ADVANCED DATASET ACQUISITION FOR IMPROVED CONSTRUCTION AND DEMOLITION WASTE CLASSIFICATION USING MACHINE LEARNING

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Abstract

Efficient sorting and recycling of construction and demolition waste (CDW) are vital to sustainable development and a circular economy in the construction industry. Building on our previous study that achieved up to 92.3% accuracy using RGB camera data, we propose an improved data set acquisition and feature extraction approach to improving classification performance. We introduce a customized measurement line with industrial RGB cameras, force transducers for volume and mass estimation, and acoustic transducers for ultrasound frequencies. By integrating these additional data sources and exploring various feature extraction techniques, such as shape indices, texture entropy, and mean intensity gradients, our approach aims to enrich the set of features for machine learning algorithms and increase classification accuracy. This research addresses the challenge of improper sorting in CDW recycling, which limits the value of recycled aggregates in high-quality applications.

1. Introduction

Construction and demolition waste (CDW, Figure 1) constitutes a significant proportion of the total waste generated worldwide. CDW is a complex mixture of different materials, some of which can be recycled, and it is important to improve the efficiency and effectiveness of CDW sorting and recycling [1]. Traditional methods of sorting CDW are time-consuming, labor-intensive, and can be potentially hazardous for workers, particularly when dealing with contaminated materials. Automating the sorting process using machine learning techniques provides a promising avenue for improving both safety and efficiency.

In recent years, machine-learning algorithms have been successfully employed for object recognition tasks, demonstrating high accuracy and reliability. With the rise of deep learning, especially convolutional neural networks, applications for image classification and object detection have expanded rapidly. There are several studies employing these techniques in the context of CDW classification, yielding promising results [2, 3].

Figure 1: Mixed CDW being landfilled.

However, one of the limitations of these approaches is that they primarily rely on visual data captured by RGB cameras. Despite their capability of recognizing and classifying different waste materials, these models face challenges when dealing with materials that are visually similar or when fragments are covered with dust or other residues. This issue highlights the need for more comprehensive data acquisition techniques to enhance the performance of machine-learning models in CDW classification.

To overcome these limitations, we put forward a specialized measurement line that synergizes multiple sensors, namely, an RGB camera, an acoustic sensor, and a weight-measuring device, integrated with a conveyor belt system for efficient CDW transportation. This setup aspires to generate a more comprehensive dataset for machine-learning models, encompassing visual, acoustic, and weight attributes of CDW fragments. The overarching goal is to devise a robust, high-accuracy classification system capable of differentiating between various CDW types, thereby streamlining the recycling and reusing processes of CDW.

This paper presents the development of this comprehensive measurement line, demonstrating its potential for improving CDW sorting and recycling.

2. Development of the Multimodal Data Acquisition System

The central component of our system is a conveyor belt mechanism, selected for its efficiency in transporting a steady stream of CDW fragments (Figure 2). The conveyor belt ensures a consistent presentation of the material to the sensors, maintaining a regular distance and orientation, which is crucial for obtaining reliable and reproducible data. Furthermore, the speed of the conveyor can be adjusted to match the requirements of the data acquisition process.

Above the conveyor belt, an RGB camera is placed to capture high-resolution images of the CDW fragments. The frame is equipped with an adjustable light source to control illumination conditions, ensuring consistent lighting across different imaging sessions.

Beyond visual data (Figure 3), our system integrates an acoustic sensor and a weight-measuring device to expand the spectrum of collected data. The weight-measuring device operates based on the force exerted onto the rollers that guide the conveyor belt, providing insightful data about the weight characteristics of different CDW fragments.

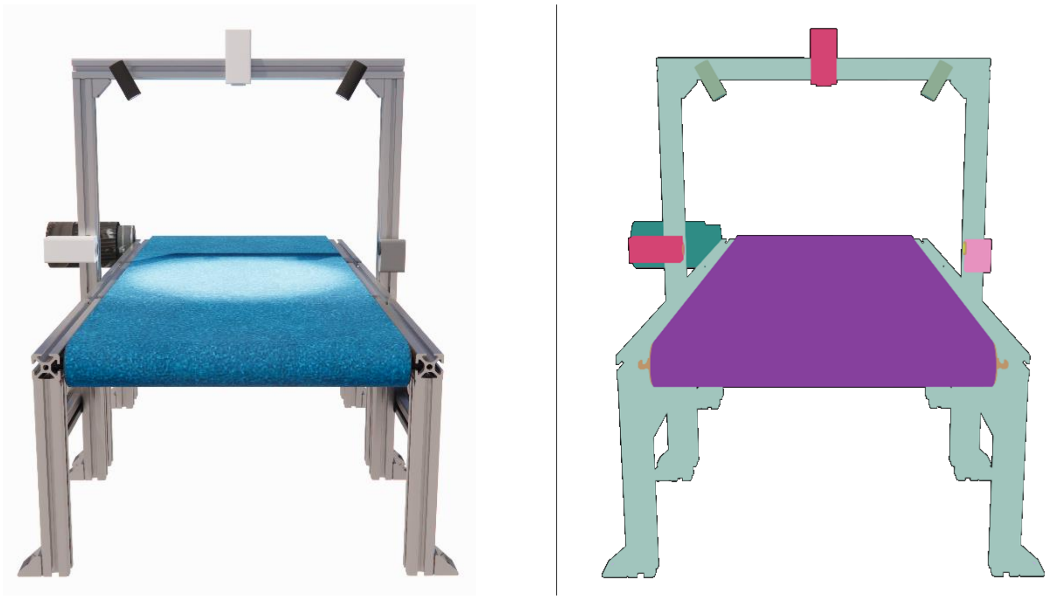

Figure 2: Prototype of the developed multimodal acquisition system; the colored components (right) represent: (i) a frame (light turquoise), (ii) a motor (teal), (iii) a conveyor belt (purple), (iv) cameras (red), (v) acoustic unit (pink), and (vi) lights (green); the computational unit and weight measuring transducers are not visible in these images.

The classification is based on the detection of ultrasonic waves reflected by the surface of the material under the test (Figure 4). HC-SR04 ultrasonic sensors were employed for the measurements, with the transducers positioned to maximize the radiation characteristics towards the target sample. These sensors are operated using an Arduino UNO microcontroller connected to a PC. Additionally, a 1/8" Brüel & Kjær measurement microphone is affixed to the mount to capture the signal reflected from the sample's surface. The obtained signal is further processed using a Brüel & Kjær Nexus measurement amplifier, with a conversion setting of 100 mV/Pa. Subsequently, the amplified signal is displayed on a Rigol MSO5074 digital oscilloscope.

The measured signals exhibit a short, narrowband signal at approximately 40 kHz. The dataset comprises 8 sets of 20 measurement instances. Initially, the signals were normalized by subtracting their mean value. Although this normalization procedure eliminates potential information regarding the acoustic absorption of the material, it is deemed acceptable given the intended robustness of the classification method under uncalibrated field conditions. Notably, all signals demonstrate a prominent amplitude peak followed by a smaller peak, often preceded by minor activity. To facilitate a more comprehensive analysis, two-time windows were selected.

Figure 5 illustrates the first (green) window, which encompasses the period preceding the large peak to ensure the inclusion of the smaller peak whenever present. The second (red) window is a narrowed-down interval surrounding the two larger peaks. Examining the peak ratio within the second window proved instrumental in segregating the data into three clusters, with one cluster exclusively containing one specific material. Furthermore, the variance observed in the first window facilitated the division of one of the remaining clusters into two distinct materials, while the other cluster was split into two as well. The outcome of this analysis is presented in Figure 6.

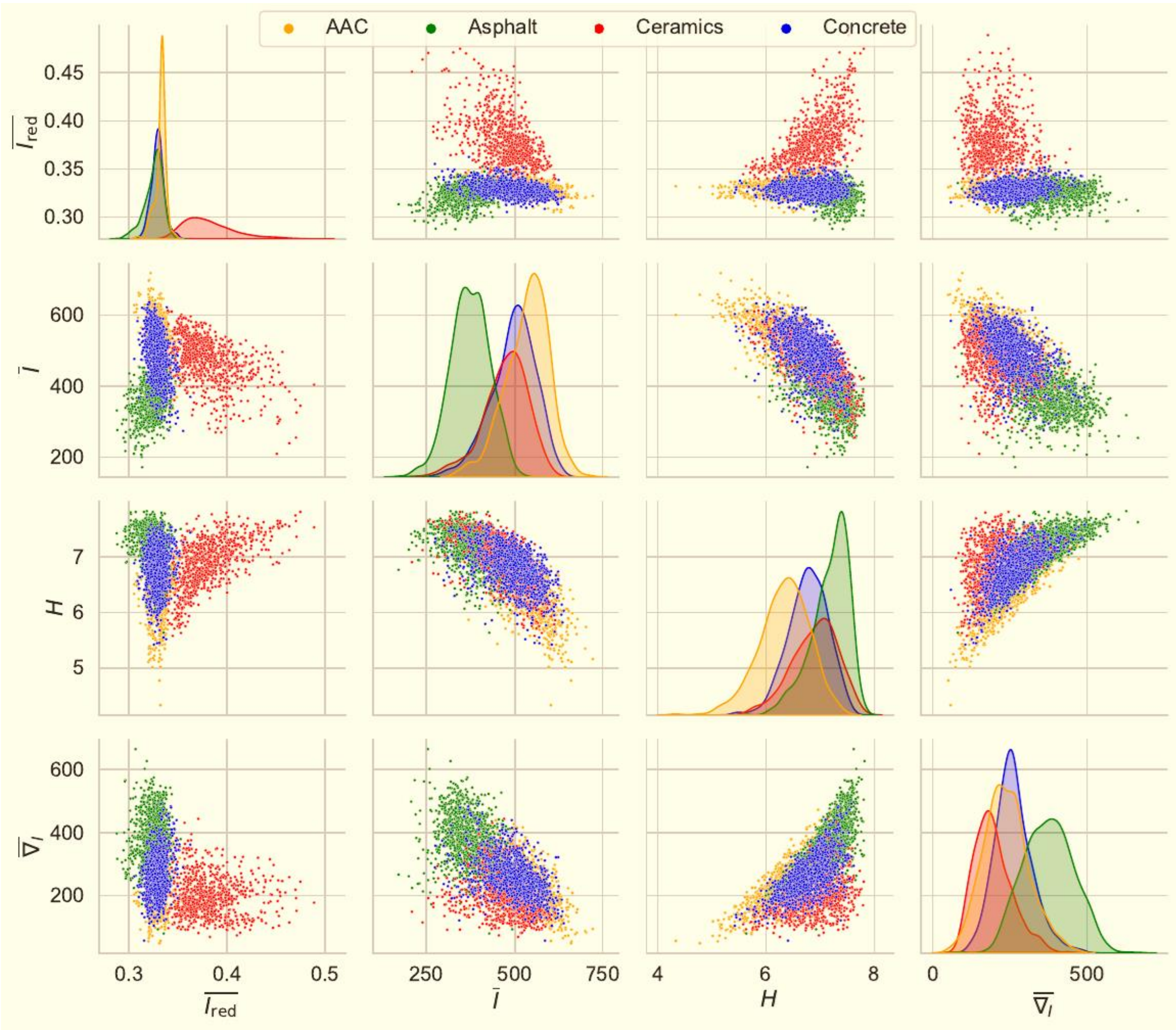

Figure 3: Correlation of features extracted from RGB images [4].

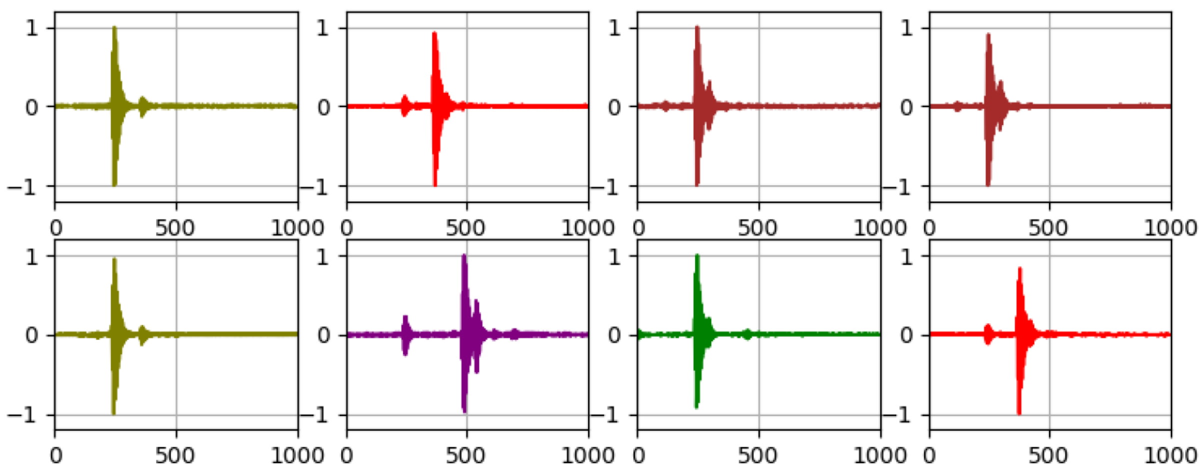

Figure 4: Variability of reflected signals measured for different materials.

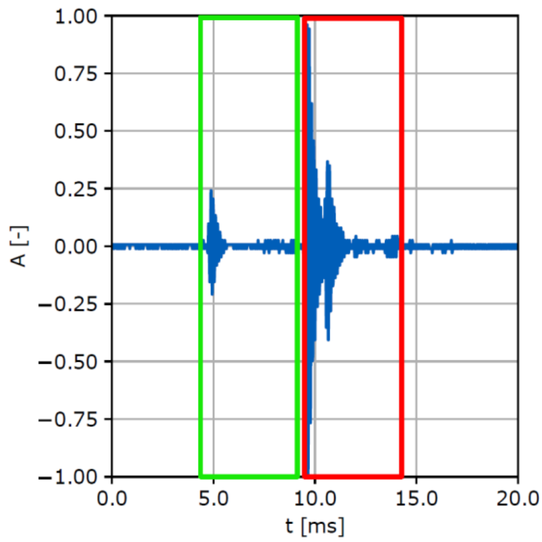

Figure 5: Windows to extract features from the retrieved ultrasound signal.

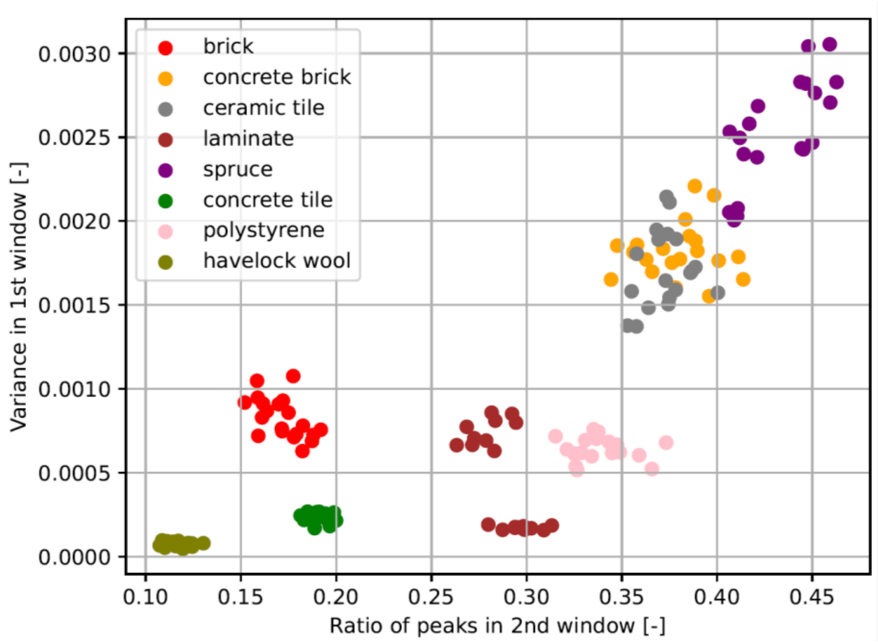

Figure 6: Clustering of materials in the space of extracted features from the measurements of reflected ultrasound signal.

3. Fusion of Data from Different Sensors

Effective use of multimodal data in a classification task requires not just the collection of data from different sensors, but also the strategic fusion of these data. The process of data fusion combines the information from each sensor, exploiting the unique strengths of each data type to improve the overall classification performance. In the context of CDW classification, this means integrating the information derived from RGB images and acoustic sensor measurements to better differentiate between different types of CDW fragments.

The first step in this process is the independent feature extraction from each sensor's data. For the visual data, we continue to use the methodology described in our previous work [4], which includes the extraction of various textural features from high-resolution images. Meanwhile, for the acoustic data, we apply standard signal processing techniques to extract spectral and temporal features, such as presented in Section 2.

Once the feature sets from all sensors have been extracted, the next step is their fusion. There exist several strategies for data fusion, commonly categorized into three levels: early (or data level) fusion, intermediate (or feature level) fusion, and late (or decision level) fusion.

In early fusion, the raw data from each sensor is combined before any processing or feature extraction takes place. However, due to the disparate nature of visual and acoustic data, early fusion is not feasible in our case.

In intermediate fusion, the feature sets from each sensor are combined into a single, high-dimensional feature vector, which is then fed into the classification model. This approach allows the classifier to make decisions based on all available information, but it also increases the dimensionality of the input data, which may lead to challenges associated with the so-called "curse of dimensionality."

Lastly, in late fusion, each sensor's feature set is independently fed into separate classifiers, and the final decision is made based on the combination of these separate decisions. This approach exploits the strength of each sensor in recognizing certain types of CDW fragments but relies heavily on a robust strategy for decision-making.

In this study, we opt for the intermediate fusion approach, mainly due to its capability to leverage the complementary nature of visual and acoustic features. The fused high-dimensional feature vector will then be fed to machine learning classifiers, including gradient-boosting decision trees (GB) and multi-layer perceptron (MLP), which have demonstrated promising results in our previous work.

4. Training Machine Learning Models for CDW Classification

The first step in the training process is to split the entire dataset into two subsets: a training set and a validation set. The training set is used for teaching the model, while the validation set is utilized for testing the model's accuracy on unseen data and tuning the hyperparameters. The standard practice is to use around 70-80% of the dataset for training, and the remaining 20-30% for validation.

The training process involves adjusting the model's parameters so that the model's predictions on the training data are as accurate as possible. This is done by defining a loss function that quantifies the discrepancy between the model's predictions and the actual labels. The model's parameters are then iteratively updated using optimization algorithms, such as gradient descent, in a way that minimizes this loss.

For both GB and MLP models, the training process involves several rounds of iterative learning. In the case of GB, a series of weak learners (decision trees) are trained, where each successive learner tries to correct the mistakes of the previous one. For MLP, a different approach is used, where the model learns to map the input (features) to the output (labels) using several layers of artificial neurons (or perceptrons), and the weights of these neurons are adjusted during the training process.

Once the training is complete, the model's performance is evaluated on the validation set. This step is crucial to ensure the model's ability to generalize well to unseen data and avoid overfitting, a scenario where the model performs well on the training data but poorly on new, unseen data.

Finally, once the models are well-trained and have demonstrated satisfactory performance on the validation set, they can be deployed for the real-time classification of CDW fragments in the sorting and recycling plants.

5. Transition to Industrial-Scale CDW Sorting

An industrial-scale sorting line would first and foremost require the development of a robust conveyor system able to accommodate high volumes of CDW. The system described in our study, while effective for research-scale analysis, would need to be significantly upscaled in terms of both size and speed. Notably, this would involve careful design considerations to maintain the precision of data capture while increasing the throughput of the system.

The sensor network we have developed, comprised of acoustic, weight, and RGB camera sensors, could also be effectively scaled to meet the demands of an industrial environment. Large-scale applications would require a comprehensive setup of sensors at multiple points along the conveyor line to ensure comprehensive data capture for each CDW fragment. This would involve additional hardware and installation requirements but could potentially be offset by significant increases in sorting efficiency and recycling rates.

Training machine learning models for industrial-scale applications would entail processing and analyzing substantially larger volumes of data. This might require more powerful computational resources and potentially the application of distributed computing or cloud-based machine learning services. However, the benefits of this approach are significant, with the potential for the models to continuously improve over time as they process more data, increasing the efficiency and accuracy of CDW sorting.

The models would also need to be made robust against variances in CDW types, lighting conditions, sensor calibration, and other factors that might be more variable in an industrial setting compared to a controlled research environment. This could be achieved by continuously updating the training datasets with new data from the industrial sorting line, effectively enabling the models to learn and adapt to changing conditions.

Importantly, while our research provides a proof-of-concept for a sensor-fused, machine-learning-based approach to CDW sorting, the transition to the industrial-scale application would require significant collaboration with industry partners, government agencies, and other stakeholders. The practicalities of implementing such a system, such as financial costs, regulatory requirements, and operational logistics, would all need to be carefully considered.

8. Conclusion

In this study, we have showcased a pioneering approach to construction and demolition waste (CDW) sorting and recognition using a fusion of multiple sensor data and machine-learning models. Our work underscores the significant potential of integrating acoustic, weight, and RGB imaging data to enhance the classification accuracy of CDW fragments, overcoming the limitations inherent in relying on visual data alone.

The prospect of applying these methodologies on an industrial scale presents exciting possibilities for the field of waste management and recycling. While there are practical considerations for transitioning our research-scale system to an industrial context, our study offers a roadmap for implementing a sophisticated, sensor-fused, machine-learning-based CDW sorting line. This could revolutionize the CDW recycling industry, enhancing efficiency, and increasing recycling rates, thereby contributing to a more sustainable construction industry.

However, it is crucial to note that transitioning to such a system will require significant collaboration among industry partners, government agencies, and other stakeholders. Further research and development will also be needed to fine-tune the models and adapt them to the variable conditions of an industrial setting.

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