KI-Waste - Combining Image Recognition and Time Series Analysis in Refuse Sorting

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ABSTRACT

Refuse sorting is a key technology to increase the recycling rate and reduce the growths of landfills worldwide. The project KI-Waste combines image recognition with time series analysis to monitor and optimise processes in sorting facilities. The image recognition captures the refuse category distribution and particle size of the refuse streams in the sorting facility. The time series analysis focuses on insights derived from machine parameters and sensor values. The combination of results from the image recognition and the time series analysis creates a new holistic view of the complete sorting process and the performance of a sorting facility. This is the basis for comprehensive monitoring, data-driven optimisations, and performance evaluations supporting workers in sorting facilities. Digital solutions allowing the workers to monitor the sorting process remotely are very desirable since the working conditions in sorting facilities are potentially harmful due to dust, bacteria, and fungal spores. Furthermore, the introduction of objective sorting performance measures enables workers to make informed decisions to improve the sorting parameters and react quicker to changes in the refuse composition. This work describes ideas and objectives of the KI-Waste project, summarises techniques and approaches used in KI-Waste, gives preliminary findings, and closes with an outlook on future work.

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CCS CONCEPTS

• **Applied computing → Enterprise applications**; *Business process monitoring*; • **Computing methodologies → Neural networks**; **Object identification**; *3D imaging*.

KEYWORDS

Refuse Sorting, Image Recognition, Process Monitoring, Optimisation, Worker Support

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1 INTRODUCTION

The global amount of refuse produced by households is still on the increase worldwide. The European Union generates about 482 kg of refuse per capita annually. This number is growing since countries with lower-than-average numbers, like Romania, Poland, Czech Republic, and Slovakia, are increasing their output thus closing the gap to countries with already high numbers like Denmark or Germany [12]. Recycling is a key factor in conquering these amounts of refuse and moving towards a curricular economy [1]. Refuse sorting is an importing enabler for recycling and usually requires multiple different machines in a facility, each machine designed to extract a specific fraction out of the refuse [7]. The ever-changing refuse composition is major challenge in automated sorting. Thus, to ensure a constant sorting quality over time the sorting machinery are designed to be highly adaptive, but the continuous adaption and monitoring of the sorting machinery in facilities still have huge potentials for improvement [3].

The KI-Waste project aims to analyse refuse streams and optimise sorting facility performance by combing image recognition and time series analysis. The image recognition is applied to refuse streams at key points in the sorting facility. The time series analysis focuses on parameters and measurements from various machines in the sorting process. Data from both image recognition and time series analysis are joined together creating a complete picture of the sorting facility's state and the quality of the refuse streams in it. This joint database paves the way for comprehensive analyses and optimisations of individual machines, but more importantly, also the overall performance of the sorting process and hence the sorting facility in total. These analyses and optimisations provide important support for workers in a sorting facility. Firstly, it allows them to monitor the sorting process comprehensively and gives them objective operating numbers about changes in sorting performance over time. Secondly, the workers can also judge the sorting quality remotely reducing their exposure to dust, bacteria, and fungal spores.

This paper explains related work to the KI-Waste project in Section 2 and gives an overview of the current and planned activities in the project in Section 3. Finally, Section 4 summarises the preliminary results of KI-Waste and gives an outlook on future project activities.

2 RELATED WORK

Current sorting facilities use a multitude of different machinery to extract usable fractions like plastic, wood, metals etc. from the collected refuse. The first machine is usually a pre-shredder tearing open bin liners and shredding large pieces into smaller ones. Depending on the input refuse and the desired output fractions, a multitude of shredding, separation, and sorting machines can follow, usually connected by conveyor belts transporting the refuse streams from machine to machine. A good way to judge the shredding, separation, and sorting performance is to monitor key characteristics of the refuse streams transported on the conveyor belts [7, 18].

Image recognition is a powerful inspection method since different substances like plastic, wood, or metals have different spectral reflection characteristics, i. e., they differ in their characteristic absorption spectra. Multispectral cameras record images in several wavelength bands resulting in a spectral fingerprint of a material [15, 16]. The capturing of visible light with its red, green and blue (RGB) spectra is commonly supplemented by also capturing the near-infra-red (NIR) spectrum thus creating a four-channel multispectral systems for sorting applications [4, 13, 14, 19]. In addition to these two-dimensional (2D) multispectral systems, a tree-dimensional (3D) acquisition captures geometric properties useful in automatic material separation.

Line-based or snapshot method are available for multispectral and 3D acquisition of a surface. Line-based systems can rely on rather simple lighting systems, can be coupled to conveyor belts as in-line systems, and their image geometry only requires a correction perpendicular to the feed direction. Area-based systems require a correction of the perspective image, need a homogeneous illumination over a large area, and require overlapping images to capture all important information. Thus, area-based systems require an increased effort in post-processing compared to line-based systems. When combining 2D and 3D capturing to monitor refuse on a conveyor belt, it is desired to combine similar recording methods. In the case of line-based recording, this motivates the combination of 3D light section methods with multi-spectral line camera systems. For area-based recording, 2D multi-spectral cameras are preferably combined with hypercube stereo 3D image recording to create the full image.

The resulting images of the refuse on the conveyor belt are the input for image recognition software identifying predefined refuse categories on a pixel-wise basis in the images. Building on the pixel-wise segmentation, the image is split up into specific regions for which several properties can be extracted like refuse category distribution, particle size, or average region height. Traditional image processing techniques based on colour and gradient features are typically not able to handle the large appearance and shape variations occurring in mixed refuse. Novel machine learning techniques based on convolutional neural networks (CNNs) [10] are a proven way to overcome these issues. Such CNNs have shown great performance on a variety of tasks including image classification [9], object localisation [6] and semantic segmentation [11]. For this project state-of-the-art CNN architectures for semantic segmentation, like DeepLabv3+ [2], are investigated.

The results of the image recognition are an important aspects in the optimisation and management of the refuse sorting process. Many approaches designed for digitisation in manufacturing, often summarised under the term Industry 4.0, are finding their way into refuse sorting [5, 17]. On the one hand, Industry 4.0 approaches facilitate the automation of tasks that are stressful or dangerous for human workers. On the other hand, they also allow to create new solutions like predictive maintenance of sorting machinery, digital twins, and holistic optimisations of complete sorting facilities [17]. Fusion of data generated by image recognition with other sensors, e. g., image recognition with acceleration sensors, is the basis of many new solutions in either of the two cases. While the fusion of image data with time series data was pioneered in welding application, it now finds its way into other industries as well [8].

3 SYSTEM DESIGN

This section describes the individual building blocks used in KI-Waste to determine the refuse composition and how image and time series data are combined for system optimisation and worker support applications.

3.1 Image Capturing

The high variety in substances and the different aspects of the application scenarios require a thorough investigation of possible image capturing systems that can provide high-quality images for subsequent processing steps. This also includes the assessment of challenging environmental conditions like dust, dirt, lighting influences, ambient temperature, vibrations, and energy supply issues. Hardware solutions are to be designed to overcome said challenges but still allow for different possible digital sensor positions along the conveyor belt. One particular aspect is the test and evaluation of the lighting concepts, including the position of the light source, alignments with conveyor belts and sensor systems, and the required lighting wavelengths. A reliable hardware setup with good lighting is the prerequisite to capture high-quality, 2D, four-channel multispectral images that can be aligned and combined with the information from the geometric acquisition systems delivering a

3D outline. The combined and aligned 2D multispectral and 3D registered image data is the input for subsequent image processing recognising individual substances and estimating the size of separated pieces in the images.

KI-Waste investigates both line-scan and area-based capturing systems. When using area-based systems a multi-spectral snapshot camera is combined with area-based stereo cameras to derive the 3D surface model. The line-scan approach combines a line-scan-based multispectral system with a light-sectioning method that uses laser-line projection to determine surface profiles. The continuous combination of these contours establishes a complete 3D scan of the surface. Furthermore, multispectral imaging is a prerequisite to capture the chemical properties of the various pieces of refuse. This can range from four channels, where three channels capture the RGB and one captures the NIR spectrum, up to 25 channels for a more detailed spectral resolution.

The alignment of all channels in the multispectral image with each other and also with the 3D outline is very important. The hardware setup is designed so that all capturing devices cover the same acquisition area. Nevertheless, it is not possible to get a perfect correspondence between the different imaging modalities, since the hardware differs in sensor sizes and optics. Therefore, it is required to establish calibration methods registering the captured image data to each other thus providing the required alignment. Finally, all image modalities are transformed into one common coordinate system by geometric mapping, ensuring that each pixel has a direct correspondence between geometric and spectral information.

3.2 Image Classification

To extract refuse properties like category distribution, particle size, or average region height from the conveyor belt images, each image is segmented pixel-wise into the predefined refuse categories. This pixel-wise segmentation is also called semantic segmentation, as every pixel is assigned a semantic meaning in form of a specific refuse category. The task of semantic segmentation is not trivial and can be best solved by state-of-the-art fully-convolutional CNNs like DeepLabv3+ [2] and similar variants designed as deep architectures with a huge number of trainable parameters. To train these networks successfully, the parameters need to be trained with hundreds or thousands of representative ground truth images, where each pixel is correctly annotated with the underlying category.

Unfortunately, manually obtaining pixel-wise ground truth segmentations is a difficult and time-consuming task, while the amount of annotated training data correlates with the performance level of the final CNN model. To reduce the manual labelling effort, the possibility of using mono-material refuse containing only a single refuse category, is investigated. After obtaining mono-material refuse of predefined categories, the mono-material refuse is shredded and images of the shredded refuse on the conveyor belt are recorded. These images of shredded refuse should be as close as possible to the images in the sorting facility. As the refuse categories of all mono-material images are known beforehand, they can be used to pretrain the segmentation networks without the tedious manual annotation task. Additionally, mono-material refuse of different categories can be mixed in predefined ratios to create refuse of mixed materials, where the proportions of individual refuse categories are known and can be used as labels. CNNs pretrained with such mono- and mixed-material images are then used for obtaining initial segmentations, which are further refined manually and used for training the final segmentation networks that operate on mixes-material refuse.

The output of the semantic segmentation networks is then used for further analysis and refuse processing parameters adjustment. For this, several properties of the visible refuse can be calculated when combining the semantic segmentation output with the 3D surface information like refuse category distribution, particle size, and the height of specific regions of the image. Since the full pixel-wise semantic information is available, the properties can either be calculated for the whole image, or for smaller regions of interest to allow a more fine-grained analysis. The extracted information is shared over a predefined interface for the subsequent time series analysis.

3.3 Combined Data Analysis and Services

The data of the image classification is combined with time series data from sensors and parameter settings of the sorting machinery. Hence, a complete digital representation of the sorting process is generated, creating the basis for a joint analysis of image recognition and time series data. Several challenges have to be overcome to successfully generate the complete digital representation of the sorting process in the KI-Waste project.

The first challenge is that several parameters of the sorting process are not digitally recorded yet. Since the sorting process is currently not continuously optimised, there was no need to do so. Hence, additional sensors are required capturing the parameters previously kept constant but which are now subject of adjustments and optimisations. The second challenge is the interface specification towards the machinery and image recognition. Considering the interfaces towards the machinery, existing interface like field busses can be used. Since these interfaces were primarily designed and used for diagnostic purposes in the past, extensions or upgrades are required to support continuous data delivery. The interface to the image recognition is entirely new. It has to be integrated well with the image recognition and the joint data analysis and needs to be extendable for future applications. The third challenge concerns the level of detail in the data delivered by the machinery and the image recognition. The level of detail is specified by the sampling rates, the number captured values and parameters, and the granularity of each value and parameter. A fitting compromise of the level of detail has to be found for all data sources.

The solutions of these challenges pave the way for data analyses and services developed in the KI-Waste project. The analysis in its simplest form consists of key performance indicators presented to workers via dashboards. The next stage is the creation of process knowledge describing the coherences between refuse composition, machine setting and sorting quality. The results of these analyses are developed into worker support services indicating critical trends. The subsequent step is the continuous optimisation of the sorting plant based on the collected data. Current sorting facilities are set up for an average refuse composition but are not continuously optimised to seasonal changes. With the availability of data describing the refuse streams and the operating conditions, the sorting quality can be continuously adjusted over the year. Workers receive suggestions for optimisations and are thus supported in their decisions about parameter adaptations.

Tracking the composition of the input refuse and the sorted output fractions is another important aspect. The sorting facility is located between the refuse collectors and the recycling companies utilising the shredded and sorted fractions. The data analysis can validate if the refuse supplier fulfils pre-sorting requirements. Similarly, the sorting facility can prove the fulfilment of required sorting quality to the recycling companies. Furthermore, if the recycling companies receive descriptions about contaminations in the fractions, they are able to relax their contamination limits since they can adapt their recycling processes based on said descriptions.

4 CONCLUSION & OUTLOOK

KI-Waste researches the applications of digitisation and data analytics in refuse sorting facilities. KI-Waste uses a combination of image recognition and time series analysis to create a holistic view of the sorting process. While the image recognition is focused on detecting the composition of refuse streams, the time series analysis is targeted at machine parameters and sensor values. The combined view enables novel analyses and services supporting workers in sorting facilities, starting at simple monitoring solutions, including the identification of coherences, and concluding in the continuous optimisation of the sorting facility.

The KI-Waste project is currently in its first phase focusing on hardware design, interface definition, and data collections. The current collection of high-quality time series data and training data for the image classification is cumbersome and cost intensive, but an absolute necessity. This data collection is the basis for all future work in the project including improvements of the camera and lighting setup, training of image recognition models, domain-specific adaption and improvements of the image recognition models, validation of the image recognition results, combination of time series and image recognition data, and all further analysis and optimisations.

Future research and product development can build on KI-Waste's recommendations for image capturing hardware setups, image recognition models, guidelines for the required level of details in the data, and adaptable interface specifications. The possibilities of the combined data analysis reach far beyond the aspects researched in KI-Waste. The potential of predictive models derived from the combined data analysis is one example. Such models could be used for predicting maintenance needs and to forecast future sorting performance for a given refuse composition.

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