A Review of Generalizable Transfer Learning in Automatic Emotion Recognition

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Automatic emotion recognition is the process of identifying human emotion from signals such as facial expression, speech, and text. Collecting and labeling such signals is often tedious and many times requires expert knowledge. An effective way to address challenges related to the scarcity of data and lack of human labels, is transfer learning. In this manuscript, we will describe fundamental concepts in the field of transfer learning and review work which has successfully applied transfer learning for automatic emotion recognition. We will finally discuss promising future research directions of transfer learning for improving the generalizability of automatic emotion recognition systems.

Keywords: transfer learning, generalizability, automatic emotion recognition, speech, image, physiology

1. INTRODUCTION

Emotion plays an important role in human-human or human-computer interaction. Emotionally-aware systems enable the better understanding of human behavior and facilitate uninterrupted and long-term interaction between humans and computers (Beale and Peter, 2008). The recent development of laboratory and real-world sensing systems allows us to fully capture multimodal signal information related to human emotion. This has resulted in a large amount of publicly available datasets with high variability in terms of elicitation methods, speaker demographics, spoken language, and recording conditions. Despite the high availability of such datasets, the amount of data included in each dataset is limited and the emotion-related labels are scarce, therefore prohibiting the reliable training and generalizability of emotion recognition systems. In order to address this challenge, recent studies have proposed transfer learning methods to provide reliable emotion recognition performance, even in unseen contexts, individuals, and conditions (Abdelwahab and Busso, 2018; Lan et al., 2018; Latif et al., 2018; Gideon et al., 2019).

Emerging transfer learning methods can leverage the knowledge from one emotion-related domain to another. The main premise behind such techniques is that people may share similar characteristics when expressing a given emotion. For example, anger may result in increased speech loudness and more intense facial expressions (Siegman and Boyle, 1993). Fear is usually expressed with reduced speech loudness and may produce increased heart rate (Hodges and Spielberger, 1966). These emotion-specific characteristics might be commonly met among people, contributing to the similarity among the various emotional datasets. Therefore, transfer learning approaches can learn common emotion-specific patterns and can be applied across domains for recognizing emotions in datasets with scarce or non-labeled samples. Such techniques can further result in generalizable systems, which can detect emotion for unseen data.

The current manuscript discusses ways in which transfer learning techniques can overcome challenges related to limited amount of data samples, scarce labels, and condition mismatch, and result in robust and generalizable automated systems for emotion recognition. We first introduce
basic concepts in transfer learning (section 2) and discuss the development of major transfer learning methods and their applications in conventional machine learning fields, such as computer vision (section 3). We then review state-of-art work in automatic emotion recognition using transfer learning for speech, image, and physiological modalities (section 4). Finally, we discuss potential promising research directions of transfer learning for improving the generalizability of automatic emotion recognition systems (section 5).

2. BASIC CONCEPTS IN TRANSFER LEARNING

In this section, we will provide the basic definition of transfer learning and discuss several ways to categorize transfer learning methods.

2.1. Definitions

Domain in transfer learning generally refers to a feature space and its marginal probability distribution (Pan et al., 2010). Given a specific domain, a task includes a label space and an objective function that needs to be optimized. Source domain usually refers to a set of data with sufficient data samples, large amount of labels, and potentially high quality (e.g., lab environment). In contrast, the data from a target domain may include limited number of samples and small amount or non-existent labels, and potentially be noisy. Given a source and a target, transfer learning approaches attempt to improve the learning of the target task using knowledge from the source domain.

2.2. Association Metrics Between Source and Target Domains

The selection of the source domain plays an important role in the transfer learning process. A source domain sharing a lot of similarities with the target, is more likely to yield efficient transfer (Pan and Yang, 2009). Similarity can be quantified through the distance between source and target with respect to their data structure (e.g., feature or label distribution), recording conditions (e.g., recording equipment, elicitation methods), and data sample characteristics (e.g., participants with similar demographics, speech samples of same language).

Proposed transfer learning methods typically use a distance metric to maximize the similarity between the source and target domain. Commonly used distance metrics include: (a) Kullback-Leibler divergence (KL divergence), employing a cross-entropy measure to calculate similarity in the probability distribution between the source and the target domain; (b) Jensen-Shannon divergence (JS divergence), a symmetric version of the KL divergence; (c) Maximum Mean Discrepancy (MMD) and multi-kernel MMD, creating an embedding of the source and target domains on the Reproducing Kernel Hilbert Space (RKHS) and comparing their mean difference; (d) Wasserstein Distance, also known as Earth-Mover (EM) Distance, quantifying the domain difference when there is very little or no overlap between two domain distributions by computing the transport map for every probability density between two domains.

2.3. Categorization of Transfer Learning Techniques

The state-of-art application of transfer learning on automatic emotion tasks can be categorized in two main approaches. The first refers to the availability of labels in the target domain. Supervised transfer learning includes information from labeled data from both the source and target domain during the learning task, while unsupervised learning includes information only from the labels of the source domain (Pan and Yang, 2009). Unsupervised transfer learning enables the design of reliable machine learning systems, even for domains for which labeled data are not available. The second categorization refers to the availability of one or multiple datasets in the source. Single-source transfer learning contains only one dataset, while multi-source transfer learning leverages multiple sets of data in the source domain (Ding et al., 2019).

3. EMERGING WORK ON SUPERVISED AND UNSUPERVISED TRANSFER LEARNING

This section provides an overview of previously proposed methods in the field of transfer learning, summarized into three main categories: (a) statistical-based transfer learning; (b) region selection through domain relevance; and (c) deep transfer learning approaches. We will further discuss these three categories in the following subsections.

3.1. Statistical-Based Transfer Learning

Three types of statistical approaches have been proposed for transfer learning: (a) distribution alignment aims to minimize the shift between the source and target domain to reduce the domain difference; (b) latent space extraction recovers common components between two domains; (c) classifier regularization will increase the ability of regularization for the classifier to predict labels in the target domain.

3.1.1. Alignment Between Source and Target Distributions

The marginal alignment methods aim to find a mapping between source and target distributions. This can be done by setting pairwise constraints between the two domains (Saenko et al., 2010; Kulis et al., 2011). Gopalan et al. (2011) utilized the Grassmann manifold and the incremental learning to search a transformation path between the domains. This method was further improved by Gong et al. (2012), who proposed the Geodesic Flow Kernel (GFK). The Grassmann manifold and Maximum Mean Discrepancy (MMD) are also used in other approaches such as the Domain Invariant Projection (DIP) proposed by Baktashmotlagh et al. (2013). Marginal alignment is one of the first methods appearing in the field of transfer learning, which attempts to find a common distribution between the source and target domains. Despite its promising results, marginal alignment might not always fully align two completely distinct domains to an entirely same distribution, especially
when these include a high mismatch (e.g., different emotional expressions or recording settings).

3.1.2. Latent Space Extraction
The shared subspace extraction methods assume that the feature space of each domain consists of the domain-specific and the domain-invariant components, and comprise one of the most commonly used approaches in transfer learning. These methods attempt to map both the source and target data to a subspace which only keeps the common information between domains to minimize the difference between them. In order to find such a subspace, Pan et al. (2010) proposed the Transfer Component Analysis (TCA) using the Maximum Mean Discrepancy (MMD) and Reproducing Kernel Hilbert Space (RHKS), and significantly reduced the distribution mismatch using a low-dimensional subspace. Additional methods for achieving this goal include boosting [Becker et al., 2013 and Domain-Invariant Component Analysis (DICA); Muandet et al., 2013]. Due to inherent similarities across emotions, the idea of extracting a common latent space has been successfully applied to automatic emotion recognition tasks (Deng et al., 2013; Zheng et al., 2015).

3.1.3. Classifier Regularization
Other approaches have attempted to utilize a regularized version of the classifier trained on the source domain in order to predict the labels in the target domain. Support Vector Machines (SVM) have been widely explored in this process. Yang et al. (2007) proposed the Adapting SVM (A-SVM) which learns a difference function (also referred to as “delta function”) between an original and adapted classifier using an objective function similar to the one in the SVM. Other methods include the Projective Model Transfer SVM (PMT-SVM), Deformable Adaptive SVM (DA-SVM), Domain Weighting SVM (DWSVM) (Aytar and Zisserman, 2011), which adapt the weights of a source model to the target domain using various pre-defined constraints (e.g., assign different weights for source and target domain in DWSVM). Bergamo and Torresani (2010) also explored the efficacy of transferring knowledge between different SVM structures using feature Augmentation SVM (AUGSVM), Transductive learning SVM (TSVM) and Domain Transfer SVM (DT-SVM) (Duan et al., 2009). Other types of statistical models, such as maximum entropy classifiers, have been also explored in this process (Daume and Marcu, 2006). Due to its simplicity and efficacy in small data samples, classifier regularization has been applied on various emotion recognition tasks based on physiological signals (Zheng and Lu, 2016).

3.2. Region Selection Through Domain Relevance
The region selection approaches have been mostly introduced in computer vision and rely on the concept of how humans understand a given image. For example, instead of giving equal attention to every part of an image, humans would concentrate more on specific salient objects. Therefore, these approaches aim to identify salient regions of an image by generating a domainness map, and separate the image into a different level of domainness (Tommasi et al., 2016). This domainness feature is further utilized to promote knowledge transfer. Other studies have proposed methods using sparse coding (Long et al., 2013) or abstract auxiliary information (e.g., skeleton or color of an image) (Motiian et al., 2016), which also simulate the way humans comprehend an image as a whole. Hjelm et al. (2018) also utilized the different domain relevance of each part of the image to extract and maximize the mutual information. The region selection methods are very close to the way humans perceive information, and the domainness map makes the methods straightforward and explainable. While similar ideas can also be applied to non-image-related tasks, the determination of domainness levels and validation of the extracted domainness map can be less straightforward.

3.3. Deep Transfer Learning Methods
Deep learning methods are widely explored and applied on transfer learning. Two main types of deep learning approaches have demonstrated promising performance for knowledge transfer: (a) domain adaptation using deep learning, which aims to transfer the knowledge or mitigate the domain difference between source and target with respect to the neural network embedding; and (b) the adversarial and generative learning, which aims to generate data embeddings that are least separable between the source and the target.

3.3.1. Domain Adaptation Using Deep Learning
The large amount of publicly available datasets has yielded several pre-trained deep learning models [e.g., VGG (Simonyan and Zisserman, 2014), VGG-Face (Parkhi et al., 2015), VGG-M-2048 (Chatfield et al., 2014) and AlexNet (Krizhevsky et al., 2012)] which have achieved good performance in image and speech recognition tasks. To address the mismatch between different domains, it is possible to utilize the parameter/structure of pre-trained models to achieve knowledge transfer (e.g., using a model with the same number of hidden layers and same weights learned from the source data). A promising method for achieving this is fine-tuning, which replaces and learns the last layers of the model, while re-adjusting the parameters of the previous ones. A challenge with fine-tuning lies in the fact that the parameters learned on the source task are not preserved after learning the target task. In order to address this “forgetting problem,” Rusu et al. (2016) proposed the progressive neural network, which keeps the network trained on the source data, based on which it builds an additional network for the target. Jung et al. (2018) also addressed this problem by keeping the decision boundary unchanged, while also making the feature embeddings extracted for the target close to the ones of the source domain. Utilizing a pre-trained model on the source data includes the following advantages: (a) it speeds up the training process; (b) it potentially increases the ability of generalization, as well as the robustness of the final model; (c) it automatically extracts high-level features between domains.

Although neural network fine-tuning and progressive neural networks can yield benefits to the training process in terms of computational time and ability to generalize (Yosinski et al., 2014), these methods sometimes fail to address the domain difference and may have a poor performance when the source
and target have small overlap. An alternative approach to this has been proposed by Ghifary et al. (2014), who added adaptation layers to the conventional deep learning models and used the Maximum Mean Discrepancy (MMD) for minimizing the domain distribution mismatch between the source and target domains. Instead of making use of a well-trained model, the source data are used in conjunction with the target data in the training process to determine the domain distance. Further research includes determining which layer to be used as the adaptation layer, applying multiple adaptation layers in a model, etc (Tzeng et al., 2014; Long et al., 2015). Moreover, the Joint convolutional neural net (CNN) architecture or Joint MMD (JMMD) (Tzeng et al., 2015; Long et al., 2017) aims to align similar classes between different domains by taking into account the structural information between them.

Various studies on deep transfer learning for automatic emotion recognition have yielded promising results on speech and image datasets (Gideon et al., 2017; Kaya et al., 2017; Abdelwahab and Busso, 2018; Li and Chaspari, 2019). These methods have been less explored for physiological signals, potentially due to the small amount of available data for this modality.

3.3.2. Adversarial and Generative Methods

The idea of adversarial learning for knowledge transfer was proposed by Ganin and Lempitsky (2014) in the domain adversarial neural network (DANN). DANN contains three parts: a feature extractor, a domain classifier, and a task classifier. The feature extractor attempts to learn feature representations which minimize the loss of the task classifier and maximize the loss of the domain classifier. Instead of modifying the loss function based on the distance between two domains, the DANN is able to automatically extract the feature which is common for both domains while maintaining the characteristics of each class (Ganin et al., 2016). Variants of DANNs have further been widely explored. The Domain Separation Network (DSN) proposed by Bousmalis et al. (2016), modified the feature extractor into three encoders (i.e., one for the source, one for the target, and one for both) in order to separate the domain-specific from domain-invariant embeddings. DSN also replaced the domain classifier with a shared decoder, to further ensure that the domain-invariant embedding is useful and can promote the generalizability of the model. According to the multi-adversarial domain adaptation network proposed by Pei et al. (2018), a separate task classifier is trained for every class, which makes different classes less likely to have overlapping distributions. As the number of available datasets increases, networks which handle multiple sources of data are also explored (Xu et al., 2018; Zhao et al., 2018). In order to further avoid the negative transfer, partial transfer learning, which can be done via Bayesian optimization (Ruder and Plank, 2017), is applied in the adversarial neural networks in order to transfer knowledge from large domains to more specific, smaller domains by selecting only part of the source data in the training process (Cao et al., 2018).

Inspired by the two player game, the generative adversarial nets (GAN) were further proposed by Goodfellow et al. (2014) containing a generator and a discriminator. The generator generates fake data from a random distribution and aims to confuse the discriminator, while the discriminator focuses on distinguishing between the real and generated data. In this process, both models can learn from each other and fully explore the patterns of data, since the informed generation of synthetic samples can potentially overcome the mismatch between the source and the target task. Modifications of GAN-based networks are also proposed. For example, Radford et al. (2015) introduced the Deep Convolutional Generative Adversarial Networks (DCGAN) to combine the CNN with GAN. The Wasserstein GAN (WGAN) integrated the Wasserstein distance in the loss function and further improved the training stability (Arjovsky et al., 2017).

The adversarial and generative adversarial neural networks have been successfully applied to speech- and image-based emotion recognition tasks (Wang and Zheng, 2015; Motiian et al., 2017; Sun et al., 2018) with promising results.

4. TRANSFER LEARNING FOR AUTOMATIC EMOTION RECOGNITION

In this section, we discuss the application of transfer learning on three modalities commonly used in the automatic emotion recognition task: (a) speech; (b) video (or image); and (c) physiology. Sentiment analysis is not included in this manuscript, since it is related to crowd-sourced data, which are beyond the scope of the review.

4.1. Transfer Learning for Speech-Based Emotion Recognition

Because of the multi-faceted information included in the speech signal, transfer learning has been widely applied in speech-based emotion recognition (Table 1). Previously proposed approaches attempt to transfer the knowledge between datasets collected under similar conditions (e.g., audio signals collected by actors in the lab) (Abdelwahab and Busso, 2015, 2018; Sagha et al., 2016; Zhang et al., 2016; Deng et al., 2017; Gideon et al., 2017; Neumann and Vu, 2019) or using the knowledge from acted-in-lab audio signals to spontaneous speech collected in-the-wild (Deng et al., 2014b; Mao et al., 2016; Zong et al., 2016; Song, 2017; Gideon et al., 2019; Li and Chaspari, 2019).

Different types of transfer learning architectures have been explored in speech-based emotion recognition, including the statistical methods (Deng et al., 2013, 2014a,c; Abdelwahab and Busso, 2015; Song et al., 2015; Sagha et al., 2016; Zong et al., 2016; Song, 2017), the adversarial or generative networks (Chang and Scherer, 2017; Abdelwahab and Busso, 2018; Gideon et al., 2019; Latif et al., 2019), and other neural network structures (Mao et al., 2016; Deng et al., 2017; Gideon et al., 2017; Li and Chaspari, 2019; Neumann and Vu, 2019; Zhou and Chen, 2019). A commonly used input of the aforementioned approaches includes the feature set proposed by the INTERSPEECH emotion challenge and INTERSPEECH paralinguistic challenges (Schuller et al., 2009b, 2010, 2013), which typically contains the first 12 Mel Frequency Cepstral Coefficients, root-mean-square energy, zero-crossing rate, voice probability, and fundamental frequency (Deng et al.,
TABLE 1 | Overview of previously proposed transfer learning methods for speech-based emotion recognition.

| References | Dataset | In-lab/real-world transfer learning | Acted/spontaneous transfer learning | Emotional labels | Cross-linguistic transfer learning | Type of transfer learning | Input features |
|------------|---------|-----------------------------------|------------------------------------|-----------------|----------------------------------|--------------------------|----------------|
| Deng et al., 2013 | source: TUM AVIC (Schuller et al., 2009a), EMO-DB (Burkhardt et al., 2005), eINTERFACE (Martin et al., 2006), SUSAS (Hansen and Bou-Ghazale, 1997), VAM (Grimm et al., 2008), target: FAU AEC (Steidl, 2009) | In-lab; real-world | Acted & spontaneous | Valence | English | Autoencoder for aligning source to target | INTERSPEECH 2009 emotion challenge |
| Deng et al., 2014 | source: SUSAS (Hansen and Bou-Ghazale, 1997), ABC (Schuller et al., 2007), target: FAU AEC (Steidl, 2009) | source: In-lab; real-world | target: Real-world | source: Acted; spontaneous | target: Spontaneous | Valence | English | Adaptive denoising autoencoder (DAE) | INTERSPEECH 2009 emotion challenge |
| Deng et al., 2014c | source: SUSAS (Hansen and Bou-Ghazale, 1997), ABC (Schuller et al., 2007), target: FAU AEC (Steidl, 2009) | source: In-lab; real-world | target: Real-world | source: Acted; spontaneous | target: Spontaneous | Valence | English | Encoders trained separately for domains | INTERSPEECH 2009 emotion challenge |
| Deng et al., 2014a | source: SUSAS (Hansen and Bou-Ghazale, 1997), ABC (Schuller et al., 2007), target: FAU AEC (Steidl, 2009) | source: In-lab; real-world | target: Real-world | source: Acted; spontaneous | target: Spontaneous | Valence | English | Shared-hidden-layer autoencoder. A common encoder which also aims to minimize reconstruction error | INTERSPEECH 2009 emotion challenge |
| Song et al., 2015 | source/target: EMO-DB (Burkhardt et al., 2005), eINTERFACE (Martin et al., 2006) | In-lab | Acted | Angry, disgusted, fear, happy, sad | English | Transfer principal component analysis and sparse coding based method | INTERSPEECH 2010 paralinguistic challenge |
| Abdelwahab and Busso, 2015 | source: IEMOCAP (Busso et al., 2008), SEMAINE (McKeeown et al., 2011), target: RECOLA (Ringeval et al., 2013) | In-lab | Acted & spontaneous | Arousal and valence | English, French | Domain adaptation for SVM incremental adaptation for SVM | INTERSPEECH 2011 speaker state feature |
| Mao et al., 2016 | source: EMO-DB (Burkhardt et al., 2005), ABC (Schuller et al., 2007), target: FAU AEC (Steidl, 2009) | source: In-lab | target: Real-world | source: Acted | target: Spontaneous | Valence | English | Sharing priors between related source and target classes | INTERSPEECH 2009 emotion challenge |
| Sagha et al., 2016 | source/target: EMO-DB (Burkhardt et al., 2005), SAVEE (Haq et al., 2008), EMOVO (Costantini et al., 2014), Polish (Staroniewicz and Majewski, 2009) | In-lab | Acted | English, German, Italian, Polish | Kernel canonical correlation analysis (KCCA) | INTERSPEECH 2009 emotion challenge |
| Zhang et al., 2016 | source: RAVESS (Livingstone and Russo, 2018), target: UMSSSE (Zhang et al., 2015) | In-lab | Acted | Angry, happy neutral, sad | No | Multi-task learning | INTERSPEECH computational paralinguistics challenge 2013 |
| Zong et al., 2016 | source/target: EMO-DB (Burkhardt et al., 2005), eINTERFACE (Martin et al., 2006), AFEW (Dhall et al., 2012) | In-lab & real-world | Acted & spontaneous | Angry, disgusted, afraid, happy, neutral, sad | English | Domain-adaptive least-squares regression (DaLSR) | INTERSPEECH 2009 emotion challenge |
| Song, 2017 | source/target: EMO-DB (Burkhardt et al., 2005), eINTERFACE (Martin et al., 2006), FAU AEC (Steidl, 2009) | In-lab & real-world | Acted & spontaneous | Angry, disgusted, afraid, happy, sad | English | Linear subspace learning | INTERSPEECH 2010 paralinguistic challenge |
| Deng et al., 2017 | source/target: EMO-DB (Burkhardt et al., 2005), GeWEC (Bänziger and Scherer, 2010) | In-lab | Acted | Categorical emotions | German | Denoising autoencoder | INTERSPEECH 2009 emotion challenge |
### Table 1: Transfer Learning in Emotion Recognition (Continued)

| References | Dataset | In-lab/real-world transfer learning | Acted/spontaneous transfer learning | Emotional labels | Cross-linguistic transfer learning | Type of transfer learning | Input features |
|------------|---------|------------------------------------|-------------------------------------|-----------------|-------------------------------|--------------------------|----------------|
| Gideon et al., 2017 | **source/target:** IEMOCAP (Busso et al., 2008), MSP-IMPROV (Busso et al., 2016) | In-lab | Acted | Angry, neutral, sad, happy | No | Progressive neural network (PNN) | Geneva minimalistic acoustic parameter set (GeMAPS) |
| | **source:** AMI (Carletta et al., 2005) **target:** IEMOCAP (Busso et al., 2008) | **source:** Real-world | Acted & spontaneous | Valence and activation | No | Deep convolutional generative adversarial networks (DCGAN) | Speech spectrogram |
| Abdelwahab and Busso, 2018 | **source:** IEMOCAP (Busso et al., 2008), MSP-IMPROV (Busso et al., 2016) **target:** MSP-Podcast (Lotfian and Busso, 2017) | In-lab | Acted & spontaneous | Arousal, valence, dominance | No | Domain adversarial neural network (DANN) | INTERSPEECH computational paralinguistics challenge 2013 |
| Gideon et al., 2019 | **source/target:** IEMOCAP (Busso et al., 2008), MSP-IMPROV (Busso et al., 2016) **PRIORI Emotion** (Khorram et al., 2018) | In-lab & real-world | Acted & spontaneous | Valence | No | Adversarial discriminative domain generalization (ADDaG) | Mel Filter Bank (MFB) |
| Li and Chaspari, 2019 | **source:** IEMOCAP (Busso et al., 2008), CREMA-D (Cao et al., 2014), RAVDESS (Livingstone and Russo, 2018), eNTERFACE (Martin et al., 2006) **target:** IEMOCAP (Busso et al., 2008) | In-lab | **source:** Acted | Angry, happy, sad, afraid | No | Feedforward neural network fine-tuning progressive neural network (PNN) | INTERSPEECH 2009 emotion challenge |
| Neumann and Vu, 2019 | **source/target:** IEMOCAP (Busso et al., 2008), MSP-IMPROV (Busso et al., 2016) | In-lab | Acted | Angry, happy, sad, neutral | No | A latent feature space was learned on source domain using an encoder-decoder. Such space was added as feature vector in attentive convolutional neural network | MFCC feature |
| Latif et al., 2019 | **source/target:** EMO-DB (Burkhardt et al., 2005), SAVEE (Jackson and Haq, 2014), EMOVO (Costantini et al., 2014), URDC (Latif et al., 2018) | In-lab & real-world | Acted & spontaneous | Positive/negative valence | German, Urdu Italian, English | Similar to GAN structure but source data was used instead of generated fake data. | Geneva minimalistic acoustic parameter set (GeMAPS) |
| Zhao et al., 2019 | **source:** eGender (Burkhardt et al., 2010) **target:** EMO-DB (Burkhardt et al., 2005), IEMOCAP (Busso et al., 2008) | **source:** Real-world | spontaneous | Continuous prediction or classification: neutral, happiness, sadness, anger | English | Learn age and gender attributes separately then transfer these knowledge by feeding such information to emotion model. | INTERSPEECH 2010 configuration |

(Continued)
TABLE 1 | Continued

| References                | Dataset                                      | In-lab/real-world transfer learning | Acted/spontaneous transfer learning | Emotional labels | Type of transfer learning | Input features                                                                 |
|----------------------------|----------------------------------------------|-------------------------------------|-------------------------------------|-----------------|---------------------------|--------------------------------------------------------------------------------|
| Zhou and Chen, 2019        | source: Aibo-Ohm and Aibo-Mont (Steidl, 2009) | In-lab                              | source: Spontaneous                | Binary           | Class-wise                 | Geneva minimalistic acoustic parameter set (GeMAPS)                              |
|                            | target: EMO-DB (Burkhart et al., 2009)       |                                     | target: acted                      | negative / positive |                           |                                                                                |

2013, 2014b, 2017; Mao et al., 2016; Sagha et al., 2016; Zhang et al., 2016; Zong et al., 2016; Song, 2017; Abdelwahab and Busso, 2018; Li and Chaspari, 2019; Zhao et al., 2019.

Statistical values of these descriptors, including maximum, minimum, range, time position of the maximum and minimum, average, standard deviation, skewness, kurtosis, as well as the first- and second-order coefficient of a linear regression model are extracted from the frame-based measures. Other approaches also include the speech spectrogram as an input to convolutional-based neural networks (Gideon et al., 2019). Previously proposed transfer learning methods for speech emotion recognition employ same classes for the source and target data. Two commonly used baseline methods against which the proposed transfer learning approaches are compared include in-domain training and out-of-domain training (only used data from source domain). The first performs training and testing by solely using labeled data from target domain, while the second trains the model on the source data and tests on the target. Results indicate that the proposed transfer learning methods outperform the out-of-domain methods, and are equivalent to or sometimes surpass in-domain training, indicating the potential of leveraging multiple sources of emotion-specific speech data to improve emotion recognition performance.

Besides speech data, audio signals from music clips have been also applied for emotion recognition (Zhang et al., 2016). However, because of the limited number of emotion-based datasets with music signals, as well as the significant domain mismatch between music and speech, this application is relatively less explored.

4.2. Transfer Learning for Video/Image-Based Emotion Recognition

Facial expressions convey a rich amount of information related to human emotion. A variety of transfer learning techniques have been explored for video/image-based automatic emotion recognition (Table 2). The state-of-art transfer learning approach to the video-based emotion recognition includes obtaining high-level features using mainly a convolutional neural network (CNN) trained on large sources of data (e.g., VGG; Simonyan and Zisserman, 2014) (Kaya et al., 2017; Aly and Abbott, 2019; Ngo and Yoon, 2019, or transferring the knowledge from higher-quality auxiliary image datasets (e.g., skeleton or color of an image, image with description text) (Xu et al., 2016). Source datasets in this case might not necessarily contain the same labeled classes as the target dataset. Occluded facial images, which are common in daily life, are also utilized to help with the generalization and robustness of the overall system (Xu et al., 2015). More advanced transfer learning approaches, such as adversarial methods, are less explored in this process. A possible reason is that the high-level image features are relatively easier to obtain and knowledge from other domains might not be able to significant help. Another reason could be the selection of source domain is more important for facial emotion recognition (Sugianto and Tjondronegoro, 2019). In order to recognize emotions from video clips, every frame of the clip is analyzed and the final decision is made based on voting methods, such as major voting on the separate frames (Zhang et al., 2016). Face detection methods, such as the deformable parts model (DPM) (Mathias et al., 2014), may also be used to avoid the influence of irrelevant regions of the video frame (Kaya et al., 2017).

4.3. Transfer Learning for Emotion Recognition Based on Physiological Signals

A small amount of previous work has attempted to perform transfer learning on physiological signals for emotion recognition (Table 3). Among the various physiological signals, the electroencephalogram (EEG) is the most commonly used in transfer learning, probably due to the rich amount of information included in this signal. Because of the limited number of datasets including physiological signals, as well as the high variability across people, the knowledge transfer between different datasets is less efficient and relatively less explored. Commonly used transfer learning applications attempt to train subject-specific (personalized) models by providing knowledge learned from subjects similar to the one in the test (Lin and Jung, 2017; Lin, 2019), or simply consider all the members in the group by assigning different weights (Li et al., 2019). Other methods include statistical approaches, such as Principal
Component Analysis (PCA) and adaptive subspace feature matching (ASFM) (Chai et al., 2017). As the development of wearable devices progresses and more physiological data related to emotional experiences become available, transfer learning methods appear to depict a great potential in this domain.
TABLE 3 | Overview of transfer learning methods for emotion recognition based on physiological signals.

| References | Dataset | Elicitation method | In-lab | Real-world | Emotional labels | Type of transfer learning |
|------------|---------|--------------------|--------|------------|-----------------|---------------------------|
| Zheng et al., 2015 | SEED (Zheng and Lu, 2015) | Video | In-lab | | Three emotions (positive, neutral, and negative) | Personalized transfer learning |
| Chai et al., 2016 | SEED (Zheng and Lu, 2015) | Video | In-lab | | Three emotions (positive, neutral, and negative) | Transfer component analysis (TCA) |
| Zheng and Lu, 2016 | SEED (Zheng and Lu, 2015) | Video | In-lab | | Three emotions (positive, neutral, and negative) | Kernel principal component analysis (KPCA) |
| Lin and Jung, 2017 | Oscar soundtrack EEG dataset (Lin et al., 2010) | Music | In-lab | | Valence and arousal | Conditional transfer learning framework to determine |
| Chai et al., 2017 | SEED (Zheng and Lu, 2015) | Video | In-lab | | Three emotions (positive, neutral, and negative) | How transferable is a model to a given individual |
| Lan et al., 2018 | SEED (Zheng and Lu, 2015) | Video | In-lab | | Three emotions (positive, neutral, and negative) | Adaptive subspace feature matching |
| Lin, 2019 | MDME (Lin et al., 2015) | Music | In-lab | | Binary valence and arousal | Transfer component analysis (TCA) |
| Li et al., 2019 | SEED (Zheng and Lu, 2015) | Video | In-lab | | Three emotions (positive, neutral, and negative) | Geodesic flow kernel (GFK) Domain adaptation |
| Zhang et al., 2019 | SEED (Zheng and Lu, 2015) | Video | In-lab | | Three emotions (positive, neutral, and negative) | Kernel principal component Analysis (KPCA) |

TABLE 4 | Overview of current research.

| Signal | Common transfer learning method | Overview |
|--------|---------------------------------|----------|
| Speech | Statistical-based transfer learning | Speech signal has been widely used for emotion recognition, both statistical and deep learning methods are widely explored. |
| Video/image | Deep transfer learning methods | Motivated by the wide adoption of deep learning in image processing, such methods are widely used for emotion recognition in the last years. |
| Physiological | Statistical-based transfer learning | Neural networks were not widely used for physiological signals in recent years, but researchers have started to apply deep transfer learning methods. |

5. DISCUSSION

In this section, we will provide a brief summary of the current application of transfer learning on automatic emotion recognition and outline potential aspects for future research.

5.1. Summary of Current Research

Previous work has explored transfer learning for automatic emotion recognition in the three commonly used signals (i.e., speech, video, and physiology) (Table 4). Transfer learning for speech aims to transfer the knowledge between the different datasets using the state-of-art transfer learning methods, such as adversarial or generative networks. Image-based transfer learning is mainly utilized to extract high-level features from images or their auxiliary data (e.g., image description text) using convolutional neural networks (CNN). For physiological signals, transfer learning has promoted the design of personalized models through statistical methods, though the data scarcity and high inter-individual variability yield highly variable results across subjects. Speech and video signals allow for the design of sophisticated systems that can detect multiple emotions (i.e., up to seven emotions), while physiological data usually yield more coarse-grained emotion recognition.

5.2. Potential Future Directions

5.2.1. Multi-Modal Transfer Learning for Emotion Recognition

Multi-modal sources of data have been widely used in automatic emotion recognition tasks in order to supplement information...
from multiple modalities and reduce potential bias from one single signal (Busso et al., 2004; Wöllmer et al., 2010). However, transfer learning methods play a very limited role in this process. Common knowledge transfer in multi-modal methods include fine-tune well trained models to a specific type of signal (Vielzeuf et al., 2017; Yan et al., 2018; Huang et al., 2019; Ortega et al., 2019), or fine-tune different well-trained models to both speech and video signals (Ouyang et al., 2017; Zhang et al., 2017; Ma et al., 2019). Other usage of transfer learning for multi-modal methods includes leveraging the knowledge from one signal to another (e.g., video to speech) to reduce the potential bias (Athanasiadis et al., 2019). While these methods provide a promising performance, applying the more recent transfer learning methods, or utilizing more types of signals and leveraging knowledge between multiple signals, is likely to improve transfer learning and boost emotion recognition accuracy.

5.2.2. Transferring Emotionally-Relevant Knowledge Between In-lab and Real-Life Conditions
Most of the current studies focus on transferring knowledge between datasets collected in the lab, due to the relative less availability of real-world dataset, especially for the speech or physiological signals. (Abdelwahab and Busso, 2015, 2018; Zheng et al., 2015; Chai et al., 2016, 2017; Sagha et al., 2016; Zhang et al., 2016; Zheng and Lu, 2016; Gideon et al., 2017; Lin and Jung, 2017; Lan et al., 2018; Li and Chaspari, 2019). While some of these datasets try to simulate a naturalistic scenarios, they are still very different from actual real-world conditions, since they contain less noisy data, collected in high quality conditions (e.g., no occluded video or far-field speech), and might not be able to successfully elicit all possible emotions met in real-life conditions (e.g., grief). Recently, there have been multiple efforts to collect emotion datasets in the wild, such as the PRIORI (Khorram et al., 2018) and the AVEC In-The-Wild Emotion Recognition Challenge (Dhall et al., 2015). Exploring the ability of transferring knowledge from data collected in the lab to data obtained in real-life conditions can significantly extend the applicability of emotion recognition applications in real-life (e.g., quantifying well-being, tracking mental health indices; Khorram et al., 2018).

5.2.3. Multi-Source Transfer Learning
With the advent of a large number of emotion recognition corpora, multi-source transfer learning methods provide a promising research direction. By leveraging the variability from multiple data sources collected under different contextual and recording conditions, multi-source transfer learning might be able to provide highly robust and generalizable systems. Multi-source transfer learning can also lay a foundation for modeling various aspects of human behavior different than emotion (e.g., mood, anxiety), where only a limited number of datasets with a small number of data samples are available. Multi-source transfer learning has not been explored for automatic emotion recognition task, which also makes it a great future research direction.

5.2.4. Distinct Labels Between the Source and Target Domains
A potential challenge in automatic emotion recognition lies in the fact that the various datasets might include different types of emotional labels, which can introduce high mismatch between the source and target domains. Especially in the case where the source domain includes data collected in the lab, the corresponding labels mostly only include basic emotions (e.g., happy, anger, fear, surprise, and neutral). However, the emotional classes in the target domain might be slightly different, since they might include subtle real-world emotions, such as frustration, dispossession, etc. Understanding and modeling associations between primary and secondary emotions can potentially contribute toward more accurate emotion inferences in real-life.

5.2.5. Transfer Learning for Cross-Cultural and Cross-Linguisitc Emotion Recognition
Emotions can be expressed in different ways across different cultures and languages. For example, emotions may be expressed in a direct and noticeable way in Western countries, while emotional expression tends to be more subtle in parts of Asia (Davis et al., 2012; Gökçen et al., 2014). Even though previous studies have explored the knowledge transfer across European languages (e.g., German, French, Italian, and Polish) (Sagha et al., 2016), indicating that languages are not a key factor for automatic emotion recognition, extensive experiments with non-Western languages/cultures might be able to provide additional insights for advancing the field of transfer learning in emotion recognition. At the same time, most emotional datasets include Caucasian subjects, while a few samples of collected data contain participants from different ethnicities and races (Schuller et al., 2009a). It would be beneficial to examine potential discrepancies related to the linguistic speaking style and facial expressions for building generalizable emotion recognition systems across cultures.

6. CONCLUSION
In this manuscript, we reviewed emerging methods in supervised and unsupervised transfer learning, as well as successful applications and promising future research directions of transfer learning for automatic emotion recognition. We first provided an overview of basic transfer learning methods mostly used in image and speech processing, including statistical approaches, deep transfer learning, and region selection through domain relevance. We then expanded upon transfer learning applications for emotion recognition studying three main modalities of speech, image, and physiological signals. Findings from previous work suggest the feasibility of transfer learning approaches in building reliable emotion recognition systems, yielding improved performance compared to in-domain learning (i.e., training and testing models on samples from the same dataset). Despite the encouraging findings, various implications for future work exist by leveraging multiple sources and modalities of emotional data, which have the potential
to yield transferrable emotional embeddings toward novel computational models of human emotion, and human behavior in general.

**AUTHOR CONTRIBUTIONS**

KF made contributions to the conception, design, and analysis of existing work, and drafted the research article. TC contributed to the conception and design of the work, and revised the article.

**FUNDING**

This research was funded by the Engineering Information Foundation (EiF18.02) and the Texas A&M Program to Enhance Scholarly and Creative Activities (PESCA).

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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