supposed to represent a single speaker (clustering purity is very high); however, several clusters can be related to the same speaker. A final clustering stage, which consists either in a HAC or an ILP clustering, is then performed in order to obtain a one-to-one relationship between clusters and speakers.

3.1. HAC clustering with GMMs

In this clustering stage, speakers are processed separately according to the gender previously detected. Speakers can now be modeled with GMMs, thanks to the high purity clustering resulting from the previous BIC-based HAC (the threshold λ is equal to 3). In the previous steps, features were not normalized because the channel contribution was useful to differentiate the speakers. In this clustering step, the channel contribution is removed with a normalization by mean and variance. Speaker models are obtained for each cluster, by applying a Maximum A Posteriori (MAP) adaptation on a Universal Background Model (UBM). The 256 UBM components used as a base (one for each gender) result from the concatenation of the two bandwidth-dependent 128 component GMMs used earlier (male/narrowband, male/wideband to process male clusters, and female/narrowband, female/wideband to process female clusters). This HAC uses the Cross-Likelihood Ratio (CLR) [13] to estimate the similarity between clusters, and the clustering process stops when the CLR gets higher than a threshold determined empirically. This system, including this HAC/GMM clustering, as well as the previous steps, is widely described in [14], and is very close to that of LIMSI [15].

3.2. ILP clustering with i-vectors

In this approach, which acts as an alternative to the HAC/GMM, clustering is expressed as an Integer Linear Programming problem. Speakers are modeled with i-vectors, and similarity between i-vectors is estimated with a Mahalanobis distance [5]. The i-vector approach has become the state of the art in the field of Speaker Verification [16]. The i-vectors reduce acoustic data of a speaker into a low-dimension vector by retaining only the most relevant information about that speaker. The i-vector approach was first adapted to speaker diarization using the *k-means* algorithm, using distances between i-vectors, to find utterances of speakers within a corpus where the number of speakers is known *a priori* [17]. In speaker diarization, the number of speakers is unknown.

According to the segmentation resulting from the gender detection, a 60-dimensional i-vector is extracted from each cluster along with a 1024 GMM-UBM trained on the ESTER1 data. The GMM-UBM and i-vectors are extracted using the Alize toolkit [18]. I-vectors are length-normalized in an iterative process [19, 20] using a sub-set of the ESTER1 training corpus. Extraction of acoustic features is performed using 19 MFCC parameters supplemented with the energy, as well as the first and second order derivatives. The clustering problem consists in jointly minimizing the number C of cluster centers chosen among the N i-vectors, as well as minimizing the dispersion of i-vectors within each cluster. The set $C \in \{1, \dots, N\}$ is to be automatically determined. The objective solving function of

¹<http://www-lium.univ-lemans.fr/en/content/liumspkdiation>

the ILP problem (eq. 1) is minimized subject to the following constraints:

$$\text{Minimize: } \sum_{k=1}^N x_{k,k} + \frac{1}{\delta} \sum_{k=1}^N \sum_{j=1}^N d(k,j) x_{k,j} \quad (1)$$

$$\text{Subject to: } x_{k,j} \in \{0, 1\} \quad k \in C, j \in C \quad (1.2)$$

$$\sum_{k=1}^N x_{k,j} = 1 \quad j \in C \quad (1.3)$$

$$x_{k,j} - x_{k,k} \leq 0 \quad k \in C, j \in C \quad (1.4)$$

$$d(k,j) x_{k,j} < \delta \quad k \in C, j \in C \quad (1.5)$$

Where $x_{k,k}$ (eq. 1) is a binary variable equal to 1 when the i-vector k is a center. The number of centers C is implicitly included in equation 1: indeed, $C = \sum_{k=1}^N x_{k,k}$. The distance $d(k,j)$ is computed using the *Mahalanobis* distance between i-vectors k and j . $1/\delta$ is a normalization factor. The binary variable $x_{k,j}$ is equal to 1 when the i-vector j is assigned to the center k . Each i-vector j will be associated with a single center k (eq. 1.3). Equation 1.4 ensures that the cluster k is selected if an i-vector is assigned to cluster k . The i-vector j associated with the center k (i.e. $x_{k,j} = 1$) must have a distance $d(k,j)$ shorter than the threshold δ empirically determined (eq. 1.5).

The ILP problem is solved by the *glpsol* solver included in the *GNU Linear Programming Toolkit*².

3.3. HAC/GMM vs. ILP/i-vector experiment

The results of experiments conducted on the January 2013 test corpus of the REPERE evaluation campaign (cf. section 2), with both HAC and ILP clustering methods, are given in Table 1. Although the data used here differs from that of the original ILP clustering formulation the results are consistent with [5].

HAC/GMM		ILP/i-vector	
Threshold	DER (%)	Distance δ	DER (%)
0.0	19.55	75	17.01
-0.1	18.80	80	16.60
-0.2	19.76	85	15.94
-0.3	17.57	90	15.45
-0.4	17.69	95	15.45
-0.5	17.83	100	15.03
-0.6	17.70	105	14.70
-0.7	16.22	110	15.56
-0.8	17.26	115	15.46
-0.9	17.44	120	15.33
-1.0	18.29	125	16.18

Table 1: Diarization Error Rate (DER), with several thresholds, for HAC clustering and ILP clustering, on the REPERE January 2013 test corpus.

The metric used to measure performance in the speaker diarization task is the Diarization Error Rate (DER). DER was introduced by NIST as the fraction of speaking time which is not attributed to the correct speaker, using the best matching

between references and hypothesis speaker labels. The scoring tool was developed by LNE³ as part of the ETAPE and the REPERE campaigns. The main difference between this scoring tool and the one from NIST is on the speaker hypothesis and reference mapping. The tool from LNE relies on the Hungarian algorithm, which gives an optimal solution for the problem of assignment in a $O(n^3)$ polynomial time, whereas the NIST tool uses an algorithm based on heuristics [21].

The DER obtained with the HAC/GMM clustering approach, with various CLR thresholds ranging from 0 to -1, is compared to the DER obtained with the ILP/i-vector clustering approach, with various δ thresholds ranging from 75 to 125.

The DER of the input segmentation for these two clustering experiments, which corresponds to the BIC-based HAC output ($\lambda = 3$), is 22.63%. The best result obtained with the HAC approach is 16.22% DER, with threshold -0.7. This result is a bit abnormal compared to the surrounding results which are close to 17.5%. The ILP clustering DERs are more stable with relation to thresholds, even if some irregular (but minor) variations occurred. The DERs obtained with the ILP/i-vector approach are still better than those of HAC/GMM, with a global DER oscillating around 15.5%.

4. Improvements on computation efficiency

The ILP problem is solved with the Branch and Bound (B&B) algorithm of the solver tool. B&B is a general algorithm to determine, in particular, the optimal solution of discrete optimization problems. This algorithm may result in a systematic enumeration of all possible solutions for a given problem, but an analysis of this problem can be done to discard the fruitless candidate solutions. Contrary to HAC, B&B algorithm is not executed in polynomial time and, in some cases, may lead to unreasonable processing durations (several hours). It is therefore essential, with this kind of algorithm, to formulate the problem by limiting the number of variables and constraints to deal with.

We first present a reformulation of the ILP clustering. This reformulation aims to reduce the number of binary variables and constraints given as input to the solver. The ILP problem can be restricted to the only binary variables $x_{k,j}$ for which $d(k,j) < \delta$. From that optimization, we considered the ILP clustering problem as the search for connected sub-components in a totally connected graph. Indeed, the matrix associating distances between clusters can be seen as a connected graph. Its simplification by removing the unnecessary edges, which correspond to the distances between the clusters (the graph nodes), allows the system to find connected sub-components. These sub-components correspond to independent speaker clustering problems to be processed.

4.1. ILP clustering with overall distance filtering

In the original formulation of the ILP clustering problem, as presented in section 3.2, we note that eq. 1.5 is the only equation where the constraint on the distance between clusters is expressed. This distance notion can be applied to each of the other constraints: the ILP problem can be restricted to the only binary variables $x_{k,j}$ for which $d(k,j) < \delta$, instead of freely expressing constraints on k and j . The distances between the i-vectors are necessarily computed before the ILP problem formulation; therefore, we propose to reformulate the objective solving function to be minimized subject to constraints as:

²<http://www.gnu.org/software/glpk/>

³The French National Laboratory of Metrology and Testing

let $C \in \{1 \dots N\}$, let $K_{j \in C} = \{k/d(k, j) < \delta\}$

$$\text{Minimize: } \sum_{k \in C} x_{k,k} + \frac{1}{\delta} \sum_{j \in C} \sum_{k \in K_j} d(k, j) x_{k,j} \quad (2)$$

$$\text{Subject to: } x_{k,j} \in \{0, 1\} \quad k \in K_j, j \in C \quad (2.2)$$

$$\sum_{k \in K_j} x_{k,j} = 1 \quad j \in C \quad (2.3)$$

$$x_{k,j} - x_{k,k} < 0 \quad k \in K_j, j \in C \quad (2.4)$$

Compared to the previous formulation of the ILP clustering, as expressed in section 3.2, eq. 1.5 is removed because distances are implicitly taken into account in eq. 2.2, eq. 2.3, and eq. 2.4, by using the set K_j in place of C .

Given a value j , the set K_j represents the set of possible values of k (taken between 1 and N) for which distances between clusters k and j are shorter than the δ threshold.

4.2. Speaker clustering as graph exploration

The matrix associating distances between clusters (i-vectors) can be interpreted as a graph, where the clusters are represented by the nodes, and the distances between the clusters are represented by the edges. The original formulation of the ILP problem (eq. 1) can be interpreted as a totally connected graph, as illustrated in the top scheme of Figure 2.

4.2.1. Decomposition into sub-components

The overall distance filtering we introduced in the ILP problem reformulation (eq. 2) can be applied to the totally connected graph of the original ILP clustering problem (eq. 1). The decomposition of that graph in connected sub-components splits the overall problem into several elementary sub-problems.

The totally connected graph can be simplified with the connectivity concept of the graph theory, by removing all the unnecessary edges corresponding to distances longer than the δ threshold (middle scheme of Figure 2). This simplification transforms the completely connected graph into a set of connected sub-components. These connected sub-components can easily be found by iteratively using the depth-first search algorithm. The resulting subgraphs, which constitute independent subproblems that can be processed separately, are composed of a reduced number of elements. In some cases, the subgraphs only consist in only a single node, which means that the corresponding speaker cluster can not be associated to any other cluster.

4.2.2. Search for Star subgraphs

All of the sub-components can be processed with a clustering algorithm to identify the cluster centers; however, most of the sub-component centers are obvious. The search of the cluster centers can be formulated as the search of Star-graphs in the set of connected sub-components (bottom scheme of Figure 2). A Star-graph is a special kind of tree composed of one central node attached to k leaves (with a single depth level). The complexity of the Star-graph search is done in $O(n^2)$, where n is the number of clusters for which $n - 1$ nodes are connected. If a sub-graph is a Star-graph, there is no need to perform a clustering: the central node corresponds to the center of the clus-

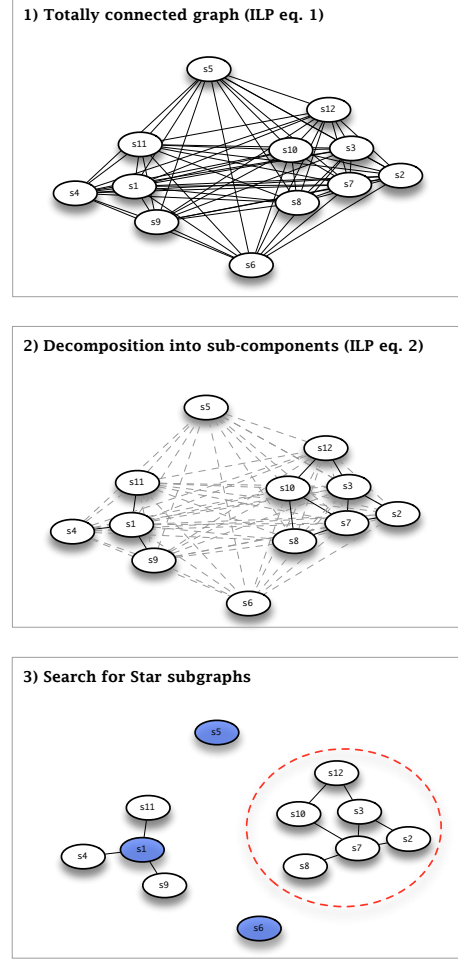


Figure 2: Graph representation of the speaker clustering problem: top, the completely connected graph; middle, the decomposition into sub-components; bottom, the search for Star subgraphs: the colored clusters are identified as centers, and the dashed circle indicates an ILP clustering to be performed.

tering sub-problem, so clusters corresponding to the leaves will be directly associated to that cluster center. If the sub-graph is neither a Star-graph, nor an isolated node (which is a particular Star-graph without leaves), then the clustering sub-problem has to be processed with a clustering algorithm. In our experiments, we used the ILP clustering formulation, as described in section 4.1, in order to compare the efficiency of the graph content clustering in terms of the number of variables and constraints.

5. Experiments and discussion

The experiments performed to observe the efficiency of the improvements consist in a comparison between each of the methods proposed in section 4. In Table 2, we present raw values and statistics (minimum, maximum, mean) on the number of binary variables and constraints of the ILP problems, for each of the shows in the corpus. The threshold was set to 105, since

Show name	# C	ILP (eq. 1)		ILP (eq. 2)		Sub-components + ILP (eq. 2)		Sub-components + Star-graphs + ILP (eq. 2)	
		# Var.	# Const.	# Var.	# Const.	# Var.	# Const.	# Var.	# Const.
BFMStory 2012-01-10	68	4624	9180	84	84	32	32	0 [†]	0 [†]
BFMStory 2012-01-23	76	5776	11476	86	86	24	24	0 [†]	0 [†]
BFMStory 2012-02-14	67	4489	8911	87	87	38	38	13	13
BFMStory 2012-02-20	77	5929	11781	95	95	36	36	10	10
CultureEtVous 2012-01-13	13	169	325	17	17	9	9	0 [†]	0 [†]
CultureEtVous 2012-01-16	15	225	435	23	23	14	14	0 [†]	0 [†]
CultureEtVous 2012-01-17	15	225	435	15	15	0*	0*	0 [†]	0 [†]
CultureEtVous 2012-01-18	17	289	561	17	17	0*	0*	0 [†]	0 [†]
CultureEtVous 2012-01-19	16	256	496	18	18	4	4	0 [†]	0 [†]
CultureEtVous 2012-02-14	18	324	630	18	18	0*	0*	0 [†]	0 [†]
CultureEtVous 2012-02-15	21	441	861	23	23	4	4	0 [†]	0 [†]
CaVousRegarde 2011-12-20	39	1521	3003	69	69	57	57	0 [†]	0 [†]
CaVousRegarde 2012-01-19	39	1521	3003	73	73	57	57	0 [†]	0 [†]
CaVousRegarde 2012-01-25	43	1849	3655	79	79	61	61	0 [†]	0 [†]
EntreLesLignes 2011-12-16	41	1681	3321	77	77	55	55	45	45
EntreLesLignes 2012-01-27	35	1225	2415	41	41	14	14	0 [†]	0 [†]
EntreLesLignes 2012-05-11	45	2025	4005	71	71	43	43	13	13
LCPIInfo13h30 2012-01-24	55	3025	5995	59	59	9	9	0 [†]	0 [†]
LCPIInfo13h30 2012-01-25	51	2601	5151	69	69	39	39	0 [†]	0 [†]
LCPIInfo13h30 2012-01-27	39	1521	3003	47	47	14	14	0 [†]	0 [†]
PileEtFace 2011-11-19	28	784	1540	52	52	38	38	25	25
PileEtFace 2011-12-01	30	900	1770	42	42	22	22	0 [†]	0 [†]
PileEtFace 2012-01-12	29	841	1653	41	41	24	24	0 [†]	0 [†]
PileEtFace 2012-01-19	42	1764	3486	72	72	48	48	18	18
PileEtFace 2012-01-26	38	1444	2850	70	70	55	55	27	27
TopQuestions 2012-01-25	33	1089	2145	41	41	19	19	0 [†]	0 [†]
TopQuestions 2012-02-14	26	676	1326	36	36	22	22	0 [†]	0 [†]
TopQuestions 2012-02-22	40	1600	3160	62	62	34	34	29	29
Minimum	-	169	325	15	15	0	0	0	0
Average	-	1743.36	3449	53	53	27.57	27.57	6.43	6.43
Maximum	-	5929	11781	95	95	61	61	45	45

Table 2: Number of variables (# Var.) and numbers of constraint (# Const.) for the 4 ILP methods in the problem submitted to the ILP solver (Results by show. #C is the number of clusters in the input diarization).

this value gives the best results with these data (*cf.* Table 1). The DER obtained is identical regardless of the method used (14.70% DER). Note that the number of variables and constraints are dependent on the number of clusters given as input (*cf.* column #C in Table 2).

Compared to the original formulation of the ILP clustering approach (*ILP (eq. 1)*), most of the binary variables and constraints have been removed thanks to the overall distance filtering method (*ILP (eq. 2)*). Splitting the overall ILP problem into sub-problems, using the sub-components decomposition method, reduces even more the number of variables and constraints (*Sub-components + ILP (eq. 2)*). Three of the shows do not need the ILP clustering (*cf.* * in Table 2). The reason is the distance between all the clusters of these shows are longer than the δ threshold, so, the related sub-graphs are composed of only a single node. The solution is so trivial that it is unnecessary to use the ILP clustering approach on the resulting subgraphs. Finally, the search for *Star-graphs* further more reduces the number of variables and constraints (*Sub-components + Star-graphs + ILP (eq. 2)*). 70% of the shows do not need to be processed with the ILP clustering (*cf.* † in Table 2), because their sub-graphs either consist in a single node, or are stars.

5.1. Reduction in number of variables and constraints

The numbers of binary variables and constraints presented in Table 2 were determined by reading the files containing ILP problems given to the solver tool. The purpose of the following

section is to explain these values according to the ILP formulations expressed in sub-sections 3.2 and 4.1.

Regarding the formulation of ILP (eq. 1) for a clustering composed of N clusters, there are N^2 binary variables and $2 \times N \times (N - 1) + N$ constraints. Equation 1.2 does not generate constraints in the problem, it is implicitly generated by the solver tool. Equation 1.3 generates a constraint for each cluster, hence N constraints. Equation 1.4 generates $N - 1$ constraints for each cluster, *i.e.*, $N \times (N - 1)$ since no constraint is generated for the case $k = j$. Equation 1.5 generates one constraint for each $d(k, j) < \delta$, and another constraint for each $d(k, j) > \delta$ (equal to $x_{k,j} = 0$). This last constraint is not expressed in the ILP formulation, and as in eq. 1.4, no constraint is generated for the case $k = j$. Therefore, Equation 1.5 finally generates $N \times (N - 1)$ constraints.

Regarding the formulation of ILP (eq. 2), the number of constraints is dependent on the threshold δ . Increasing the threshold reduces the number of constraints filtered by distance, and increases the number of edges in the related graph. With a threshold set to infinity, the number of constraints would be $N + N \times (N - 1)$, and the graph would be completely connected. Equation 2.3 generates N constraints, and equation 2.4 generates $N \times (N - 1)$ constraints. With the ILP formulation we introduced in this paper, the number of constraints is equal to the number of variables. A constraint is expressed for each candidate cluster center (N binary variables), and another constraint is formulated for each edge leaving a node (*i.e.*, there is one constraint, generated by eq. 2.3, for each $d(k, j) > \delta$ when

$k \neq j$).

5.2. Speaker clustering as graph exploration

We came with to the idea of considering the clustering problem as a graph thanks to the ILP clustering, on which we have been working for several years, especially to globally process large collections of audiovisual recordings. It appears that the graph approach we proposed in this paper is efficient enough to question the interest of the clustering method to process the “complex” sub-components of the graph (which are neither Star-graphs nor isolated nodes). As presented in Table 2, only 8 of the 28 shows that composed the corpus required an ILP clustering to be performed on the sub-components. In Table 3, we compare the DERs between with and without ILP clustering for processing those complex sub-components.

Distance δ	ILP (eq. 2)	No-clustering	1-single-cluster
75	17.01	17.01	17.01
80	16.60	16.60	16.60
85	15.94	16.49	15.37
90	15.45	15.81	15.18
95	15.45	15.81	15.18
100	15.03	15.48	15.74
105	14.70	16.40	16.33
110	15.56	17.48	18.32
115	15.46	17.60	18.40
120	15.33	16.84	18.85
125	16.18	16.73	19.38

Table 3: Diarization Error Rate (DER) of the graph approach, with and without ILP clustering, on the REPERE January 2013 test corpus.

Three strategies to deal with the complex sub-components have been compared. The left column (*ILP (eq. 2)*) presents the DERs obtained when the ILP clustering is performed to process the complex sub-components. The middle column (*No-clustering*) presents the DERs obtained when nothing is done with the clusters related to the complex sub-components (*i.e.*, the clusters are not merged at all). The right column (*1-single-cluster*) presents the DERs obtained when all the clusters of a complex sub-component are merged into a single cluster.

We observe, on the upper part of Table 3, that the *1-single-cluster* strategy gives identical or better DERs than that of the *ILP* strategy. The opposite can be observed on the lower part of Table 3. The best DER from the *1-single-cluster* strategy (15.18%) is only 0.48% worst than the best DER obtained with the *ILP* strategy (14.70%), and those results are both centered around the same distance δ . On the other hand, the *No-clustering* strategy does not seem to be interesting since the results obtained are always worse than that of the other strategies.

Using the ILP clustering to process the complex sub-components of the graph still provides a better results, as long as the selected threshold δ is not set too low, compared to its optimal value. Note that several clustering approaches have already been studied in detail, and compared, in order to process large-scale clustering on sparse speaker content graphs [22].

6. Conclusions

We have reformulated the ILP clustering to include an overall distance filtering process, in order to reduce the complexity of the problems to be solved. On the January 2013 REPERE test corpus, this optimization lead to a reduction of the number of

binary variables (from 1743 to 53) and constraints (from 3449 to 53). In addition, we proposed to consider the ILP clustering problem as the search for Star-graph sub-components in a totally connected graph. The ILP clustering is only used to process complex graph sub-components, which are neither Star-graphs nor isolated nodes. The graph-content speaker clustering approach can be considered as a promising alternative to the state of the art clustering methods: even if the complex sub-components are not processed with a clustering algorithm, it gives a better DER than that of the GMM-based HAC experiment (15.18% against 16.22% DER). However, it is still better to process the complex graph sub-components with a clustering algorithm, but further investigation has to be done regardless of the clustering method used.

This graph-content clustering, on which an ILP clustering is performed to process the complex sub-components, has achieved impressive performance in terms of speed processing. We performed a test on the ESTER2 training data, which consists of 75.5 hours of annotated data. We considered the concatenation of all the local segmentations to perform an overall clustering (*i.e.*, we concatenated the outputs of the shows processed separately with the speaker diarization system presented in section 3). The concatenation represents a total of 4295 speaker clusters. The clustering based on the only reformulation of the ILP problem, as presented in eq. 2, was achieved in 8 minutes ($RT \times 0.0018$), whereas it last 2 hours and 9 minutes ($RT \times 0.0284$) with the original ILP formulation. The graph approach using the ILP (eq. 2) clustering to process the complex connected sub-components was done in 5 minutes only ($RT \times 0.0011$).

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