Abstract

Maltese, the national language of Malta, is spoken by approximately 500,000 people. Speech processing for Maltese is still in its early stages of development. In this paper, we present the first spoken Maltese corpus designed purposely for Automatic Speech Recognition (ASR). The MASRI-HEADSET corpus was developed by the MASRI project at the University of Malta. It consists of 8 hours of speech paired with text, recorded by using short text snippets in a laboratory environment. The speakers were recruited from different geographical locations all over the Maltese islands, and were roughly evenly distributed by gender. This paper also presents some initial results achieved in baseline experiments for Maltese ASR using Sphinx and Kaldi. The MASRI-HEADSET Corpus is publicly available for research/academic purposes.

Keywords: Maltese, Speech Corpora, Automatic Speech Recognition

1. Introduction

As digital resources and tools for Natural Language Processing and language-enabled interfaces become ever more common in daily use and commercial applications, it has become increasingly important to ensure that all languages are adequately represented in the digital sphere. This concern is evident, for example, in a recent resolution passed by the European Parliament to safeguard language equality in the digital age (European Parliament, 2018).

In this regard, so-called ‘under-resourced’ or ‘low-resourced’ languages have been an ongoing concern within some sectors of the NLP community. For example, in a series of white papers published in 2011-12, reviewing the level of digital support for 31 of the languages of the European Union, the METANET Initiative[1] concluded that for a significant number of these languages, support in most areas of NLP was at best fragmentary and in some cases, weak or non-existent.

The METANET papers took the step of determining the level of support for different languages with reference to specific tasks or domains, namely: machine translation, text analysis, speech/language resources and speech processing. In principle, a language could have strong support in a subset of these, with weak or fragmentary support in others. This is reminiscent of the strategy used by Krauwer (2003), who discussed the notion of an ‘under-resourced’ language in terms of a minimal set of language resources (a Basic Language Resource Kit, or BLARK) necessary to undertake further precompetitive research and education. A somewhat more wide-ranging definition was more recently offered by Besacier et al. (2014), in their review of ASR for low-resourced languages, where the criteria included the following:

- Lack of a unique writing system or stable orthography.
- Lack of linguistic expertise.
- Limited presence on the web.

1.1. The case of Maltese

Maltese, the national language of Malta, was one of the languages which, at the time of the METANET white papers, was ranked as having weak or no support under all four of the headings listed above (Rosner and Joachimsen, 2012). This is in spite of the fact that Maltese does not suffer from the first two of the list of criteria offered by Besacier et al. (2014): the language not only has a long written tradition and a stable orthography (Azzopardi, 1995; Hoherman, 2007; Gatt and Fabri, 2018), but is very well-studied linguistically at all levels, including the morphological (Mifsud, 1995), syntactic (Fabri, 1993; Cépló, 2018), and phonological (Vella, 1994), as well as in terms of its historical development (Brincat, 2011) and typological status (Comrie, 2009). On the other hand, its web presence, while comparatively small compared to that of languages such as English, could be argued to be proportional to the size of its community of speakers.

It is the fourth criterion listed by Besacier et al. (2014) – lack of electronic resources – that was the basis for the conclusions reached by Rosner and Joachimsen (2012). There are numerous factors which could have contributed to this situation. First, Maltese is a language with a small number of speakers (ca. 500,000); this fact makes NLP for Maltese appear less economically advantageous, at least for commercial developers. Second, Malta is officially a bilingual country, with English as the second language. The lack of digital support for Maltese has meant that many users resort to English for their electronic and online communication. On the other hand, this also implies that people whose language proficiency is Maltese-dominant might simply abstain from communicating through certain channels where their native language is not represented. Indeed, where speech is concerned, this is arguably also true for English speakers in Malta, since available speech interfaces, for
example on mobile devices, tend to be developed for the recognition or synthesis of varieties of English (such as British, American or Australian) with a larger number of speakers, while Maltese English, which has been argued to be a variety in its own right (Grech, 2015), is unsupported. As a matter of fact, digital support for the Maltese language has improved drastically since the publication of the METANET white paper (and this is likely true for a number of other languages covered by the white paper series). To take some examples, large annotated corpora for Maltese are now available, with accompanying tools for segmentation and labelling, including tokenisation and part-of-speech annotation (Gatt and Cépló, 2013). Advances have been made in the development of electronic lexicons (Camilleri, 2013) and in automatic morphological analysis and labelling (Borg and Gatt, 2017; Ravishankar et al., 2017) as well as dependency parsing (Fedemann and van der Plas, 2016; Zammit, 2018).

Advances in speech technology for Maltese have however been comparatively limited. While there have been successful attempts to build speech synthesis systems using concatenative techniques (Micallef, 1997; Borg et al., 2011), no tools currently exist for Automatic Speech Recognition (ASR). This is partly due to a substantial data bottleneck where resources for speech engineering are concerned.

1.2. Aims of the present paper
The present paper addresses this gap, presenting a new corpus for ASR, built in the context of ongoing work in the MASRI (Maltese Automatic Speech Recognition) project. The paper describes the MASRI-HEADSET Corpus (MHC), the first corpus in Maltese suitable for training ASR systems.

The rest of this paper is structured as follows. Section 2 describes the design strategy and the recording process leading up to the corpus. In Section 3, we demonstrate its suitability for creating acoustic models for ASR by running some experiments in CMU-Sphinx and Kaldi. We also discuss the construction of pronunciation models of Maltese. Section 4 concludes the paper with a brief overview of ongoing work on expanding Maltese speech resources, and on deploying recent techniques for ASR that reduce the dependency on large data sources.

2. The MASRI-HEADSET Corpus (MHC)
MASRI-HEADSET is the first Maltese corpus specifically designed with ASR systems in mind. While it is comparatively small, it constitutes the first step in the creation of larger-scale resources for speech recognition in Maltese.

In this section, we describe the design of MHC, including the selection of participants whose voices were recorded for the corpus, as well as the process whereby textual prompts were selected. Finally, we discuss the characteristics of the final release version of the corpus.

2.1. Corpus Design and Collection
Participants
Expressions of interest in participation were solicited via online advertisements. Initially, 61 people expressed interest. In an effort to ensure adequate representation of accent and speaker variation, participants were selected to achieve a balanced sample in terms of gender, age and geographical location, the latter being defined in terms of the six regions of the Maltese islands defined by the National Statistics Office for data collection purposes (NSO, 2019), as shown in Figure 1. Out of a total of 61 people who expressed interest, 25 individuals were recruited. The sample is approximately gender-balanced, with 13 female and 12 male speakers (age range = 18 to 31; mean age = 23.9, SD = 3.54). Table 1 provides a summary of the participants and the average number of hours and utterances split by gender. Participation was remunerated at the rate of €15 for approximately one hour of recording. Written consent was obtained and the procedure was screened by the procedures of the University of Malta Research Ethics Committee.

|                | Female | Male |
|----------------|--------|------|
| Number of Speakers | 13     | 12   |
| Average amount per speaker | 19m:57s | 18m:53s |
| Average utterances per speaker | 158.0 | 150.8 |

Table 1: Overview of the MASRI-HEADSET Corpus

Language dominance: Given the bilingual situation in Malta, where apart from Maltese, English is also an official language, and where some individuals are English-dominant, prospective participants were asked to respond to an online language background questionnaire. The 25 participants selected were all Maltese-dominant speakers, with some also speaking dialects of Maltese, in addition...
to standard Maltese. Speakers with dominance in English rather than Maltese were not eligible for participation in this particular corpus collection.

**Sentence selection:** Approximately 200 samples of sentential prompts were selected from the Korpus Malti v3.0 (Gatt and Céplő, 2015). Samples were built using the following procedure, which was intended to ensure that each sample would contain as broad a range of phonological and phonotactic variation as possible:

1. The full corpus was transcribed automatically using a rule-based grapheme-to-phoneme (G2P) mapping procedure;
2. A trigram model over phone sequences was constructed based on the full corpus;
3. The corpus text was broken up into blocks of approximately 75 orthographic words each, with each block paired with its orthographic transcription. Blocks were randomly shuffled. Samples were then constructed by greedily adding blocks to a sample, as per the following algorithm:
4. For \( i = 1 \) to \( n \) samples, with size \( m \):
   (a) initialise sample \( s_i \) to \( \emptyset \)
   (b) While \( |s_i| < m \), sample the next best block and include it in \( s_i \)

where the ‘next best block’ is defined in terms of coverage: given the current distribution of trigrams in blocks already included in the sample, the best next block is the one that results in the greatest amount of variation in the sample once it is included. Once a sample was constructed, prompts containing proper names and/or words in English were pruned.

The result of this procedure was a set of samples, each consisting of blocks of text (our prompts). Each of the 25 participants was required to read each block of text in the sample assigned to them.

**Recording methods:** Speech recordings were made in a quiet room at the Faculty of ICT at the University of Malta. The recordings were done in a dual fashion: close (using a headset) and far-field (via a microphone at a distance of approximately 3 metres from the participant). Only one audio file contains a male speaker with no background noise.

Each speaker read prompts from one of the samples, showing on a computer screen in random order using SpeechRecorder (Draxler and Jänsch, 2004), which was also used to capture the recordings. The headset recordings were captured using a Sennheiser PC-8 (48KHz) mic/headset and the recording sessions typically lasted between 45 minutes and one hour for each of the participants.

### 2.2. Characteristics of the Release Version

After recording, the data underwent a process of pruning and normalisation, resulting in the following characteristics:

- The MHC has an exact duration of 8 hours and 6 minutes. It has 3864 audio files.
- Every audio file contains only the voice of one single speaker with no background noise.
- Utterances with stuttering and/or mispronunciations were pruned.
- Data in MHC is classified by speaker, with all recordings of one speaker stored in a separate directory.
- Data is also classified according to the gender (male / female) of the speakers.
- Audio files in the MHC are distributed in a 16khz @ 16bit mono format.
- The MHC corpus contains 3864 utterances (one per audio file), with a total of 11,503 unique words or tokens.
- Every audio file has a unique ID that is compatible with ASR engines such as Kaldi (Povey et al., 2011) and CMU-Sphinx (Lamere et al., 2003).
- All textual transcriptions in MHC are lowercased. All punctuation is removed, with the exception of hyphens (-) and apostrophes (’), which are part of Maltese orthography.

Table 2 provides a detailed overview of each participant in terms of the total time recorded and the number of utterances read.

### 3. Experiments

In this section, we describe a number of experiments in constructing ASR systems using a typical architecture consisting of language model, pronunciation model and acoustic model. These are intended to provide baseline results, demonstrating that the MHC is suitable for training ASR systems using off-the-shelf toolkits, namely, the Pocketsphinx (Huggins-Daines et al., 2006) and Kaldi (Povey et al., 2011) engines. The choice of these toolkits was based on the following rationale.

MHC is a relatively small dataset compared, for example, to standard datasets for English (Panayotov et al., 2011; Roter, 2019). State of the art systems, such as DeepSpeech (Amodei et al., 2016), Wav2Letter (Collobert et al., 2016) or Espresso (Wang et al., 2019) are known to require datasets which are orders of magnitude larger than MHC. At the same time, Sphinx and Kaldi remain widely used for quick prototyping, and perform a series of transformations on input data that make them less data hungry than more sophisticated systems. Since our aim is to produce an initial set of baseline results, these toolkits were appropriate.

7Pocketsphinx is a real-time version of the CMU-Sphinx (Lamere et al., 2003).
Table 2: Details for MASRI-HEADSET Corpus

| Speaker ID | Total time | No. of Utterances |
|------------|------------|-------------------|
| F.01       | 12m:57s    | 112               |
| F.02       | 13m:27s    | 127               |
| F.03       | 24m:19s    | 182               |
| F.04       | 20m:48s    | 166               |
| F.05       | 19m:35s    | 174               |
| F.06       | 18m:11s    | 125               |
| F.07       | 22m:56s    | 161               |
| F.08       | 19m:29s    | 171               |
| F.09       | 21m:15s    | 170               |
| F.10       | 23m:16s    | 169               |
| F.11       | 17m:46s    | 144               |
| F.12       | 21m:18s    | 178               |
| F.13       | 24m:10s    | 175               |
| M.01       | 15m:20s    | 118               |
| M.02       | 22m:02s    | 164               |
| M.03       | 15m:18s    | 117               |
| M.04       | 17m:19s    | 125               |
| M.05       | 22m:26s    | 159               |
| M.06       | 17m:57s    | 179               |
| M.07       | 21m:26s    | 177               |
| M.08       | 19m:17s    | 170               |
| M.09       | 20m:05s    | 166               |
| M.10       | 18m:02s    | 134               |
| M.11       | 20m:08s    | 164               |
| M.12       | 17m:18s    | 137               |

3.1. Training and test data

For the purposes of these experiments, the MHC was randomly divided into training (3614 files, totalling 7h:35m:21s) and test (250 files, totalling 30m:57s) sets. Note that the corpus, as distributed, does not reproduce the split, but is distributed as one whole set. Nevertheless, one can reproduce the experiments of this paper with the help of our "LREC2020 Experiment Files" available in our project website.

While the selected test set is small, it was sampled to ensure representativeness, by including 10 audio files from each of the 25 speakers represented in the corpus. The aim is thus to enable an evaluation of a relatively simple ASR model on test data with limited speaker variation (in the sense that data from all speakers is also represented in the training set).

In constructing a language model and pronunciation dictionary for the experiments reported below, none of the utterances or lexical items in the test set were included.

3.2. The Language Model

The language model was created using part of the Korpus Malti v3.0 (Gatt and Čeplo, 2013), a corpus of written or transcribed Maltese divided into different genres, including: culture, news, academic, religion, sports, etc. The corpus is annotated with part of speech information and has a size of approximately 250 million tokens. A substantial proportion of the tokens are also lemmatised.

For the purposes of these experiments, sentences containing Maltese-English code-switching or extensive borrowing from English were excluded – English words were identified via the CMU Pronunciation Dictionary [Weide, 1995]. We also removed sentences with digits and proper names (to distinguish between proper names and other tokens, we used CIEMPIESS-PNPD [Mena, 2019]). After the selection process, we ended up with more than 28,000 sentences. In addition, we included the transcriptions from the MHC training data (3,614 in total) so as to reduce perplexity.

Using the above data, a 3-gram language model was produced using the SRI Language Modelling Toolkit.[9]

For the experiments with Sphinx, the model could be directly included in ARPA format; for Kaldi, the format was transformed using the off-the-shelf Kaldi executable arpa2fst.

3.3. The Pronunciation Model

Traditional ASR systems, such as Sphinx, Kaldi or HTK [Young and Young, 1993], require a pronunciation model in the form of a pronunciation dictionary. The format of these kind of dictionaries is very simple: a list of words alphabetically sorted, each of them followed by a sequence of phonemes separated by spaces. An example is shown in figure 2 for the lemma abbanduna ‘to abandon’ and its derivations.

Figure 2: Format of the Pronunciation Dictionary

Words in the Korpus Malti v3.0 corpus were converted into their phonetic transcription using a grapheme-to-phoneme tool (G2P), which is a new Python 3 implementation of an earlier model by [Borg et al. (2011), originally built in the context of a text-to-speech system for Maltese (see Section 1.). The phoneme set used by the G2P tool is given in the Appendix, Table 5.

The resulting pronunciation dictionary contains more than 4,000 words. Table 3 shows the phoneme distribution in the MHC corpus.

Table 5 reveals that there is no point in considering G2P rules for the low-pitch vowels due to their small counts. While such vowels are known to help to improve naturalness in speech synthesis systems, their low frequency suggests they might have limited value for ASR. We leave this as a question for future work.

[9] http://www.speech.sri.com/projects/srilm/
### 3.4. Sphinx Setup

For this experiment, Sphinx was configured using standard settings: continuous Hidden Markov Models (HMM) with 3 states per HMM and 1,050 tied states. The number of tied states was determined empirically by running the training stage several times and selecting the model with the lowest Word Error Rate (WER).

As features, we computed MFCC vectors through Sphinx for all of the 13 coefficients, plus the first and second derivatives.

In addition to the above setup, we also performed additional experiments applying Linear Discriminant Analysis (LDA) and Maximum Likelihood Linear Transform (MLLT).

### 3.5. Kaldi Setup

We carried out two experiments in Kaldi: one with traditional HMMs and the other with neural networks using the `nnet4d3` recipe. The following processes were used during HMM training:

- Linear Discriminant Analysis (LDA)
- Maximum Likelihood Linear Transform (MLLT)
- Speaker Adaptive Training (SAT)

### 3.6. Results

Table 4 shows the results for all the experiments performed, providing information about the Word Error Rate (WER) and the Sentence Error Rate (SER). The overall perplexity of the language model in all experiments was 182,374, with 87 out-of-vocabulary (OOV) words.

| Experiment                  | WER  | SER  |
|-----------------------------|------|------|
| Sphinx HMMs                 | 19.40% | 64.00% |
| Sphinx HMMs+LDA/MLLT       | 18.40% | 59.60% |
| Kaldi HMMs                  | 12.54% | 39.60% |
| Kaldi NNs                   | 10.56% | 37.60% |

Table 4: Results of the experiments performed

As the table shows, the best results were obtained by Kaldi with a neural network setup. It is interesting to note that the difference between Sphinx and Kaldi is at almost 10%. This is consistent with similar experiments done on Spanish (Mena et al., 2017).

### 4. Conclusions and future work

This paper described the design of MASRI-HEADSET (MHC), a new corpus for Maltese speech aimed to support research on automatic speech recognition (ASR). This is the first corpus of its kind for the Maltese language, for which speech resources are still somewhat limited.

Preliminary experiments with the corpus, while somewhat small-scale, suggest that high-quality acoustic models can be created in spite of the small size of the MHC, due to the low noise in the recordings. Our best results (WER of 10.56%), obtained with a neural network setup, point to the importance of performing future experiments with modern speech recognizers based on neural networks such as Deep-Speech (Amodei et al., 2016), Wav2Letter (Collobert et al., 2016) or Espresso (Wang et al., 2019).

The corpus will be freely available from our website\[^{1}\] for research purposes, with additional licensing options for commercial use.

While MHC is an important first step towards achieving adequate support for Maltese speech technology, it is limited in size. Our current work is addressing this issue, as well as

\[^{1}\]http://www.um.edu.mt/projects/masri/index.html
other challenges in developing viable ASR technology for spoken Maltese, from multiple angles. First, we are studying recent techniques for enhancing ASR in weakly supervised or unsupervised settings, with a view to maximising the use of the available data, either via pre-training (Schneider et al., 2019), or via augmentation techniques such as spectrogram perturbation (Park et al., 2019) and noise superposition (Hannun et al., 2014). Second, a crowdsourcing effort is currently underway, based on the Common Voice initiative. Common Voice (Roter, 2019) is an open-source, web-based platform created by Mozilla in order to crowd-source speech data for various languages. Language communities are encouraged to localise the Common Voice website to their language, as well as to provide a minimum of 5,000 validated sentences to be used as prompts to be read out and validated by users. This process is currently underway for Maltese, with the website having been completely localised and sentence prompts already sampled from the Korpus Malti v3.0. The prompts are currently being validated for use. Once this process is complete, users will be able to contribute to the construction of a larger, community-driven dataset for Maltese by donating their voices to the project, as well as validating other users’ voice clips. As part of this effort, we are also developing unsupervised techniques designed to automatically validate user-contributed data, using heuristics to automatically rank text-speech pairs according to the likelihood that a recorded voice clip matches a textual prompt. Finally, many of the important challenges for open-domain ASR for Maltese are connected to the complexities arising from the bilingual (Maltese/English) situation described in Section 1, where a majority first language with a relatively small number of speakers (in this case Maltese) exists alongside a far better resourced and more widely-spoken language (that is, English). A well-known issue in such intensive language contact situations is the widespread incidence of code-switching and lexical borrowing (Martin, 2009). Any viable ASR system for Maltese will also need to handle Maltese-English code-switching. We aim to address this both from the data-collection perspective, through selection of data from naturalistic sources, as well as crowd-sourcing and further data-collection efforts, and from the modelling perspective as we explore transfer learning and learning from mixed language resources.

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# Appendix A: The Maltese Phonology

## Consonants

| Bilabial | Labiodental | Alveolar | Postalveolar | Palatal | Velar | Glottal |
|----------|-------------|----------|-------------|---------|-------|---------|
| Plosive (voiceless) | p | t | k | f | g | l |
| Plosive (voiced) | b | d | g | h | |
| Affricate (voiceless) | ts | tf | | | |
| Affricate (voiced) | ðz | ðf | | | |
| Fricative (voiceless) | f | s | j | h | |
| Fricative (voiced) | v | z | ñ | | |
| Nasal (voiced) | m | n | | | |
| Lateral Approximant (voiced) | l | | | | |
| Trill (voiced) | r | | | | |
| Approximant (voiced) | | | | | |

## Vowels

| Front | Central | Back |
|-------|---------|------|
| i | i | ù |
| e: | e: | o: |
| è: | è: | ò: |
| ì | ì | ù |
| è | ì | ò |

Table 5: The Phonological System of the Maltese Language