ADDING A PARAMETRIC APPROACH TO FORENSIC SPEAKER RECOGNITION

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ABSTRACT: In the field of speaker recognition in forensic science, experts attempt to value the confidence of their results. While ideal binary decisions are unreachable, some numerical methods permit quantifying such confidence. This can be achieved using signal processing methods combined with a Bayesian approach to probabilities. Both recorded samples to be compared must be independently analysed in order to estimate the quality of available data. The continuation of the procedure depends on the reliability of these results. A quantitative step is then performed to compute models of speakers' voice using spectral and prosodic parameters. Bayesian theory on probabilities is implemented to interpret the results. It gives a fundamental relation between prior and posterior odds of recognition through the likelihood ratio. This ratio helps the court in the final decision of a judgement because it gives the degree of importance of the evidence.

KEY WORDS: Forensic speaker recognition; Parametric approach; Interpreting evidence; Likelihood ratio.

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INTRODUCTION

Voice comparison in forensic science is one of the fields where several complementary steps must be implemented to reach one aim: identification (or exclusion) of a suspect through audio recordings. One of these steps can be achieved by voice analysis with signal processing theory. Instead of giving qualitative results like some classic methods, signal processing permits scoring one hypothesis versus another. This is a quantitative procedure.

Speaker recognition can be defined as the evaluation process to measure how close a suspect voice is to a vocal recording. The first and original recording is called unknown utterance, and the one of the suspect speech is the controlled utterance.

An important step is to provide a precise analysis of the evidence because it is preferable not to carry out a voice comparison with bad quality material.

Whereas a qualitative study can be summarised in terms of auditory and phonetic examination, the parametric one directly stems from signal processing research. It is based on the peculiarities of the speaker's voices and the models that can be inferred from that.

The final step consists in interpretation of the results to calculate the degree of similarity between both unknown and controlled utterance. This is done within a Bayesian framework of probabilities in a forensic context.

The aim of this article is to bring some new knowledge from signal processing investigation. We only want to focus on new improvements.

THE PARAMETRIC APPROACH IN FORENSIC SPEAKER RECOGNITION

The parametric approach is a complementary step to the conventional study which is based on auditory, phonetic and linguistic analysis [19, 24].

The quantitative study is more complex and precise. It is based on speaker features analysis using numerical signal processing, and then on a voice characteristic modelling.

This method need to evaluate the amount of relevant data in both unknown and controlled utterances by taking into account:

- transmission channels distortion [37],
- intra-speaker variability [28],
- short duration of utterance,
- electronic voice transformation,
- integrity of the tape [23].

Then, the following step is essential to have a measurement of identity probability between two speakers. Because of full control by an expert and human intervention, this method is semi-automatic.

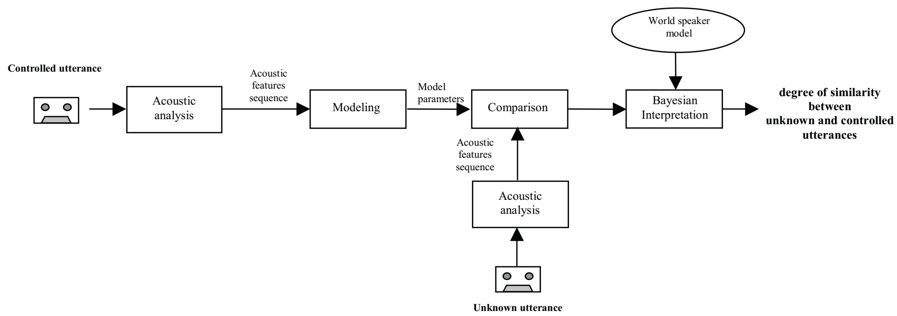

Fig. 1. Parametric approach.

Features extraction and selection

The parametric step is inspired by the CAVE-project final report [2], which is the outcome of a research activity of the European Union in speaker verification. The acoustic analysis allows a reliable representation of all information contained in voice (Figure 1).

First, a manual selection of relevant parts of utterances is made according to both prior knowledge of phonetic content [12, 25] and speech variability in utterance [11].

Then, we compute mel-frequency cepstrum coefficients (MFCC) which represent instantaneous or static features [2] of the vocal tract. The cepstral difference coefficients (ΔMFCC) are used and allow capture of dynamic information and removal of time-invariant spectral information [17, 43]. We also compute linear predictive cepstrum coefficients (LPCC) and their associated delta coefficients [18]. The pitch contour is extracted with the help of a robust estimation method developed in a previous work [28].

As we find complementary information in MFCC and LPCC [20], we use a characteristic vector that associates these 2 parameters. The procedure in [7] has been performed to select coefficients from MFCC and LPCC (and their delta). These selected parameters are used for training speaker model.

In the other hand, we take into account the pitch contour (from the vocal folds) to improve the comparison [8, 22].

A way to minimise the channel effects due to the telephone and to improve the voice comparison is to use both cepstrum difference coefficients and long-term cepstrum mean subtraction. The CMS significantly improves the performance of a system in which training and testing are done from utterances recorded under different channel conditions [26, 31].

Speaker model using GMM

A Gaussian mixture model (GMM) is a robust representation of speaker identity [35]. Indeed, Gaussian mixture density is shown to provide a smooth approximation to the underlying long-term sample distribution of observations obtained from utterances by a given speaker [4, 36]. GMM is trained to cover many “phonetic units”.

A Gaussian mixture density is a weighted sum of M densities, given by the equation:

$$P\left(x/\lambda\right) = \sum_{i=1}^{M} \pi_i f_i(x), \qquad \{1\}$$

and

$$\sum_{i=1}^{M} \pi_i = 1, \qquad \{2\}$$

with

$$f_i(x) = \frac{1}{(2\pi)^{D/2}} \left|\Sigma_i\right|^{-1/2} \exp\left\{-\frac{1}{2}(x-\mu)^T \Sigma_i^{-1}(x-\mu)\right\}, \qquad \{3\}$$

where D is the features vector dimension; π_i – mixture weights; μ_i – mean vector of a component density; Σ_i – diagonal covariance matrix of a component density; $\lambda = \{\pi_i, \mu_i, \Sigma_i\}$ is the speaker model.

The 3 multidimensional parameters of each speaker model (e.g. π_i, μ_i, and Σ_i) are determined by using EM (expectation maximisation) algorithm. This estimator finds a set of model parameters, which maximises the likelihood function [10].

Before modelling, parameters initialisation using vector quantification [34] is done. Also, some non-representative or badly estimated frames from the acoustic analysis step are rejected by this way.

This kind of featuring and modelling is shared by the best world-wide laboratories, particularly for evaluation tests [33].

Measurement of identity probability

The two kind of information (obtained from vocal tract and vocal folds) are modelled separately. The comparison procedure gives a score α_x which is the mean of the likelihood logarithm between the acoustic features vector of the unknown utterance and the controlled utterance model. The scores from the models can be combined using a fusion method [45]. They can also be interpreted individually in a next step.

INTERPRETING EVIDENCE USING BAYESIAN FRAMEWORK

Context in forensic science

As notified by Robertson and Vignaux [38], the jury surely prefers expert techniques that ensure the identification or the categorical exclusion of a candidate speaker. Speaker comparison is actually a really complex procedure that cannot give a definite verdict. Moreover, experts in voice comparison applied to forensic science never work in ideal conditions.

In most cases, there then remains more or less high uncertainty in the phase of identification. The threshold that could define or not the identification (or guilt) is then entirely left to the court [15]. Experts just intervene on the part of the file in relation with their evaluation, and not on the general debate.

A recommended interpretation to estimate the reliability of the evidence is to consider a probabilistic model using Bayes Theorem. This theorem is nowadays currently used in most forensic domains [13] such as DNA [27], footprints [14], fibres [40], tool marks [21], breaking of glass [9], paint [29] or handwriting [42], forensic investigations.

This Bayesian approach combines different background knowledge with a new piece of evidence to posterior probabilities. This method is particularly suited to scientific evidences [1] and to forensic evidences [39, 44] and makes understanding of penal action easier [6]. Moreover, the American justice is now convinced of the interest of Bayesian interpretation for scientific evidence [16].

We now describe this method which can especially be applied to speaker recognition, as outlined by Professor Champod from the Scientific Police and Criminology Institute of Lausanne – Switzerland [5] and by the last Interpol symposium [3].

Mathematical background

The two supposed working hypothesis when a voice comparison is required in a legal procedure are:

– the one charged by the prosecution,
– the one supposed by the defence.

They correspond to someone's identification by the way of voice analysis, or, on the contrary, to the non-identification. The question is then to find how the scientific clue named unknown utterance can support the prosecution thesis or not.

Let us considered the two following hypothesis:

– $H1$: the author of the unknown utterance is really the speaker of the controlled utterance,
– $H2$: the author of the unknown utterance is not the suspect but someone else.

From these assumptions, the court wishes to know odds for the suspect to be the speaker of the unknown utterance, the knowing background knowledge (I) and remarks (E) of the voice comparison expert. In mathematical terms, the court is about to evaluate odds ($H1 \mid E, I$) of hypothesis $H1$ versus alternative hypothesis $H2$. These are posterior odds:

$$\text{Odds}(H1|E,I) \quad \frac{\text{Probability}(H1|E,I)}{\text{Probability}(H2|E,I)}, \qquad \{4\}$$

gives us:

$$\text{Odds}(H1|E,I) \quad \frac{\text{Probability}(E|H1,I)}{\text{Probability}(E|H2,I)} \frac{\text{Probability}(H1|I)}{\text{Probability}(H2|I)}, \qquad \{5\}$$

so,

$$\text{Odds}(H1|E,I) \quad LR \times \text{Odds}(H1|I), \qquad \{6\}$$

i.e.

$$\text{Posterior Odds} = \text{Likelihood Ratio} \times \text{Prior Odds}. \qquad \{7\}$$

Note that $P(E \mid H1, I)$ is the probability that the evidence match with the suspect given he committed the crime.

This formula is very interesting for LR influence. A LR greater than one can significantly increase posterior odds since they are linked to prior odds with a multiplication relation.

Consequences

Prior odds are measures of credit lent to $H1$ against $H2$ before the expert voice comparison. Their estimations depend only on the court or jury assessment whose opinions are expressed in terms of odds (a certain number of possibilities to only one).

LR values the evidence of the unknown utterance. It is a ratio of the probability of the scientific observation – E (the suspect being supposed to be the author of the unknown utterance ($H1$), to the probability of the same (E) with the complementary hypothesis ($H2$).

Nevertheless this sole LR is not sufficient to decide on the procedure way out. It just quantifies a likelihood value versus another one. The only thing the expert is concerned about is this LR; he has not any competence to estimate prior odds.

LR interpretation

For forensic investigation, LR obtained in a Bayesian theory is not to be interpreted either. If present circumstances do not permit a good estimation of prior odds, we could bring some statistical knowledge on the level of the LR. In particular, a LR close to unity makes the evidence irrelevant.

Another way to understand the usefulness of interpreting evidence runs as follows: suppose that the qualitative study concludes to the similarity between the two sample voices (without any certainty). Then, this Bayesian framework allows one to show if the unknown voice is very common in the population, or if it is a particular one. So, it gives to the judge the degree of importance of the evidence.

Direct application to forensic speaker recognition

To calculate the LR, we need an estimation of both probabilities it deals with, according to the studied criminal background [30].

Values obtained through a Gaussian Mixture Model are defined in a continuous domain. Probability $(E \mid H1, I)$ and Probability $(E \mid H2, I)$ can then be replaced by a probability density function $f(.)$ [1].

On the one hand, some other values are estimated from a large panel of utterances of the own suspect speech under *H*1 hypothesis (these utterances have the same length than the unknown one). Their distribution is approximated by a Gaussian mixture density function $f(E \mid H1, I)$.

Probability $(E \mid H1, I)$ is therefore substituted for $f(\alpha_x \mid H1, I)$. Note that α_x is obtained at the comparison stage between both unknown and controlled records. Moreover, it is possible to take into account both the intra-speaker voice variability in the controlled utterance, and the differences between transmission channels of both unknown and controlled utterance.

On the other hand, values are estimated from models of speakers under *H*2 hypothesis, on the same way as in the comparison stage. Their distribution is again approximated by a Gaussian mixture density function $g(E \mid H2, I)$.

These models are built with a varied database of speakers [32], representative of all ages, accents or origin groups of French men and women.

Probability (E | H2, I) is therefore replaced by $g(\alpha_x \mid H2, I)$. The likelihood ratio is then:

$$LR \quad \frac{f(\alpha_x \mid H1, I)}{g(\alpha_x \mid H2, I)}. \qquad \{8\}$$

We have found by bringing principal component analysis for example that data which come from vocal track and vocal folds are not correlated. Hence, we can compute independently two likelihood ratios corresponding to each information. Then, the final LR is obtained from the product of these two latter quantities.

EXPERIMENT IN A FORENSIC CASE

This case concerns a malevolent call to the fire brigade coming from a private person. The inquiry showed that 2 persons were present in the premises during the call. The judge asked then the Gendarmerie to record the voice of the 2 persons and to make a speaker recognition so as to determine if one of these persons is the perpetrator.

The unknown utterance consists in an anonymous call in French, with no particular accent. The speech duration is 38 seconds. The unknown utterance quality was rather good. The controlled session contained read and spontaneous speech recorded with a professional microphone. Those recording were used to calculate the 2 suspect's models (λ_1, λ_2).

The scores α_{Xi} were calculated by comparing the models of the 2 speakers (λ_1, λ_2) with the unknown utterances. This is achieved for each kind of information (obtained from vocal track and vocal folds, see Table I and Table II).

For the two speakers, as described previously, and according to the hypothesis $H1$, a Gaussian mixture density function is evaluated from the comparison to their own utterances in order to assess the intra-speaker voice variability. In concrete terms, according to the previous section, two models of the same voice are computed using suspect speaker utterances. Then scores are calculated by running a cross comparison between these utterances and the models of the same speaker A probability density function is estimated with all these scores (Figures 2, 3, 4 and 5 – green dot characters). Then the $f(\alpha_{xi} \mid H1, I)$ is separately calculated for vocal track data and vocal folds information (Tables I and II).

After that, according to the hypothesis $H2$, the Gaussian mixture density is evaluated from models of representative speakers. Scores are obtained by the comparison of unknown record with all speakers models from the database. Then $g(\alpha_{xi} \mid H2, I)$ is calculated for each kind of information (Tables I and II). It gives the inter speaker voice variability (Figures 2, 3, 4 and 5 – blue star characters).

TABLE I. RESULTS OF INTRA- AND INTER-SPEAKERS VARIABILITY (FOR VOCAL TRACT)

Speaker	*Vocal tract*		
	α_{xi}	$f(\alpha_{xi} \mid$ H1,I)	$g(\alpha_{xi} \mid$ H2,I)
1	19.72	0.57	2.34
2	20.11	1.13	$9.4.10^{-4}$

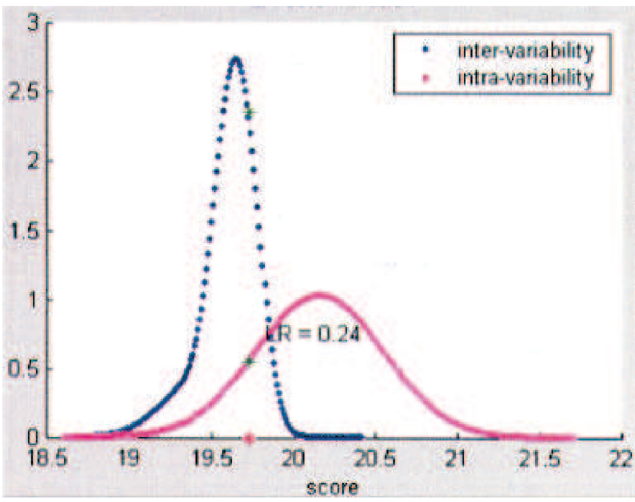

Fig. 2. Probability density functions for speaker 1 (obtained from vocal tract).

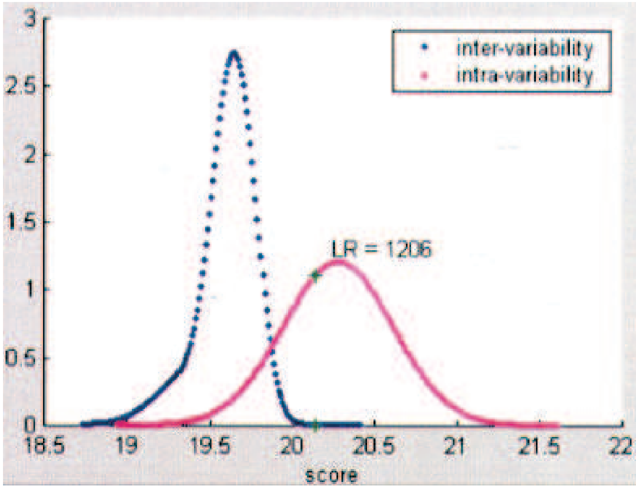

Fig. 3. Probability density functions for speaker 2 (obtained from vocal tract).

TABLE II. RESULTS OF INTRA- AND INTER-SPEAKERS VARIABILITY (FOR VOCAL FOLDS)

Speaker	*Vocal folds*		
	α_{xi}	$f(\alpha_{xi} \mid H1,I)$	$g(\alpha_{xi} \mid H2,I)$
1	–3.81	0.45	0.39
2	–2.56	0.82	0.19

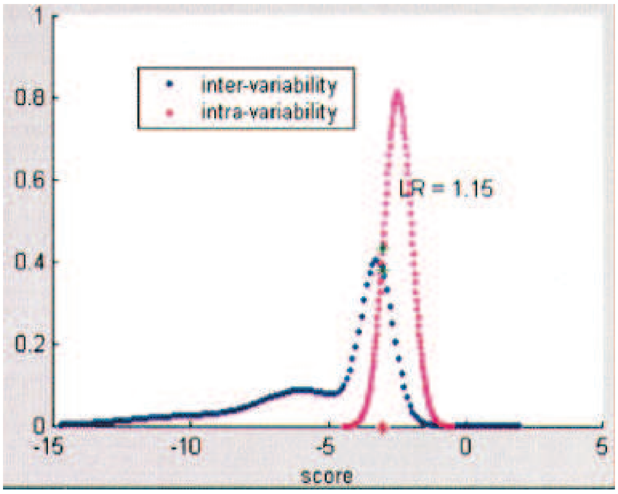

Fig. 4. Probability density functions for speaker 1 (obtained from vocal folds).

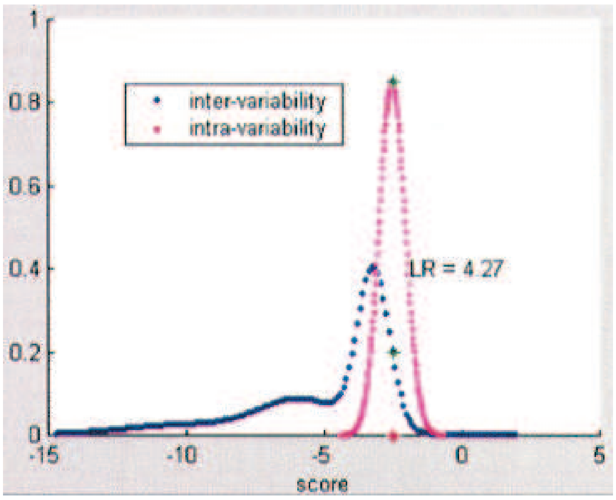

Fig. 5. Probability density functions for speaker 2 (obtained from vocal folds).

The likelihood ratio between the probabilities under the hypotheses *H*1 and *H*2 can be computed by dividing $f\,(\alpha_{xi} \mid H1, I)$ by $g\,(\alpha_{xi} \mid H2, I)$, for both vocal tract and vocal folds information. Then, the final LR is the product of the 2 latter LR obtained from vocal tract and vocal folds (Table III).

TABLE III. LR FINAL RESULTS

Speaker	v. tract LR	v. folds LR	LR
1	0.24	1.15	0.27
2	1206	4.27	5150

Having the unknown utterance and the speaker model λ_2, the prior odds, given to the suspect 2 to be the perpetrator, on the basis of other evidence, can be multiplied by 5150 if the method described here is used. On the other hand, the prior odds, given to the suspect 1 to be the perpetrator, can be multiplied by 0.27.

At the sight of all evidence elements collected, this suspect 2 confessed to being the perpetrator.

DISCUSSION

Both qualitative and quantitative approaches are very important in forensic speaker recognition. We have to provide to the judge some reliable results using all kinds of method.

The parametric approach gives some statistical data about all characteristics of the examined voice. It is a complementary study with an auditory and a phonetic analysis. Furthermore, the Bayes approach helps us to make the expert conclusion intelligible for judges.

The parametric method has been evaluated on a database, which is recording by our laboratory. This database consists in 200 men and women, from 18 to 55 years old, speaking for at least 10 minutes, and randomly chosen all over the country. People have been recorded two times via the telephone channel and directly in our laboratory. We will soon increase voices number. The speakers conditions take into account forensic cases.

Furthermore, with this database and this parametric method, it is not realistic to provide a recognition rate because the forensic expert computes a LR and because the procedure is not completely automatic. Experiments on this database give some useful results to situate the meaning of the LR (Table IV). These data could be compared with the Evett scale of LR [13]. Moreover, we could bring some statistical knowledge obtained from thousands tests. Then, we could give a verbal scale of probability according to the likelihood ratio.

TABLE IV. FEW LR RESULTS DEPENDING ON THE SPEAKER (THE ONE TO RECOGNISE, AND SOME IMPOSTORS)

Speaker	minimum LR	maximum LR	Median LR
Good recognition	1.4	1200000	850
First impostor	0.2	8.6	3.4
Average impostor	0.0006	0.11	0.003

CONCLUSION

Conventional approach (i.e. auditory, phonetic and linguistic analysis) is also required to forensic speaker recognition.

We have found that the quantitative approach confers some additional information. The quality control, the selection of segments of both unknown and controlled utterances and the state of the art of the parametric method give us a high confidence level on the voice comparison.

At the end of the procedure, the evidence is interpreted by using a Bayesian framework, which allows to help significantly the court to take their final decision of judgement because it gives the degree of importance of the evidence.

Furthermore, as mentioned by more and more authors [1, 5, 6, 13, 38], this Bayesian approach allows us to avoid the prosecutor's and the defence's fallacies.

Moreover, this framework is an adequate answer to the problem of the conventional verbal scale of conclusion for expressing expert opinion which is logically incorrect and inappropriate for experts [41].

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