Optimal Transport-based Adaptation in Dysarthric Speech Tasks

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Abstract

In many real-world applications, the mismatch between distributions of training data (source) and test data (target) significantly degrades the performance of machine learning algorithms. In speech data, causes of this mismatch include different acoustic environments or speaker characteristics. In this paper, we address this issue in the challenging context of dysarthric speech, by multi-source domain/speaker adaptation (MSDA/MSSA). Specifically, we propose the use of an optimal-transport based approach, called MSDA via Weighted Joint Optimal Transport (MSDA-WJDOT). We confront the mismatch problem in dysarthria detection for which the proposed approach outperforms both the Baseline and the state-of-the-art MSDA models, improving the detection accuracy of 0.9% over the best competitor method. We then employ MSDA-WJDOT for dysarthric speaker adaptation in command speech recognition. This provides a Command Error Rate relative reduction of 16% and 7% over the baseline and the best competitor model, respectively. Interestingly, MSDA-WJDOT provides a similarity score between the source and the target, i.e. between speakers in this case. We leverage this similarity measure to define a Dysarthric and Healthy score of the target speaker and diagnose the dysarthria with an accuracy of 95%.

In many real-world applications, the mismatch between training data (source) distribution and test data (target) distribution significantly degrades the performance of machine learning algorithms. In this paper, we address this problem in the context of assessment and recognition of dysarthric speech, in a multi-source domain/speaker adaptation (MSDA/MSSA) setting. Specifically, we propose the use of an optimal-transport based approach, called MSDA via Weighted Joint Optimal Transport (MSDA-WJDOT). We confront the mismatch problem in dysarthria detection for which the proposed approach outperforms both the baseline and the state-of-the-art MSDA models, increasing detection accuracy by 0.9% over the best competitor method. We then employ MSDA-WJDOT for dysarthric speaker adaptation in a command speech recognition task. Our approach reduces the command error rate by 16% and 7% over the baseline and the best competitor model, respectively. Interestingly, MSDA-WJDOT provides a similarity score between the source and the target, i.e. between speakers in this case. We leverage this similarity measure to define a Dysarthric and Healthy score of the target speaker and diagnose the dysarthria with an accuracy of 95%.

Index Terms: dysarthric speech, speaker adaptation, multi-source domain adaptation, dysarthria detection

1. Introduction

Many machine learning algorithms assume that the test and training datasets are sampled from the same distribution. However, in many real-world applications, new data can exhibit a distribution change (domain shift) that degrades the algorithm performance. In speech tasks, such as speech recognition, this shift can be observed when the recording conditions are varying (e.g., different noisy/clean environments). This problem can be solved through Domain Adaptation (DA) [1,5], that is a particular case of transfer learning [3]. DA methods consist in leveraging a labelled dataset, called source domain, to build a model that well performs on the dataset of interest, called target domain. The source and target domains are supposed to be similar and, typically, the labels for the target domain are not available (unsupervised DA).

Beside the recording conditions mismatching, speech tasks suffer of differences between speakers (e.g., different accents, different speaking style). This mismatch is even more evident in speech-impaired people as the speech characteristics also depend on the type and the severity of the disorder. We refer to this problem as speaker adaptation.

In this work, we focus on unsupervised domain adaptation and unsupervised speaker adaptation in pathological speech, when multiple sources are available. Therefore, in this framework, we assume to have access to multiple labelled training data sets (e.g., multiple speakers data) that are different, but related, to the dataset of interest (e.g., the speaker of interest) for which labels are not available. We consider as pathological speech the one recorded from people affected by dysarthria. This is a motor speech disorder consisting in the disruption of the normal control of the vocal tract musculature that is common in elderly people and in conditions such as Parkinson Disease, Amyotrophic Lateral Sclerosis and post-stroke motor impairments [1-3].

We consider speech recorded from people with affected by dysarthria, that is a motor disorder consisting in the disruption of the normal control of the vocal tract musculature [3]. Dysarthria can express different speech characteristics based on the location of the neurological damage. However, it is possible to individuate common tendencies in dysarthric patients, such as mumbled speech, an acceleration or deceleration in the speaking rate, abnormal pitch and rhythm. Further, dysarthric individuals are more subject to a fatigue factor that affects the voice. We here investigate two case studies, that are domain adaptation in dysarthria detection and dysarthric speaker adaptation for command speech recognition.

Dysarthria detection is currently evaluated by neurology experts through the use of clinical assessment tools that attribute a score to the capacity of the subject to perform perceptual and/or acoustic tasks. This procedure can be laborious and time consuming. Therefore, a rapid and objective dysarthria detection procedure could help the therapist in the diagnosis.

In the last years, the research community started to look at dysarthria detection by learning a mapping from the acoustic features to the text label [5,7]. In [8], the authors proposed an interpretable DNN model in which they added an interme-
We propose to solve both adaptation problems by adopting an Optimal Transport (OT) [31][32] based approach, named Multi-Source Domain Adaptation Weighted Joint Distribution (MSDA-WJDOT), firstly introduced in [33]. This method looks for a convex combination of the joint source distributions with minimal Wasserstein distance to the proxy joint target distribution, in which the labels are replaced by the prediction of a classifier. The source weights and the target classifier are simultaneously learned. The advantage of MSDA-WJDOT over the other MSDA approaches is that the source weights provide a similarity measure between each source and the target domain. This can be leveraged to select only the relevant sources and it also offers an interpretable model. For instance, in the case of speaker adaptation, these weights reflect the similarity between speakers.

2. MSDA-WJDOT

In this section, we recall MSDA-WJDOT firstly proposed in [33]. This method approaches to the MSDA problem by estimating the similarity between the source and target domains, in the Wasserstein sense, and learning a target classifier using only the most similar source datasets.

Let us suppose to have $J$ sources $(X_j, Y_j)$ with $N_j$ samples. MSDA-WJDOT assumes to have access to a differentiable embedding function $g$ from the input space to an embedding space $G$. If the embedding is not available MSDA-WJDOT becomes a two-step procedure where $g$ is learned in the first step. This can be done by

$$
\min_{g, f_S} \sum_{j=1}^{J} \frac{1}{N_j} \sum_{i=1}^{N_j} \mathcal{L}(f_S \circ g(x_j^i), y_j^i),
$$

where $f_S$ is a global classifier common to all sources. Alternatively, the authors in [33] suggests to estimate $g$ with the Multi-Task Learning (MTL) framework [34], i.e. by

$$
\min_{g, (f_j)_{j=1}^{J}} \sum_{j=1}^{J} \frac{1}{N_j} \sum_{i=1}^{N_j} \mathcal{L}(f_j \circ g(x_j^i), y_j^i),
$$

where $f_j$ represents the classification function of the $j$-th source. Note that Eqs. (1) and (2) provide two different ways to estimate $g$, while the source classifiers $f_S$ and $f_j$ are not further used in MSDA-WJDOT.

Once $g$ is given, we can define the source joint distributions $p_{S,j}$, for $1 \leq j \leq J$, with support on the product space $G \times Y$, where $Y$ is the label space. We define a convex combination of the source distributions

$$
p_S = \sum_{j=1}^{J} \alpha_j p_{S,j}
$$

with $\alpha \in \Delta^J$. MSDA-WJDOT aims at finding a classification function $f$ that aligns the target distribution $p_T$ with a convex combination $\sum_{j=1}^{J} \alpha_j p_{S,j}$ of the source distributions with convex weights $\alpha$ on the simplex $\Delta^J$. This can be expressed as

$$
\min_{\alpha, f} W_D \left( \hat{p_T}, \sum_{j=1}^{J} \alpha_j \hat{p_{S,j}} \right),
$$

where $W_D$ is the Wasserstein distance. A remarkable advantage of this approach is that the weights $\alpha$ are learned simultaneously with the classifier $f$, which allows to distribute
the mass based on the similarity between the source and the target domains, both in the feature and in the output spaces. Consequently, misleading and unrelated source domains are in practice not used and this allows to learn a more accurate classifier.

In the following we refer to MSDA-WJDOT as MSDA-WJDOT or MSDA-WJDOTMTL to specify if the embedding is learned by Eq. 1 or 2, respectively.

3. Experimental setup

3.1. Dysarthria detection

3.1.1. Dataset

TORGO is one of the most popular dysarthric speech corpora [32]. It consists of aligned acoustic and articulatory recordings from 15 speakers. Seven of these speakers are control speakers without any speech disorders, while the remaining eight speakers present different levels of dysarthria. We used the TORGO dataset to generate multiple-sources and target domain. In particular, we generated 15 noisy datasets by combining the raw signals with different types of noises from a noise dataset (available here). Each noisy dataset has been synthesized by PyDub Python library [38] summing the same type of noise signal to the raw data. We then used the libROSA Python library [39] to extract 13 MFCCs plus deltas and delta-deltas, computed every 10ms from 25ms Hamming windows followed by a z-normalization per track. We fixed the number of sources equal to 14 and we tested 4 noisy domains as target: F16, Buccaneer2, Factory2 (B1), Factory2 (F2), Destroyerengine (D).

3.1.2. MSDA-WJDOT model details

The feature extraction function \( g \) is performed by a Bidirectional Long Short-Term Memory (BLSTM) recurrent network with two hidden layers, each containing 50 memory blocks. We train the BLSTM as sequence-to-vector model, by taking the final hidden state at the last time step as a fixed-length utterance representation to generate the command probability given the whole sequence. The source and target classifier functions \( \{ f_j \}, \{ f_S \} \) are learned as one feed-forward layer taking the last hidden state as input. The weights were initialized with Xavier initialization. Training is performed with Adam optimizer with 0.9 momentum and \( \epsilon = e^{-8} \). The learning rate exponentially decays at each epoch. We grid-search the initial learning rate value and the decay rate.

3.2. Command speech recognition

3.2.1. Dataset

To investigate the Dysarthric Speaker Adaptation we employ the AllSpeak dataset [40], that consists of speech recordings from 29 Italian native speakers. Seventeen of these (thirteen males, four females) are affected by Amyotrophic Lateral Sclerosis, while the remaining twelve (six males, six females) are healthy control speakers. The dataset contains 25 commands in Italian, relative to basic needs such as “I am thirsty”. This dataset is very challenging due to the small amount of recordings. Indeed, only 2387 and 1857 examples have been recorded from control and dysarthric speakers, respectively.

We perform speaker adaptation of each dysarthric speaker by using all the remaining speakers as training dataset. The unlabelled target speaker data is split into adaptation set (80%) and testing (20%) set, which contains one example of each command. To train MSDA-WJDOT, we simultaneously employ the source training dataset and the adaptation target speaker dataset.

3.2.2. MSDA-WJDOT model details

The embedding function \( g \) is represented by a BLSTM with five hidden layers, each containing 250 memory blocks. Finally, a softmax layer performs the classification task. Here, we do not consider the MTL variant as the dataset size is limited and learning a source-classifier \( f_j \) with a very small amount of data may result hard. All weights are initialized with Xavier initialization. Training is performed with Adam optimizer with 0.9 momentum and \( \epsilon = e^{-8} \). Learning rate is fixed to 0.001.

4. Results

4.1. Competitor models

We compare the proposed approach with well-established MSDA approaches: Importance Weighted Empirical Risk Minimization (IWERM) [35] and two extensions of JDOT [36] to the MSDA case (see [33] for more details). To better measure the adaptation contribution, we also report the performance of a Baseline model in which the global classifier \( f_g \), learned on the source domains, is used as target classifier. In addition, in Sec. 4.3, we provide the performance of a supervised speaker adaptation (SSA) model, in which we add a feed-forward linear layer atop the input to the Baseline model and train it on the target dataset [41]. We consider this approach as the lower bound of the SA performance error.

4.2. Dysarthria detection

In all experiments, we observed that learning \( g \) by the Multi-Task Learning approach always provides a better performance. Hence, for an easier reading of Table 1, we only report the performances in which the extractor \( g \) is given by the MTL.

For all the target domains, IWERM performs poorly, even underperforming the Baseline. This is probably due to the difficulties in computing the probability density function of the acoustic input, that presents a high complexity. Indeed, to make the computation feasible, we firstly extracted a lower-dimensional vector from the audio signal by PCA. All the remaining MSDA methods outperform the Baseline. Among them our MSDA-WJDOT provides the best accuracy for all target domains. More precisely, MSDA-WJDOT provides a relative error reduction of 56.7% and 32.6% over the error of the Baseline and the best competitor model, respectively.

4.3. Command speech recognition

Table 2 reports the results in terms of Command Error Rate (CER). A first remark is that, although the Baseline always achieved a CER between 15% and 20% on the validation set, it often had low accuracy on the target speaker. Once again, this emphasizes the difficulty of an ASR system to generalize to a new dysarthric speaker and the importance of the speaker adaptation in this context.

The unsupervised speaker adaptation carried out by MSDA-WJDOT outperforms all the methods by providing the best Average CER. Indeed, it reduces the CER of 16% and 7% over the Baseline and the MSDA competitors, respectively. Surprisingly, MSDA-WJDOT achieves an Average CER similar to the SSA approach, in which the labels are used. It is crucial to recall that MSDA-WJDOT provides a measure of similarity between the target and the sources and, hence,
Table 1: Dysarthria detection accuracy on four target datasets: F16, Buccaneer2 (B2), Factory2 (F2), Destroyerengine (D). The mean and standard deviation of the accuracy are reported for the Baseline, IWERM, two extensions of JDOT and the proposed MSDA-WJDOT approach.

| Target domain | F16 | B2 | F2 | D | Average |
|---------------|-----|----|----|---|---------|
| Baseline      | 93.59 ± 0.38 | 93.76 ± 0.22 | 93.23 ± 0.66 | 92.46 ± 0.82 | 93.26 |
| IWERM [35]    | 66.22 ± 0.01 | 66.38 ± 0.01 | 66.25 ± 0.05 | 66.30 ± 0.09 | 66.29 |
| CJDOT [36]    | 95.35 ± 0.55 | 97.39 ± 0.09 | 96.71 ± 0.07 | 92.98 ± 0.75 | 95.61 |
| MJDOT [36]    | 95.81 ± 0.42 | 97.22 ± 0.09 | 96.53 ± 0.12 | 93.12 ± 0.67 | 95.67 |
| MSDA-WJDOT    | 97.32 ± 0.36 | 97.82 ± 0.13 | 97.76 ± 0.10 | 95.42 ± 0.24 | 97.08 |

Table 2: Command Error Rate (CER) for each dysarthric target speaker provided by the Baseline, SSA, MSDA-WJDOT and the competitor models.

| Speaker | Baseline | CJDOT [35] | MJDOT [36] | SSA | MSDA-WJDOT |
|---------|----------|------------|------------|-----|------------|
| M01     | 35.79    | 32.77      | 31.93      | 31.93 | 31.00      |
| M02     | 34.26    | 36.75      | 36.75      | 37.71 | 54.17      |
| F01     | 63.16    | 52.63      | 49.12      | 49.12 | 60.00      |
| F02     | 48.50    | 40.00      | 40.00      | 40.00 | 36.00      |
| M03     | 46.44    | 68.89      | 71.11      | 57.78 | 55.56      |
| M04     | 30.00    | 31.20      | 32.00      | 36.40 | 24.00      |
| M05     | 18.62    | 17.46      | 15.08      | 14.29 | 17.39      |
| F03     | 68.33    | 61.74      | 70.43      | 62.61 | 56.52      |
| M06     | 48.67    | 34.78      | 33.91      | 35.65 | 26.09      |
| M07     | 11.00    | 7.20       | 8.00       | 8.80  | 20.00      |
| M08     | 39.50    | 36.00      | 41.60      | 33.60 | 32.00      |
| M09     | 24.79    | 16.81      | 18.49      | 19.33 | 13.04      |
| F04     | 48.07    | 38.60      | 38.60      | 38.60 | 40.91      |
| M10     | 18.00    | 12.80      | 12.00      | 12.80 | 16.00      |
| M11     | 56.50    | 47.20      | 48.80      | 45.60 | 40.00      |
| M12     | 7.50     | 5.60       | 7.20       | 4.80  | 4.00       |
| M13     | 30.91    | 45.45      | 43.64      | 21.82 | 9.09       |
| A. CER  | 38.11    | 34.46      | 34.37      | 32.05 | 31.16      |

4.4. The α weight and the dysarthria detection

As we showed in Fig. 1 MSDA-WJDOT associates speakers with similar voice characteristics. As additional analysis, we investigated the possibility of leveraging the α weights of the command classifier to detect dysarthria. Specifically, we attempt to classify a speaker as healthy or dysarthric based on his/her similarity with the other subjects.

Let define $I_c$ as the set indexing the control speakers and $I_d$ as the set of indices related to dysarthric speakers. We then define the Healthy Score ($HS$) and the Dysarthric Score ($DS$) as follow:

$$HS = \sum_{j \in I_c} \alpha_j, \quad DS = \sum_{j \in I_d} \alpha_j.$$  \hspace{1cm} (4)

We can use these scores to perform dysarthria detection by stating that

A speaker is affected by dysarthria if $DS > HS$.

Fig. 2 reports the computed scores for all dysarthric speakers and for 5 control speakers. As we can see the controls subjects are always classified as healthy while for the patients, except for F02, we have $DS > HS$. This results in a final accuracy of 95%.

5. Conclusions

In this work, we addressed unsupervised domain and speaker adaptation in the challenging context of pathological speech by employing MSDA-WJDOT [33]. We have shown the effectiveness of our proposed method on dysarthria detection and spoken command recognition, by comparing it with with well-established MSDA approaches and a Baseline model, in which a global classifier is learned on the source datasets and directly tested on the target data, without adaptation. Our method provides the best performance on both applications. Interestingly, MSDA-WJDOT also provides source-target similarity coefficients α that, in speaker adaptation, result in a measure of speaker relatedness. From this, we derived the Healthy (HI) and Dysarthric (DI) Index of a target speaker and diagnosed the dysarthria, achieving an accuracy of 95%.

Future directions could delve into the dysarthria assessment by individuating intervals of values in which the DI corresponds to dysarthria severity levels (e.g., mild, moderate, severe). This may bring to very efficient ASR systems that simultaneously improve their performance via SA, and compute the DI warning the subject when the index is close to the right endpoint of its interval. Such a device could predict the disease degeneration...
Figure 2: HS and DS computed for healthy (in green) and dysarthric (in red) speakers.

and allow the patient to act in time in order to prevent it.

6. References
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