ESANN 2017 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 26-28 April 2017, i6doc.com publ., ISBN 978-287587039-1.
Available from http://www.i6doc.com/en/.

An EM transfer learning algorithm with applications in bionic hand prostheses

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Abstract. Modern bionic hand prostheses feature unprecedented functionality, permitting motion in multiple degrees of freedom (DoFs). However, conventional user interfaces allow for contolling only one DoF at a time. An intuitive, direct and simultaneous control of multiple DoFs requires machine learning models. Unfortunately, such models are not yet sufficiently robust to real-world disturbances, such as electrode shifts. We propose a novel expectation maximization approach for transfer learning to rapidly recalibrate a machine learning model if disturbances occur. In our experimental evaluation we show that even if few data points are available which do not cover all classes, our proposed approach finds a viable transfer mapping which improves classification accuracy significantly and outperforms all tested baselines.

1 Introduction

Biomorphic wearable robotics promises massive improvements in prosthetic research, with current research prototypes of hand prostheses featuring up to 20 active degrees of freedom (DoF) [1]. The most intuitive interface for controlling such a prosthesis is by residual muscle signals, which are recorded via electromyography (EMG), and subsequently classified to infer the intended motion. However, current commercially available interfaces rely on simple thresholding techniques which can only control a single DoF at a time, severely limiting the benefit of the advanced prostheses hardware [3]. In order to directly access all DoFs, classification of multivariate EMG features can be applied [3]. However, the task is complicated by non-stationarities in the EMG signal due to electrode shifts, posture changes, sweat, fatigue, etc. [3, 5]. A novel approach to counteract such disturbances is *transfer learning*, i.e. adapting a learned model to a situation where data has a different representation, such that the trained classifier is applicable again [6, 7].

In this contribution, we extend this approach and present a novel algorithm for linear supervised transfer learning, namely an expectation maximization algorithm, optimizing the fit of the transferred data to a prototype-based model trained by Generalized Matrix Learning Vector Quantization (GMLVQ).

*Funding by the DFG under grant number HA 2719/6-2, the CITEC center of excellence (EXC 277), and the EU-Project "Input" (grant number 687795) is gratefully acknowledged.

We evaluate our approach on an artificial data set as well as real-world myoelectric data as used for bionic prosthesis control. If few data points are available for transfer learning and/or if not all classes are contained in the training data, our proposed approach is able to outperform all tested baseline algorithms.

2 An EM Algorithm for Transfer Learning on GMLVQ

Generalized Matrix Learning Vector Quantization (GMLVQ) is a prototype-based classification algorithm incorporating metric learning [8]. Let $X \in \mathbb{R}^{m \times M}$ be our training data matrix with each column representing one data point and let $y_i \in \{1, \ldots, L\}$ be the label for data point $\vec{x}_i$. Then, GMLVQ sets labelled prototypes $\vec{w}_1, \ldots, \vec{w}_K \in \mathbb{R}^m$, such that data points are close to a prototype with the same label and distant to all prototypes with a different label [8]. The distance measure is a quadratic form $d_\Omega(\vec{x}, \vec{w}) = (\vec{x} - \vec{w})^T \Omega^T \Omega (\vec{x} - \vec{w})$. The matrix $\Omega \in \mathbb{R}^{m \times m}$ is adapted during training, such that d_Ω supports class discrimination (metric learning) [8]. After training, new data can be classified by assigning the label of the closest prototype according to d_Ω.

Our aim is to apply a GMLVQ model trained on a data set in some space $\mathcal{X} \subseteq \mathbb{R}^m$ (called *source space*) to data in another space $\hat{\mathcal{X}} \subseteq \mathbb{R}^n$ (called *target space*) without having to retrain the model. More precisely, we want to infer a *transfer function* $h : \hat{\mathcal{X}} \to \mathcal{X}$ which maps data from the target to the source space, such that the (marginal and conditional) distribution of the transferred data matches the source space data. As such, we are facing a *transfer learning* problem [6]. In particular, assume a generative model in the source space $p(\vec{x}, y)$, and a data set from the target space $\{(\hat{x}_j, y_j)\}_{j=1,\ldots,N}$. One way to shape the transfer learning problem in terms of a cost function is a maximum likelihood formulation: $\max_h \prod_{j=1}^N p(h(\hat{x}_j), y_j)$.

In this contribution, we base our generative model on GMLVQ. In particular, we construct the model $p(\vec{x}, y) = \sum_{k=1}^K p(\vec{x}|k, y) \cdot p(y|k) \cdot p(k)$, where $p(\vec{x}|k, y)$ is the data likelihood for the kth prototype. We model this likelihood as a Gaussian with mean $\vec{w}_k$ and precision matrix $\Lambda = \Omega^T \Omega$. We define $p(y|k) := 1$ if y equals the label of prototype k and 0 otherwise.

If we take the logarithm of the likelihood, our transfer learning problem becomes

$$\max_h \sum_{j=1}^N \log \left[\sum_{k=1}^K \mathcal{N}\left(h(\hat{x}_j) \middle| \vec{w}_k, \Lambda\right) \cdot p(y_j|k) \cdot p(k) \right] \tag{1}$$

To make this optimization feasible, we introduce two approximations. 1) We approximate h by a linear function, parametrized by a matrix $H \in \mathbb{R}^{m \times n}$. 2) We optimize the likelihood via expectation maximization, as introduced by [2], with k being the latent variable. We initialize H as the $m \times n$ identity matrix (with zero-padding if required) and then compute iteratively: the posterior for the latent variables given the current transfer matrix H (E-Step):

$$\gamma_{k|j} := p(k|H \cdot \hat{x}_j, y_j) = \frac{p(H \cdot \hat{x}_j|k, y_j) \cdot p(y_j|k) \cdot p(k)}{\sum_{k'=1}^K p(H \cdot \hat{x}_j|k', y_j) \cdot p(y_j|k') \cdot p(k')} \tag{2}$$

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and the new transfer matrix H, such that the expected log-likelihood according to $\gamma_{k|j}$ is maximized (M-Step):

$$\begin{aligned}&\max_{H} \sum_{j=1}^{N} \sum_{k=1}^{K} \gamma_{k|j} \cdot \Big(\log \big[\mathcal{N}(H \cdot \hat{x}_j | \vec{w}_k, \Lambda) \big] + \log \big[p(y_j|k) \big] + \log \big[p(k) \big] \Big) \\ =&\min_{H} \sum_{j=1}^{N} \sum_{k=1}^{K} \gamma_{k|j} \cdot (H \cdot \hat{x}_j - \vec{w}_k)^T \cdot \Lambda \cdot (H \cdot \hat{x}_j - \vec{w}_k) \end{aligned} \tag{3}$$

In conjunction, both steps improve the original log likelihood, as shown by [2]. Further, the M-Step is a convex optimization problem which can be solved analytically by setting

$$H = W \cdot \Gamma \cdot X^T \cdot (X \cdot X^T)^{-1} \tag{4}$$

where $W = (\vec{w}_1, \ldots, \vec{w}_K)$ and $\Gamma \in \mathbb{R}^{K \times N}$ with $\Gamma_{kj} = \gamma_{k|j}$. In our experiments, we consider a variant of this model where we set the precision matrix to $\frac{1}{\sigma^2} \cdot \Lambda$ and let σ go to 0, which results in $\gamma_{k|j}$ becoming 1 if the kth prototype is the closest prototype to the jth data point and 0 otherwise.

3 Experiments

In our experimental evaluation we are interested in the test classification accuracy of a GMLVQ classifier on target space data, after our proposed EM transfer learning approach has been applied. We compared with four baselines: 1) The accuracy of the GMLVQ model in the source space (*source*), 2) the accuracy of the model if directly applied to the target space data (*naive*), 3) the accuracy of a newly trained GMLVQ model using only the target space data (*retrain*), 4) a gradient-based transfer learning approach on the GMLVQ cost function as suggested by [7] (*GMLVQ*), and 5) the adaptive Support Vector Machine (*a-SVM*) for domain adaptation as proposed by [9]. Note that most classic transfer learning algorithms (such as Kernel Mean Matching) are not comparable as they are unsupervised [6]. We implemented all algorithms in MATLAB using the *quadprog* solver for a-SVM. For GMLVQ, we used the SOM Toolbox 2.0 [1]. We conducted our experiments on a Linux machine with a Intel Xeon CPU with four cores and 2.53 GHz clock.

Artificial Data: We generated an two-dimensional source data set with three classes and 100 data points per class. The classes were normally distributed with $\sigma = 0.3$ around means $(-1, 0)$, $(0, 0)$ and $(1, 0)$ respectively. On this source data, we trained a GMLVQ model with one prototype per class. As target data, we distributed the three classes around means $(0.1, -2)$, $(0, 0)$ and $(-0.1, 2)$, such that the second dimension carried discriminative information. This transformation models real-world disturbances, such as electrode shift (change of discriminative dimension) and sweat (scaling). As training data for transfer learning we used data from the first two classes only. In application, recording as few classes as

[1] `https://github.com/ilarinieminen/SOM-Toolbox`

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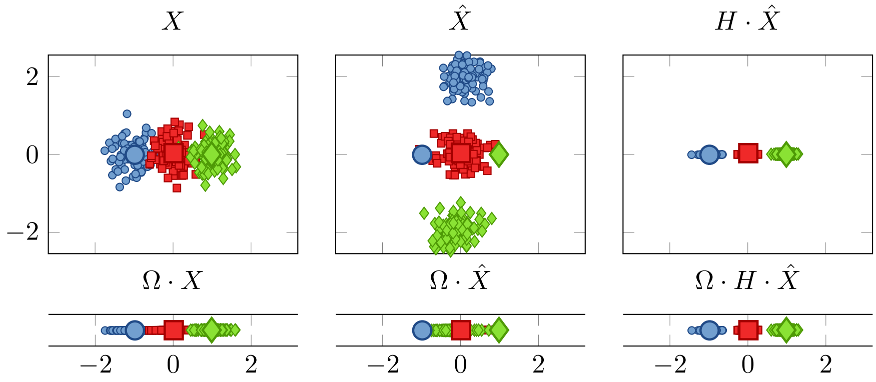

Figure 1: A visualization of the artificial dataset. GMLVQ prototypes are highlighted via bigger size. Shapes indicate the class label. The left column shows the source space data X, the middle column the target space data $\hat{X}$, and the right column the transferred data $H \cdot \hat{X}$. The bottom row displays all data after multiplication with Ω.

possible is desirable to reduce the number of movements users have to execute for re-calibration of their prosthetic device.

Our proposed approach consistently identified a transfer mapping H which extrapolated to the missing class (Fig. 1). Quantitative results are displayed in figure 2 (top). We report the average test accuracy across ten crossvalidation trials versus the number of labelled target data points available for transfer learning. Even with only four data points, our proposed approach yields almost no classification error ($< 1\%$), while all baselines lie above 20%. Only for 32 an 64 data points, GMLVQ transfer learning catches up. Further, on our experimental machine our proposed algorithm was more than ten times faster compared to all baselines (Fig. 2, upper right).

Myoelectric Data: Our second data set consists of real EMG-data of hand motions, recorded with a high-density grid of 96 EMG electrodes (details are provided in [4]). Current prosthetic hardware features only a smaller number of electrodes [3], which we simulated by only using data from a ring of eight equidistant electrodes placed transversally around the forearm. As target space data we selected eight other electrodes, shifted transversally by $8mm$ compared to the initial configuration. Such electrode shifts occur frequently in real-life applications of upper limp prostheses and pose a significant challenge to state-of-the-art systems [3]. Each of our ten participants executed 15 to 35 runs of a series of six hand movements (wrist pronation/supination, wrist flexion/extension and hand opening/closing) plus resting. Data was preprocessed by standard filters (refer to [4]). As features, we used the log-variance for each EMG channel on time windows of $100ms$. For each participant, we executed a leave-one-

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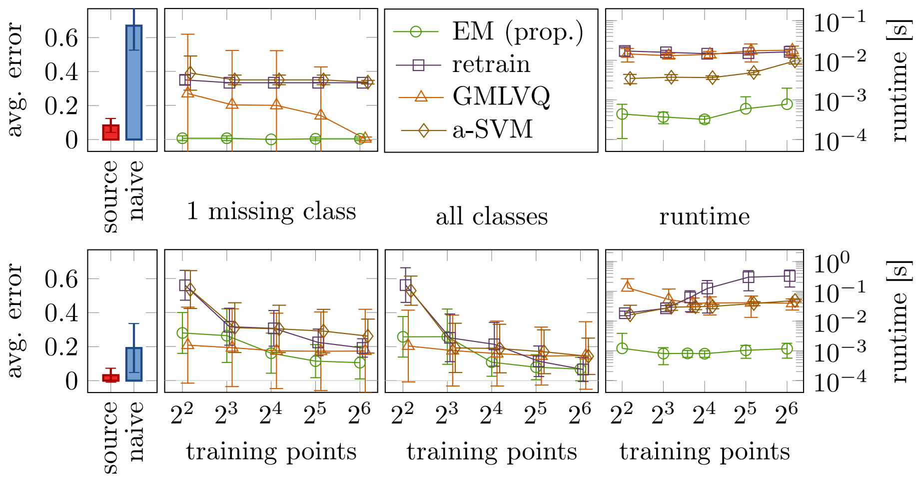

Figure 2: Average classification error (left) and runtimes (right) for the artificial data set (top) as well as the myoelectric data set (bottom). We show the number of available target space training data points on the x axis (in log scaling) and the average classification error (linear scale) and runtime (log scale) respectively on the y axis. The standard deviation across trials is marked by error bars.

out-crossvalidation across the runs. In each trial, we trained a GMLVQ model with two prototypes per class on the source data. Runs with error above 15% were excluded from the analysis. Within the crossvalidation trials we varied the number of target space data points and the number of classes available for transfer learning (EM and GMLVQ), as well as retraining.

The results for all subjects (223 trials overall) are shown in figure 2 (bottom). We observed several significant effects using a one-sided Wilcoxon signed rank test: 1) Classification performance degrades if an electrode shift is applied ($p < 10^{-3}$). 2) If at most one class is not contained in the target space training data, and sufficient training data are available (at least twelve data points, corresponding to $1.2s$ of recording time), our proposed algorithm outperforms a naive application of the source space model ($p < 10^{-3}$). 3) If few data points are available (< 64), or if not all labels are covered in the target space training data, our proposed algorithm outperforms a model trained solely on the target data ($p < 10^{-3}$). 4) If at most one class is not contained in the target space training data, and if sufficient training data are available (≥ 32 points, corresponding to $3.2s$ of recording time), our proposed algorithm outperforms gradient-based learning on the GMLVQ cost function, as well as a-SVM ($p < 10^{-2}$).

Finally, on our experimental machine our proposed algorithm was roughly 40 times faster compared to GMLVQ transfer learning, 50 times faster compared to a-SVM and roughly 300 times faster compared to training a new model.

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4 Conclusion

In this contribution we have proposed a new approach for supervised linear transfer learning, namely an expectation maximization (EM) approach, maximizing the data likelihood of the transferred target space data according to a source space model. While our derivation focused on a particlar model (GMLVQ), it can be applied analogously for full probabilistic models, such as Gaussian Mixture Models, or other prototype-based models, such as neural gas or k-means.

In our experimental evaluation we have shown that our proposed EM algorithm is able to identify a viable transfer mapping rapidly, even if only few target space points are available and some labels are not represented in the training set. Therefore, our approach offers an attractive alternative to classic supervised learning in cases where a model for the same task in a related space is available and obtaining training data in the new space is costly. This is particularly the case for our experimental domain, wearable biomorphic prostheses, where obtaining training data depends on carefully timed patient input. As such, our results give reason to hope that robust and easily adjustable prostheses control algorithms may become possible in the near future.

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