Development of Hybrid ASR Systems for Low Resource Medical Domain Conversational Telephone Speech

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Abstract

Language barriers present a great challenge in our increasingly connected and global world. Especially within the medical domain, e.g. hospital or emergency room, communication difficulties, and delays may lead to malpractice and non-optimal patient care. In the HYKIST project, we consider patient-physician communication, more specifically between a German-speaking physician and an Arabic-, Vietnamese-, or Ukrainian-speaking patient. Currently, a doctor can call the Triaphon service to get assistance from an interpreter in order to help facilitate communication. The HYKIST goal is to support the usually non-professional bilingual interpreter with an automatic speech translation system to improve patient care and help overcome language barriers. In this work, we present our ASR system development efforts for this conversational telephone speech translation task in the medical domain for two language pairs, data collection, various acoustic model architectures, and dialect-induced difficulties.

1 Introduction

In our globally connected world, it is becoming increasingly common to migrate to foreign countries, whether for work, refugee movements, or other reasons. Consequently, language barriers between locals and foreigners pose a frequent everyday problem. This can be particularly challenging for patient-physician communication during anamnesis, especially in the emergency room, leading to potential degradation of patient care. The German Triaphon service\textsuperscript{1} is designed to help with communication in these situations, where no common language is shared between patient and physician.

The service provides a usually non-professional bilingual interpreter to help with patient-physician communication. Nevertheless, communication regarding medical terms remains critical since these might not be known by the (medically not trained) interpreter, and the impact of erroneous or delayed translation might be particularly severe here. In the HYKIST\textsuperscript{2} project, the goal is to develop a speech translation system to support the interpreter with automatic speech translation. In this context, several challenges arise, like varying acoustic and recording conditions due to different devices and changing environments as well as bilingual input through a single recording channel, since the phone in the emergency room is shared by the physician and patient. Additionally, we deal with telephone speech, as the interpreter is called via phone.

In this paper, we present our efforts on building automatic systems for transcribing the telephone speech encountered in this project. We collect data of (simulated) patient-physician conversations assisted by a Triaphon interpreter and create manual annotations. Results are presented on all four languages considered in the HYKIST project, i.e., Arabic, German, Vietnamese, and Ukrainian.

2 Related Work

There has been research work specifically addressing tasks within the medical domain. A common issue for medical domain ASR is challenging acoustic conditions and a privacy-related lack of domain-specific data [1–3]. The domain-specific medical terminology presents another challenge. In [4], a multilingual system for the medical domain is presented. Another approach to handle the medical domain is correcting ASR errors on the output level [5]. Earlier works presented ASR systems for the four target languages, e.g. a system for Arabic in [6]. German ASR systems were developed within the Quaero project [7] and similarly, Vietnamese was part of the Babel project [8].

3 Data

3.1 HYKIST data

Within the HYKIST project, our partner Triaphon recorded the Arabic-German and Vietnamese-German trialogues, while we recorded the Ukrainian-German trialogues, i.e. conversations between three persons: patient and physician on the emergency room end of the line using the same phone device, and an interpreter on the other end of the line. The patient speaks the non-German language – Arabic or Vietnamese – while the doctor speaks German. The interpreter speaks both languages and helps the patient and doctor communicate. Finding suitable speakers for each role was a challenging task since each role has a limiting factor on availability. The physician speaker role requires medical training, limiting the speaker to physicians, doctors, and nurses. While the patient role has the lowest bar on skill set, contacting and finding people with no or little German language skills in Germany was challenging. The interpreter role also posed challenges since the role requires bilingualism.

For the Ukrainian-German trialogues, we recruited doctors and nurses from the hospitals in Aachen and established connections with Ukrainian refugees. We used the Triaphon telephone service system to conduct the recordings. The speakers were instructed to speak as normally as possible, in order to facilitate a natural conversation with speech pauses, intonations, and hesitations. Further, the physician was instructed to embed medical terms into the conversation.

The audio recordings of the simulated conversations were manually transcribed within the project. The tran-
Table 1: Data statistics for labeled telephone conversational speech data. Diversity level specifies the variability in the acoustic conditions of the speech data.

| Language   | Dataset   | Usage | # Spks | Hours | Medical Domain | Target-domain match | Diversity level |
|------------|-----------|-------|--------|-------|----------------|---------------------|-----------------|
| Arabic     | In-house  | train | 3379   | 786   | no             | Medium              | Medium          |
|            | HYKIST    | adapt | 3      | 2     | yes            | High                | Low             |
|            |           | dev   | 4      | 3     |                |                     |                 |
|            |           | test  | 6      | 6     |                |                     |                 |
| German     | In-house  | train | 1723   | 177   | no             | Medium              | Medium          |
|            | HYKIST    | adapt | 5      | 5     | yes            | High                | Low             |
|            |           | dev   | 6      | 6     |                |                     |                 |
|            |           | test  | 10     | 10    |                |                     |                 |
| Vietnamese | In-house  | train | 2240   | 219   | no             | Medium              | Medium          |
|            | HYKIST    | adapt | 1      | 1     | yes            | High                | Low             |
|            |           | dev   | 3      | 3     |                |                     |                 |
|            |           | test  | 2      | 2     |                |                     |                 |
| Ukrainian  | In-house  | train | 1593   | 407   | no             | Medium              | Medium          |
|            | HYKIST    | dev   | 37     | 2     | yes            | High                | High            |
|            |           | test  | 39     | 2     |                |                     |                 |

scribers were provided with an initial transcription guideline, which was extended and modified with the help of the transcribers based on the encountered speech.

The data has been split into three subsets for each language: development and test data, as well as adaptation data, ensuring no speaker overlap between the sets. In Table 1, the data statistics are shown for the adapt, dev, and test sets for each individual language. As shown the adapt, dev, and test set data from the HYKIST recordings are very limited. For the dev and test sets the number of available hours is on the lower end. To further complicate the HYKIST data, the number of speakers is limited, resulting in a low diversity level of the testing data. This is due to the lack of speakers who can participate since each speaker’s role requires an uncommon skill set. Therefore we sourced additional training data from our industry partner AppTek and other sources to tackle the impact of the data issues.

3.2 In-house data

Our industry partner AppTek provided us with a decent amount of general annotated 8 kHz sampling rate conversational telephone speech data. We are restricted to 8 kHz sampling rate due to the requirement of access over plain telephone services. The audio data consists of telephone conversations of customers with varying call centers. In Table 1, the data statistics for the in-house training sets for each of the four languages are shown. We can see that we have a discrepancy in the amount of in-house training data between the languages. Especially, the amount of available German and Vietnamese data is very low. For Ukrainian, the available data set is medium-sized. Arabic has the largest amount of data. Additionally, for the Arabic and Vietnamese data, we have speakers with accents and/or dialects. For the Arabic data, we received four distinct datasets with different dialects: Syrian, Lebanese, Gulf, and Egyptian. In the Vietnamese data, the speakers with accents are combined into one single dataset.

3.3 Monolingual text data

Our project partner AppTek provided monolingual text data for each of the four languages. The data includes text from various sources. In Table 2, the number of running words for each language is shown. The available data amount varies between the languages, favoring German and Ukrainian while Arabic is at the lower end.

3.4 Domain

As shown in Table 1, the data covers various domains. The target domain of the HYKIST project is medical conversational telephone speech. This specific domain is not covered by the in-house training data, which covers conversational telephone speech. By listening to a number of randomly chosen audios and comparing them to our target domain, we subjectively determined target-domain match and diversity level and ranked them as low, medium, and high. The target-domain match specifies if the speech data matches our HYKIST scenario. The diversity level indicates if the speech data covers varying acoustic conditions, like speakers, accents, noises, etc.

4 Methods

4.1 Lexicon

The initial pronunciation lexicon for the Vietnamese language was taken from the Babel project\(^3\). The initial German lexicon was sourced from the Quaero project\(^4\). For the Arabic system, the initial lexicon was provided by AppTek. With the toolkit Sequitur Grapheme-To-Phoneme\(^5\), the initial lexica are extended, creating the training lexicon.

For decoding the HYKIST data, we further augment the lexicon with medical terms. We acquired different sources for the medical terms. Some medical terms were provided by our project partner Triaphon. We scraped the web for more medical terms from medical websites and literature.

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\(^3\)https://www.iarpa.gov/research-programs/babel
\(^4\)http://www.quaero.org/
\(^5\)https://github.com/sequitur-g2p/sequitur-g2p
The generation of phoneme sequences for these medical terms proved challenging since the pronunciation is sometimes not clear. For example, how are Latin or English (medical) terms pronounced in each language? Solving these issues requires an understanding of the language itself and is sometimes not clearly answerable. The final recognition lexica have a size of 370k words for Arabic, 202k for German, and 11k for Vietnamese, see Table 2.

4.2 Acoustic model

To train the acoustic model, we follow the training pipeline described in [10] to establish a Gaussian mixture model (GMM) hidden Markov model (HMM) baseline for each of the languages. This model is used to obtain an alignment of the speech data with the labels. The neural network (NN) used for the hybrid model is trained on these alignments in a supervised way using the frame-wise cross-entropy (ICE) loss, following the setup from [10, 11]. The experimental details for these models are described in Section 5.

4.3 Language model

The language models (LMs) employed all use full-words and are count-based 4-grams. We follow the same training recipe for all languages using the SRILM toolkit [12] to build our LMs using modified Kneser-Ney smoothing. The initial step is to build a LM for each individual monolingual text corpus. Afterwards we evaluate the LMs on the dev set and compute the weight for each LM separately. The weights determine the contribution of each individual LM to the combined LM. The final step is to prune the LM in order to reduce its size, resulting in one LM per language.

5 Experimental setups

In this section, we describe our experimental setups. We use RETURNN\(^6\) [13] for supervised training. Decoding is performed with RASR\(^7\) [14] We plan to publish training and decoding configurations online.\(^8\)

The training recipe for the baseline systems for each language is similar and only varies in detail. For all models, we generate alignments via a Gaussian mixture hidden Markov model process to be used as labels for neural network training. All models are trained from scratch in a supervised manner with fCE. The acoustic model labels are generated using a Gaussian mixture HMM alignment. We apply another training iteration by training the BLSTM model with the better alignments and then generate alignments again. These alignments are used to train the final best Conformer acoustic model.

6 Experimental results

In Table 2, we can see that the LMs’ performance varies drastically. Out-of-vocabulary (OOV) rate gives the percentage of words with in the evaluation corpus which are not within the lexicon and therefore cannot be recognized. The Arabic and German vocabulary results in OOV rates between 1.0% and 1.6% for the evaluation data sets. The Vietnamese vocabulary covers the dev and test set very well with a OOV rate of 0.1% and 0.2% respectively. In contrast, the Ukrainian vocabulary does not cover the dev and test set as well, resulting in a OOV of 5.9% and 7.7% respectively. The evaluation metric perplexity (PPL) informs how well a LM fits to a given evaluation dataset. The German and Vietnamese LMs perform much better compared to the Arabic and Ukrainian LMs. The issue with Arabic LM training is that the medical-domain text data is written in Modern Standard Arabic, but the Arabic dialects have different spelling and words which lead to perplexity degradation. The high Ukrainian OOV rate leads to a PPL degradation. Additionally, some Ukrainians speak a mix of Ukrainian and Russian leading to further PPL degradation.

| Table 2: LMs for all four languages on the corresponding HYKIST dev and test sets. All LMs are 4-grams. |
|-----------------|-----------------|-----------------|--------------|--------------|-----------------|--------------|
| Language        | # words in train | vocab size      | dev size     | OOV PPL      | test size      | OOV PPL       |
| Arabic          | 112M            | 370k            | 1.6% 972     | 1.0% 972     | 6%             | 1.0% 972      |
| German          | 2400M           | 202k            | 1.4% 72      | 1.6% 78      | 7%             | 0.2% 69       |
| Vietnamese      | 500M            | 11k             | 0.1% 67      | 0.2% 69      | 6%             | 0.2% 69       |
| Ukrainian       | 1100M           | 313k            | 5.9% 492     | 7.7% 669     | 7%             | 7.7% 669      |

Each language-specific baseline is trained with the according in-house monolingual 8 kHz sampled telephone data. Table 3 shows the performance of the ASR systems. The systems for each language show varying performance due to the inherent difficulty of the language and the data.

Among the four languages, the German system shows the best performance, followed by Vietnamese, Ukrainian and lastly Arabic. There are several reasons which contribute to this observation. The German and Vietnamese transcriptions are of higher quality compared to the Arabic transcriptions. Furthermore, the Vietnamese have accented speech, and the Arabic data includes several dialects which add complexity.

Otherwise, the performance trends of the ASR systems for the four languages are similar. Moving from a Gaussian mixture HMM framework to hybrid HMM framework with a recurrent NN (BLSTM) leads to a relative word error rate reduction (WER) of 35-44% on HYKIST test. Changing the neural acoustic

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\(^6\)https://github.com/rwth-i6/returnn
\(^7\)https://github.com/rwth-i6/rasr
\(^8\)https://github.com/rwth-i6/returnn-experiments
\(^9\)https://github.com/rwth-i6/returnn-experiments
encoder topology to incorporate self-attention mechanism (Transformer and Conformer) reduces the WER by a 6-8% relative on HYKIST test.

Arabic is a morphologically rich language. Especially for Arabic dialect data, many words can be written in different ways which can lead to high substitution word errors. Thus, Table 3 shows character error rates (CERs) for Arabic on HYKIST dev and test sets. It achieves 17.2% and 21.3% CER on dev and test sets, respectively.

Table 3: WERs [%] for baselines on HYKIST data. Trained in a purely supervised manner on the monolingual in-house data.

| Language | AM          | WER [%] | CER [%] |
|----------|-------------|---------|---------|
|          | dev | test | dev | test |
| Arabic   | Gauss. mix. | 73.2 | 77.0 | 38.6 | 40.5 |
|          | BLSTM | 43.4 | 42.9 | 22.6 | 25.2 |
|          | Conformer | 36.8 | 40.4 | 17.2 | 21.5 |
| German   | Gauss. mix. | 39.1 | 38.7 | |
|          | BLSTM | 27.1 | 24.0 | |
| Vietnamese | Transformer | 26.0 | 22.3 | |
|          | Gauss. mix. | 62.2 | 59.7 | |
|          | BLSTM | 32.9 | 38.4 | |
|          | Transformer | 31.0 | 35.1 | |
| Ukrainian | BLSTM | 29.1 | 41.3 | |
|          | Conformer | 26.1 | 39.5 | |

One issue with dialect Arabic is that it is difficult to find a large amount of text data to train a good LM, especially in the medical domain unlike for the case of Modern Standard Arabic (MSA). Thus, depending on the application, it is possible to do some kind of mapping between dialect Arabic words and MSA words to reduce the confusion made by frequent dialect words. However, mixing dialect and MSA words in the output sentence is not consistent anymore but could work for other tasks such as speech translation where we mainly care about the translated output at the end. In general, this mapping approach would work only if all components of the final system are trained in a consistent way by using this mapping. Thus, we conduct an experiment where we selected the top 200 frequent dialect words and mapped them to MSA words manually. We train a new LM using this mapping and the PPLs are shown in Table 4. Note that we interpolate with LMs trained on MSA text data. The WERs and CERs after applying this mapping are reported in Table 4. With that, we can observe that we can achieve 3% and 4% relative improvement in terms of WER on dev and test sets respectively.

Finally, we can highlight the inherent difficulty of the task at hand. Several factors contribute to this, including challenging acoustic conditions and telephony bandwidth recordings, background noise. In addition, the medical domain adds complexity because of the scarcity of in-domain data, medical terms, usage of medical face masks, and stressed or emotional speakers. The speakers’ dialects and accents also contribute as well as the inherent difficulties of the Arabic languages. Our future work will focus, among others, on providing and exploiting custom-recorded in-domain data in training, multilingual supervised training as well as a multilingual decoder. Moreover, we use unsupervised methods and large pre-trained models and present the results in [21].

7 Conclusion

In this work, we present our efforts on building ASR systems for conversational telephone speech in the medical domain for two language pairs. The patient-physician conversations in the HYKIST project do not share a common language, are supported by non-professional bilingual interpreters, in order to facilitate medical anamnesis. The recorded project-specific speech data comprised of simulated conversations are described along with additional data sources which can be exploited for developing ASR systems. Challenges within the project are the acoustic conditions in a hospital, for example, the emergency room, accents, and dialects, as well as the medical terms used during patient-physician conversations. We present and compare supervised baselines using different acoustic encoder topologies within the hybrid HMM framework. Additionally, we present a dialect mapping method to handle the challenges presented by the Arabic dialects.

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