Cross-Modal Common Representation Learning with Triplet Loss Functions

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Abstract

Common representation learning (CRL) learns a shared embedding between two or more modalities to improve in a given task over using only one of the modalities. CRL from different data types such as images and time-series data (e.g., audio or text data) requires a deep metric learning loss that minimizes the distance between the modality embeddings. In this paper, we propose to use the triplet loss, which uses positive and negative identities to create sample pairs with different labels, for CRL between image and time-series modalities. By adapting the triplet loss for CRL, higher accuracy in the main (time-series classification) task can be achieved by exploiting additional information of the auxiliary (image classification) task. Our experiments on synthetic data and handwriting recognition data from sensor-enhanced pens show an improved classification accuracy, faster convergence, and a better generalizability.

1 Introduction

Cross-modal retrieval such as common representation learning (CRL) [Peng et al., 2017] for learning across two or more modalities (i.e., image, audio, text and 3D data) has attracted a lot of attention recently. It can be applied in a wide range of applications such as multimedia management [Lee et al., 2020] and identification [Sarafianos et al., 2019]. Extracting information from several modalities and adapting the domain with cross-modal learning allows to use information in all domains [Ranjan et al., 2015]. CRL, however, remains challenging due to the heterogeneity gap (inconsistent representation forms of different modalities) [Huang et al., 2020].

A limitation of CRL is that most approaches require the availability of all modalities at inference time. However, in many applications certain data sources are only available during training by means of elaborate laboratory setups [Lim et al., 2019]. For instance, consider a human pose estimation task that uses inertial sensors together with RGB videos during training. A camera setup might not be available at inference time due to bad lighting conditions or other application-specific restrictions. This requires a model that allows inference on the main modality only, while auxiliary modalities may only be used to improve the training process (as they are not available at inference time) [Hafner et al., 2022].

For CRL, we need a deep metric learning (DML) technique that aims to transform training samples into feature embeddings that are close for samples that belong to the same class and far apart for samples from different classes [Wei et al., 2016]. As DML requires no model update (simply fine-tuning for training samples of new classes), DML is an interesting approach for continual learning [Do et al., 2019]. Typical DML methods use simple distances (e.g., Euclidean distance) but also highly complex distances (e.g., canonical correlation analysis [Ranjan et al., 2015] and maximum mean discrepancy [Long et al., 2015]). While CRL learns representations from all modalities, single-modal learning commonly uses pair-wise learning. The triplet loss [Schoff et al., 2015] selects a positive and negative triplet pair for a corresponding anchor and forces the positive pair distance to be smaller than the negative pair distance. While research of triplet selection for single-modal classification is very advanced [Do et al., 2019], pair-wise selection for CRL is investigated for specific applications only [Zhen et al., 2015; Lee et al., 2020; Zhang and Zheng, 2020].

Our Contribution. Models that use rich data (e.g., images) usually outperform those that use a less rich modality (e.g., time-series). We therefore propose to train a shared representation using the triplet loss between pairs of image and time-series data to learn a common representation between both modality embeddings (cf. Figure 1). This allows to improve the accuracy for single-modal inference in the main task. We prove the efficacy of our DML-based triplet loss for CRL both with simulated data and in a real-world application. More specifically, our proposed CRL technique 1) improves the MTS classification accuracy and convergence,
2) results in a small MTS-only network independent from the image modality while allowing for fast inference, and 3) has better generalizability and adaptability [Huang et al., 2020]. Code and datasets are available upon publication.

The paper is organized as follows. Section 2 discusses related work followed by the mathematical foundation of our method in Section 3. The experimental setup is described in Section 4 and the results are discussed in Section 5.

2 Related Work

In this section, we discuss related work, in particular approaches for learning a common representation from different modalities (in Section 2.1) and DML (in Section 2.2) to minimize the distance between feature embeddings.

2.1 Cross-Modal Representation Learning

For traditional methods that learn a common representation, a cross-modal similarity for the retrieval can be calculated with linear projections as basic models [Rasiwasia et al., 2010]. However, cross-modal correlation is highly complex, and hence, recent methods are based on a modal-sharing network to jointly transfer non-linear knowledge from a single modality to all modalities [Wei et al., 2016]. Huang et al., 2020 use a cross-modal network between different modalities (image to video, text, audio and 3D models) and a single-modal network (shared features between images of source and target domains). They use two convolutional layers (similar to our proposed architecture) that allows the model to adapt more trainable parameters. However, while their auxiliary network uses the same modality, our auxiliary network is based on another modality. Lee et al., 2020 learn a common embedding between video frames and audio signals with graph clusters, but at inference both modalities must be available. Sarafianos et al., 2019 proposed an image-text modality adversarial matching approach that learns modality-invariant feature representations, but their projection loss is used for learning discriminative image-text embeddings only. Hafner et al., 2022 propose a model for single-modal inference. However, they use image and depth modalities for person re-identification without a time-series component, which makes the problem considerably different. Lim et al., 2019 handled multisensory modalities for 3D models only.

2.2 Deep Metric Learning

Networks trained for the classification task can produce useful feature embeddings with efficient runtime complexity $O(NC)$ per epoch, where $N$ is the number of training samples and $C$ the number of classes. The classical cross-entropy (CE) loss, however, is not useful for DML as it ignores how close each point is to its class centroid (or how far apart from other class centroids). The pairwise contrastive loss [Chopra et al., 2005] minimizes the distance between feature embedding pairs of the same class and maximizes the distance between feature embedding pairs of different classes dependent on a margin parameter. The issue is that the optimization of positive pairs is independent from negative pairs, but the optimization should force the distance between positive pairs to be smaller than negative pairs. Do et al., 2019

The triplet loss [Yoshida et al., 2019] addresses this by defining an anchor and a positive as well as a negative point, and forces the positive pair distance to be smaller than the negative pair distance by a certain margin. The runtime complexity of the triplet loss is $O(N^3/C)$, and can be computationally challenging for large training sets. Hence, several works exist to reduce this complexity such as hard or semi-hard triplet mining [Schroff et al., 2015], or smart triplet mining [Harwood et al., 2017]. Often, data is evolving over time, and hence, [Semedo and Magalhães, 2020] proposed a formulation of the triplet loss where the traditional static margin is superseded by a temporally adaptive maximum margin function. While Zeng et al., 2017; Li et al., 2021 combine the triplet loss with the CE loss, Guo et al., 2019 use a word-based triplet selection with $L_2$-normalization for language modeling, but considered all negative pairs for triplet selection with fixed similarity intensity parameter. In our experiments, we use a triplet loss with a dynamic margin together with word level triplet selection.

Most of the related work uses the Euclidean metric as distance loss, although the triplet loss can be defined based on any other (sub-)differentiable distance metric. Wan and Zou, 2021 proposed a method for offline signature verification based on a dual triplet loss that uses the Euclidean space to project an input image to an embedding function. While Rantzsch et al., 2016 use the Euclidean metric to learn the distance between feature embeddings, Zeng et al., 2017 use the Cosine similarity. Hermans et al., 2017 state that using the non-squared Euclidean distance is more stable, while the squared distance made the optimization more prone to collapsing. Recent methods extend the canonical correlation analysis (CCA) [Ranjan et al., 2015] that learns linear projection matrices by maximizing pairwise correlation of cross-modal data. To share information between the same modality (i.e., images), typically the maximum mean discrepancy (MMD) [Long et al., 2015] is minimized.

3 Methodology

We define the problem of common representation learning and present DML loss functions in Section 3.1. In Section 3.2 we propose the triplet loss for cross-modal learning.

3.1 Common Representation Learning

A multivariate time-series (MTS) $U = \{u_1, \ldots, u_m\} \in \mathbb{R}^{m \times l}$ is an ordered sequence of $l \in \mathbb{N}$ streams with $u_i = \{u_{i,1}, \ldots, u_{i,l}\}, i \in \{1, \ldots, m\}$, where $m \in \mathbb{N}$ is the length of the time series. The MTS training set is a subset of the array $U = \{U_1, \ldots, U_m\} \in \mathbb{R}^{m \times l}$, where $mU$ is the number of time series. Let $X \in \mathbb{R}^{n \times p}$ with entries $x_{i,j} \in [0, 255]$ represent an image from the image training set. The image training set is a subset of the array $X = \{X_1, \ldots, X_n\} \in \mathbb{R}^{n \times p}$, where $nX$ is the number of time series. The aim of joint MTS and image classification tasks is to predict an unknown class label $v \in \mathbb{O}$ for single class prediction or $v \in \mathbb{O}$ for sequence prediction for a given MTS or image (see also Section 4.2). In addition to good prediction performance, the goal is to learn representative embeddings $f_c(U)$ and $f_v(X) \in \mathbb{R}^{xw}$ to map MTS and image data into a fea-
ture space $\mathbb{R}^{q \times w}$, where $f_c$ is the output of the convolutional layer(s) $c \in \mathbb{N}$ of the latent representation.

We force the embedding to live on the $q \times w$-dimensional hypersphere by using a Softmax attention, i.e., $\|f_c(U)\|_2 = 1$ and $\|f_c(X)\|_2 = 1 \forall c$ (see [Weinberger et al., 2005]). In order to obtain a small distance between the embeddings $f_c(U)$ and $f_c(X)$, we minimize DML functions $\mathcal{L}_{\text{DML}}(f_c(X), f_c(U))$. Well-known DML metrics are the distance-based mean squared error (MSE) $\mathcal{L}_{\text{MSE}}$, the spatio-temporal cosine similarity (CS) $\mathcal{L}_{\text{CS}}$, the Pearson correlation (PC) $\mathcal{L}_{\text{PC}}$, or the distribution-based Kullback-Leibler (KL) divergence $\mathcal{L}_{\text{KL}}$. In our experiments, we additionally evaluate the maximum mean discrepancy (MMD) $\mathcal{L}_{\text{MMD}}$, Bray Curtis (BC) $\mathcal{L}_{\text{BC}}$, and Poisson $\mathcal{L}_{\text{PO}}$ losses. We study their performance in Section 5. A combination of classification and CRL losses can be realized by dynamic weight averaging [Liu et al., 2019] as a multi-task learning approach that performs dynamic task weighting over time (see Appendix A.1).

### 3.2 Triplet Loss

While the training with the previous loss functions uses inputs where the image and MTS have the same label, pairs with similar but different labels can improve the training process. This can be achieved using the triplet loss [Schroff et al., 2015] which enforces a margin between pairs of image and MTS data with the same identity to all other different identities. As a consequence, the convolutional output for one and the same label lives on a manifold, still enforcing the distance and thus discriminability to other identities. We therefore seek to ensure that the embedding of the MTS $U_i^a$ (anchor) of a specific label is closer to the embedding of the image $X_i^a$ (positive) of the same label than it is to the embedding of any other image $X_i^b$ (negative) of another label (see Figure 2).

Thus, we want the following inequality to hold for all training samples $(f_c(U_i^a), f_c(X_i^a), f_c(X_i^b))\in\Phi$:

$$\mathcal{L}_{\text{DML}}(f_c(U_i^a), f_c(X_i^a)) + \alpha < \mathcal{L}_{\text{DML}}(f_c(U_i^a), f_c(X_i^b)),$$

where $\mathcal{L}_{\text{DML}}(f_c(X), f_c(U))$ is a DML loss, $\alpha$ is a margin between positive and negative pairs, and $\Phi$ is the set of all possible triplets in the training set. Based on (1), we can formulate a differentiable loss function that we can use for optimization:

$$\mathcal{L}_{\text{Triplet}}(U^a, X^a, X^b) = \sum_{i=1}^{N} \max \left[ \mathcal{L}_{\text{DML}}(f_c(U_i^a), f_c(X_i^a)) - \mathcal{L}_{\text{DML}}(f_c(U_i^a), f_c(X_i^b)) + \alpha, 0 \right],$$

where $c \in \mathbb{N}$. Selecting negative samples that are too close to the anchor (in relation to the positive sample) can cause slow training convergence. Hence, triplet selection must be handled carefully and application-specific [Do et al., 2019].

To have a larger number of trainable parameters in the latent representation with a greater depth, we evaluate one and two stacked convolutional layers, each trained with a shared loss $\mathcal{L}_{\text{Triplet}}$.

### 4 Experiments

We now demonstrate the efficacy of our proposal. In Section 4.1 we generate sinusoidal time-series with introduced noise (main task) and compute the corresponding Gramian angular summation field (GASF) with different noise parameters (auxiliary task), see Figure 1. In Section 4.2 we combine online (inertial sensor signals, main task) and offline data (visual representations, auxiliary task) for handwriting recognition (HWR) with sensor-enhanced pens. This task is particularly challenging due to different data representations based on images and MTS data. For both applications, our approach allows only to use the main modality (MTS) for inference. We further analyze and evaluate different DML functions to minimize the distance between the learned embeddings.

#### 4.1 Cross-Modal Learning on Synthetic Data

We first investigate the influence of the triplet loss for cross-modal learning between synthetic time-series and image-based data. For this, we generate signal data of 1,000 timesteps with different frequencies for 10 classes (see Figure 3a) and add noise from a continuous uniform distribution $U(a, b)$ for $a = 0$ and $b = 0.3$. We use a recurrent CNN with the CE loss to classify these signals. From each signal without noise, we generate a GASF [Wang and Oates, 2015]. For classes with high frequencies, this results in a fine-grained pattern, and for low frequencies in a coarse-grained pattern. We generate GASFs with different added noise between $b = 0$ (Figure 3b) and $b = 1.95$ (Figure 3c). A small CNN classifies these images with the CE loss. To combine both networks, we train each signal-image pair with the triplet loss. As the frequency of the sinusoidal signal is closer for more similar class labels, the distance in the manifold embedding should also be closer. For each batch, we select negative sample pairs for classes with the class label $CL = 1 + \left\lfloor \frac{\max(c - 1)}{25} \right\rfloor$ as lower bound for current epoch $c$ and maximum epoch $\max_c$. We set the margin $\alpha$ in the triplet loss separately for each batch such that $\alpha = \beta \cdot (CL_p - CL_n)$ depends on the positive $CL_p$ and negative $CL_n$ class labels of the batch and is in the range [1, 5] with $\beta = 0.1$. The batch size is 100 and $\max_c = 100$. Appendix A.2 provides further details.

#### 4.2 Cross-Modal Learning for HWR

**Method Overview.** Figure 4 gives a method overview. The main task is online HWR to classify words written with a sensor-enhanced pen and represented by MTS of the different
pen sensors. To improve the classification task with a better generalizability, the auxiliary network performs offline HWR based on an image input. We pre-train ScrabbleGAN [Fogel et al., 2020] on the IAM-OffDB [Liwicki and Bunke, 2005] dataset and for all MTS word labels generate the corresponding image as the positive MTS-image pair. Each MTS and each image is associated with \( v \), a sequence of \( L \) class labels from a pre-defined label set \( \Omega \) with \( K \) classes. For our classification task, \( v \in \Omega^L \) describes words. The MTS training set is a subset of the array \( U \) with labels \( V_U = \{v_1, \ldots, v_{n_U}\} \in \Omega^{n_U} \times L \). The image training set is a subset of the array \( X \), and the corresponding labels \( V_X = \{v_1, \ldots, v_{n_X}\} \in \Omega^{n_X} \times L \). Offline HWR techniques are based on Inception, ResNet34, or GTR [Yousef et al., 2018] modules. The online method is improved by sharing layers with a common representation by minimizing the distance of the feature embedding of the convolutional layers \( c \in \{1, 2\} \) (integrated in both networks) with a shared loss \( L_{\text{shared}} \). We set the embedding size \( \mathbb{R}^{q \times 10} \) to \( 400 \times 200 \). Both networks are trained with the connectionist temporal classification (CTC) [Graves et al., 2009] loss \( L_{\text{CTC}} \) to avoid pre-segmentation of the training samples by transforming the network outputs into a conditional probability distribution over label sequences.

**Datasets for Online HWR.** We make use of two word datasets proposed in [Ott et al., 2022b]. These datasets are recorded with a sensor-enhanced pen that uses two accelerometers (3 axes each), one gyroscope (3 axes), one magnetometer (3 axes), and one force sensor at 100 Hz [Ott et al., 2020; 2022a]. One sample of size \( m \times l \) represents an MTS of a written word of \( m \) timesteps from \( l = 13 \) sensor channels. One word is a sequence of small or capital characters (52 classes) or with mutated vowels (59 classes). The OnHW-words500 dataset contains 25,218 samples where each of the 53 writers contributed the same 500 words. The OnHW-wordsRandom dataset contains 14,641 randomly selected words from 54 writers. For both datasets, 80/20 train/validation splits are available for writer-(in)dependent (WD/WI) tasks. We transform (zero padding, interpolation) all samples to 800 timesteps.

**Image Generation for Offline HWR.** In order to couple the online MTS data with offline image data, we use a generative adversarial network (GAN) to generate arbitrarily many images. ScrabbleGAN [Fogel et al., 2020] is a state-of-the-art semi-supervised approach that consists of a generator \( G \) that generates images of words with arbitrary length from an input word label, a discriminator \( D \), and a recognizer \( R \) promoting style and data fidelity. For the generator, four character filters \( (k_m, k_e, k_c, k_l) \) are concatenated, multiplied by a noise vector and fed into a class-conditioned generator. This allows for adjacent characters to interact, e.g., enabling cursive text. We train ScrabbleGAN with the IAM-OffDB [Liwicki and Bunke, 2005] dataset and generate three different datasets. Exemplary images are shown in Figure 5. First, we generate 2 million images randomly selected from a large lexicon (OffHW-German), and train the offline HWR architectures. Second, we generate 100,000 images based on the same word labels for each of the OnHW-words500 and OnHW-wordsRandom datasets (OffHW-words500, wordsRandom), and fine-tune the offline HWR architectures.
Methods for Offline HWR. OrigamiNet [Yousef and Bishop, 2020] is a state-of-the-art multi-line recognition method using only unsegmented image and text pairs. An overview of offline HWR methods is given in Appendix A.3. Similar to OrigamiNet, our offline method is based on different encoder architectures with one or two additional 1D convolutional layers (each with filter size 200, Softmax activation [Zeng et al., 2017]) with 20% dropout for the latent representation, and a common representation decoder with BiLSTMs. For the encoder, we make use of Inception modules from GoogLeNet, the ResNet34 architecture, and re-implement the newly proposed gated, fully convolutional method gated text recognizer (GTR) [Yousef et al., 2018]. See Appendix A.4 for detailed information on the architectures. We augment the networks on the generated Offline-German dataset for 10 epochs, and fine-tune on the Offline-[500, wordsRandom] datasets for 15 epochs. For comparison with state-of-the-art techniques, we train OrigamiNet and compare with IAM-OffDB. For OrigamiNet, we apply interline spacing reduction via seam carving [Avidan and Shamir, 2007], resizing the images to 50% height, and random perspective (rotating and resizing lines) and random elastic transform [Wigington et al., 2017]. We augment the Offline-German dataset with random width resizing and apply no augmentation for the Offline-[words500, wordsRandom] datasets for fine-tuning.

Offline/Online Common Representation Learning. Our architecture for online HWR is based on [Ott et al., 2022b]. The encoder extracts features of the inertial data and consists of three convolutional layers (each with filter size 400, ReLU activation) and one convolutional layer (filter size 200, ReLU activation), a max pooling, batch normalization and a 20% dropout layer. As for the offline architecture, the network then learns a latent representation with one or two convolutional layers (each with filter size 200, Softmax activation) with 20% dropout and the same CRL decoder. The output of the convolutional layers of the latent representation are minimized with the $L_{\text{share}}$ loss. The layers of the common representation are fine-tuned based on the pre-trained weights of the offline technique. Here, two BiLSTM layers with 60 units each and ReLU activation extract the temporal context of the feature embedding. As for the baseline classifier, we train for 1,000 epochs. For evaluation, the main MTS network is independent of the image auxiliary network by using only the weights of the main network.

Triplet Selection. To ensure (fast) convergence, it is crucial to select triplets that violate the constraint from Equation 1. Typically, it is infeasible to compute the loss for all triplet pairs or this leads to poor training performance as poorly chosen pairs dominate hard ones. This requires an elaborate triplet selection [Do et al., 2019]. We use the Edit distance (ED) to define the identity and select triplets. The ED is the minimum number of substitutions $S$, insertions $I$ and deletions $D$ required to change the sequences $h = (h_1, \ldots, h_r)$ into $g = (g_1, \ldots, g_t)$ with length $r$ and $t$, respectively. We define two sequences with an ED of 0 as positive pair, and with an ED larger than 0 as negative pair. Based on preliminary experiments, we use only substitutions for triplet selection that lead to a higher accuracy compared to additional insertions and deletions (whereas these would also change the length difference of image and MTS pairs). We constrain $p - m/2$, the difference in pixels $p$ of the images and half the number of timesteps of the MTS, to be maximal ±20. The goal is a small distance for positive pairs, and a large distance for negative pairs that increases with a larger ED (between 1 and 10). And despite a limited number of word labels, there still exist a large number of image-MTS pairs per word label for every possible ED (see Figure 6). For each batch, we search in a dictionary of negative sample pairs for samples with $ED = 1 + \left\lfloor \frac{\max_e - e}{100} \right\rfloor$ as lower bound for the current epoch $e$ and maximal epochs $\max_e$. For every label we randomly pick one image. We let the margin $\alpha$ in the triplet loss vary for each batch such that $\alpha = \beta \cdot ED$ is depending on the mean ED of the batch and is in the range $[1, 11]$ with $\beta = 10^{-3}$ for MSE, $\beta = 0.1$ for CS and PC, and $\beta = 1$ for KL. The batch size is 100 and $\max_e = 1,000$.

5 Experimental Results

Hardware and Training Setup. For all experiments we use Nvidia Tesla V100-SXM2 GPUs with 32 GB VRAM equipped with Core Xeon CPUs and 192 GB RAM. We use the vanilla Adam optimizer with a learning rate of $10^{-4}$.

5.1 Evaluation of Synthetic Data

We train the time-series (TS) model 18 times with noise $b = 0.3$, and the combined model with the triplet loss for all 40 noise combinations ($b \in \{0, \ldots, 1.95\}$) with different DML functions. Figure 7 shows the validation accuracy averaged over all trainings as well as the combined cases separately for noise $b < 0.2$ and noise $0.2 \leq b < 2.0$ (for the $L_{\text{CS}}$ loss). The accuracy of the models that use only images and in combination with MTS during inference reach an accuracy of 99.7% (which can be seen as an unreachable upper bound for the TS-only models). The triplet loss improves the final TS baseline accuracy from 92.5% to 95.36% (averaged over all combinations) while combining TS and image data leads to a faster convergence. Conceptually similar to [Huang et
are similar in the red box (character x) or blue box (character p) for \( f_2(X_i) \), or the last pixels (character t) of \( f_2(U_i) \) for \( \mathcal{L}_{PC} \) marked green.

Table 1: Feature embeddings \( f_2(X_i) \) and \( f_2(U_i) \) of exemplary image \( X_i \) and MTS \( U_i \) data of the convolutional layer \( c = conv_2 \) for different deep metric learning functions for positive pairs \((ED = 0)\) and negative pairs \((ED > 0)\) trained with the triplet loss. The feature embeddings are similar in the red box (character x) or blue box (character p) for \( f_2(X_i) \), or the last pixels (character t) of \( f_2(U_i) \) for \( \mathcal{L}_{PC} \) marked green.

Table 2: Evaluation results (WER and CER in \%, averaged over two splits) of the baseline MTS-only technique and our cross-modal techniques for the inertial-based OnHW datasets [Ott et al., 2022b] with and without mutated vowels (MV) for two convolutional layers \( c = 2 \). We propose writer-(in)dependent (WD/WI) results.

6 Conclusion
We evaluated DML-based triplet loss functions for CRL between image and time-series modalities with class label specific triplet selection. On synthetic data as well as on different HWR datasets, our method yields notable accuracy improvements for the main time-series classification task and can be decoupled from the auxiliary image classification task at inference time. Our cross-modal triplet selection further yields a faster training convergence with better generalization on the main task.
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A Appendices

We present the multi-task learning technique in Section A.1, and show more details on learning with the triplet loss on synthetically generated signal and image data in Section A.2. We present an method overview for offline handwriting recognition (HWR) in Section A.3, and propose more details of our architectures in Section A.4. Section A.5 presents results of representation learning for HWR.

A.1 Multi-Task Learning (MTL)

We simultaneously train the $L_{\text{CTC}}$ loss for sequence classification combined with one or two shared losses $L_{\text{shared},1}$ and $L_{\text{shared},2}$ for common representation learning (CRL). As both losses are in different ranges, the naive weighting

$$L_{\text{total}} = \sum_{i=1}^{T} \omega_i L_i,$$

with pre-specified, constant weights $\omega_i = 1, \forall i \in \{1, \ldots, T\}$ can harm the training process. Hence, we apply dynamic weight average (DWA) [Liu et al., 2019] as an MTL approach that performs dynamic task weighting over time (i.e., after each batch).

A.2 Training Synthetic Data with the Triplet Loss

Signal and Image Generation. We combine the networks for both, signal and image classification, to improve the classification accuracy over each single-modal network. The aim is to show that the triplet loss can be used for such a cross-modal setting in the field of common representation learning. Hence, we generate synthetic data where the image data contains information of the signal data. We generate signal data $\hat{x}$ with $\hat{x}_{i,k} = \sin \left(0.05 \cdot \frac{t_i}{T} \right)$ for all $t_i \in \{1, \ldots, 1,000\}$ where $t_i$ is the timestep of the signal. The frequency of the signal is dependent on the class label $k$. We generate signal data for 10 classes (see Figure 8a). We add noise from a continuous uniform distribution $U(a, b)$ for $a = 0$ and $b = 0.3$ (see Figure 8b), and add time and magnitude warping (see Figure 8c). We generate a signal-image pair such that the image is based on the signal data. We make use of the Gramian angular field (GAF) that transforms time series into images. The time series is defined as $x = (x_1, \ldots, x_n)$ for $n = 1,000$. The GAF creates a matrix of temporal correlations for each $(x_i, x_j)$ by rescaling the time series in the range $[p, q]$ with $-1 \leq p < q \leq 1$ by

$$\hat{x}_i = p + (q - p) \cdot \frac{x_i - \min(x)}{\max(x) - \min(x)}, \forall i \in \{1, \ldots, n\},$$

and computes the cosine of the sum of the angles for the Gramian angular summation field (GASF) [Wang and Oates, 2015] by

$$\text{GASF}_{i,j} = \cos (\phi_i + \phi_j), i,j \in \{1, \ldots, n\},$$

with $\phi_i = \arccos (\hat{x}_i), \forall i \in \{1, \ldots, n\}$, being the polar coordinates. We generate image datasets based on signal data with different noise parameters $b \in \{0.0, \ldots, 1.95\}$ to show the influence of the image data on the classification accuracy. Figure 9 exemplarily shows the GASF plots for the noise parameters $b = \{0, 0.5, 1.0, 1.5, 1.95\}$. We present the GASF for the classes 0, 5 and 9 to show the dependency of the frequency of the signal data on the GASF.

Models. We use the following models for classification. Our encoder for time series classification consists of a 1D convolutional layer (filter size 50, kernel 4), a max pooling layer (pool size 4), batch normalization, and a dropout layer (20%). The image encoder consists of a layer normalization and 2D convolutional layer (filter size 200), and batch normalization with ELU activation. It follows a 1D convolutional layer (filter size 200, kernel 4), max pooling (pool size 2), batch normalization, and 20% dropout. For both models, it follows a common representation, i.e., an LSTM with 10 units, a Dense layer with 20 units, a batch normalization layer, and a Dense layer of 10 units (for 10 sinusoidal classes). These layers are shared between both models.

A.3 Overview of Offline HWR Methods

In the following, we give a detailed overview of offline HWR methods to select a suitable lexicon and language model free method. There is no recent paper summarizing the work for offline HWR. For an overview of offline and online HWR datasets, see [Plamondon and Srihari, 2000; Hussain et al., 2015]. Table 3 presents related work. Methods for offline HWR range from hidden markov models (HMMs) to deep learning techniques that became predominant such as convolutional neural networks (CNNs), temporal convolutional networks (TCNs) and recurrent neural networks (RNNs). RNN techniques are well explored including long short-term memories (LSTMs), bidirectional LSTMs (BiLSTMs), and multidimensional RNNs (MDRNN, MDLSTM). Recent methods are generative adversarial networks (GANs) and Transformers. We note the use of a language model (LM) and its size $k$, and the data level the method works with, i.e., paragraph or full text level (P), line level (L) and word level (W). We present evaluation results for the IAM-OffDB [Liwicki and Bunke, 2005] and RIMES [Grosicki and El-Abed, 2011] datasets including the word error rate (WER) and character error rate (CER).

HMMs. Methods based on HMMs from last decades are [Bertolami and Bunke, 2018; Dreuw et al., 2011; Li et al., 2014; Pastor-Pellicer et al., 2015]. Recently, [Español-Boquera et al., 2011] proposed HMM+ANN, a HMM modeled with Markov chains in combination with a multilayer perceptron (MLP) to estimate the emission probabilities. [Kozielski et al., 2013] presented Tandem GHMM that uses moment-based image normalization, writer adaptation and discriminative feature extraction with an 3-gram open-vocabulary of size 50k with an LSTM for recognition. [Doetsch et al., 2014] proposed an LSTM unit that controls the shape of the squashing function in gating units decoded in a hybrid HMM. This approach yields the best results based on HMMs.

RNNs: MDLSTMs. The 2DLSTM approach by [Graves and Schmidhuber, 2008] combines multidimensional LSTMs (MDLSTMs) with the CTC loss. The MDLSTM–RNN approach [Bluche, 2016] works at paragraph level by replacing the collapse layer by a recurrent version. A neural network performs implicit line segmentation by computing attention weights on the image representation. [Voigtlaender et al., 2016] proposed an efficient GPU-based implementation of MDLSTMs by processing the input in a diagonal-wise fash-
Figure 8: Plot of the 1D signal data for 10 classes.

Figure 9: Plot of the Gramian angular summation field (GASF) based on 1D signal data with added noise for the classes 0 (top row), 5 (middle row) and 9 (bottom row).

RNNs: LSTM and BiLSTMs. RNNs for HWR marked an important milestone reaching impressive recognition accuracies. Sequential architectures are perfect to fit text lines due to the probability distributions over sequences of characters and due to the inherent temporal aspect of text [Kang et al., 2020]. [Graves et al., 2009] introduced the BiLSTM layer in combination with the CTC loss. [Pham et al., 2014] showed that the performance of LSTMs can be greatly improved using dropout. [Voigtlaender et al., 2015] investigated sequence-discriminative training of LSTMs using the maximum mutual information (MMI) criterion. While [Bluche, 2015] utilized a RNN with a HMM and a language model, [Menasri et al., 2012] combined a RNN with a sliding window Gaussian HMM. GCRNN [Bluche and Messina, 2017] combines a convolutional encoder (aiming generic and multilingual features) and a BiLSTM decoder predicting character sequences. Also, [Puigcerver, 2017] proposed a CNN+BiLSTM architecture (CNN–1DLSTM–CTC) that uses the CTC loss. The start, follow, read (SFR) [Wigington et al., 2018] model jointly learns text detection and segmentation. [Dutta et al., 2018] used synthetic data for pre-training and image normalization for slant correction. The methods by [Chowdhury and Vig, 2018; Sueiras et al., 2018;
| Method | Information | LM size k | Level | IAM-OFFDB | RIMES |
|--------|-------------|-----------|-------|-----------|-------|
| HMM    | Markov chain with MLP | w/ (5) | × | 13.50 | 6.90 |
| HMM+ANN [Español-Boquera et al., 2011] | | | | | |
| Tandem GHMM [Kozielski et al., 2013] | GHMM and LSTM, writer adaptation | w/ (50) | × | 13.30 | 5.10 |
| LSTM-HMM [Doetsch et al., 2014] | Combination of LSTM with HMM | w/ (50) | × | 12.20 | 4.90 |
| 2DLSTM [Graves and Schmidhuber, 2008] | Combined MDLSTM with CTC | w/o | | 27.50 | 8.30 |
| - MDLSTM-RNN [Bluche, 2016] | 150 dpi | w/o | × | 29.50 | 10.10 |
| - | 150 dpi | w/ (50) | × | 16.60 | 6.50 |
| - | 300 dpi | w/o | × | 24.60 | 7.90 |
| - | 300 dpi | w/ (50) | × | 16.40 | 5.50 |
| - [Voigtlaender et al., 2016] | GPU-based, diagonal MDLSTM | | | 9.30 | 3.50 |
| - SepMDLSTM [Chen et al., 2017] | Multi-task approach | w/o | | 34.55 | 11.15 |
| - [Bluche et al., 2017] | MDLSTM, attention, | w/o | × | 21.16 | 6.34 |
| - Line segmentation 150 dpi | w/o | × | - | 11.10 | - |
| - Line segmentation 150 dpi | w/o | × | - | 7.50 | - |
| - MDLSTM [Castro et al., 2018] | | | | 10.50 | 3.60 |
| RNN    | Sliding win. Gaussian HMM, RNN | w/ (20) | | 18.20 | 25.90 |
| BiLSTM [Graves et al., 2009] | | | | | |
| HMM+RNN [Menasti et al., 2012] | | | | | |
| Dropout [Pham et al., 2014] | LSTM with dropout | w/o | | 35.10 | 10.80 |
| [Voigtlaender et al., 2015] | Maximum mutual information | | | 12.70 | 4.80 |
| [Bluche, 2015] | | | | 10.90 | 4.40 |
| GCRN [Bluche and Messina, 2017] | CNN+BiLSTM | w/ (50) | | 13.60 | 5.10 |
| CNN-1DLSTM-CTC [Puiu and Cerver, 2017] | CNN+BiLSTM+CTC (128 x W) | w/o | × | 18.40 | 5.80 |
| NN+BiLSTM+CTC | w/ (50) | × | 12.20 | 4.40 | 9.00 |
| End2End [Krishnan et al., 2018] | LSTM encoder-decoder | w/o | | 16.19 | 6.34 |
| End2End | LSTM w/o | w/ | × | 32.89 | 9.78 |
| SFR [Wigington et al., 2018] | Text detection and segmentation | w/o | × | 23.20 | 6.40 |
| CNN-RNN [Dutta et al., 2018] | Unconstrained | w/ | | 12.61 | 4.88 |
| CNN-RNN | Full-Lexicon | w/o | | 4.80 | 2.52 |
| CNN-RNN | Text-Lexicon | w/o | | 4.07 | 2.17 |
| CNN-RNN | Unconstrained | w/o | × | 17.82 | 5.70 |
| [Chowdhury and Vig, 2018] | Seq2seq, w/o LN | w/o | | 25.50 | 17.40 |
| CNN-RNN | w/LN | w/o | | 22.90 | 13.10 |
| CNN-RNN | w/LN + Focal Loss | w/o | | 21.10 | 11.40 |
| CNN-RNN | w/LN + Focal Loss + Beam Search | w/o | | 16.70 | 8.10 |
| [Sueiras et al., 2018] | LSTM encoder-decoder, attention | w/o | | 15.90 | 4.80 |
| [Chung and Delcieu, 2019] | ResNet+LSTM, segmentation | w/o | × | 8.50 |
| [Ingle et al., 2019] | BiLSTM | × | 30.70 |
| [Michael et al., 2019] | GRAIL | × | 35.20 |
| CNN-1DLSTM-CTC | Seq2seq CNN+BiLSTM (64 x W) | w/o | × | 5.24 |
| CNN-1DLSTM-CTC | Feature Pyramid Network, 150 dpi | w/o | × | 15.60 |
| CNN-1DLSTM-CTC | AFD module | w/o | | 8.87 | 5.94 |
| [Poznanski and Wolf, 2016] | CNN + connected branches, CCA | w/o | | 6.45 | 3.44 |
| CNN-1DLSTM-CTC | CNN+CTC (32 x W) | w/o | × | 4.90 |
| CNN-1DLSTM-CTC | OrigamiNet [Yousef and Bishop, 2020] | VGG (500x500) | × | × | - |
| CNN-1DLSTM-CTC | VGG (500x500), w/o LN | w/o | × | | 51.37 |
| CNN-1DLSTM-CTC | ResNet26 (500x500), w/o LN | w/o | × | | 34.55 |
| CNN-1DLSTM-CTC | ResNet26 (500x500), w/LN | w/o | × | | 10.03 |
| CNN-1DLSTM-CTC | ResNet26 (500x500), w/LN | w/o | × | | 7.24 |
| CNN-1DLSTM-CTC | ResNet26 (500x500), w/LN | w/o | × | | 8.93 |
| CNN-1DLSTM-CTC | ResNet26 (500x500), w/LN | w/o | × | | 6.37 |
| CNN-1DLSTM-CTC | ResNet26 (500x500), w/LN | w/o | × | | 76.90 |
| CNN-1DLSTM-CTC | ResNet26 (500x500), w/LN | w/o | × | | 6.13 |
| CNN-1DLSTM-CTC | GTR-8 (500x500), w/o LN | w/o | × | | 72.40 |
| CNN-1DLSTM-CTC | GTR-8 (500x500), w/LN | w/o | × | | 5.64 |
| CNN-1DLSTM-CTC | GTR-8 (750x750), w/LN | w/o | × | | 5.50 |
| CNN-1DLSTM-CTC | GTR-12 (750x750), w/LN | w/o | × | | 4.70 |
| DAN [Wang et al., 2020] | Decoupled attention module | w/o | × | 19.60 | 6.40 |
| GAN    | Original data | w/o | | 25.10 | - |
| ScrabbleGAN [Fogel et al., 2020] | Augm. | w/o | | 24.73 | - |
| Transformer [Kang et al., 2020] | Augm. + 100k synth. | w/o | | 23.98 | - |
| Transformer | Self-attention for text/imagens | w/o | × | 15.45 | 4.67 |
| Transformer | CNN encoder, Transformer decoder | w/o | × | 6.70 |
| Transformer | With augmentation | w/o | × | 6.30 |
| Other  | Finite state transducer (lexicon) n-gram | | | 19.10 | - |

Table 3: Evaluation results (WER and CER in %) of different methods on the IAM-OFFDB [Liwicki and Bunke, 2005] and RIMES [Grosicki and El-Abed, 2011] datasets. We state information about the method and the size of the language model (LM). LN = layer normalization. P = paragraph or full text level. L = line level. W = word level. The table is sorted by year.
Figure 10: Offline HWR method based on Inception modules [Szegedy et al., 2015].

Ingle et al., 2019; Michael et al., 2019] make also use of BiLSTMs. While [Carbonell et al., 2019] uses a feature pyramid network (FPN), the adversarial feature deformation module (AFDM) [Bhunia et al., 2019] learns ways to elastically warp extracted features in a scalable manner. Further methods that combine CNNs with RNNs are [Liang et al., 2017; Sudholt and Fink, 2018; Xiao and Cho, 2016], while BiLSTMs are utilized in [Carbune et al., 2020; Tian et al., 2019].

TCNs. TCNs use dilated causal convolutions and have been applied to air-writing recognition by [Bastas et al., 2020]. As RNNs are slow to train, [Sharma et al., 2020] presented a faster system which is based on text line images and TCNs with the CTC loss. This method achieves 9.6% CER on the IAM-OffDB dataset. [Sharma and Jayagopi, 2021] combined 2D convolutions with 1D dilated non-causal convolutions that offers a high parallelism with a smaller number of parameters. They analyzed re-scaling factors and data augmentation, and achieved comparable results for the IAM-OffDB and RIMES datasets.

CNNs. [Poznanski and Wolf, 2016] utilized a CNN with multiple fully connected branches to estimate its n-gram frequency profile (set of n-grams contained in the word). With canonical correlation analysis (CCA), the estimated profile can be matched to the true profiles of all words in a large dictionary. As most attention methods suffer from an alignment problem, [Wang et al., 2020] proposed a decoupled attention network (DAN) that has a convolutional alignment module that decouples the alignment operation from using historical decoding results based on visual features. The gated text recognizer (GTR) [Yousef et al., 2018] aims to automate the feature extraction from raw input signal with minimum required domain knowledge. The fully convolutional network without recurrent connections is trained with the CTC loss. Thus, the GTR module can handle arbitrary input sizes and can recognize strings with arbitrary length. This module has been used for OrigamiNet [Yousef and Bishop, 2020] that is a segmentation-free multi-line or full page recognition system. OrigamiNet yields state-of-the-art results on the IAM-OffDB dataset, and shows an improved performance of GTR over VGG and ResNet26. Hence, we use the GTR module as our visual feature encoder for offline HWR (see Section A.4).

GANs. Handwriting text generation (HTG) is a relatively new field. The first approach by [Graves, 2014] was a method to synthesize online data based on RNNs. The technique HWGAN by [Ji and Chen, 2020] extends this method by adding a discriminator $D$. DeepWriting [Aksan et al., 2016] is a GAN that is capable of disentangling style from content and thus making digital ink editable. [Haines et al., 2016] proposed a method to generate handwriting based on a specific author with learned parameters for spacing, pressure and line thickness. [Alonso et al., 2019] used a BiLSTM to get an embedding of the word to be rendered, and added an auxiliary network as recognizer $R$. The model is trained with a combination of an adversarial loss and the CTC loss. ScrabbleGAN by [Fogel et al., 2020] is a semi-supervised approach that can generate arbitrarily many images of words with arbitrary length from a generator $G$ to augment handwriting data and uses a discriminator $D$ and recognizer $R$. The paper proposes results for original data, with random affine augmentation, using synthetic images and refinement.

Transformers. RNNs prevent parallelization due to their sequential pipelines. [Kang et al., 2020] introduced a non-recurrent model by the use of Transformer models by using multi-head self-attention layers at the textual and visual stages. Their method is unconstrained to any pre-defined vocabulary. For the feature encoder, they used modified ResNet50 models. The full page HTR (FPHR) method by [Singh and Karayev, 2021] uses a CNN as encoder and a Transformer as decoder with positional encoding.

A.4 Details on Architectures for Offline HWR

In this section, we give details about the integration of Inception [Szegedy et al., 2015], ResNet [He et al., 2016] and GTR [Yousef et al., 2018] modules into the offline HWR system. All three architectures are based on publicly available implementations, but we changed or adapted the first layer for the image input and the last layer for a proper input for our latent representation module.

Inception. Figure 10 gives an overview of the integration of the Inception module. The Inception module is part of the well known GoogleNet architecture. The main idea is to consider how an optimal local sparse structure can be approximated by readily available dense components. As the merg-
The integration of pooling layer outputs with convolutional layer outputs would lead to an inevitable increase in the number of output and would lead to computational blow up, we apply the Inception module with dimensionality reduction to our offline HWR approach [Szegedy et al., 2015]. The input image is of size $H \times W$. What follows is the Inception (3a), Inception (3b), a max pooling layer ($3 \times 3$) and Inception (4a). We add three 1D convolutional layers to get an output dimensionality of $400 \times 200$ as input for the latent representation.

**ResNet34.** Figure 11 gives an overview of the integration of the ResNet34 architecture. Instead of learning unreferenced functions, [He et al., 2016] reformulated the layers as learning residual functions with reference to the layer inputs. This residual network is easier to optimize and can gain accuracy from considerably increased depth. The ResNet block let the layers fit a residual mapping denoted as $\mathcal{H}(x)$ with identity $x$, and fits the mapping $\mathcal{F}(x) := \mathcal{H}(x) - x$. The original mapping is recast into $\mathcal{F}(x) + x$. We reshape the output of
A.5 Detailed HWR Evaluation

Offline HWR Results. Table 4 shows offline HWR results on our generated OffHW-German dataset and on the IAM-OffDB [Liwicki and Bunke, 2005] dataset. ScrabbleGAN [Fogel et al., 2020] yields an WER of 23.61% on the IAM dataset, while OrigamiNet [Yousef and Bishop, 2020] achieves an CER of 4.70% with 12 GTR modules. As the training takes more than one day for one epoch on the large OffHW-German dataset, we train OrigamiNet with four GTR modules, and achieve 0.11% CER on the generated dataset and 15.67% on the IAM dataset, which is higher than the model with 12 GTR modules. While the paper did not propose WER results, OrigamiNet yields only an WER of 90.40%. With our own implementation of four GTR modules and one convolutional layer for the common representation, our model achieves similar results. While GTR modules yield slightly lower CERs on the OffHW-German dataset than our architectures with Inception and ResNet modules, the WERs are significantly higher. Fine-tuning the architecture with four GTR modules and one convolutional layer for the common representation, our model achieves similar results. While GTR modules and one convolutional layer for the common representation learning, our model achieves similar results.

Online HWR Results. Table 6 gives an overview of CRL results based on one convolutional layer (c = 1) for the common representation. Consistently, cross-modal learning can improve the baseline results. The triplet loss can yield better results for the OnHW-wordsRandom dataset than standard DML function, while the triplet loss marginally decreases results for the OffHW-words500 dataset. Here, the $\mathcal{L}_{\text{PC}}$ loss yields the best results. For OnHW-wordsRandom, the $\mathcal{L}_{\text{CC}}$ and $\mathcal{L}_{\text{PC}}$ loss functions outperform other DML functions.

Table 4: Evaluation results (WER and CER in %) for the generated dataset with ScrabbleGAN [Fogel et al., 2020] OffHW-German and the IAM-OffDB [Liwicki and Bunke, 2005] dataset. We propose writer-dependent (WD) and writer-independent (WI) results.

| Method                  | WER  | CER  | WER  | CER  |
|-------------------------|------|------|------|------|
| ScrabbleGAN             | -    | -    | 23.61 | -    |
| [Fogel et al., 2020]    | -    | -    | 23.61 | -    |
| OrigamiNet (12 × GTR)   | -    | -    | 4.70  | -    |
| [Yousef and Bishop, 2020]| -    | -    | 4.70  | -    |

Table 5: Evaluation results (WER and CER in %) for the generated OffHW-words500 and OffHW-wordsRandom datasets for one and two convolutional layers (c). We propose writer-dependent (WD) and writer-independent (WI) results.

| Method | OffHW-words500 WER | CER | OffHW-wordsRandom WER | CER |
|--------|--------------------|-----|-----------------------|-----|
| WD     | WI                 | WI  | WD                    | WI  |
| c = 1  | 2.94               | 0.76| 0.95                  | 0.23| 1.98              | 0.35 | 2.05              | 0.37|
| c = 2  | 2.51               | 0.69| 0.85                  | 0.22| 1.82              | 0.34 | 1.95              | 0.38|

Table 6: Evaluation results (WER and CER in %) of the baseline MTS-only technique and our cross-modal learning technique for the inertial-based OnHW datasets [Ott et al., 2022] with and without mutated vowels (MV) for one convolutional layer c = 1.

| Method                  | OffHW-words500 WER | CER | OffHW-wordsRandom WER | CER |
|-------------------------|--------------------|-----|-----------------------|-----|
| $\mathcal{L}_{\text{CTC}}$, w/ MV | 40.40             | 12.61| 66.51                | 34.65| 42.06             | 7.81 | 82.55             | 32.34|
| $\mathcal{L}_{\text{CTC}}$, w/o MV | 46.56             | 15.25| 66.69                | 35.63| 43.66             | 8.48 | 83.28             | 34.34|

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