ESANN 2019 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 24-26 April 2019, i6doc.com publ., ISBN 978-287-587-065-0. Available from http://www.i6doc.com/en/.

Transfer Learning for transferring machine-learning based models among various hyperspectral sensors

Patrick Menz, Andreas Backhaus and Udo Seiffert

Biosystems Engineering, Fraunhofer Institute of Factory Operation and Automation (IFF), Magdeburg - Germany

Abstract. Using previously generated machine learning models under changing sensor hardware with nearly the same performance is a desirable goal. This constitutes a model transfer problem. We compare a Radial Basis Function Network adapted for transfer learning to a classical data alignment approach. This approach to transfer machine-learning models is tested on a task of material classification using hyperspectral imaging recorded with different camera systems and the aim to make camera systems interchangeable. The results show that a machine-learning based algorithm outperforms a state-of-the-art hyperspectral data alignment algorithm.

1 Introduction

Hyperspectral imaging is increasingly establishing itself as an important and powerful instrument through its non-invasive evaluation method in different fields of application, such as quality control, forensics, remote sensing and much more. For example, the technology is used on crop plants to estimate the health and nutrition status as well as estimating parameters like the maturity of fruits. As another example, it is applied in sorting systems to distinguish between different types of coffee. However, all fields of application have the common property to require methods that converts the spectral information into the desired target measurement as described above. This relationship between reflectance spectrum and target values is often not easily describable in closed mathematical form. Therefore, data-driven methods derived from the area of machine learning are increasingly used to fill this gap. Due to the high computational demand and processing time needed to generate a suitable machine-learning model, it is desirable to generate these base models just once. In addition, data acquisition can be expensive and, particularly in a biological context, is often not easily repeatable. Unfortunately, these base models can lose their stability and robustness over time, for example, through an aging sensor, using a new camera system or changing environmental conditions. Therefore, measures have to be taken to ensure a constant performance of the base model trained from reference data.

In this paper, we suggest a new method of transferring machine-learning based models using transfer learning and test its performance applied on Radial Basis Functions Networks. To compare the results, a reference method for calibration transfer based on Alternating Trilinear Decomposition (ATLD) algorithm [1] has been used to eliminate spectral offsets between different instruments. This method has only been tested in combination with a PLS regression models [1].

ESANN 2019 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 24-26 April 2019, i6doc.com publ., ISBN 978-287-587-065-0. Available from http://www.i6doc.com/en/.

2 Datasets

We created two different types of datasets with several hyperspectral camera systems to obtain the results in this paper. These datasets are characterized by uniformity regarding their materials and by diversity regarding their classification difficulty.

2.1 Coffee

It has already been proven in [2], that the classification of different coffee types is easily possible with hyperspectral imaging. With Arabica, Robusta and immature Arabica, three different coffee types have been used forming a 3-class problem with 10,000 spectra per class. This provides a sufficient database for the machine-learning task. Furthermore, in order to achieve constant conditions, each set of coffee beans is identical for each camera recording.

2.2 Sugar

As already introduced in [3], a dataset with 9 varieties of sugar has been used again. The special property of this dataset is the fact that all sugar types have the same empirical formula but the molecule structure differs. Therefore, the individual sugars are particularly hard to distinguish by visual inspection.

However, the classification task is rather simple for some selected types of sugar with short-wave infrared camera systems (SWIR). Therefore, only the most difficult ones like sugar ester P1570 and S1570 have been used to create the dataset SugarH with 10,000 spectra per class.

2.3 Hyperspectral Camera Systems

There are four different pushbroom camera systems involved in this study as shown in Table 1.

	Cam1	Cam2c	Cam3	Cam2s	Cam4
Type	SWIR-320me	SWIR-320me	SWIR-384me	SWIR-384me	Headwall SWIR
Range in [nm]	970 - 2500	970 - 2500	950 - 2500	950 - 2500	900 - 2500
Bands	256	256	288	288	273
Spatial resolution	320px	320px	384px	384px	384px
Used for dataset	Coffee, SugarH	Coffee	Coffee, SugarH	SugarH	Coffee, SugarH

Table 1: Detailed specification of used hyperspectral camera systems.

As summarized in Table 1, this study considers only SWIR camera systems. Two pairs of cameras are even of the same type from the same series (Cam1 and Cam2c, Cam2s and Cam3, respectively). It should be noted that every camera system is unique in respect to their sampling of the reflectance spectra at slightly different wavelengths.

3 Existing methods

There is one naive method for a sensor data transfer and this is simply interpolating the spectra to the target camera wavelengths. Further investigations on hard classification problems have already shown that a simple interpolation is not sufficient for a sensor data transfer [4]. It was not possible to obtain nearly the base models classification performance. However, interpolation might be sufficient for very simple classification tasks.

Another published method is the transfer of calibration models by using the ATLD algorithm and a transfer rule for new data from another camera system [1]. Publication [1] just considered a regression problem with a simple machine-learning method like Partial-Least-Squares (PLS). So far, this method has not been proven on classification tasks and in combination with more advanced machine-learning methods, though.

3.1 Eliminating offsets with calibration transfer

The existence of offsets in reflectance between different camera systems can be shown, which persists despite standardization with a standard optical calibration pad. It is described in [1] how to determine these offsets with the ATLD algorithm and use them to transfer new sensor data into the base model data space. Nevertheless, new samples from the same data space for each new camera system are needed to calculate the offsets correctly. If the offset is stable enough through the camera systems and is irrespective of the classification problem and the data space, a calibration pad with gradually decreasing reflectance can be used to determine the offset. This general offset can then be used as a transfer rule for every new data from the classification task. However, to compare the results of [1] with more advanced machine-learning methods, samples from the same data space (coffee, sugar) are used.

By evaluating the results from [1], it was found that the offset could be calculated more accurately by using the Self-weighted Alternating Trilinear Decomposition (SWATLD)[5].

4 Transfer Learning on Radial Basis Functions Networks

Transfer learning is a commonly used machine-learning method in order to transfer model knowledge in a changing data environment. The basic assumption of many machine-learning algorithms is that both training data and unknown (new) data are in the same feature space having the same distribution [6]. Nevertheless, in some situations, this basic assumption does not hold. This section uses the idea of transfer learning applied to the task at hand.

4.1 Idea

The particular transfer learning method was introduced in [7] for GMLVQ and used in [8] to transform disturbed sensor data for an arm prosthesis. The underlying assumption is that the disturbed data is the result of a linear transformation from the original

ESANN 2019 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 24-26 April 2019, i6doc.com publ., ISBN 978-287-587-065-0. Available from http://www.i6doc.com/en/.

dataspace. The goal here is to find the inverse transformation as described in formula in (1).

$$\hat{x} = T\,x, \quad with\, T \in \mathbb{R}^{m\,x\,\hat{m}} \\ x = T^{-1}\,\hat{x}\,. \tag{1}$$

This transformation matrix T^{-1} will be trained in [7] and [8] with the GMLVQ.

However, for the datasets used in this study, Radial Basis Functions Networks (RBF Networks) resulted in better classification performances. Due to these results, the main idea from [7] and [8] has been adopted and applied to the concept of RBF Networks. The previously learned parameters of the base RBF Network remain unchanged and only T^{-1} is trained.

4.2 Mathematical explanation

The mathematical background is briefly shown here. More details on the standard RBF can be found in [9]. Starting point is

$$T^{-1} \leftarrow \underset{T^{-1}}{\operatorname{argmin}}\, E_{RBF}, \tag{2}$$

were E_{RBF} is the error function or also called energy function of Radial Basis Function Networks. Inserting the transformation rule (1) into the RBF's objective function results in the following energy function:

$$E = \frac{1}{2}\sum_{n}\sum_{k}\left(\sum_{j=1}^{J} w_{kj}\, exp\left(-\frac{\left\|T^{-1}\,\hat{x}^{n} - \mu_j\right\|^2}{2{\sigma_j}^2}\right) - t_k^n\right)^2. \tag{3}$$

In order to optimize this energy function with any optimization technique like gradient descent, the partial derivative of T^{-1} from (3) is needed, which can be determined as follows:

$$\frac{\partial E}{\partial T^{-1}} = \sum_n \sum_k \sum_j (y_k(\hat{x}^n) - t_k^n)\; y_k(\hat{x}^n)\; \frac{\partial}{\partial T^{-1}}\left(-\frac{\left\|T^{-1}\,\hat{x}^n - \mu_j\right\|^2}{2{\sigma_j}^2}\right), \tag{4}$$

where $\hat{x}$ are data points from the target camera system and T is a square matrix based on base model input sizes (spectral bands). This means, to fit new sensor data to base model input sizes, we have interpolated these data, to obtain the wavelength range of the previous camera system, which has been used to generate the base model originally.

5 Results

All the following results are subjected to the procedure shown in Fig. 1. The classification model part and thus the base models were generated by an RBF Network

ESANN 2019 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 24-26 April 2019, i6doc.com publ., ISBN 978-287-587-065-0.
Available from http://www.i6doc.com/en/.

with 40 prototypes. For generating the base models, the lower part of Fig. 1 is not needed.

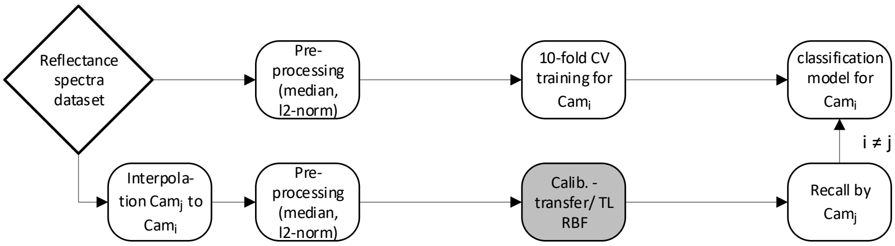

Fig. 1: Scheme of procedure

Table 2 contains all results. The original classification rates are on the main diagonal (bold fonts). Any other entry is a sensor data point transferred to the respective target models. In order to allow for a correct validation, this ensures that training samples used either for the base model or the transfer model are not used as test samples at all.

Calibration model transfer: Coffee

Trans-fer of	Base model of Cam1	Cam2c	Cam3	Cam4
Cam1	**0.929**	0.701	0.821	0.508
Cam2	0.644	**0.923**	0.843	0.639
Cam3	0.829	0.892	**0.943**	0.551
Cam4	0.760	0.444	0.520	**0.928**

Calibration model transfer: SugarH

Trans-fer of	Base model of Cam1	Cam2s	Cam3	Cam4
Cam1	**0.910**	0.508	0.534	0.500
Cam2	0.500	**0.960**	0.550	0.500
Cam3	0.534	0.874	**0.957**	0.505
Cam4	0.561	0.500	0.500	**0.981**

Transfer Learning RBF: Coffee

Trans-fer of	Base model of Cam1	Cam2c	Cam3	Cam4
Cam1	**0.929**	0.923	0.923	0.902
Cam2	0.920	**0.923**	0.910	0.898
Cam3	0.936	0.934	**0.943**	0.920
Cam4	0.918	0.927	0.909	**0.928**

Transfer Learning RBF: SugarH

Trans-fer of	Base model of Cam1	Cam2s	Cam3	Cam4
Cam1	**0.910**	0.906	0.902	0.902
Cam2	0.952	**0.960**	0.950	0.912
Cam3	0.953	0.958	**0.957**	0.938
Cam4	0.968	0.967	0.968	**0.981**

Table 2: Results by recalling data from another camera system. The gray bars indicate the performance of the combination of camera and method.

The aim was to get nearly the same classification performance on any non-main diagonal element. It is easy to see, that a simple correction of offsets as used in [1] may be applicable for rather simple classification tasks. For hard classification problems, that need advanced machine-learning methods, such as the SugarH dataset, the offset correction fails and will be outperformed by transfer learning, which has nearly the same computationally effort.

ESANN 2019 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 24-26 April 2019, i6doc.com publ., ISBN 978-287-587-065-0. Available from http://www.i6doc.com/en/.

By introducing a new separated hyperparameter, it is actually possible to reach in some cases a higher classification performance as the base model itself. To compare the results, both methods got 1,000 new samples to achieve these results. That means, by adding just 10% of the data points from the base model, a significantly better target model can be obtained.

6 Conclusion

We adopted the concept of transfer learning originally designed for prototype-based classifiers to work in an RBF Network. This approach significantly outperforms the concept of an offset correction for those cases more advanced machine learning methods have to be applied. However, new samples from the target camera system within the same data problem domain are still needed. A fraction of the original quantity appears to be sufficient, though. It was not possible to simply swap the inverse transformation matrix from one classification problem to another.
Due to this fact, learning a unified camera characteristic to provide a general T^{-1} for each camera pair is out of question.

Transferring machine-learning based models among various hyperspectral sensors remains an open research topic.

References

[1] Y. Liu, W. Cai, and X. Shao, "Standardization of near infrared spectra measured on multi-instrument," (eng), *Analytica chimica acta*, vol. 836, pp. 18–23, 2014.

[2] A. Backhaus, F.Bollenbeck and U.Seiffert, "High-Throughput quality control of coffee varieties and blends by artificial neural networks from hyperspectral imaging," *1st International Congress on Cacoa, Coffee and Tea*, pp. 88 – 92, 2011.

[3] F. Melchert, A. Matros, M. Biehl, and U. Seiffert, "The sugar dataset: A multimodal hyperspectral dataset for classification and research," *Machine Learning Reports*, no. 3, pp. 15–18, 2016.

[4] P. Menz, A. Backhaus and U. Seiffert, "Transferring machine learning models within a soft sensor system to achieve constant task performance under changing sensor hardware," *Machine Learning Reports*, no. 3, pp. 19–22, 2016.

[5] Z.-P. Chen, H.-L. Wu, J.-H. Jiang, Y. Li, and R.-Q. Yu, "A novel trilinear decomposition algorithm for second-order linear calibration," *Chemometrics and Intelligent Laboratory Systems*, vol. 52, no. 1, pp. 75–86, 2000.

[6] S. J. Pan and Q. Yang, "A Survey on Transfer Learning," *IEEE Trans. Knowl. Data Eng.*, vol. 22, no. 10, pp. 1345–1359, 2010.

[7] B. Paaßen, A. Schulz, and B. Hammer, "Supervised Linear Transfer Learning for Generalized Matrix LVQ," *Machine Learning Reports*, no. 4, pp. 11–19, 2016.

[8] C. Prahm, B. Paassen, A. Schulz, B. Hammer, and O. Aszmann, Ed., Transfer learning for rapid re-calibration of a myoelectric prosthesis after electrode shift: Proceedings of the 3rd International Conference on NeuroRehabilitation (ICNR2016), 18.-21. Oktober, 2016, Segovia, Spain. Cham, s.l.: Springer International Publishing, 2017.

[9] C. M. Bishop, *Neural networks for pattern recognition*. Oxford: Oxford Univ. Press, 1995.