TELKOMNIKA Telecommunication Computing Electronics and Control
Vol. 24, No. 2, April 2026, pp. 481~489
ISSN: 1693-6930, DOI: 10.12928/TELKOMNIKA.v24i2.27443

Time encoded signal processing and recognition with vector quantization: applied to Arabic numerals

Abdelmajid Lamkadam[1], Mohammed Karim[2]
[1]Department of Mathematics and Computer Science, LIMAS Laboratory, Faculty of Sciences, Sidi Mohamed Ben Abdellah University, Fez, Morocco
[2]Department of Physics, LIMAS Laboratory, Faculty of Sciences, Sidi Mohamed Ben Abdellah University, Fez, Morocco

Article Info

Article history:

Received Aug 1, 2025
Revised Dec 23, 2025
Accepted Jan 30, 2026

Keywords:

Hybridization
Linear discriminant analysis
Speaker recognition
Time encoded signal-processing and recognition
Vector quantization

ABSTRACT

This article presents our contribution to speaker recognition using Arabic numerals. This recognition is based on hybridization between the time encoded signal processing and recognition (TESPAR) technique and vector quantization (VQ), in order to consolidate the classification step thanks to this combination. To set up an effective and efficient recognition system, we used a corpus recorded under ideal conditions, minimizing the differences between the reference corpus and the test corpus. We also applied the linear discriminant analysis (LDA) technique in order to discriminate the acoustic vectors and minimize the representative space. This hybridization indicated a quantifiable increase in the speaker recognition rate with the ten Arabic numerals (0–9).

Corresponding Author:

Abdelmajid Lamkadam
Laboratory of Engineering, Modeling and Systems Analysis (LEMSA), Faculty of Sciences
Sidi Mohamed Ben Abdellah University
Fez, Morocco
Email: abdelmajid.lamkadam@usmba.ac.ma

1. INTRODUCTION

Several models and techniques have been designed for speech recognition [1], [2]. However, speech is a dynamic phenomenon evolving over time; these existing solutions are not adapted to the management of this temporal aspect. However, the time encoded signal processing and recognition (TESPAR) technique has been implemented to fill this gap and integrate this temporal aspect.

The majority of recognition problems [3], [4] system from a mismatch between the training and test conditions. It is therefore crucial to reduce these differences between training and test corpus in order to improve existing recognition systems. Most current speech recognition systems [5], [6] usually take only one aspect into account, either temporal or frequency.

Firstly, we presented the vector quantization (VQ) [7]–[10] and TESPAR [11]–[16] techniques and their functional diagrams, as well as their advantages and disadvantages, which will enable us to approach the globally coupled recognition system, they take into account the acoustic characteristics of the voice signal and are more resistant to noise that degrades speech recognition quality. We then compared the two classification algorithms VQ and TESPAR, to assess these algorithms' advantages and disadvantages. Each of these two classification techniques, VQ [8], [9] and TESPAR [12], [13], has limitations, such as the lack of a temporal aspect for VQ and the frequency aspect for TESPAR.

The basic idea behind this hybridization is to combine these two aspects and other advantages to improve recognition rate. To ensure appropriate performance, it is important to have a corpus recorded under optimal conditions. And when comparing these corpus, robust, efficient and effective methods [17], [18] must be used, which are robust to noise, speaker variations and with a good representation of the acoustic characteristics.

To improve the recognition process, we compared the existing hybridizations [19]–[24], which helped us to propose and approach a new hybridization between these two classifiers VQ and TESPAR. In addition, the representation space of acoustic vectors is often of large size, to maximize the separation of the classes that are assigned to each acoustic vector and to obtain a robust and optimal representation, it is necessary to retain only the discriminating parameters. The majority method used is linear discriminant analysis (LDA) [25]–[27], the LDA which makes it possible to obtain discriminant parameters by applying a linear transformation of the input space to a space of reduced size.

An analysis and comparison of the results obtained are carried out throughout this work, in order to evaluate, verify and recognize our speakers accurately and without failure, enabling better authentication using just the ten Arabic numerals (0–9).

2. SPEECH RECOGNITION

2.1. Principle

Techniques that manipulate and identify the speech signal fall into three levels: (i) learning level (signal), (ii) extraction level (vectors), and (iii) classification level (models). Recognition techniques facilitate the learning and encoding of information present in the speech signal from the data extracted during the analysis phase. After the extraction of acoustic vectors, classification follows, which separates elementary speech segments into appropriate classes. This operation involves statistical or connectionist modeling, using computer methods from the fields of signal processing. Then comes the recognition phase which is the comparison of the elementary segments of speech previously learned to make the most probable decision, it does the pattern matching, often carried out by algorithms such as: dynamic time warping (DTW), hidden Markov models (HMM), VQ, artificial neural network (ANN), support vector machines (SVM), Gaussian mixture models (GMM) and TESPAR.

2.2. Problems and limitations

Recent studies in speech recognition raise thorny questions related to identify problems that remain unanswered at this stage. These questions are associated with variability caused by:

- The speaker: age and behavior
- Recording conditions: noise and equipment
- The root: geography
- The language: vocabulary

So, the problem with speaker recognition is how best to model the units representing the speech signal. There are several possible types of model for modelling the properties of a given signal:

- Dynamic models, which characterize the dynamic properties of the signal
- Deterministic models, which exploit the intrinsic properties of the signal
- Statistical models, which characterize the stochastic properties of the signal

To resolve some of the challenges associated with speaker recognition, several studies have recently examined the challenges of recognition under a variety of conditions, and several hybridizations and combinations have been implemented.

3. VOICEPRINT CLASSIFIERS

3.1. Types

Speech recognition algorithms or recognizers are also classified according to the simplifying hypotheses under which they are intended to operate. There are essentially two types of recognition, depending on the information we wish to extract from the speech signal: (i) speaker recognition, to identify the person speaking and (ii) speech recognition, which focuses mainly on identifying what, is being said.

There are two types of speaker recognition: text-dependent and text-independent. There is also recognition for a single speaker, for several speakers, and speaker-independent recognition. In the case of speech recognition, a distinction is made between a system dedicated to isolated words, connected words and a third for continuous speech. These classification techniques vary depending on the aspects of the speech signal that are considered: some take into account the temporal or frequency aspect, others the linear or linear aspect, others are based on the statistical or probabilistic aspect.

3.2. Vector quantization

This section presents the vector quantization technique and describes its principle, coding process, as well as its advantages and limitations.

a. Principle: the VQ technique allows extracting a dictionary of representative vectors (centroids) from acoustic vectors; this dictionary reflects their spatial distribution as closely as possible. Such a representation facilitates the exploitation of the correlation between the elements of a vector, thus allowing a reduction in its dimensionality. Quantizing a vector x amounts to representing it by a vector y_i close to a finite dictionary Y. The dictionary Y is obtained by partitioning the original space into M classes. However, the size of the dictionary plays a very important role in the quantization error.
b. Coding: the construction of a dictionary can be summarized as follows: (i) the average error it generates is determined from an initial dictionary. The algorithm stops if the value falls below a certain threshold and (ii) otherwise, each centroid is replaced by the average of all vectors belonging to the class represented by the centroid, and then the process is repeated with the new data set. This algorithm leads only to a local optimum, which makes the choice of initialization crucial; the VQ coding model is shown in Figure 1.

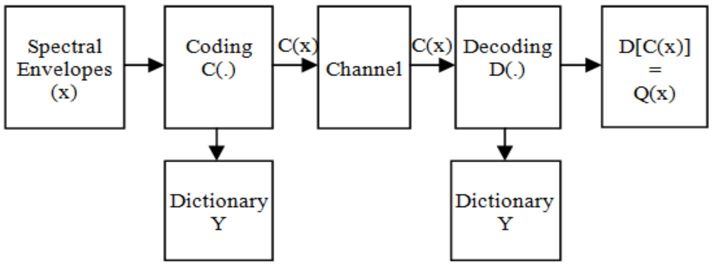

Figure 1. VQ coding model

c. Advantages: this technique offers the following advantages: based on the frequency domain, spectral analysis, reduction in working and calculation space, and statistical aspect of the speech signal.
d. Disadvantages (limits): this classifier shows some weak points (Table 1) such as: lack of a temporal aspect, limited vocabulary, and discrimination accuracy problems.

Table 1. Comparison criteria between VQ and TESPAR

Criteria	VQ	TESPAR
Temporal		✓
Frequency	✓	
Linear	✓	
Statistical	✓	
Connectionist		✓
Vocabulary	Limited	No limited
Speaker	Mono	Multi

3.3. TESPAR technique

This section presents the TESPAR technique, including its principle, coding process, as well as its advantages and limitations.

a. Principle: TESPAR is an efficient method for encoding a signal. It offers the ability to process and identify time-encoded signals and to characterize waveforms as a function of time. The approach is particularly advantageous in the areas of voice recognition and biomedical signal analysis. Unlike other methods that focus on frequency or other signal characteristics, TESPAR focuses on how signals change over time. The technique is based on the analysis and extraction of relevant features from speech signals using time coding. It identifies patterns and structures in speech signals that can be used for recognition. An important feature of TESPAR is its ability to process signals in real time, making it the method of choice for applications requiring a fast response, such as speech recognition in voice command or automatic transcription systems.
b. Coding: TESPAR analyses the shape of a signal by dividing it into segments of equal time and then assigning symbols to each segment according to certain characteristics of the signal in that segment.

These characteristics can include information such as amplitude, slope, and variance. Once each segment is represented by a symbol, a TESPAR matrix is constructed. This matrix is a compact representation of the original signal, where each row represents a segment of time and each column represents a symbol assigned to that segment. The TESPAR matrix can then be used for signal analysis and recognition. The steps of the TESPAR coding model are illustrated in the following Figure 2.

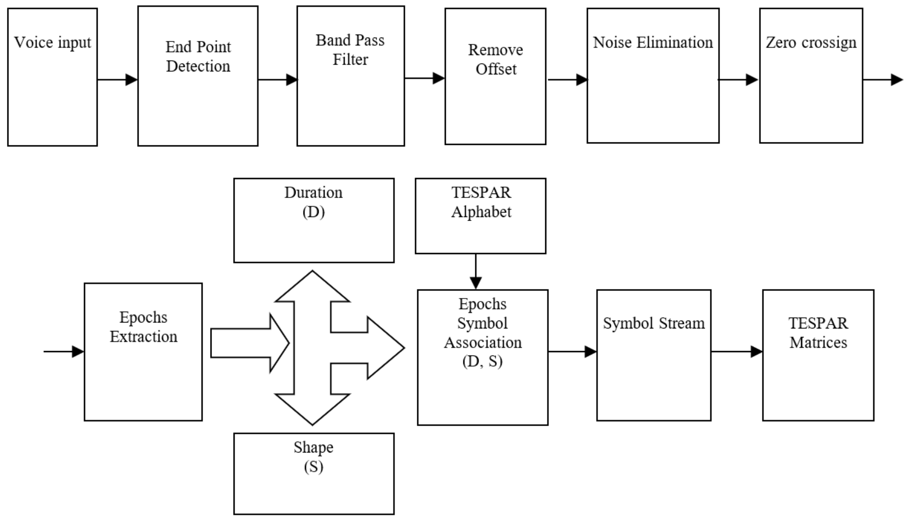

Figure 2. TESPAR coding model

c. Advantages: the advantages of this approach are summarized in the following notes: temporal and real-time processing, fast efficient analysis and recognition, noise filtering, simplicity and problem reduction, and integration into smart cards (digital signal processor (DSP) processors).
d. Disadvantages (limits): this classifier shows some weak points (Table 1) such as: lack of a frequency aspect and non-linear.

3.4. Comparison of classifiers

This section presents a comparison between the VQ and TESPAR classifiers based on the algorithms used and the evaluation criteria.
a. Algorithms used: VQ uses the K-means algorithm and TESPAR uses the K-nearest neighbor (KNN) algorithm.
b. Comparison criteria: the criteria and the comparison result between VQ and TESPAR techniques are shown in Table 1.

3.5. Hybridization

3.5.1. Approaches used

Recent methods have emerged to enhance the robustness of recognition systems. Their commonality lies in the use of various techniques combined to arrive at a final decision. One of these approaches is the use of multiple classifiers, which involves applying various classifiers to the same speech signal, with the decision being based on the recombination of the scores obtained with each technique. These approaches emphasize the standardization of the scores obtained from each recognition system, as well as the selection of efficient hybridization strategies.

3.5.2. Some existing hybridizations

Comparing the results of these different hybridizations is complex, because the databases, libraries, extractors used and evaluation criteria differ greatly from one hybridization to another. Also, the characteristics of the sound signals used and the filtering and segmentation methods are also specified.

Nevertheless, we can list and declare among these works those which have presented encouraging results such as: DTW-VQ, HMM-VQ, GMM-VQ, TESPAR-ANN, and ANN-VQ. This collection of combinations or hybridizations is not exhaustive. Other methods exist, but they are more specific to particular cases and more or less important.

4. METHODOLOGY AND WORK

4.1. Corpus and the test base

Table 2 lists the acoustic characteristics required to create the reference corpus for the 10 Arabic numerals (0 to 9). A recording of the corpus was made for 10 Moroccan speakers. Each digit in the base {0-9} is recorded 10 times, and tested 10 times by 10 speakers. All the tests are carried out using the mel-frequency cepstral coefficients (MFCC) extractor integrated into TESPAR. Once all the samples have been analyzed, it is fairly straightforward to compare them, or more precisely to measure the similarity of the sample to be identified in relation to the reference samples.

Table 2. Acoustic characteristics of speech corpus

Parameter	Value
Format	Mono (.wav)
Sampling	8 kHz
Codage	16 bits
Frames number	50
Recording time	5 secondes/digit
Windowing	Hamming

4.2. Software and tools used

Audacity was used as a tool for acquiring and analyzing sound files, while MATLAB software was chosen for the processing environment, as it offers numerous signal processing functions (m-files). This language is also similar to the notation used in linear algebra and numerical analysis, and it is open to other toolboxes for performing advanced and complex operations on vectors and matrices representing acoustic characteristics.

4.3. Hybridization approach

TESPAR and VQ are two techniques used in signal processing and pattern recognition. Combining them can improve the efficiency of signal coding and recognition, particularly in speech recognition. In this present work we are only interested in hybridization at the level of classifiers. The proposed hybridization is VQ-TESPAR. This hybridization presents our new contribution to the classification phase of the speaker recognition system, as it takes into account several aspects of signal processing.

4.4. Hybridization proceeding

4.4.1. Processing and extraction of acoustic vectors

The first stage consists of preprocessing the speech signal and extracting the relevant acoustic features: (i) acquire, filter out unwanted noise and normalize the voice signal and (ii) extraction of acoustic vectors using MFCC (integrated into TESPAR). The processing and extraction process is shown in Figure 3.

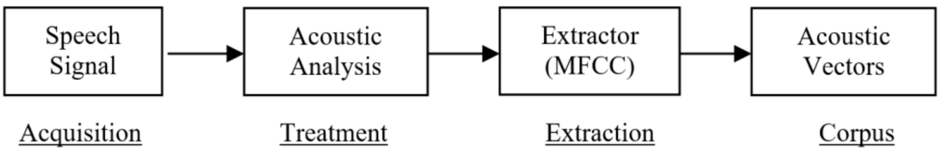

Figure 3. Treatment and extraction model

4.4.2. TESPAR coding

At this stage, the processed signal is encoded using the TESPAR technique; (i) transform the analog signal into a sequence of TESPAR symbols (based on elementary waveforms) and (ii) extract key parameters: duration, amplitude, and frequency.

4.4.3. Vector quantization

The TESPAR-coded information is then processed using vector quantization; (i) group TESPAR sequences into feature vectors, (ii) use VQ to compress and classify these vectors, reducing redundancy, and (iii) assign each vector to a codebook optimized for pattern recognition.

4.4.4. Reduction of representation space

The extracted acoustic vectors are generally of large dimensionality, which increases computational complexity; (i) the acoustic vectors resulting from the extraction operation are very large in quantity, so to reduce this quantity and keep only the relevant parameters and (ii) to optimize the recognition operation with an acceptable calculation time, we used the LDA discriminator which aims to reduce the representation space of these acoustic parameters.

4.4.5. Recognition and classification

The final stage corresponds to the recognition and classification process; (i) apply machine learning techniques such as to identify patterns and (ii) compare the VQs to a database of known patterns. Figure 4 shows the hybridization phases of the two methods VQ and TESPAR.

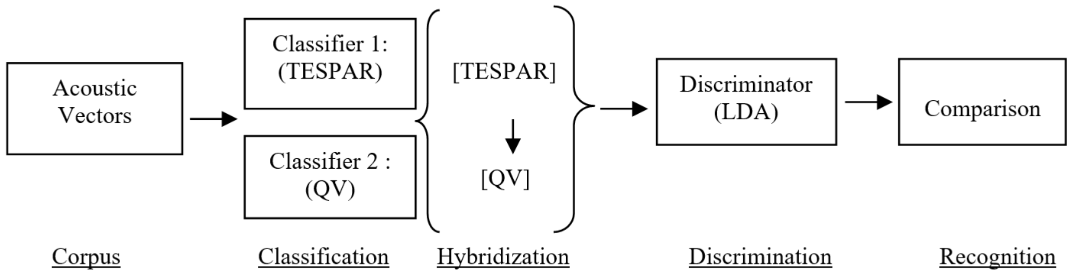

Figure 4. VQ and TESPAR hybridization model

4.5. Explanation

In the TESPAR technique, reference and test models are represented as matrices, aligned in time, generating a score used for recognition. Whereas in the VQ method, reference models are represented by code sequences, while test models are illustrated by spectral parameter sequences. An average quantization distortion is evaluated on the reference models for each test instruction, and this evaluation is then used with the decision threshold in the verification process. By using the VQ technique for this representation, the amount of calculations and storage is considerably reduced. Finally, the DTW method is called to obtain a score (minimum distance) between the reference and test VQ codes, which will be used for the final decision.

5. RESULTS AND DISCUSSION

Comparing a single digit (pronounced in Arabic) with several digits in the number base (0 to 9) led to the following comparative result (Table 3 and Figure 5). The average result (Table 4 and Figure 6) for recognizing the 10 Arabic numerals is as follows:

- TESPAR recognition (67%) was slightly better than VQ (62%)
- The new hybridization showed measurable increases in the recognition rate (72.5%)
- Recognition by the new hybridization (VQ-TESPAR) is better than the VQ and TESPAR techniques used individually for each digit in the corpus (0-9) (Table 3 and Figure 5)

To objectively compare the results of this work with other hybridizations such as TESPAR-SVM or TESPAR-HMM, which are still in development, the same corpus must be used under the same conditions.

Table 3. Digit recognition rate using VQ, TESPAR methods and the hybridization performed

Digit	VQ (%)	TESPAR (%)	Hybridization (%)
0 (Siffr)	80	80	90
1 (Wahed)	70	75	80
2 (Ithnan)	60	70	75
3 (Thalatha)	40	50	50
4 (Arbaa)	60	70	70
5 (Khamsa)	50	60	70
6 (Sitta)	80	80	90
7 (Sabaa)	50	60	60
8 (Thamania)	70	75	80
9 (Tisaa)	60	50	60

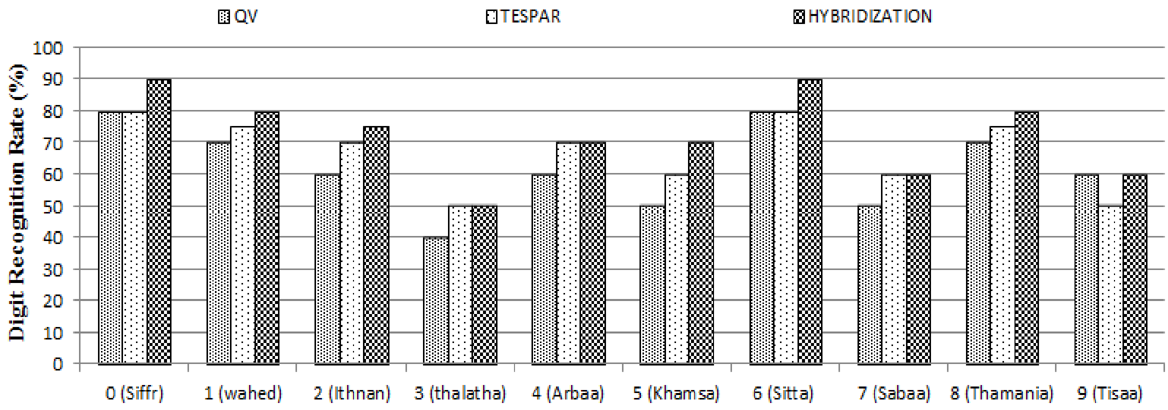

Figure 5. Illustration (comparison) of digit recognition rate results

Table 4. Average recognition rate using VQ, TESPAR methods and the hybridization performed

Technique	VQ (%)	TESPAR (%)	Hybridization (%)
Average	62	67	72.5

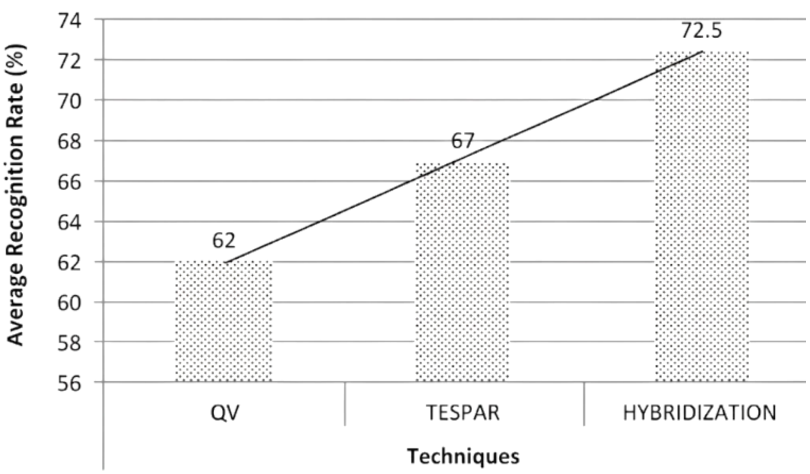

Figure 6. Illustration (comparison) of average recognition rate results

6. CONCLUSION

At the beginning of this work, we demonstrated the processing processes of the two classification methods, VQ and TESPAR, as well as their algorithms. We compared these two classifiers based on the most well-known and commonly used aspects of speech processing. Then we cited the various hybridized systems already developed over the past decade. Indeed, these studies, dedicated to hybridizing certain methods, have produced improved and efficient results. This, of course, led to the idea of proposing a hybrid method based on two existing techniques, to increase the level of comparison and raise the quality of recognition. With the hybridization achieved at this level, we have achieved encouraging results, paving the way for innovative combinations and hybridizations like with DTW, SVM, and HMM. A study on the possibility of applying this work to smart cards could be planned, in order to create a real mini voice authentication system based on smart cards.

ACKNOWLEDGMENTS

We would like to thank the LEMSA Laboratory of the Faculty of Sciences, Fez, Morocco, for the resources made available to us for this work.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Abdelmajid Lamkadam	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			
Mohammed Karim		✓		✓		✓				✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

[1] J. R. Zumalt, "Voice recognition technology: Has it come of age?," *Information Technology and Libraries*, vol. 24, no. 4, pp. 180–185, Dec. 2005, doi: 10.6017/ital.v24i4.3382.
[2] L. Li, Y. Lin, Z. Zhang, and D. Wang, "Improved deep speaker feature learning for text-dependent speaker recognition," in *2015 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference, APSIPA ASC 2015*, IEEE, Dec. 2016, pp. 426–429, doi: 10.1109/APSIPA.2015.7415306.
[3] A. Kourd and K. Kourd, "Arabic Isolated Word Speaker Dependent Recognition System," *British Journal of Mathematics & Computer Science*, vol. 14, no. 1, pp. 1–15, Jan. 2016, doi: 10.9734/bjmcs/2016/23034.
[4] F. A. A. Laleye, E. C. Ezin, and C. Motamed, "Automatic fongbe phoneme recognition from spoken speech signal," in *ICINCO 2016 - Proceedings of the 13th International Conference on Informatics in Control, Automation and Robotics*, SCITEPRESS - Science and Technology Publications, 2016, pp. 102–109, doi: 10.5220/0006004101020109.
[5] R. Charan, A. Manisha, R. Karthik, and M. R. Kumar, "A text-independent speaker verification model: A comparative analysis," in *Proceedings of 2017 International Conference on Intelligent Computing and Control, I2C2 2017*, IEEE, Jun. 2018, pp. 1–6, doi: 10.1109/I2C2.2017.8321794.
[6] A. M. Ahmed and A. K. Hassan, "Speaker Recognition Systems in the Last Decade – A Survey," *Engineering and Technology Journal*, vol. 39, no. 1B, pp. 30–40, Mar. 2021, doi: 10.30684/etj.v39i1b.1589.
[7] A. Brew and P. Cunningham, "Vector quantisation mappings for speaker verification," in *Proceedings - International Conference on Pattern Recognition*, IEEE, Aug. 2010, pp. 560–564, doi: 10.1109/ICPR.2010.142.
[8] M. K. Gill, R. Kaur, and J. Kaur, "Vector Quantization based Speaker Identification," *International Journal of Computer Applications*, vol. 4, no. 2, pp. 1–4, Jul. 2010, doi: 10.5120/806-1146.
[9] D. Hayet and L. M. Tayeb, "Using vector quantization for universal background model in automatic speaker verification," in *CEUR Workshop Proceedings*, 2012, pp. 112–120.
[10] B. Q. Al-Abudi and M. S. Mahdi, "Speaker Authentication Using Vector Quantization," *Baghdad Science Journal*, vol. 6, no. 4, pp. 804–810, Jan. 2025, doi: 10.21123/bsj.2009.11888.
[11] E. Lupu, Z. Feher, and P. G. Pop, "On the speaker verification using the TESPAR coding method," in *SCS 2003. International Symposium on Signals, Circuits and Systems. Proceedings (Cat. No.03EX720)*, IEEE, pp. 173–176, doi: 10.1109/SCS.2003.1226976.
[12] K. S. Prasad, K. A. Sheela, and M. Sridevi, "Optimization of TESPAR features using robust F-ratio for speaker recognition," in *Proceedings of ICSCN 2007: International Conference on Signal Processing Communications and Networking*, IEEE, Feb. 2007, pp. 20–25, doi: 10.1109/ICSCN.2007.350673.
[13] P. O. Adar and M. O. Odhiambo, "TESPAR coded speech quality evaluation (TCSQE)," in *AFRICON 2009*, IEEE, Sep. 2009, pp. 1–6, doi: 10.1109/AFRCON.2009.5308198.
[14] G. You and Y. Li, "Environmental sounds recognition using TESPAR," in *2012 5th International Congress on Image and Signal Processing, CISP 2012*, IEEE, Oct. 2012, pp. 1796–1800, doi: 10.1109/CISP.2012.6469781.
[15] G. P. Pop, E. Lupu, and E. Onaca, "Pathological Voice Assessment using TESPAR Analysis," 2014, pp. 237–240, doi: 10.1007/978-3-319-07653-9_48.
[16] G. P. Pop, "Discriminate animal sounds using TESPAR analysis," in *IFMBE Proceedings*, 2017, pp. 185–188, doi: 10.1007/978-

3-319-52875-5_41.
[17] P. K. Kurzekar, R. R. Deshmukh, V. B. Waghmare, and P. P. Shrishrimal, "A Comparative Study of Feature Extraction Techniques for Speech Recognition System," *International Journal of Innovative Research in Science, Engineering and Technology*, vol. 03, no. 12, pp. 18006–18016, Dec. 2014, doi: 10.15680/ijirset.2014.0312034.
[18] J. K. Sandhu, "A Comparative Study of Feature Extraction and Classification Techniques for Punjabi Speech Recognition," *Journal of Information Systems Engineering and Management*, vol. 10, no. 46s, pp. 1–17, May 2025, doi: 10.52783/jisem.v10i46s.8769.
[19] L. Jingjiao, S. Jie, and L. Yanquan, "A hybrid model of hidden Markov models and a self-organizing neural network model in speech recognition," in *WCC 2000 - ICSP 2000. 2000 5th International Conference on Signal Processing Proceedings. 16th World Computer Congress 2000*, IEEE, 2002, pp. 742–746, doi: 10.1109/icosp.2000.891618.
[20] T. G. Clarkson, C. C. Christodoulou, Y. Guan, D. Gorse, D. A. Romano-Critchley, and J. G. Taylor, "Speaker identification for security systems using reinforcement-trained pRAM neural network architectures," *IEEE Transactions on Systems, Man and Cybernetics Part C: Applications and Reviews*, vol. 31, no. 1, pp. 65–76, 2001, doi: 10.1109/5326.923269.
[21] M. Z. Ilyas, S. A. Samad, A. Hussain, and K. A. Ishak, "Speaker verification using vector quantization and Hidden Markov Model," in *2007 5th Student Conference on Research and Development, SCORED*, IEEE, 2007, pp. 1–5, doi: 10.1109/SCORED.2007.4451419.
[22] M. KeshavarzBahaghighat, F. Sahba, and E. Tehrani, "Text-dependent Speaker Recognition by Combination of LBG VQ and DTW for Persian Language," *International Journal of Computer Applications*, vol. 51, no. 16, pp. 23–27, Aug. 2012, doi: 10.5120/8126-1711.
[23] R. Bharti and P. Bansal, "Real Time Speaker Recognition System using MFCC and Vector Quantization Technique," *International Journal of Computer Applications*, vol. 117, no. 1, pp. 25–31, May 2015, doi: 10.5120/20520-2361.
[24] A. Lamkadam and M. Karim, "Enhanced recognition of Arabic numerals based on the combination of TESPAR and MFCC encoders," in *2024 International Conference on Circuit, Systems and Communication, ICCSC 2024*, IEEE, Jun. 2024, pp. 1–5, doi: 10.1109/ICCSC62074.2024.10617036.
[25] K. A. Sheela and K. S. Prasad, "Linear Discriminant Analysis F-Ratio for Optimization of TESPAR & MFCC Features for Speaker Recognition," *Journal of Multimedia*, vol. 2, no. 6, Nov. 2007, doi: 10.4304/jmm.2.6.34-43.
[26] H. Ali, N. Ahmad, X. Zhou, M. Ali, and A. A. Manjotho, "Linear discriminant analysis based approachfor automatic speech recognition of urdu isolated words," in *Communications in Computer and Information Science*, 2013, pp. 24–34, doi: 10.1007/978-3-319-10987-9_3.
[27] N. Zheng, X. Wu, J. Zhong, X. Liu, and H. Meng, "Speaker-aware linear discriminant analysis in speaker verification," in *Proceedings of the Annual Conference of the International Speech Communication Association, INTERSPEECH*, ISCA: ISCA, Oct. 2020, pp. 3012–3016, doi: 10.21437/Interspeech.2020-2061.

BIOGRAPHIES OF AUTHORS

Abdelmajid Lamkadam holder of a Postgraduate degree in Software Engineering and an MBA in Computer Networks from the Faculty of Sciences. He is a Ph.D. student at the Faculty of Sciences, Fez, Morocco. Member of Laboratory of Engineering, Modeling and Analysis Systems (LEMSA). Currently, he is a teacher specializing in digital infrastructure (DI) at the Higher Institute of Applied Technology (HIAT). He can be contacted at email: abdelmajid.lamkadam@usmba.ac.ma.

Mohammed Karim he is a Professor of higher Education in Computer Science and Electronics at the Faculty of Sciences, Fez, Morocco. He is the ISAI Master and the Head of the STIC Research Group. He serves as Chairman of the Organization Committee for several conferences and workshops. He works on a variety of topics, including e-learning, biomedical engineering, and computer vision. Member of Laboratory of Engineering, Modeling and Analysis Systems (LEMSA). Currently, he is the director of the Higher School of Technology in Fez, Morocco. He can be contacted at email: mohammed.karim@usmba.ac.ma.