Sorting of Black Plastics Using Statistical Pattern Recognition on Terahertz Frequency Domain Data

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Abstract

The sorting of used plastics is an ever-growing market field which is further pushed by new EU regulations in, e.g., car recycling. Modern recycling techniques require pure or almost pure fractions of polymers. These pure fractions can be generated from waste using modern sorting technologies based on specific mechanical, electrical and chemical material properties such as density, conductivity and melting point.

The thermal recycling of plastics is no longer seasonable. More modern recycling techniques require pure fractions containing only a single variety of polymer. A large portion of the plastic waste contains black or multilayer materials that are not sortable with todays' sorting technologies.

To overcome this challenge, three Fraunhofer institutes are working together to develop a new type of sorting system. As a first step, we have developed a frequency domain line-scan camera working in the terahertz range with frequencies below 300 GHz.

Since the entropy in terahertz signals below 300 GHz is not as high as needed for simple classification, more complex statistical pattern recognition methods are needed. The application of those methods to the problem of sorting black plastics as the second step in this joint project is presented in this paper. These methods have to be integrated into a real sorting system, which is the third part of our joint project. The modular approach gives the ability to integrate our sensors and algorithms into existing sorting systems.

Related Work

Recycling of polymers is of special interest. While many polymers and additives are transparent to THz waves [1,2], it has been shown, that separating polymers is possible using full-spectrum terahertz time-domain data.

Common approaches [1] try to build a physical model using the refractive index of the material or its absorption curves for classifying a small number of polymer samples. It has been shown [1] that separation of black polymers is possible using the refractive index in case the object geometry (especially its thickness) is identical or at least similar.

In [3] we have shown that the separation of plastics with different geometries is possible using Gaussian Mixture Models on the Hilbert envelope of the THz time-domain impulse response. Because using full-spectrum time-domain spectroscopy is not feasible for our use-case of inline sensors in sorting applications, we use a small-band frequency-domain THz line-scan camera, which consists of eight bistatic 90 GHz channels operating in a frequency stepped, time multiplexed fashion.

Since the materials in question do not exhibit characteristic absorption lines below 2 THz [4], amplitude analysis does not provide sufficient entropy for a meaningful analysis, hence preservation of accurate phase information is essential. This is accomplished by phase-synchronizing transmitter and receiver, resulting in a constant reference phase for each sampled frequency point across all measurement cycles.

Baseband signals for transmitter and receiver are generated using Direct Digital Synthesis (DDS) followed by an upconverter and a frequency multiplier stage, resulting in a signal with a center frequency of 30 GHz with 4 GHz bandwidth. These signals are again frequency tripled to reach the intended working band at around 90GHz (W-band) with a total bandwidth of 12 GHz. Earlier measurements [4,5] have shown this to be the lowest frequency band where signal entropy is high enough to perform expedient analysis relevant to our use-case.

The line scan camera is realized in a transmission geometry, i.e. the transmitter illuminates the samples from one side of the belt and the receiver detects the signal on the opposite side. In the receiver, the signal is downconverted to a predetermined intermediate frequency. The downconversion mixer outputs an in-phase (I) and a quadrature (Q) signal, making it possible to recover the phase information of the received high frequency signal. Both I and Q are then filtered and sampled for each of the 128 frequency steps yielding a data vector that is passed to the classification step.

In literature there are many methods for separating non-trivial separable data vectors into classes. Starting with simple vector space transformation as PCA and ICA and their classification using linear approaches, recently support vector machines with radial basis kernels have been replaced by approaches using deep learning. Especially neural networks as simple feed-forward multi-layer perceptrons and their extension using convolutional kernels show improvements in classification performance although models can get very large. These methods have become more popular since computing power for training is getting cheaper.

Another approach needing less training data is the modelling of classes using Gaussian Mixture Models that is commonly used in speech recognition [6] and discussed in [1] for time-domain data, but can be used for any at least medium-large dataset of training and test data.

System Overview

The sorting system consists of a conveyor belt on which the plastic flakes are transported, a valve bar for pneumatic ejection, a THz sensor and also a RGB line scan camera. An overview of the overall system can be found in Figure 1.

The purpose of the RGB camera is its high spatial resolution which cannot be achieved with the THz sensor because the wavelength is in the millimeter range. Both sensors are mounted in such a way that the scan lines of the RGB camera and the THz sensor coincides. The data of the RGB camera is not used to classify the material but to enhance the spatial resolution of the THz sensor and the robustness of the classification result. Two problems arise from the low spatial resolution of the THz sensor. One problem is that the shape of the sample determined by the THz sensor alone is too coarse to allow a precise ejection by the air valves. This problem is getting worse when the material flow is too compact. The second problem arises when the material is only partly visible at one pixel or when different materials contribute to the detected spectrum of one pixel. Ignoring this fact would add too much noise to the learning and the classification process. The data fusion of the THz and the RGB image provides the possibility to recover the shape of the objects with a high spatial resolution. This can be either used to improve the ejection of the material or to detect pixels with a spectrum composed by two different materials resulting from neighbored or overlapping flakes. Furthermore, the RGB image can be used to improve the performance by identifying the location of the flakes in the image and disregarding all pixels of the background in the following processing steps.

Two sorting machines are planned to be build up with the THz sensor technology. The first is the integration in a small-scaled sorting system called TableSort (Figure. 2a). Its purpose is to test different hardware configurations of cameras or material transportation in a prototypical manner and already making an assessment of the achievable segregation of flakes of different types of polymers. TableSort already exhibits all relevant components of a sorting machine mentioned above. After the design phase of the hardware configuration is accomplished, the integration into FlexSort (Figure 2b) is realized. FlexSort is a modular large-scale sorting system in a container which can also be transported to recycling facilities to test the segregation on a big amount of plastic waste.

Algorithm

Overview

In contrast to very-deep learning methods using convolution models and pre-trained models like ImageNet [7] we have to deal with real-time requirements during the classification. In this paper we discuss three different methods of doing classification on our dataset.

Our algorithm is divided in 3 major steps: Preprocessing, pixel-wise classification and object classification. As a first step a preprocessing as noise reduction and normalization of the antenna geometry is done. This step is comparable to the white-balance in optical systems. As we get complex-valued measurements of the absorption spectrum, we do a complex division by the recorded reference signal for normalizing. As we can update the reference value periodically, we can do normalization of basic belt pollution in this step, too. Therefore, reference measurements $E_r(\omega)$ are periodically taken in transmission when no sample is present, summarizing the effects of the frequency-dependent intensity of the emitted wave $E_0(\omega)$ and the attenuation by the conveyor belt. As an approximation we get following $E_d(\omega)$ as the received wave when a sample is present.

$$E_d(\omega) = E_r(\omega) \cdot \exp\left(\frac{-\omega\kappa(\omega)d}{c_0}\right) \cdot \exp\left(\frac{-i\omega(n(\omega)-1)d}{c_0}\right)$$

The result of the complex division of $E_d(\omega)$ by $E_r(\omega)$ is independent of the intensity of the emmited wave. To reduce the computational time for the normalization which has to be computed for every pixel, this complex division is computed on the frame grabber in hardware.

The second step is the pixel-wise classification of measurement data, this paper will focus on. Although there are many classification methods in literature, most of them have the disadvantage that the model size and classification runtime cannot be controlled easily. For this reason we decide on comparing two methods whose model size can be controlled easily and is independent on the amount of data used for training.

The third step is the aggregation of classification results for any pixels of an object as a decision input to the sorter. One can show that a simple addition of the classes’ probability is feasible for our first test set. The algorithm decides for the class with the major probability or rejects in hard cases. This step has to be refined during integration in the full sorter in future.

Classification Task

A **multi-layer perceptron** is a feed-forward artificial neuronal network that can represent a continuous function with only a single hidden layer. Thus in our case it can give a good indication for our material class. In our experiments we use 100 hidden neurons although the exact number of hidden neurons does not influence the results as long as it is large enough to model the physical properties. As an activation function we use sigmoid functions in the hidden layers and softmax function in output layer for mapping the outputs to a probability distribution for each material class. As neural networks tend to overfit during training we additionally added a dropout layer with a dropout probability of 0.7 between the two hidden layers to reduce overfitting.

Although a multi-layer perceptron seem to be good enough, we have complex-valued measurements of our absorption spectrum. Those can be interpreted as a two-channel image vector. **Convolutional Neural Networks** with 3D-Convolution have been used for implicitly converting color channels in computer vision problems. In our case this gives the possibility of using a combination of amplitude and phase information by implicitly learning the relation between them. As a starting point for a network structure we use a convolution of input data using a 1x3x2 kernel that has two effects. It can learn a smoothing or differentiating in frequency direction in the same step. As subsampling layer we suggest a simple max-pooling using a 1x2x1 mask with a stride of 1 in frequency direction. This subsampling output is fed into a multi-layer perceptron of similar structure as mentioned before used for classification directly using this CNN. So in fact we suggest a extension of classifying directly on the measurement data with some self-learning feature extraction.

In contrast to implicitly modeling the class probabilities we suggest another generative model by fitting the training data to a weighted sum of multivariate Gaussian distributions. This so called **Gaussian Mixture Model** leads to two advantages. On the one side the training data does not have to be uniformly distributed across the training classes. On the other side the number of needed training data is not as high as the iterative process of learning neural networks needs.

All of those pixel-wise classifications give a score of fitness for each predicted class. This score is normalized to the range $[0,1]$ to fit the probability-theoretic requirements and be comparable across multiple pixels using softmax normalization if this is not done in the classifier itself.

Evaluation

Measures

We use the common measures precision and recall as a measure for our algorithm results. Precision and recall are commonly used in information retrieval. In our approach we restrict the classification to a two-class problem, that can be extended to a multi-class problem by cascading multiple classifiers. Let A and B be the classes of materials to be sorted, e.g. A is Polypropylene and B is ABS.

Let t_A be the number of samples that are truly sorted as material A and t_B the number of samples that are truly sorted as material B. Additionally let f_A be the number of samples that are sorted as material A although they are material B in ground truth and f_B the analogue for material A being sorted as B. We get the definition of Rec_A and $Prec_A$

$$Rec_A = \frac{t_A}{t_A + f_B}$$

$$Prec_A = \frac{t_A}{t_A + f_A}$$

In our application recall can be interpreted as the fraction of the material A in input stream being sorted as A. Precision can be interpreted as the purity of the material being sorted as A. This is same in analogy for material B.

Dataset

As mentioned in [3] before, we have used a small dataset of about 200 flat and homogeneous materials for first classification using the time-domain data. Since our limited frequency range gives less entropy in the absorption signal, we need much more data for training our data-driven classifiers. For this purpose we got about 25 different batches of material from different recyclers. Each batch consist of more than 100 flakes sized between $2\ cm^2$ and $5\ cm^2$. This set is split in a test- and training dataset in ratio 1:2. We verified the given material class told by the recycling using a FT-IR spectrometer (Bruker ALPHA with Eco-ATR) for each batch.

This groundtruth data is propagated to the whole batch. For each batch we repeated two measurements using our line-scan THz camera in combination with our RGB image for segmentation. As a result we get 6-10 measurement points per flake and more than 10 thousand measured points in whole. Because the number of 25 batches is not as large as it is needed for clearly separating test- and training data, we expect little effects of overfitting in our results. According to the material our current dataset consists of, mainly 3 cases of evaluation can be defined where a large-enough amount of training-data is present:

- ABS vs. PP,HDPE,LDPE
- Plastics vs. wood (use-case from automotive recycling)
- PP vs. PE (although material in dataset is probably too homogenous)

Results

In this part we show the results of our experiments starting with a simple pure-plastics use-cases of separating Polystyrenes and Polyolefines (Table 2). It can be shown that there is no significant difference in classification accuracy between the different classifiers as long as they use the same amount of training data and the basic requirements in the distribution of training data specific for this classifier are met. It is clear that the Gaussian Mixture Models outperform the cases, where only the amplitude of the signal is used for classification because the Gaussian Modelling needs less data for training and converges faster. The Multi-layer-perceptron gets less precision in class PP,PE. The reason can be the limited number of hidden neurons. In contrast, the convolutional network gets a slightly better performance because it does multiple implicit filtering of the data using the convolutional kernels. Additionally we can show that the supervised separation of wood and plastics as our second use-cases is possible with our concept. Given an input of 89% plastics and 11% wooden flakes we can achieve a much higher precision and for both test classes doing our classification using Gaussian Mixture Models as shown in Table 3. The approaches using neural networks give much less accuracy because they implicitly learn the a-priori distribution in the training data set. This leads to the requirement of using uniformly-distributed classes in training process, which might not be possible in all use cases.

Conclusion and Outlook

We have shown that the separation of black plastics is possible using small-band terahertz time-domain data and data-driven classification methods. While some classification have disadvantages by design, e.g. the need of uniformly distributed training data, both Gaussian Mixture Models and Feed-Forward Neural networks seem sufficient for our classification tasks. By using the next improved sensor generation with a higher dynamic range and the use of more different data for training and testing we expect a much better performance in harder separation tasks. Especially a more diverse set of different object geometries and materials is an interesting challenge.

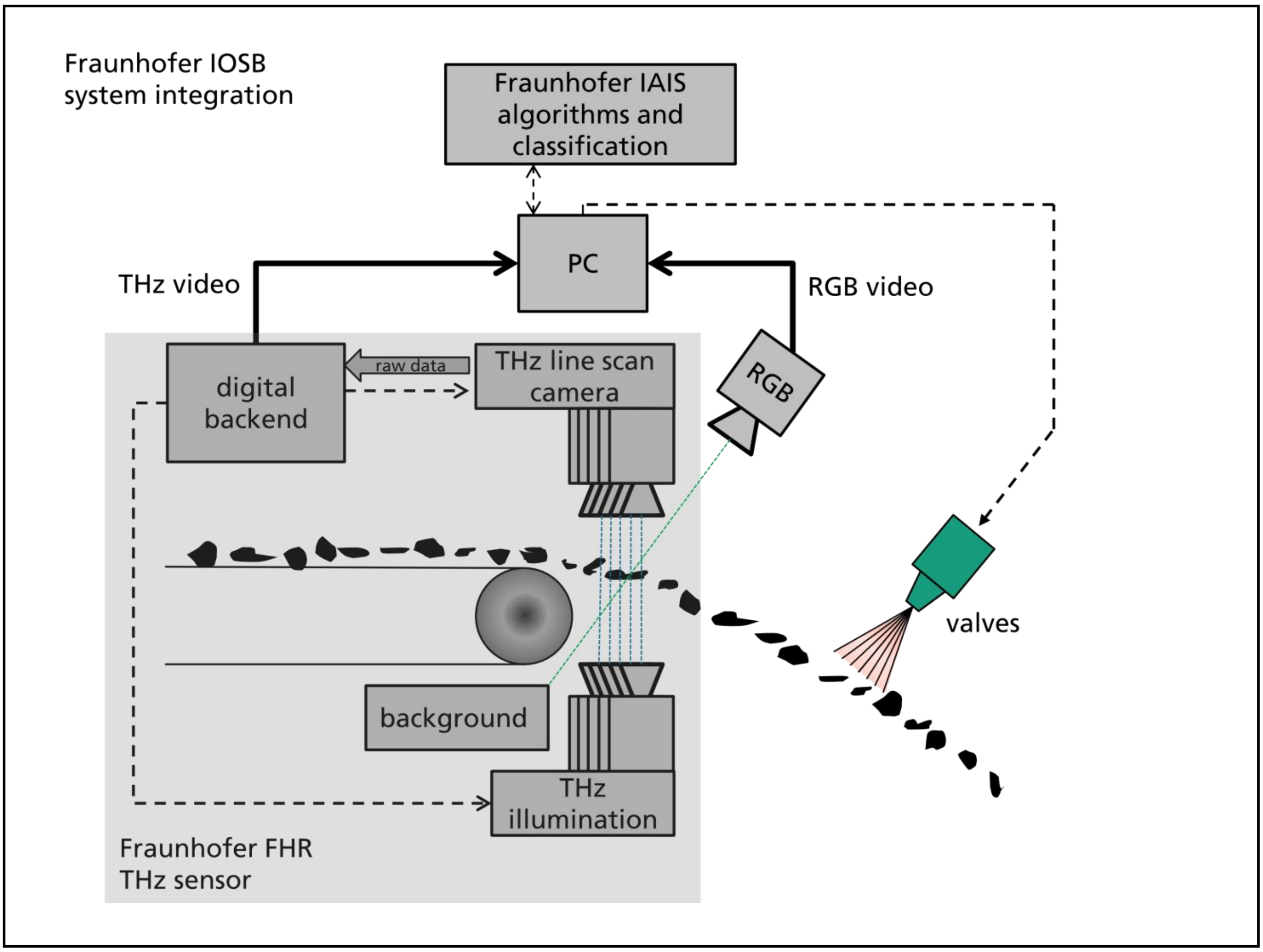
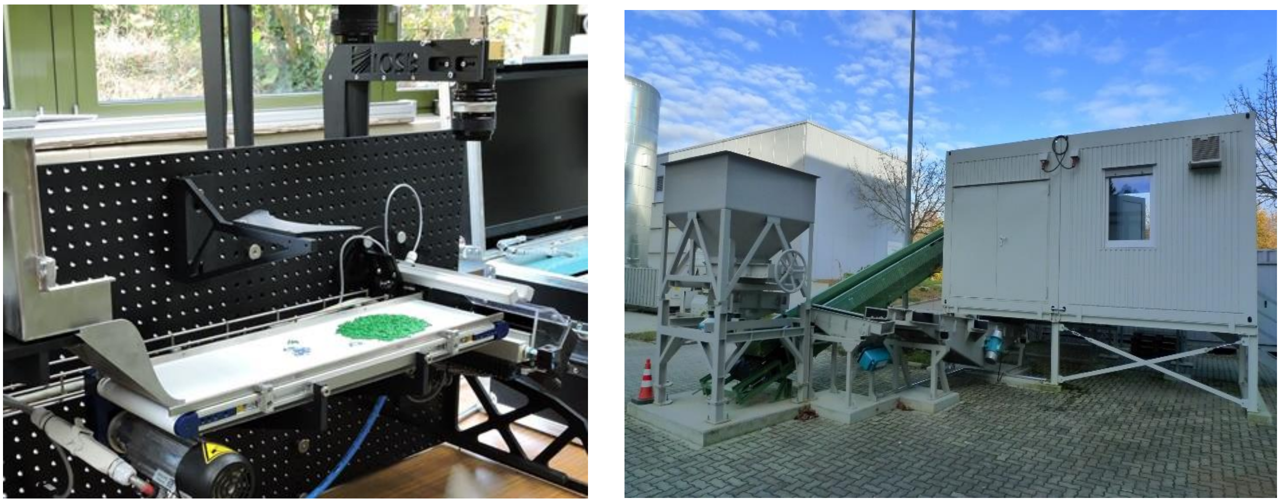


Figure 1: Overview of full sorting system



(a) (b)

Figure 2: Two different realizations for the integration of the THz sensor in TableSort (a) and FlexSort (b)

Table 1: Distribution of materials in our recycling flake dataset

Material	Different batches	Approx. number of flakes
ABS	5	1000
HDPE	3	600
LDPE	1	200
PP	7	1400
PVC	1	150
Wood	2	300

Table 2: Precision and recall for separating between equally distributed test set of ABS and PE,PE using amplitude feature and 582 flakes for training for the different classifiers

Classifier	Precision ABS	Recall ABS	Precision PP,PE	Recall PP,PE
GMM	93 %	97 %	96 %	92 %
MLP	96 %	96 %	85 %	95 %
ConvNN	91 %	92 %	91 %	90 %

Table 3: Precision and recall for separating between wood and plastics using amplitude feature and 642 flakes for training for the different classifiers

Classifier	Precision plastics	Recall plastics	Precision Wood	Recall Wood
GMM	100 %	99 %	94 %	97 %
MLP	95 %	36 %	100 %	35 %
ConvNN	98 %	100 %	100 %	71 %

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