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This document is the Accepted Version [AM]

Citation:

AGUIAR DE LIMA, Thales and DA COSTA-ABREU, Marjory (2019). A survey on Automatic Speech Recognition systems for Portuguese language and its variations. *Computer Speech & Language*, p. 101055. [Article]

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A Survey on Automatic Speech Recognition Systems for Portuguese Language and its Variations

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Abstract

Communication has been an essential part of being human and living in society. There are several different languages and variations of them, so you can speak English in one place and not be able to communicate effectively with someone who speaks English with a different accent. There are several application areas where voice/speech data can be of importance, such as health, security, biometric analysis or education. However, most studies focus on English, Arabic or Asian languages, neglecting other relevant languages, such as Portuguese, which leaves their investigations wide open. Thus, it is crucial to understand the area, where the main focus is: what are the most used techniques for feature extraction and classification, and so on. This paper presents a survey on automatic speech recognition components for Portuguese-based language and its variations, as an understudied language. With a total of 101 papers from 2012 to 2018, the Portuguese-based automatic speech recognition field tendency will be explained, and several possible unexplored methods will be presented and discussed in a collaborative and overall way as our main contribution.

Keywords: automatic speech recognition, text-to-speech, speech recognition, Portuguese, survey

1. Introduction

For thousands of years, the ability to communicate is seen as one of the most important human interactions [112]. By writing, drawing, making gestures, and speaking, the individual can share ideas, demonstrate their feelings, make allies, and even enemies. Communication impacts on relationships, cultural diversity and social backgrounds [92]. While every kind of communication has a uniqueness, there is a random aspect that makes it part of the individual. Such characteristic cannot be dissociated from their social and cultural group [65].

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This scenario is also the case for oral communication, a natural human social phenomenon. The uniqueness of speech can be found on the 7097 living languages in the world, according to [22]. The same source defines a living language as “one that has at least one speaker for whom it is their first language”.

The great variety of currently spoken languages, however, does not mean that they are uniformly distributed over the world population. Since only 23 are spoken by more than half of the world population [22]. The most popular spoken languages benefit from a significant number of resources for Automatic Speech Recognition (ASR), Natural Language Processing, and Computational Linguistics. An unpopular language, on the other hand, suffers from a lack of resources for research and development of dedicated technologies. Thus, the importance that the development of such techniques has for under-resourced languages is worth mentioning.

Some languages, however, are in-between popularity and resourceness. That is the case for the Portuguese language, the sixth most spoken language in the world by native speakers [22]. However, it is far from having the same amount of resources as Mandarin, Spanish or English. This distinct position of the language instigated researchers to focus its efforts on it between 2012 and 2018.

Many breakthroughs in computer science research can be credited to the increasing number of computational resources developed or recently made available. ASR is on track with these advances and presented substantial improvements in classification tasks [7]. However, under-resourced languages usually retrain popular acoustic models on a new target language. That is not only unreliable [96] but also inconsiderate phonetic and grammatical differences of communication systems [9].

This paper proposes to summarise and evaluate studies on ASR for the Portuguese language and its variations, as well as to find literature gaps and draw directions for future research. Therefore, creating a starting point for new scientists on the topic.

This paper is organised as follows. Section 2 will present the criteria used to select the works for this review, followed by Section 3 with an introduction to ASR. Next, the Section 4 overviews the resources available for ASR, introducing a list of Corpus in Section 4.1, and a set of tools and software explored in the search course in Section 4.2. Then an overview of feature vectors in Section 6, followed by some applications in Section 5. A categorisation for Speech-to-Text (STT) systems is given with respect to the approaches in Section 7. After, the Section 8 highlight the research gaps and possible directions, concluding in Section 9.

2. Our contribution search methodology

To limit the scope of this piece of research, we have decided to limit our web search starting in 2012, which produced a list of 663 papers. They were manually searched with the support tool Google Scholar, using a full-text search through all databases that this tool may reach. Also, a proper search was done in the following databases: Elsevier, IEEE, Springer, and ACM. The passphrases “speech

recognition” and word “Portuguese” were included, while “scielo”, “text-to-speech”, “named entity”, “emotion”, and “sign language” were excluded. The reason to exclude works with some of these keywords was that they could lead to a context for speech recognition that diverges from the computational definition.

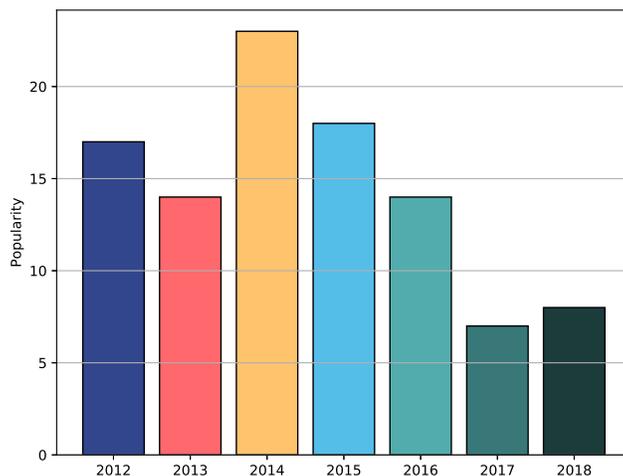


Figure 1: Distribution of published works on Portuguese ASR between from January 01 of 2012 and December 31 of 2018.

From the collection, we removed papers that focused on language processing, insufficiently described their results or methods, or presented conclusions unsupported by the results. Also, we only included journal or conference papers as scientific resources. Furthermore, the language variations (such as regional dialects or idioms) were not restricted, given that they would impact on a small number of samples for this survey. These restrictions screened the total of papers to 101 publishes in the search period.

Information for statistical measures was gathered for each paper. Among the collected information, the feature extraction and classification methods were highlighted, alongside datasets and software.

On the graph shown in Figure 1, the distribution of papers over the selected time interval is displayed. It reveals a considerable drop in published works on the subject after 2014, which is another justified reason for us to understand the area and highlight the possible paths for researching.

This section presented the strategy used to collect the works and how the publications are distributed in the search period. In summary, this set of information allows this paper to be used as a starting point to initiate future research. Next, a short introduction to ASR systems is given.

3. Automatic speech recognition

An ASR system can be seen as a mathematical model that can make a speech-to-text conversion, generating text corresponding to the recognised pieces

of speech input [27].

Far from being trivial, such models may have to deal with a signal containing different kinds of noises, various speakers, and its particular characteristics. Examples of these characteristics are the rhythm or pace, accent, dialectical pronunciation, peculiar intonations, and even mispronunciations [65].

The variety of languages led ASR systems to have mainly developed into different language-specific systems to cope with resource availability such as speech corpus [9].

Even though ASR systems still comprise of language-specific models, recent research is showing that multi-language models are not only feasible but can also be used to bootstrap models for low or under-resourced languages. It is possible to argue that human languages are, in fact, not that different from each other when it comes to computational modelling [116, 126]. Despite this, it is of high importance to focus on specifics of the main spoken languages that are still under-investigated, such as Portuguese.

As already said, this survey focuses on researches that use Portuguese language and its variations, and since multi-lingual speech recognition is a trend on the field, it will be covered in this research as well. The researches that relate to speech recognition but could not be strictly classified as an speech recognition problem are also covered. For instance, disease diagnoses, assisting language acquisition and speech style detection, given that the proposed models are very related to ASR.

Works that focus on the state of the art of automatic speech recognition systems usually comprises several components, each contributing to the overall ability to incorporate knowledge from acoustic or phonetic modelling, language modelling, and lexical or pronunciation modelling. In fact, for a long time, the most common approach for proposing new models involved trying to take advantage of knowledge from different sources to improve the model efficiency [17].

On a somewhat different direction, big data approaches try to take advantage of the training data to propose or improve existing models [43]. This approach has received a long-time negative criticism due to the idea that they propose black-box models, making it difficult to interpret how the model works, and even giving descend to the very reliability to these models, since it is harder to predict when a model will fail [118]. Even with these concerns, the performance improvement of recent deep learning models are undeniable when compared to already-established models [129].

The following sections will present some of the primary resources that are associated with automatic speech recognition.

4. Resources for automatic speech recognition

Since the research on Portuguese is limited, it has been challenging to develop technologies for such communication systems. Thus, this section presents the primary resources, described in the collected works, for Portuguese languages.

Although, it is essential to remember that the resourceness for a language is defined according to the acoustic model and the amount of data required to prevent overfitting and other problems [40]. For instance, the same language could be considered as either well-resourced and under-resourced when applied to a classifier based on Deep Neural Network (DNN) and Multilayer Perceptron (MLP) or Support Vector Machines (SVM) approach, respectively, since the former needs far more data than the latter [9]. A vital collection ASR resources for Portuguese is given by [68], where several tools and corpora are mentioned, including the LapsMail corpus.

To better understand, the resources are divided into databases and toolkits. The next two sections will explore the main recent contributions for Portuguese automatic speech recognition.

4.1. Corpus

Public representative databases are essential for any research in speech recognition. In this area, when referring to a database, the authors use the terminology “Corpus” (or “Corpora”) [88]. During this research, we did not find works that used a large set of structured sentences, that is, a text corpora. Therefore, all datasets presented in this section are speech corpora, a collection of voice recordings. Several papers have a data acquisition procedure, both as to its primary goal [3, 15, 19, 20, 32, 38, 51, 78, 79, 84, 91, 98] or as a requirement for feeding proposed models. Thus, this section will present the corpora and their features related to a speaker (gender, age, etc.), signal (noise, recording rate, etc.), and their availability.

Tables 2 and 3 displays the features of the most recent noisy corpora employed in the literature, while Tables 4 and 5 the clean corpora. Whereas Tables 2 and 5 have monolingual datasets, Tables 3 and 4, on the other hand, have multilingual corpora. Their size is mixed because some authors measure them by hours, while others by the number of utterances. So, without loss of representation, when the size is in utterances and hours, it will be appended with u and h , respectively.

The majority of papers that collected data did not make it public nor detailed it enough. For instance, [81] compiled a series of speech audios from Parkinson’s disease patients but did not provided any means for others to obtain this data. Similarly, some authors specified the dataset attributes in details; however, did not include any reference for validity [100]. Other papers did not include enough information, leaving some rather essential features occult, represented by ‘.’.

Table 1: List of Portuguese corpora along with their utterance features.

Papers	Corpus	Size	Noisy	Lang	kHz	Speakers	Gender	Age	Level	Open
[32, 62, 64]	Euronews	940h	✓	10	-	-	-	-	LVCSR	✗
[3]	ASP-I	1.004u	✓	1	8	8	3/5	52-78	Word	✗
[3]	ASP-II	850u	✓	1	16	18	6/10	19-62	Word	✗
[15]	HESITA	27h	✓	1	16	-	-	-	LVSR	✓
[19, 57, 85]	DIRHA	9.200u	✓	4	48	30	15/15	25-50	LVSR	✓
[12, 26, 82, 129]	Spoltech	2.540u	✗	1	44.1	477	-	-	*	✗
[25]	Furtado	330u	✗	1	44.1	33	9/24	20-50	Word	✗
[28, 45, 55, 54, 61, 114, 117, 124, 126]	Global	450h	✗	22	16	2.100	1050/1050	-	Word	✗
	Phone									
[37, 74]	MLDC	90h	✗	1	16	986	714/272	60-100	Word	✗
[34, 35, 36]	CNG	21h	✗	1	22	510	286/224	3-10	Word	✗
[51]	EPSCS	3h	✗	1	-	101	56/55	5-6	Word	✗
[53]	KALAKA-2	113h	✓	6	16	-	-	-	LVCSR	✗
[70]	LapsMail	2.150u	✓	1	16	25	4/21	-	LVSR	✓
[36, 72]	BD-PUBLICO	20h	✗	1	-	100	50/50	19-30	Word	✓
[84]	CORALBR	21h	✗	1	-	362	183/179	18-60	LVSR	✓
[81]	PDSC	1.5h	✗	1	48	22	16/13	25-80	Word	✗
[94]	Biochaves	400u	✓	1	8	8	2/6	-	Word	✓
[122]	Tecnovoz	22.627u	✗	1	-	368	-	-	Word	✗
[33, 36, 72, 73]	EASR	44,033u	✗	1	16	778	203/575	60-100	Word	✗
[79]	LestRead	20h	✓	1	-	284	-	6-10	Word	✗
[44]	AZTIAHO	10h	✓	8	16	40	20/20	20-98	LVCSR	✗
[86]	AUDIMUS	75.5h	✗	-	32	-	-	-	LVCSR	✗
[30, 40, 43, 48, 120]	GoogleVoice	3034.5h	✓	34	-	-	-	-	LVCSR	✗
[20]	BrSD	3,7h	✗	-	-	80	40/40	9-81	Word	✗

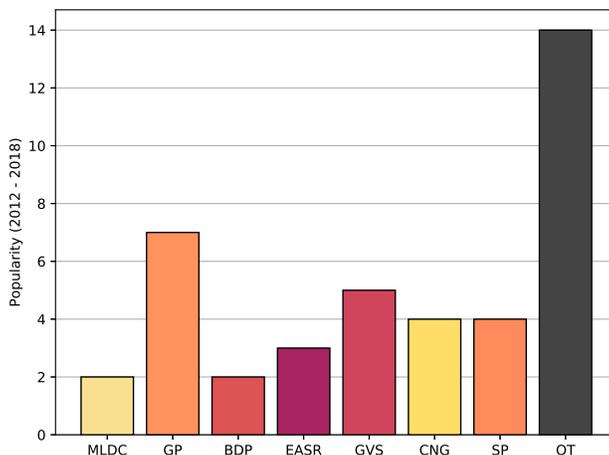


Figure 2: The popularity of corpora from 2012 to 2018. Global Phone (GP); BD-PUBLICO (BDP); European Portuguese Elderly Speech (EASR); Google Voice Search (GVS); Corpus of European Portuguese Childrens Speech (CNG); Spoltech (SP); Sum of popularity of other datasets (OT).

Table 2: List of monolingual noisy Portuguese corpora along with their signal characteristics.

Papers	Corpus	Size	kHz
[3]	ASP-I	1.004u	8
[3]	ASP-II	850u	16
[15]	HESITA	27h	16
[70]	LapsMail	2.150u	16
[94]	Biochaves	400u	8
[79]	LestRead	20h	-

Even though the number of corpora seems enough, the quantity of data is still scarce. Besides, there was no corpus composed of phoneme recordings in the period. Although some works make use of phonetic features [35, 51], but their utterances are recorded as words. Furthermore, the corpora with word recordings are more prevalent, followed by Large Vocabulary Speech Recognition (LVSR), and Large Vocabulary Continuous Speech Recognition (LVCSR). The last two being more challenging to process, while the Word and LVSR are harder to gather compared to LVCSR because they need to create several phonetically rich sentences (prompts) that subjects must read.

Global Phone is the most popular corpus, as shown in Figure 2, it was explored in [28, 45, 54, 61, 114, 124]. This dataset is a project introduced by [95], and further updated in [98, 97], aiming to be a multilingual corpus and uniform across all languages. In the current state of this collection and this research, the project has 22 languages and more than 450 hours of transcribed data. For each language, there are approximately 100 speakers with relative

Table 3: List of multilingual noisy Portuguese corpora along with their signal characteristics.

Papers	Corpus	Size	Lang	kHz
[32, 62, 64]	Euronews	940h	10	-
[19, 57, 85]	DIRHA	9.200u	4	48
[53]	KALAKA-2	113h	6	16
[44]	AZTIAHO	10h	8	16
[30, 40, 43, 48, 120]	GoogleVoice	3034.5h	34	-

Table 4: List of multilingual clean Portuguese corpora along with their signal characteristics.

Papers	Corpus	Size	Lang	kHz
[28, 45, 55, 54, 61, 114, 117, 124, 126]	Global Phone	450h	22	16

balance about gender; thus, it has more than 2.100 native speakers.

The GlobalPhone data was recorded with basically the same instruments, and a similar environment to guarantee a high standardisation across languages. Due to this uniformity and the presence of multiple languages, this corpus was used in most of the works from 2012 to 2018. However, only the language models are available for download, while the speech, text, and dictionary data are distributed under a research and commercial license by two distributors¹.

Around 52% of datasets have a type of noise on its audios or text, which allows researchers to investigate the noise robustness of their models. However, only 29% of the datasets have more than one language (5 noisy listed in Table 2 plus 1 listed in Table 3, from a total of 21 datasets). From these, only GlobalPhone has clean recording, making it challenging to research under both these conditions.

Another concerning characteristic of speech datasets is about the number, quantity, and age of speakers. Besides, knowing which tasks each volunteer had to perform is also of interest, since it may define the work as Word Recognition, Large Vocabulary Speech Recognition (LVSR), Large Vocabulary Continuous Speech Recognition (LVCSR), Phoneme Recognition, and others [83]. All those features are listed in Table 7, for public datasets, and Table 6, for restrict.

Furthermore, the majority of corpus are not balanced concerning speaker gender, which can impact on ASR systems [83], as shown in Tables 7 and 6. The DIRHA [19] and BD-PUBLICO [67] are balanced, while LapsMail [70] and EASR [72] are not.

Therefore, there is a considerable amount of datasets for ASR in Portuguese, but most of them are small and lacks on both balance and standardisation. Consequently, this is often used as the motivation of their acquisition since most of them were collected aiming to a specific application. For example, children

¹European Language Resources Association (ELRA) and Appen Buttler Hill Pty Ltd. (ABH)

Table 5: List of monolingual clean Portuguese corpora along with their signal characteristics.

Papers	Corpus	Size	kHz
[12, 26, 82, 129]	Spoltech	2.540u	44.1
[25]	Furtado	330u	44.1
[37, 74]	MLDC	90h	16
[34, 35, 36]	CNG	21h	22
[51]	EPCSC	3h	-
[36, 72]	BD-PUBLICO	20h	-
[84]	CORALBR	21h	-
[81]	PDSC	1.5h	48
[122]	Tecnovoz	22.627u	-
[33, 36, 72, 73]	EASR	44.033u	16
[86]	AUDIMUS	75.5h	32
[20]	BrSD	3.7h	-

speech disorders [51] and voice commands from throat microphone [87] were acquired in the Portuguese language. Thus, the data is still scarce, but very diverse with noise, age, medical, commands, and other features.

4.2. Tools and software

When developing a new model or working on annotating a new corpus, the decision to use existing tools may be essential to save time by taking advantage of experiences and improvements made by previous research. This section briefly mentions some tools used by researchers that appears in at least two of our selected papers. Thus, these tools and software are related to Portuguese language.

The HTK is one of the first freely available software to be used by the research community. It was made with [14] and written in C language. Besides, it provides recipes to build baseline systems with Hidden Markov Models (HMM). From our list of paper, the ones which use this toolkit are [122, 123, 129]. It can also be used for other applications rather than speech recognition.

Sphinx, employed by [18, 70, 100, 111], is another popular software package developed under Berkeley Software Distribution licence in Java programming language by researchers from Carnegie Mellon University [119] and maintained by a thriving community for decades, just like HTK.

The Praat [11] software is a GUI-based tool for visual analyses and manipulation of audio files. This software was tested in [111] to develop an automatic phonetic aligner for Brazilian Portuguese. In addition, this tool was also explored in [34, 44, 35, 59, 81]. Furthermore, this is the most popular open-source tool for speech phone alignment and corpus annotation. However, this tool was most used as a feature-extraction software, as well as openSMILE, as it has some popular features available.

Table 6: Restrict Portuguese corpora and its speakers characteristics. In the Gender column, the format X/Y is for Female/Male speakers.

Corpus	Speakers	Gender	Age	Level
Euronews	-	-	-	LVCSR
ASP-I	8	-	-	Word
ASP-II	18	-	-	Word
Spoltech	477	-	-	*
Furtado	33	9/24	20-50	Word
Global Phone	2,100	-	-	Word
MLDC	986	714/272	60-100	Word
CNG	484	-	3-10	Word
EPCSCAT	101	56/55	5-6	Word
PDSC	22	16/13	25-80	Word
EASR	778	203/575	60-100	Word
LestRead	284	-	6-10	Word
AZTIAHO	40	20/20	20-98	LVCSR
AUDIMUS	-	-	-	LVCSR

Table 7: Public Portuguese corpora and its speakers characteristics. In the Gender column, the format X/Y is for Female/Male speakers.

Corpus	Speakers	Gender	Age	Level
HESITA	-	-	-	LVSR
DIRHA	30	15/15	25-50	LVSR
LapsMail	25	4/21	-	LVSR
BD-PUBLICO	100	50/50	19-30	Word
CORALBR	362	183/179	18-60	LVSR
Biochaves	8	2/6	-	Word

Julius [4] was initially developed with Kyoto University. It has several speech recognition features, such as forced-alignment tools, and almost real-time computing. Created initially for Japanese, it has expanded to accept other languages, while maintaining the goal of being a very efficient toolkit for LVCSR. As HTK, it is based on HMM models.

The Kaldi software [76], used by [8, 28, 26, 47, 55, 61, 85, 114, 116, 126], began to be developed in 2009, on a workshop in Johns Hopkins University entitled “Low Development Cost, High-Quality Speech Recognition for New Languages and Domains” [77]. This software is becoming very popular in the research community. In fact, it is the most popular among our collection of papers. Its model is based on a Subspace Gaussian Mixture Model (SGMM), coded on C++ programming language. Another speech-to-text tool that is worth mentioning is Voice Note [56].

Not only speech-to-text but also speech related applications have such tools and software. For speaker recognition systems, there is Alize, and BOSARIS [13], used in [73]. For language modelling, the SRILM allows users to quickly

generate language models for statistical classifiers.

Every tool presented in this section is free to use. Besides, Praat alongside Julius and openSMILE are open-source software. In regards to their operating system (OS) support, only HTK is available exclusively for Linux, while Praat has a Mac version and Sphinx can be compiled for this OS. However, some of the software above seem to be outdated since the last release for HTK was in 2016, Julius most recent log was in 2014, and Praat does not share this info. On the other hand, Sphinx and Kaldi are regularly updated on their respective repositories. Furthermore, C and C++ are the most popular languages for this software, even though Python and Java also have a presence. It is clear from what this section presented that the area is plentiful of tools when compared with the availability of datasets, and the use of other techniques for speech processing. This behaviour is justified by the fact that Portuguese-based solutions have not been the focus when exploring automatic speech recognition. The next section will explore the main areas that ASR for Portuguese has been applied.

5. Applications

The current state of ASR is allowing the development of systems for objectives other than converting a signal to text, such as treatment of speech dysfunctions [3, 90]. Therefore, this section will present papers that used speech recognition techniques as their secondary goal. Most of the applications rely on the monolingual approach (more details in Section 7), such as an evaluation of children reading capabilities [78, 79] further analysed in [80]. The second language learning, addressed in more details by [71], is also approached using both scored Elicited Oral Response [18] in conjunction to a test to evaluate proficiency in a language, i.e. Portuguese, and the Goodness of Pronunciation [86]. The latter is more of qualitative work, compared to the former.

The speech recognition is also applied as a more natural interface for humans to interact with computers. To establish a better interaction between children and technology, in [6], a speech-driven robot that executes a set of commands is constructed. Using voice commands, it is also possible to operate medical and graphics systems [24, 89]. A virtual assistant for the elderly was developed by [115] and [46]. The latter investigated the effectiveness of speech human-computer interaction. This system was further augmented by [39], adding gesture and touch interfaces. Named as AALfred project, it aimed to facilitate the interactions of the elderly with technologies, allowing them to access the web and some desktop application through voice commands. Then, an automatic answering system for call centres was developed [69], providing a better dialogue for clients when compared to traditional keyboard systems. Furthermore, a speech-to-speech translation system [58] able to transform some speech signals to other languages.

Other applications aimed to improve noise robustness of these systems, such as reverberating signals [123], or the Weiner Filter applied by [49]. Both achieving decent results for noise signals. While others tried to classify the speech style [121] based on three classes: Lombard, prepared, and unprepared.

Several automatic transcription systems for TV shows, generally combining MLP with HMM to achieve a 21% Word Error Rate (WER) [1]. Similar applications were developed by [5, 43, 52]. Those transcriptions allowed an automatic generation of subtitles for distinct media contents, contributing to the digital inclusion of hearing impaired people. This procedure has permitted speech recognition researches to use bigger datasets. Since the data transcription is usually made by hand, making it difficult and costly for large amounts of data. Still dealing with multimedia, a keyword spotting system for audio [122] and video [23] were developed to find specific words in speech signals. The use of topic related features in content filters were investigated in [75]. Those systems provided a mechanism to automatic summarise large amounts of digital content, based on user preferences.

In medical applications, several neurological issues affect the speech signal somehow [50]. Therefore, applications for the diagnose of Alzheimer’s disease [44] and Parkinson’s disease [81] are explored, trying to create a more efficient and less troublesome early diagnose of this clinical state.

This section has presented some applications that made use of ASR solutions to achieve a different goal. Their areas are very distinct, ranging from medical software to automatic translation for multimedia contents. The following section will summarise and introduce the most popular features from 2012 to 2018, for Portuguese language.

6. Feature vectors

On the feature extraction techniques used between 2012 and 2018, there is a decent variety and a consistency when comparing the methods used for the Portuguese language for other languages. This is a crucial step for most ASR systems [83], as it can easily improve the system accuracy and robustness [123, 49].

Through the research, several types of features were identified. Some of them are based on spectral analysis, which includes the use of Fast-Fourier Transform (FFT), filters, and some other transforms. That is the case for Mel-Frequency Cepstrum Coefficients (MFCC) [60], Perceptual Linear Prediction (PLP), and Linear Predictive Codes (LPC). To split the signal, authors generally used 25ms frames with 10ms stride. Then a Hamming Window was applied on each frame, followed by a 512 point FFT. Those are a general spectral feature analysis steps. At this point, each feature can take a different direction, such as using a Mel Filter Bank (for MFCC) or Bark Filter Banks (for LPZ and PLP). Usually, the features vectors have 13 coefficients and can come extended with first and second derivatives, and sometimes with log-energy.

The MFCC in particular is quite trendy, being used for different purposes. It arises not only on speech-to-text, but also for language identification [113], keyword spotting [122], Parkinson’s diagnose [81], and other speech related research. Furthermore, the popular 13 coefficients are put into testing by [25, 100], concluding that gains over this threshold are not significant.

Another spectral feature is PLP with log-Relative SpecTrAl, or PLP-RASTA, an extension of PLP that makes use of Relative Spectral Transform, proposed by [41]. In our research, this feature was always used alongside Modulation Spectrogram (MSG), introduced by [31]. It is one more spectral feature that is closely related to MFCC, as it uses log-filters and the power spectrum. Both MSG and PLPRASTA were used with different purposes, on transcription [1, 2, 3, 5], to estimate age and its impacts on ASR systems [74, 73], and nativeness estimation [86].

The Bottleneck Features (BN) is a relatively new approach, proposed by [125]. It is based on MFFC but includes a feed-forward MLP that combines a Linear Discriminant Analysis (LDA) and a covariance transform to create a 42 dimension feature vector. The BN is a trendy feature for multilingual datasets, used by [62, 98, 99, 124, 126], as it composes features from different languages and generate a new vector.

Other features worth mentioning, that are present on published works from 2012 to 2018, are: Low-Rank Matrix Factorisation (LRMF), Spectral-Temporal Receptive Fields (STRF), Zero-Crossing with Peak Amplitudes (ZCPA), Elementary Acoustic Events (EAE), a, extension of BN that uses deep learning called Deep Bottleneck Features (DBF), Fractal Dimensions (FD), and Heteroscedastic Linear Discriminant Analysis (HLDA).

This section summarised the features employed between 2012 and 2018. The following section will present the main contributions in Automatic Speech Recognition for Portuguese (ASRPT) from 2012 to 2018. They will be categorised and organised in a better way, following the characteristics of their acoustic models and the way information is shared.

7. Automatic speech recognition approaches for Portuguese

The traditional categorisation of ASR approaches, given by [83] and further used in [27] has three classes: Acoustic-Phonetic (AP), Pattern Recognition (PR), and Artificial Intelligence (AI). However, the field has evolved, and new classification procedures, as well as extraction methods, have been used. For instance, the Discrete Wavelet Packet Decomposition [42] and Spectral-Temporal Receptive Fields [127]. As the AI field grows, embracing new definitions and techniques such as PR [66], previous categorisations become obsolete or ambiguous.

A classification based on the acoustic model was given by [96] as Monolingual, and Multilingual. The former is defined as a system specialised into one language, while the latter is a system able to recognise many languages. The multilingual models are also subdivided, being them a set of monolingual models (language dependent) or a set of classifier with shared knowledge (language independent).

Therefore, the following sections will present a novel categorisation of the field based on the novel methods for ASRPT. Three main approaches were identified: monolingual, skew-lingual, and cross-lingual. All based on the acoustic

model strategy of sharing parameters between its units. Figure 3 display each strategy. These units can be a perceptron for MLPs or a complete acoustic model for some skew and cross-lingual models.

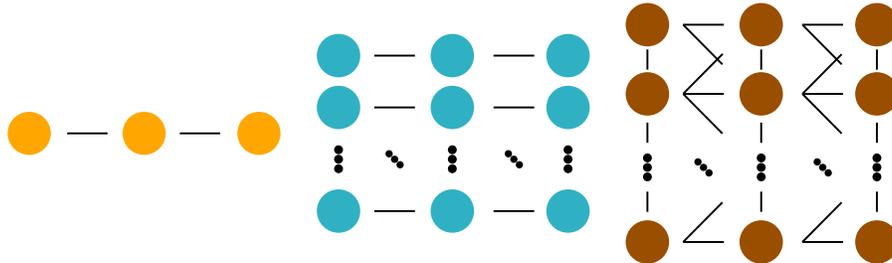


Figure 3: Parameter sharing strategy for monolingual (yellow), skew-lingual (blue), and cross-lingual (brown) acoustic model. The lines (-, \, and /) represent the parameter connections, and the coloured circles are acoustic model units; such as a perceptron or a complete classifier.

7.1. Monolingual

The Monolingual classifiers are a classical approach for acoustic models; they consist of training and testing the model with the same language [96]. This strategy has some advantages, such as overall better accuracy, more simple compared to Multilingual and Cross-Language, and the only data required is about the target language. The better results are expected, and can be visualised in Table 8, since the training and testing data are in the same domain, helping the technique to create a more accurate model. Most of the acoustic models in this category rely on classical extraction and classification methods, such as MFCC and MLP [2, 12, 17], for which the field has robust and stable software available (as shown in Section 4).

Some works still address the speech recognition on Portuguese languages with this approach, for example in [102, 101] the author uses a hybrid model based on a Fuzzy Inference System and Genetic Algorithm trained on a corpus of the Portuguese language. It is also possible to find new methods, such as Convolutional Neural Network (CNN) [94], and modifications on Linear Discriminant Analysis [93] to include noise and uncertainties in observations, therefore improving the system performance on noisy environments. Another work that addresses ASR with this approach is [103], which gave the same contribution in [104, 105, 106, 107, 108], with an SVM. Furthermore, an investigation of the DNN ability to learn window features, up to 400ms, is given by [120]. Other researchers that follow this line are [10] with an investigation of the impact of Chaotic Particle Optimisation (CPO) in the Gaussian Mixture Model (GMM) accuracy, and the HMM baseline system built by [70]. Besides, the identification of vocal ageing [59] with a combination of Artificial Neural Networks (ANN) and SVM is also classified as Monolingual, as well as the ensemble of ANNs [87] trained on a single language dataset. Then, in a different direction is [100], which evaluates the efficiency and performance impacts of well-known parameters for ASR.

While the advantages of this approach seem attractive, it also has some drawbacks. The main challenge of developing language technologies for low-resource languages (e.g. Portuguese) is the difficulty to find a suitable amount of data to train the models while preventing problems, such as overfitting [40]. Due to this issue, and the fact that monolingual techniques have to be trained on the target language, there is a performance reduction [9] when these models are applied to under-resourced languages.

The Monolingual researches showed two main similarities. First, the necessity to collect data for the target language, given that a description of the data gathering procedure is usually seen in most publications. Besides, it is also common that works on this line are addressing something else than STT, using it as an intermediate to achieve its goals. This is the case in [94], aiming to reduce the impact of noise in acoustic models, investigating the effect of biological factors in speech [74, 72], evaluating the performance of ASR systems for the elderly [73], speech dysfunction [35], the identification of different intonations of Brazilian Portuguese questions [16], voice-controlled vehicles [6], and the prevention of user intrusion for speaker identification systems [29]. Therefore, the Monolingual approach is still useful for several applications for ASR, because their goals differ from just a speech-to-text conversion, and the need for a large amount of data is alleviated since the domain has a limited set of words.

7.2. *Skew-lingual*

The multilingual approach emerged from the lack of a more generic speech recogniser, enabling the same system to convert speech from n -languages for their respective text format. However, this paper proposes a Skew-lingual, following a geometry definition of lines that do not intersect and are not parallel. This association emphasises the fact that each unit of the model does not share knowledge, working independently. The central aspect of this method is that it is composed of specific language acoustic model sets. Since each unit is language dependent, then its quantity defines the number of languages it can recognise.

Because a skew-lingual model has multiple independent classifiers, STT task is usually preceded by a language identification [96]. This process will allow the model to choose which classifier can better recognise the current utterance. There are also works focusing on language identification, such as classification of closely related languages and dialects [26], DNN performance for language classification [30, 47, 110], including Portuguese, and even GMM models [113]. Besides, an application of Fishervoice extraction with SVM was investigated in [53].

The employment of ensemble networks [17] and SVM [53] is also another option. The former, in particular, is an excellent example of a skew-lingual acoustic model. The architecture consisted of six networks; each of them classified the inputs as a language unit. After that, an ensemble network decided which of the previous classifiers were more likely to be correct. Therefore, the last network had the same function as a language identification procedure.

However, some issues are inherent to this approach. One of them is scalability, which increased with the number of languages. Even though we have seen

substantial success in recent models, we are still not sure about the feasibility of a universal model that can process any language with the same results that we see on language-specific one.

Catastrophic failure is also an aspect that should not be underrated, as it was observed by several authors when the model deals with conditions that could not be modelled by the data or the inherent constraints of models [118]. Given the somewhat random occurrence of such problems, we may see an increasing number of events for skew-lingual models, because this class of models is a more significant challenge than a language-specific one.

The literature does not have a large number of skew-lingual researchers. Due to its flaws and small gains over mono and cross-lingual methods, these techniques are not popular.

This section illustrated the advantages and disadvantages of Skew-lingual models and exemplified its characteristics with applications and researches. Next, an introduction to cross-lingual procedures will be presented.

7.3. Cross-lingual

This approach depends on the assumption that different languages have a typical structure, a mapping function that can correctly associate one to another [96]. From that, it is possible to train an acoustic model with a corpus that contains n -languages, while the presence of a target language is optional. However, the amount of data for the target language is usually low, and actually, none in some cases [124], as well as [62] for classification on an African idiom. The model was trained on 10 languages, including Portuguese, and further improved in [64] with a Connectionist Temporal Classification (which gave the same contribution [63]). Despite the number of languages that a model can recognise, there are those that combine knowledge between its units but focuses on single language classification, such as [48].

Cross-lingual systems are being further investigated, in some cases outperforming the previous classes [28]. Its ability to recognise a language for which the model was not presented during the training is essential for low-resource languages [96]. This method alleviates the need of a large amount of data for language technologies, enabling the development of more sophisticated acoustic models, such as DNNs, and CNN's while preventing common learning problems [40, 99].

There are several examples of this technique in the selected papers. For instance, an acoustic model trained with Spanish, Portuguese, and Swiss had a 24% WER for German as target language [61]. Besides, the literature provided several applications of DNNs. One of them is a study if merging phoneme classes from distinct languages can provide a classification procedure superior to pretrained DNNs [126]. Several state-of-the-art classifiers are in this category, such as SGMM adaptation [54, 55] and Connectionist Temporal Classification [82, 117, 128]. Another cross-lingual approach is given in [54, 55] with an SGMM adapted with Maximum a posteriori.

Other cross-lingual research with good outcomes is [45], where a tandem-feature approach is investigated, motivated by a more straightforward parameter

sharing strategy. In a tandem-feature, the acoustic model units are lined up one behind the other and facing the same direction [21]. This way, the knowledge of source languages are mixed in an attempt to classify the target language.

This class of models are recent, and less research is available for it. Even though cross-lingual results and applications, they are promising. In fact, for low-resource languages, these models are critical. This necessity is due to the ability to recognise languages that were not present in training. Here, an introduction for cross-lingual acoustic models was given with some clarification based on its recent publications.

Next, a general overview of field directions and gaps and the authors conclusions will be presented.

8. Research directions and gaps in Portuguese automatic speech recognition

This section aims to present suggestions about the field directions and gaps based on the essential works selected in this study and the information collected about them. In Section 4, we added information about the popularity of datasets in the period. Thus, following this reasoning, Figure 4 presents the same idea for classification methods employed on any ASR sub-module, while Figure 5 presents the extraction methods. In the next sections, an overview of future research on classification and extraction methods for ASR is presented.

8.1. Classification methods

The most recent classification procedures were, on its totality, artificial intelligence methods. The chart in Figure 4 present the HMM with the highest popularity. Its presence in the area, for an extended period, was usually high [9]. However, most of it is now overlapped because this model is commonly used in conjunction with MLPs.

Very few papers use a pure HMM [35, 70, 121], since mixtures of ANN and HMMs is providing better results [1, 28, 61, 72]. This combination is also the fact for Restricted Boltzmann Machines (RBM), which is mostly used for DNN parameters initialisation, such as pretraining [61, 114].

The popularity of DNN is close to MLPs. This pattern shows growth in deep learning approaches for ASR. It is also notable that DNN popularity is still smaller than other techniques. Since this approach requires a large amount of data, it is normal that low resource languages do not use it very often. While most of the resources for Portuguese remain with restricted access, the techniques that do not rely on large amounts of data (SVN, MLP) will increase in popularity.

However, some gaps can still be spotted. The AI field has several methods for classification. Although, for Portuguese and its variations, the diversity of techniques is not notable. A total of eight (SVM, HMM, MLP, SGMM, DNN, ANFIS-3, CPSO, and CNN) classifiers were used from 2012 to 2018. Even though these methods already presented good results for English variations, it

Table 8: Accuracy of works between 2012 and 2018.

Accuracy	f_i	F_i	Papers
50-70	1	1	[35, 57, 123]
70-80	7	8	[36, 52, 54, 59, 74, 72, 124]
80-90	10	18	[1, 2, 10, 17, 25, 32, 40, 43, 45, 48, 55, 61, 71, 114, 120, 126, 127]
90-100	10	28	[28, 35, 36, 47, 70, 69, 94, 102, 101, 122, 126, 100]
Total	28	-	-

is known that distinct languages can give different structures, phonemes, and features [96]. Therefore, it is important to try other methods, such as ANFIS variations or CNN, or even classifiers, that failed to provide good outcomes for well-resourced languages.

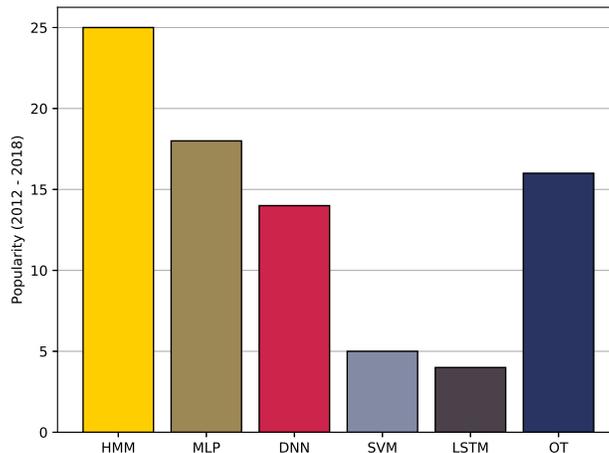


Figure 4: Popularity of classifiers between 2012 and 2018. Support Vector Machine (SVM); Hidden Markov Model (HMM); Multilayer Perceptron (MLP); Restricted Boltzmann Machine (RBM); Deep Neural Network (DNN); Sum of classifiers with one usage (OT).

One more flaw identified is the absence of clustering techniques and more combinations of classifiers with evolutionary algorithms. The clustering methods are usually applied on vector quantisation for ASR [83]. While they had no presence at all between 2012 and 2018, some evolutionary algorithms have been highlighted [109, 10, 102, 101]. While evolutionary techniques are investigated in both [102] and [10]. The first paper show results of replacing the Least Square Estimation by a Genetic Algorithm on the learning procedure of an ANFIS. The second introduces a combination of GMMs and a CPO, compare it with a pure GMM, and the authors conclude that CPO has improved over GMM. Therefore, these hybridisations are promising, but they require a more in-depth investigation, given their small number of researches.

Finally, Table 8 shows the accuracy of the selected papers. Note that a total of 28 papers are present on the table; this is because applications and dataset creation were excluded from it. Table 8 shows that most of the works have accuracy above 80%, while only one is below 70%. These results represent some maturity on the field, with decent outcomes even though it is under-resourced. Also, a hybrid method [94] is among the most accurate classifiers, reinforcing that these methods are promising.

8.2. Features

This section will present the most popular extraction methods for ASR from 2012 to 2018, besides an overview of researches on this topic. Thus, in Figure 5, the chart represents the popularity in the field for these methods.

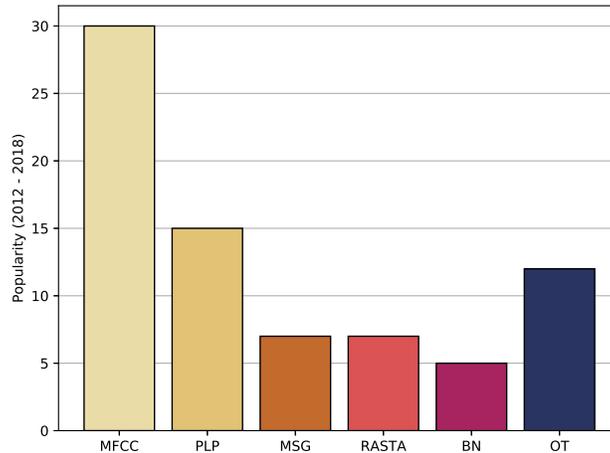


Figure 5: The popularity of feature extraction techniques from 2012 to 2018. Mel-Frequency Cepstrum Coefficients (MFCC); Perceptual Linear Prediction (PLP); Modulation Spectro-Gram (MSG); log-RelAtive SpecTrAl (RASTA); (SMILE); Sum of other extraction methods used (OT).

The MFCC is by far the most popular, along with PLP and it is likely to keep that way. Both of them have presented a more generic aspect, being employed on distinct tasks other than STT. Usually, they can provide good results on other applications rather than STT, such as language recognition [64] and age estimation [73]. In particular, MFCC present a general better accuracy, as well as simplicity over other methods [25].

However, it is important to carefully determine the best features for a given problem. As other features, explored between 2012 and 2018, also have an influence. During this period, a total of 16 features were explored. Compared to the number of distinct classifiers, the features had a more in depth exploration, being used in distinct applications and approaches.

Finally, the field is very diverse with respect to features. However, the availability of dataset may have restrict the use of some methods. Next section will describe the authors conclusions.

9. Conclusion

This paper presented a review of ASRPT from the period between 2012-2018. The information about classifiers, extraction methods, and datasets can be used to start new researches for that language. The gathered information from papers made it possible to see the area tendency and gaps for every Portuguese ASR component. Besides, they can be used to investigate the field further and explore new methods.

The researches of speech recognition for Portuguese language and its variations has shown an expected small number of investigations. Although, their accuracy falls behind the researches for more popular languages. This decay, as shown in this review, because of the lack of data for developing language technologies. So, even though some papers aim to collect speech data, most of them do not publish it freely. Such hidden information difficulted the use of more sophisticated techniques, such as DNNs and CNN's, which would require a large amount of data. Furthermore, the studies on this subject have shown a diversity of reasons to use ASR, while at the same time did not explore many classification techniques. Therefore, this area of research still has room to exploration on several components of ASR.

Finally, this paper may also be used to introduce automatic speech recognition for anyone with little information about it, especially for scientists interested in ASR.

Acknowledgments

This work was supported by the Brazilian Coordination for the Improvement of Higher Education Personnel (CAPES).

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